Modeling Demand for Medicare Part D Plans

by

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”Read and your Lord is Most Honorable. Who taught (to write) with the pen. Taught man what he knew not.”

— The Holy Quran: 96,3-5.

To my parents, Rihab, and the kids

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Chapter 1
Introduction

The Medicare Modernization Act (MMA) of 2003 established a new program, known as Medicare Part D, to provide Medicare beneficiaries with insurance coverage for prescription drugs. The implementation of Part D started on January 1st, 2006. Prior to Part D, up to 40% of Medicare beneficiaries lacked any insurance coverage for their expenditures on prescription drugs (Congressional Budget Office (2002)). The majority of those with coverage faced significant out-of-pocket expenditures. For instance, Medigap Plan J, which is the best individual drug coverage for seniors, provides drug coverage up to a cap of $3000. More generous coverage was available through employer retiree drug benefits, which only 25% of seniors had (McAdams and Schwarz (2007)). In 2003, 61.6 % of Medicare beneficiaries had annual prescribed drug expenses between $1 and $2,083, while 20.5 % had drug expenses between $2,084 and $4,723, and 8.4 % spent more than $4,724 on their medications (Stagnitti (2006)).

The situation changed significantly after the implementation of Medicare Part D. By June of 2009, more than 60% of Medicare beneficiaries obtained prescription drug coverage through a Part D plan in their region, raising the percentage of beneficiaries with drug coverage to more than 90% (Hargrave et al. (2009a)). Obtaining drug coverage resulted in significant reductions in out-of-pocket spending along with increased utilization of prescription drugs by seniors (Schneeweiss et al. (2009), Ketcham et al. (2010)). In addition, this significant expansion in coverage

was attained with costs lower than the initial government projections (Duggan et al. (2008)).

The success of this major public benefit program was accomplished through a unique design. The program relies substantially on market mechanisms to deliver the benefit. Unlike coverage of the other Medicare benefits, Part D coverage is provided entirely through private plans. Part D added a drug coverage component to Medicare Advantage plans to form Medicare Advantage Part D plans (MAPD). Medicare Advantage plans are private managed care plans available to Medicare beneficiaries as an alternative to traditional Fee-for-Service (FFS) Medicare. In addition to supplementing Medicare Advantage plans, Part D involves the creation of unique stand-alone drug insurance plans, called Part D Plans (PDPs). The program provides heavy subsidies to participating plans to protect them against such market imperfections as adverse selection and moral hazard. The essential philosophy behind this choice of design is that private markets, with enough government subsidy, could provide, through competition, adequate coverage at low prices. The evidence so far indicates that this subsidy-competition combination works, at least in the short run (Duggan et al. (2008), Heiss et al. (2006),Goldman and Joyce (2009)).

The reliance on private markets to deliver this important benefit highlights the importance of understanding how beneficiaries value different aspects of this benefit. Such understanding is essential for policy makers and regulators in order to gauge the success of the market in providing beneficiaries with coverage options that maximize their welfare. This understanding will also be needed to predict the effects of any future changes in the design of the program, such as changes in the level of subsidy or the parameters of the standard benefit. Moreover, an accurate evaluation of consumer preferences allows for a better measurement of the overall cost-effectiveness of the program.

There are several studies in the literature that use structural modeling tech-

niques to evaluate preferences of Part D beneficiaries (Keating (2007), Lucarelli et al. (2008), Heiss et al. (2010), Heiss et al. (2008), Abaluck and Gruber (2009), Frakt and Pizer (2010)). These studies, however, focus on the first two years of Part D implementation. The market in this early stage is unlikely to have matured enough to support any conclusions about the behavior of participants in the long run. Beneficiaries are likely to have made significant mistakes early on as they were learning about the market and the complex benefit structure (Abaluck and Gruber (2009), Heiss et al. (2010), Ketcham et al. (2010)). Industry reports indicate that plans were experimenting with pricing strategies that are idiosyncratic and may not represent long run pricing behavior (Simon and Lucarelli (2006)). In addition, the enrollment period for 2006 extended to the middle of the year, instead of ending by the beginning of the year as for later years. Conclusions based on behavior in this environment could potentially misrepresent behavior in future years, when the market is more established and participants are more informed.

Moreover, the majority of studies in the literature use aggregate plan enrollment data that do not distinguish between low-income-subsidy (LIS) recipients and non-LIS enrollees. The design of Part D benefit for LIS beneficiaries is considerably different from the benefit for non-LIS enrollees. LIS beneficiaries do not pay premiums or deductibles, and have coverage in the doughnut hole. They also pay small copayments. Lastly, and most importantly for demand analysis purposes, the government facilitates their enrollments by automatically and randomly assigning them to Part D plans with premiums below a region-specific benchmark. Many beneficiaries remain in their assigned plans, although they are entitled to switch to a different plan if they prefer. This random assignment means that observable enrollment patterns for LIS beneficiaries do not purely represent their active choices, and, as such, do not reflect their underlying preferences. Therefore, the inclusion of these enrollment patterns in an overall analysis of demand by Medicare Part D

enrollees will result in estimates that do not reflect the preferences of the average enrollee.

In this study, I avoid these potential problems by modeling demand for stand-alone Part D plans in the latest year of the program (2009), and by using recently available data on plan-level LIS enrollment to estimate separate demand systems for LIS beneficiaries and non-LIS enrollees. In addition, I extend my analysis to examine the heterogeneity of preference parameters for non-LIS enrollees, and how that heterogeneity relates to the distribution of consumer characteristics. Lastly, I use the demand estimates for LIS beneficiaries together with estimates of parameter heterogeneity to evaluate welfare gains to LIS beneficiaries from an alternative assignment process that matches each beneficiary to the plan that best covers her medications.

Chapter 2
The Medicare Part D Program

2.1 Overview of the Medicare Part D Program

2.1.1 Benefit Design

The MMA specifies the types of plans and prescription drug benefits that could be offered to Medicare beneficiaries under Part D. The law specifies two types of private plans that could be offered by insurance companies and other plan sponsors. A stand-alone prescription drug plan (PDP) contracts with Medicare for the sole purpose of providing the drug benefit. On the other hand, a Medicare-Advantage plan provides comprehensive coverage of all services covered by Medicare including prescription drugs. CMS defined 34 drug PDP regions, excluding territories, and each plan has to be offered throughout at least one of the 34 regions. Although not required by law, each plan generally offers identical benefit packages, except for premiums and low-income subsidy qualification, in all the regions in which it is available. In all the years of the program, premiums vary substantially both within and across regions. Insurers and other plan sponsors can, and commonly do, offer several stand-alone Part D plans with different levels of benefits in a given area. The benefits provided by a plan should be at least equal in value to the *standard* benefit defined by MMA. The structure of the standard benefit is a follows: enrollees pay 100 percent of their costs until their spending for covered drugs reaches an initial deductible. Once the deductible is reached, the plan pays 75 percent of the cost and the enrollee pays the remaining 25 percent, until the combined spending reaches

the initial coverage limit (ICL). The enrollee enters what is called the *doughnut hole*, where she is responsible for 100 percent of the drug cost until total drug spending reaches catastrophic coverage limit (CCL). For spending above the CCL, the enrollee pays 5 percent of the cost and the plan pays the rest of the cost but is reimbursed 80 percent of the cost in reinsurance payments from CMS. The deductible, ICL, and CCL are readjusted each year using the annual percentage increase in average per capita aggregate expenditures for covered Part D drugs (table 2.1). Figure (2.1) shows the structure of the defined standard benefit in 2009. The deductible for the standard benefit was $295, and the ICL and CCL were $2,700 and $6,154, respectively (Kaiser Family Foundation (2009)). This amounts to $3,400 of coverage gap, and a total of $4,350 in true out-of-pocket costs before the beneficiary reaches the catastrophic coverage zone. Catastrophic coverage limit is defined in terms of the true out-of-pocket cost, which are the beneficiaries' out-of-pocket liabilities, excluding those paid by third parties, such as supplementary employer coverage.

Sponsors may offer two other types of *basic* coverage (table 2.2): *actuarially equivalent coverage* and *basic alternative coverage*. Plans offering these basic coverage types can vary their benefit design, for instance by reducing or eliminating deductibles and charging fixed copayment as opposed to the 25 percent coinsurance of the standard benefit, so long as the share of total spending covered by the plan is the same as would be paid under the standard benefit. The fourth type of benefit is called *enhanced alternative benefit* and it has an overall actuarial value greater than the standard benefit. Plans offering enhanced coverage have reduced cost-sharing and some coverage in the doughnut hole. MMA limits subsidies to the portion of a plan's benefit that is actuarially equivalent to the standard benefit described above, which leaves beneficiary completely liable for the cost of the enhanced portion of any plan's benefit.

A certain group of medications are specifically excluded from Medicare Part D

plans and they include certain anti-anxiety and anti-seizure drugs, such as barbiturates and benzodiazepines, most prescription vitamins and minerals, and prescription drugs used for anorexia, weight loss or weight gain, fertility, cosmetic purposes or hair growth, and relief of symptoms of cold. Plans could include excluded medications in their formularies as part of their supplemental benefit that is not subsidized by Part D.

In March of 2010, Congressed passed comprehensive healthcare reform legislation that changed the design of Part D benefit (The Henry Kaiser Family Foundation (2010)). The law phases in coverage for the doughnut hole over the period 2010-2020. In 2010, seniors reaching the gap will be issued a non-taxable $250 rebate. In the year 2011, beneficiaries will receive 50% discount from pharmaceutical companies on their brand-name medications in the doughnut hole. Coverage for generic drugs is phased in starting 2010, and for brand-name drugs starting 2013. By 2020, seniors will be covered for 75% of their prescription drug expenditures in the gap. In addition, the law reduces the catastrophic coverage limit starting 2014.

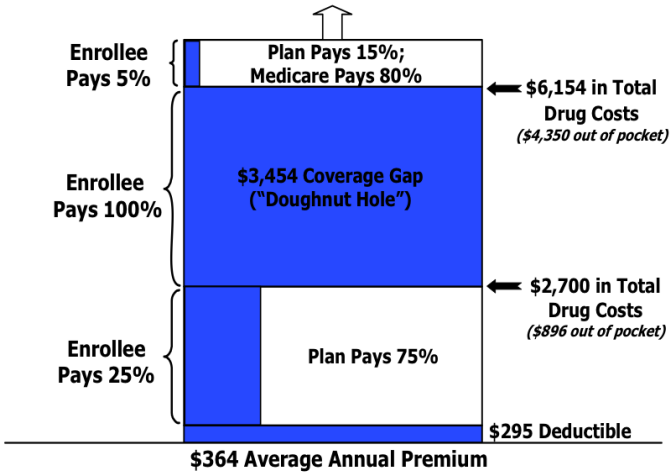

Figure 2.1: Defined Standard Benefit, 2009. Source: The Henry Keiser Family Foundation.

Table 2.1: Part D Parameters for the Defined Standard Benefit: 2006-2009

Parameter	**2006**	**2007**	**2008**	**2009**
Deductible ($)	250	265	275	295
ICL ($)	2,250	2,400	2,510	2,700
Out-of-Pocket CT ($)	3,600	3,850	4,050	4,350
Total Cost at CT ($)	5,100	5,451.25	5,726.25	6,153.75

[a] ICL= Initial Coverage Limit. CT = Catastrophic Threshold

Table 2.2: Other Part D Benefit Types.

Benefit Type	**Deductible**	**Cost Sharing**	**Actuarial Value**
Actuarially Equivalent	$295	CI or CP	= Defined Standard
Basic Alternative	$\leq$ $295	CI or CP	= Defined Standard
Extended Alternative	$\leq$ $295	CI or CP	> Defined Standard

[a] CI=Coinsurance. CP=Copay.

2.1.2 Subsidies to Insurers

The market for stand-alone prescription drug insurance is prone to significant levels of adverse selection and moral hazard. Individual drug spending is highly predictable from year to year, which means that plans charging unsubsidized premiums will only attract those who expect to have drug expenditures that are more than the charged premium (Pauly and Zeng (2004)). The history of private supplementary insurance policies (Medigap) that provide prescription drug coverage is a good illustration of this point. Medigap plans that provided drug coverage charged significantly higher premiums, principally as a result of higher costs due to adverse selection (Congressional Budget Office (2002)). The threat of adverse selection is amplified by the potential for moral hazard and by the effect of competition. Insurance plans in this context compete to attract healthy enrollees by offering less generous coverage at a reduced premium. This could potentially lead to the unraveling of the market as insurers race to the bottom and an increasing portion of beneficiaries is denied insurance that is welfare enhancing(Rothschild and Stiglitz (1976)).

To counteract these forces and ensure a viable market, Part D provides substantial subsidies to participating insurers. The aim of the subsidy is to lower premiums to an extent that makes enrollment cost-beneficial to a substantial portion of beneficiaries, including those with small expected drug expenditures. The subsidy to plans has several components. The first, called *direct subsidy*, is a prospective component that is paid as a capitation amount on behalf of each enrollee. The second component is a *reinsurance subsidy* to reimburse plans for 80 percent of an enrollee's drug expenditures beyond the catastrophic threshold. MMA specifies that the two subsidies together should cover 74.5 percent of average expected costs of all enrollees in the basic Part D benefit. The Congressional Budget Office (CBO) estimates that catastrophic coverage accounts for 27% of the average total cost of the basic benefit, which leaves 47.5 percent of the cost to be paid to plans prospectively as direct sub-

sidies (Congressional Budget Office (2004)). The direct subsidy in turn is adjusted to reflect differences in risk among enrollees in different plans. This risk adjustment provides an important additional protection against adverse selection by limiting plans' incentives to select healthy enrollees (McAdams and Schwarz (2007), Robst et al. (2007), Heiss et al. (2010), Congressional Budget Office (2004)). In addition to the direct and reinsurance subsidies, Part D offers plans protection against excess business risk that could result from participating in a newly developed market. To that effect, MMA has established risk corridors whereby the government shares with insurers a percentage of their overall losses or profits if they exceed a certain level specified by the law.

2.1.3 Low Income Subsidy

Part D provides a different kind of subsidy to beneficiaries with limited income, called *low income subsidy* (LIS). There are two groups of beneficiaries that qualify for this subsidy(The Henry J. Kaiser Family Foundation (2009)). The first group is entitled to a full subsidy, and includes beneficiaries with income below 135% of the poverty level and with resources less than $8,100 for an individual or $12,910 for a couple [1]. Included in this group are those eligible for full Medicaid coverage, regardless of their income or assets. Full subsidy beneficiaries pay no premium or deductible if they join *benchmark plans* in their region, which are basic benefit plans with premiums below a weighted average premium in the region. They are also covered in the doughnut hole and only pay reduced copayment for brand and generic drugs. The second group is entitled to a partial subsidy, and includes beneficiaries with income below 150% of the poverty level and with resources less than $12,510 for an individual and $25,010 for a couple. Partial subsidy recipients may pay part of their own premium and a deductible, depending on their income level, but also

[1] Asset limits are for the year 2010

have no coverage gap and pay smaller copayment.

Dual eligibles and those receiving SSI cash assistance are automatically deemed eligible for Part D low-income subsidy. Those enrolled in a Medicare Saving Program (MSP), which offers Medicaid assistance with premium and cost-sharing, are also automatically deemed eligible. However, automatically deemed beneficiaries could loose their eligibility for the coming year if their deemed status changes before the middle of the current year. Other low-income Medicare beneficiaries need to apply for the subsidy and meet the income and resource test. Social security benefits, veteran benefits, pensions, and annuities are all counted as income. Resources are defined as assets that are convertible to cash in 20 days or less. Those include stocks, bonds, and saving and retirement accounts, but principal homes, car, or life insurance policies are not counted. Applications are done through SSA or state Medicaid programs, and eligibility determinations are retained for the whole year. However, recipients have to reapply each year for the subsidy.

To ensure continuity of prescription drug coverage, CMS automatically and randomly assigns low-income subsidy recipients who do not sign up for a plan on their own to Part D plans with premiums below a region-specific benchmark. Beneficiaries can enroll in any qualified MAPD or PDP, but they are auto-assigned only to a qualified PDP. LIS beneficiaries, however, are allowed to switch plans throughout the year and not only during open enrollment, as is the case for other Part D enrollees. LIS recipients who choose to enroll in plans with premiums above the benchmark have to pay the portion of premium above the benchmark. As premiums change from year to year, some plans lose their LIS qualification and CMS automatically and randomly reassigns LIS beneficiaries in those plans to other plans in the region with premiums below the benchmark. Those LIS beneficiaries who signed up for a plan on their own, or switched plans after being assigned one, are not automatically reassigned when their plan looses LIS qualification. They are only notified that they

need to switch another LIS plan if they want to avoid paying any premium.

2.1.4 Plans' Biddings and Premiums

Each sponsor submits a bid to CMS reflecting its monthly charges during the coming year for providing each of its proposed plans to a typical Part D eligible. Plans estimate the average expected cost of their plan (benefits plus administrative cost), and then subtract expected federal reinsurance payments to come up with their bids for providing coverage for an enrollee with an average risk profile (Congressional Budget Office (2004)). Plans offering enhanced benefits must separately identify the portion of their bid attributable to the basic Part D benefit. CMS guidelines permit each organization to submit three different bids for plan offerings, as long as those bids represent meaningful variations and one of the options provides gap coverage (CMS (2007)).CMS computes a national average bid, using only the portion of bids attributable to the basic benefit and weighting the bids according to each plans share of the total Part D population. The average bid for 2007 was $80.43. CMS multiplies the national average bid by a specified percentage, determined each year, to compute the base beneficiary premium. For 2007, the percentage is about 34 percent, resulting in a base beneficiary premium of $27.35. This is the monthly amount beneficiaries would pay to enroll in a plan whose total bid amount was exactly equal to the average of $80.43. Enrollees joining higher-cost plans must pay $27.35 plus the difference between the plans bid and the national average bid. Those joining lower-cost plans pay less than $27.35 (Merlis (2007)). The difference between the average bid and beneficiary premium is the direct subsidy the CMS pays to plans. Therefore, the sum of expected reinsurance payment, the direct subsidy, and the beneficiary premium for each plan equals its total expected costs. To the extent that plans' actual costs differed from expectations, the difference could result in higher or lower federal reinsurance payments and could trigger transfers under

the risk corridor system (Boards of Trustees (2009)).

2.1.5 Cost Management Tools

MMA gives participating insurers significant latitude to use a variety of cost management tools in order to control cost and offer lower premiums to beneficiaries. These tools include the use of drug formularies that list medications covered by the plan and divide those medications into tiers of preference defined by the level of cost-sharing. They also include the requirement of prior authorizations and step therapy, and the use of quantity limits. The availability of such tools to plans allows them to control costs by limiting moral hazard, as well as by incentivising enrollees and their physicians to choose medications that are cost-effective. This ability to affect enrollees choice through formulary design in turn allows plans to negotiate discounted prices with drug manufacturers in exchange for a favorable placement of their drugs on the plan's formulary.

The use of cost management tools, however, is regulated by law. For instance, MMA requires plans to cover at least two drugs in each therapeutic class. In addition, CMS requires that all, or substantially all, of the drugs in the antidepressant, antipsychotic, anticonvulsant, anticancer, immunosuppressant, and HIV/AIDS categories must be covered by all formularies (Congressional Budget Office (2004)). The U.S. Pharmacopeia has developed a standard set of therapeutic classes that is pre-approved by CMS for plans' use, but plans could use their own classification subject to CMS approval. The purpose of such formulary requirements is to prevent the use by plans of formularies that discourage the enrollment of sick beneficiaries. Furthermore, enrollees have access to a multi-step process to appeal formulary listings and tier structure decisions that starts with petitioning the plan and, if the petition is denied, could go through successive stages of review by independent external review agencies, CMS, an administrative judge, and the federal courts.

2.2 The Medicare Part D Program from 2006 to 2009

2.2.1 Part D Enrollment

Prior to the implementation of Part D, up to 40 percent of Medicare beneficiaries lacked any insurance coverage for their expenditures on prescription drugs, and the majority of those with coverage faced significant out-of-pocket expenditures (Congressional Budget Office (2002), Safran et al. (2005)). In 2003, for instance, 61.6 percent of Medicare beneficiaries had annual out-of-pocket prescribed drug expenses between $1 and $2,083, while 20.5 percent had drug expenses between $2,084 and $4,723, and 8.4 percent spent more than $4,724 on their medications (Stagnitti (2006)). This led a 1999 National Economic Council study to conclude that the only meaningful prescription drug coverage for seniors is that provided through employer retiree drug benefits, which only 25 percent of seniors had (McAdams and Schwarz (2007)).

The situation changed remarkably after the implementation of the new Medicare drug benefit. Part D program has had significant enrollment success since its inception. By June 2009, more than 26 million, or 60%, of Medicare beneficiaries are enrolled in Medicare drug plans, including 17.5 million in stand-alone prescription drug plans, and 9 million in MA drug plans (Hargrave et al. (2009a)), bringing the percentage of beneficiaries with prescription drug coverage to more than 90 percent. Table (2.3) shows the levels of enrollment in the program in the years 2006 to 2009. Part D enrollment success is similar to that of Medicare Part B (Supplementary Medical Insurance), which is also a voluntary program, and has similar premium subsidies and late-enrollment penalties.

A large share of the beneficiaries with no drug coverage have low incomes. In 2007, 13-15% of beneficiaries with incomes below $30,000 had no source of drug coverage, compared to %10 of those with incomes of $40,000 or more (Cubanski

et al. (2009)). On the other hand, low income and minority beneficiaries are more likely to have their drug coverage through Part D plans, especially PDPs (Cubanski et al. (2009)). This is mostly due to the automatic enrollment of dual eligibles and other low-income subsidy recipients in Part D plans.

Beneficiaries with fair or poor health are also more likely to have their prescription drug coverage through Part D plans. Levy and Weir (2007), using data from the Health and Retirement Survey (HRS), report evidence of significant adverse selection into Part D. Kaiser Family Foundation researchers, using 2007 MCBS Access to Care module, report that 47% of beneficiaries in fair health, and 50% of beneficiaries in poor health were enrolled in a PDP, compared to 30% of beneficiaries in good or excellent health. In their analysis of their retirement perspective survey (RPS), Heiss and colleagues (2007) found that 75-80% of the healthy in their sample had coverage, which is a reasonably high percentage, albeit significantly lower than the 92% for the unhealthy group of respondents.

Table (2.4) shows enrollment trends for non-LIS beneficiaries by plan type. Enrollment in plans offering gap coverage increased significantly from 2006 to 2007, declining gradually after that. This pattern tracks the pattern of availability of such plans. On the other hand, enrollment in enhanced alternative plans increased consistently over the entire period. Such plans offer flexible cost sharing arrangements (low deductibles and tiered co-payments) in addition to a a benefit value that exceeds the actuarial value of the basic design established by MMA.

2.2.2 Market Structure, Premiums, and Plan Features

The structure of Part D market has changed significantly over the years (tables 2.5 and 2.6). The average number of Part DP plans offered in a region has increased significantly from 2006 to 2007, with only a modest decline in the period from 2007 to 2009. Premiums and deductibles have been rising consistently, whereas the

Table 2.3: Part D Enrollment 2006-2009 (In Millions)

	2006	**2007**	**2008**	**2009**
Part D Enrollment	20.4	24.2	25.7	26.9
Medicare Beneficiaries	43.4	44.3	45.2	45.9
Part D share (%)	47.00	54.63	56.86	58.61

Source: Board of Trustees Report, 2009

Excludes Retiree Drug Subsidy Enrollment

Table 2.4: Non-LIS Enrollment Patterns 2006-2009

Feature	**2006**	**2007**	**2008**	**2009**
Enhanced Alternative	32.0%	37.1%	40.0%	45.8%
Premium $>$ \$30	31.8%	34.5%	49.8%	77.0%
Gap	5.8%	14.1%	13.1%	11.8%

number of low income subsidy plans (LIS) has been declining. The proportion of plans offering coverage in the doughnut hole is higher in 2009 compared to 2006, but the nature of this gap coverage has changed overtime. In 2006, several plans provided coverage in the gap for all their formulary medications. Those include generic as well as brand name prescription drugs. However, by 2009, none of the PDPs offered gap coverage for all its formulary drugs. The majority of plans offering gap coverage limit that coverage to some generics, and to a lesser extent to many generics. This gradual disappearance of the most generous insurance plans from Part D market suggests the presence of significant levels of within-plan adverse selection. Such death spirals have been observed in other health insurance markets (Cutler and Reber (1998)), and were predicted for the market of stand-alone prescription drug insurance by Pauly and Zeng (2007). Generous plans contain an implicit tax

due to the delayed onset of catastrophic coverage. This tax and the absence of direct government subsidy for benefits beyond the basic level specified by law reinforce the effects of adverse selection into generous plans. The presence of significant levels of adverse selection could ultimately lead to a race to the bottom, where plans compete for enrollees with low expected costs by offering benefits that meet the minimum requirements, leaving consumers with limited coverage and little choice (Congressional Budget Office (2002), McAdams and Schwarz (2007)).

Despite the availability of a large number of plans in each region, enrollment in stand-alone Part D plans has been largely concentrated in a plans offered by a few national insurers. In 2006, ten organizations captured 72 percent of Part D enrollment, primarily in low-premium plans and those with name recognition (Cubanski and Neuman (2007)). The corresponding average regional Herfindahl-Hirschman Index (HHI) for stand-alone Part D contracts in 2006 is 3983, which falls in the highly concentrated range, as defined by the Department of Justice and the Federal Trade Commission (DOJ and FTC (2007)). This high level of market concentration persisted in subsequent years, albeit with a downward trend (table 2.5).

The number of low-incomes subsidy (LIS) plans available in the market has gone down significantly over the years 2007-2009. This is a very interesting phenomenon that requires further investigation. LIS plans have the advantage of being qualified to enroll dual eligibles and other LIS-recipients, most of whom are automatically and randomly enrolled in an LIS plan in their region. To qualify as an LIS plan, a plan needs to charge a price lower than the a benchmark determined by CMS on a region by region basis. The benchmark is a function of the bids submitted by the insurers operating in the region. LIS plans are in general less generous than non-LIS plans, and rely heavily on formulary design to control cost. Cost sharing is a limited tool for these plans since a significant proportion of their enrollees receive LIS subsidies that cover the majority of their cost sharing obligations. The remaining formulary

design tools are limiting the number of drugs listed and imposing access restrictions in the form of prior authorizations, step therapy requirements, and quantity limits. The majority of PDP sponsors use different formularies for LIS offerings and non-LIS offerings (55% in 2008, 78% in 2009, and 65% in 2010). LIS plans cover fewer brand drugs than non-LIS plans, are more likely to require prior authorizations for brand drugs.

The continuing reduction in the number of LIS plans is a sign that such formulary design tools were not effective in reducing costs enough for LIS plans to continue to charge a price lower than the benchmark. On the other hand, premiums for LIS plans have risen steadily (2.7). This could be a consequence of the reduction in the number of LIS plans available in the market. However, because of the bidding nature of price setting in this context, it could also be an indication of the enhanced ability of the most insurers to coordinate their bids.

Table (2.7) shows monthly premium by plan type over the period 2006 to 2009. Part D markets in any year show significant variation in monthly premiums within, as well as across, regions (Hargrave et al. (2009b)). This level of variation exists even within plans with of the same benefit type and with similar observed characteristics. Such variation is indicative of the presence and importance of plan characteristics that are not observable to the econometrician, which motivates the use of modeling techniques to account for unobserved plan heterogeneity. This variation in premiums is less pronounced for the years 2007-2009.

2.2.3 Enrollees' Experience

In addition to the high program enrollment, the majority of Part D enrollees are satisfied with the program. In their survey of retirees, Heiss and colleagues found that the majority of Part D enrollees agree that the program works well once enrollment is completed (Heiss et al. (2006)). Surveys by Kaiser Family Foundation find that

Table 2.5: Part D Plan Availability 2006-2009.

Feature	2006	2007	2008	2009
Total PDP Contracts	79	90	87	79
Total PDP Plans	1,446	1,908	1,877	1,739
Avg No. Insurers per Region	19	24	22	22
Avg No. Plans per Region	43	55	53	50
Avg Region HHI	3983	3835	2960	2199

[a] Author calculation using CMS Plan Source Files.

Table 2.6: Part D Plan Features 2006-2009.

Feature	2006	2007	2008	2009
Avg Premium	$37.40	$36.81	$40.02	$45.46
Avg Deductible	$92.83	$94.07	$105.04	$114.86
% No Deductible	58.2%	60.6%	58.6%	55.7%
% LIS Plans	29%	34%	27%	18%
% Gap Plans	12.9%	27.5%	29.1%	24.8%
% Defined Standard	9.24%	11.74%	11.91%	10.03
% Actuarially Equivalent	21.61%	13.45%	12.73%	19.05%
% Basic Alternative	26.59%	27.28%	24.64%	18.10%
% Enhanced Alternative	42.55%	47.53%	50.71%	52.82%

[a] Author calculation using CMS Plan Source Files.

Table 2.7: Average Premium by Plan Type and Year 2006-2009.

Plan Type	2006	2007	2008	2009
LIS	25.78	25.39	24.74	27.71
Basic no LIS	40.19	35.26	36.75	37.63
Enhanced no Gap	39.72	33.99	31.71	40.58
Gap	49.66	53.24	63.06	73.36

[a] Author calculation using CMS Plan Source Files.

levels of dissatisfaction with Part D have fallen from 55% at its inception to 34% at the end of 2006. The remaining areas of dissatisfaction are mainly the complexity of the program, formularies, the doughnut hole, and tedious appeal procedures (Kaiser Family Foundation (2006)).

The 2007 MCBS Access to Care module asked respondents a series of questions to rate their prescription drug coverage. Table (2.8) summarizes these ratings. The overwhelming majority of respondents with insurance covering prescription drugs report being satisfied with their coverage, including that obtained through PDPs and MAPDs. However, Part D satisfaction rates are a little lower than those of other sources of coverage, including private retiree health plans, federal retiree plans, and the VA. The other estimates in table (2.8) provide few reasons for the lower rate of satisfaction among Part D enrollees. Part D enrollees report a significantly higher incidence of changing medications due to plan formulary restrictions. This includes switching from brand name to generics, or switching to a different drug with similar therapeutic effects. The percentage of Part D enrollees who report that their drugs are not covered by their plan is about double that of beneficiaries with other sources of coverage. These findings are consistent with those of Levy and Weir (2007), who

report that HRS respondents with Part D coverage pay more out-of-pocket for a given number of medications compared to those with employer coverage. Similarly, Neuman (2007) report results from a national survey indicating that Part D enrollees had higher out-of-pocket spending and cost-related non-adherence than seniors with employer or VA coverage.

2.2.4 Government Spending

Table (2.9) shows per enrollee reimbursements to Part D private plans. Government spending on average has remained stable, around the $1,000, despite the overall trend in drug prices. This is most likely due to the ability of Part D plans to contain costs through negotiating lower drug prices with drug manufacturers and through the implementation of various utilization management techniques. LIS subsidy payments are similarly stable, albeit at a higher level of around $1,900. Risk sharing amounts represent payments to, or from, plans associated with the risk corridors arrangement established by MMA. CMS partially reinsures plans against excessive business risk by sharing losses, and profits, beyond a percentage point level that is predetermined for each year. Many Part D Plans in 2006 have obviously underestimated Part D benefit costs and submitted low bids that resulted in overall losses triggering risk corridor payments to plans of around $300 million. The situation has reversed in 2007 and 2008, with plans gaining profits that exceeded the risk corridor threshold.

Table 2.8: 2007 Beneficiaries' Prescription Drug Coverage Ratings

Variable	**PDP (%)**	**MAPD (%)**	**Other (%)**
	(CI)	(CI)	(CI)
Satisfied	92.0	95.1	96.2
	(91.1-92.9)	(94.1-96.2)	(95.5-96.9)
More Premium	37.6	25.5	30.0
	(35.9-39.2)	(28.2-31.8)	(23.3-27.8)
More Rx Cost	32.9	25.6	28.6
	(31.3-34.5)	(23.4-27.8)	(26.9-30.4)
Less Coverage	8.4	7.8	5.9
	(7.5-9.3)	(6.5-9.1)	(5.0-6.8)
Drugs not Covered	14.0	8.1	6.3
	(12.8-15.2)	(6.7-9.4)	(5.4-7.2)
Brand to Generic	27.0	25.6	26.0
	(25.4-28.5)	(23.4-27.8)	(24.3-27.6)
Switch Drug	9.2	8.1	4.5
	(8.2-10.2)	(6.7-9.5)	(3.7-5.3)
Any Rx Change	24.6	23.1	18.0
	(23.2-25.9)	(21.2-25.0)	(16.8-19.2)
Rx Cost More	19.2	15.3	15.1
	17.9-20.6	13.5-17.1	13.7-16.5

Author's calculation using MCBS Access to Care, 2007

CI's account for the complex survey design of MCBS

Table 2.9: Government Per-Enrollee Reimbursements to Part D Plans (current dollars)

	2006	2007	2008	2009
All Beneficiaries				
Direct Subsidy	867.23	746.52	680.01	700.66
Reinsurance	296.29	331.84	377.13	404.84
Total	1,163.52	1,078.36	1,057.14	1,105.5
Low-Icome				
Enrollment (millions)	8.3	9.2	9.7	10.2
LIS subsidy	1,817.05	1,819.63	1,878.57	1,949.85
Risk Sharing (billions)	0.3	-0.7	-1.3	0.9

Source: Board of Trustees Report, 2009

2009 numbers are intermediate estimates

Chapter 3
Literature Review

The literature on Medicare Part D is growing exponentially, especially with the increasing availability of data from public and private sources. Earlier studies on Part D used data from the pre-Part-D period to attempt to predict effects of program implementation on coverage for seniors, their out-of-pocket spending, and their health outcomes (Lucarelli (2006), Yang et al. (2009), Hall (2007), Pizer et al. (2008)). This review, however, will focus on studies that examined relevant aspects of Part D using data from the post-Part-D period.

Several papers and reports provide insightful descriptions of the program in terms of its basic design and trends in insurer participation, plan offerings, and pricing behavior (Cubanski and Neuman (2007), Hargrave et al. (2009a), Duggan et al. (2008), McAdams and Schwarz (2007)). Simon and Lucarelli (2006) use CMS data on plan prices, features, and formularies to examine the determinants of premiums for Part D plans in 2006. They find that premiums are correlated with drug pricing by companies and reflect the level of coverage offered by plans. However, the simulated out-of-pocket measure they use is weakly correlated, and often positively related to premium. They also report evidence of varying approaches to pricing by different insurers. Lakdawalla and Yin (2009) examined whether the increases in Part D enrollment lead insurers to negotiate lower drug prices with pharmacies. They found evidence to that effect, and estimated that most insurer savings are passed on to enrollees.

Another group of papers examine consumers' experience with the program, including how they understood the design and functioning of the program, how they valued the coverage provided to them by participating plans, and how the program affected their out-of-pocket spending and drug utilization. Levy and Weir (2008) used data from the 2004 and 2006 waves of the Health and Retirement Study to examine the impact of Part D program on enrollees' use of medications and their out-of-pocket spending, and to estimate the extent of adverse selection into the program. They found substantial selection into Part D, but no significant change in the use of prescription drugs in response to Part D. Their findings suggest that the Part D program has experienced adverse selection but not moral hazard.

Ketcham et al. (2010) analyzed the choices of Medicare beneficiaries of Part D plans in 2006 and 2007, and found that, despite the complexity of the choice context, consumer choices, measured by overspending, improved substantially even in only one year. They also found that consumers responded to financial incentives to switch plans, downgrading the importance of inertia in retaining current enrollees. They emphasize the importance of considering the role of experience and market responses in reducing participants' errors and biases that occurred in the early years of the program.

McFadden and his research group published a series of important studies based on results from their Retirement and Perspective Survey (RPS). Their papers examine a host of issues relevant to this research using a variety of modeling perspectives and techniques. In their first study, they found that despite complexity of the program, a majority of Medicare population made the right decision of not delaying enrollment in the program (McFadden (2006)). However, they found that consumers do not seem to place much value on the insurance component of alternative plans, concluding that they are likely to have difficulty choosing among plans to fine-tune their prescription drug coverage. They also found that low income, less educated elderly

with poor health or some cognitive impairment are significantly less informed and may fail to take advantage of the program.

In the second paper (Heiss et al. (2006)), the authors used results from the first and second rounds of RPS to evaluate beneficiaries choices before and after the implementation of Part D program. Seniors in their survey gave Part D mixed reviews, with the majority being troubled by the deductible and gap provisions of the standard benefit, and finding it difficult to determine current and future formularies of the plan they evaluate.

In Heiss et al. (2010), the authors examine the decisions taken by active choosers, particularly those who were not automatically enrolled into Part D. They develop a stylized inter-temporal optimization model, and compare the normative analysis of this model to actual enrollment decisions by RPS respondents. They evaluate respondents' decision to enroll, their time of enrollment, and their plan choice. They find that beneficiaries's enrollment choices were in general in line with what the model predicts given their health status and the market conditions. However, they also find that beneficiaries were less rational in their choices among plans, often selecting inexpensive plans when plans with more expensive and comprehensive coverage were actuarially more favorable to them.

In examining consumers' choices of plans, they obtained implicit prices of plan features by estimating hedonic linear regressions, controlling for insurer and state, and compared those implicit price estimates to estimates of willingness-to-pay (WTP) obtained by estimating a multinomial logit model for plan choice. In addition, they compared those implicit prices to actuarial estimates of the cost of offering a particular feature. They found that, in general, hedonic prices were lower than actuarial costs of features. On the other hand, they find a reasonable match between implicit prices and WTPs for some features, especially generic gap coverage for those with high drug expenditures, but not for other features, such as zero deductible, drug

tiers, and authorization requirements.

In the last paper in the series (Heiss et al. (2008)), the authors model Part D enrollment and plan choice using a dynamic discrete choice process. The model incorporates dynamics of health status, drug use, and mortality, in the spirit of Yang et al. (2009). They calibrate the model parameters and use individual-level data on enrollment and plan choice for the first three years of the program to evaluate the performance of the model. They then use the model to perform policy simulations concerning the late-enrollment penalty, government subsidies, and risk adjustment. Their model predicts high enrollment among the healthy, but evidence of significant adverse selection at the stage of plan generosity. In their policy simulations, they find that a targeted 16% increase in the government subsidy of Part D will be required to preserve consumer choice in plan generosity.

The model of Heiss et al. (2008) is informative, but has a few limitations. Unlike Yang et al. (2009), they do not explicitly model demand for drugs, assuming that people will use whatever medications they need as determined by their health status. In addition, they assume perfect competition and use a zero-profit criteria to determine equilibrium outcomes. This is problematic for two reasons. First, empirically, health insurance markets are known to be oligopolistic and concentrated (Robinson (2004)), Dafny et al. (2009)). Second, theoretically, perfect competition in an insurance market with asymmetric information may result in no equilibrium (Rothschild and Stiglitz (1976)). Lastly, they do not account for non-monetary plan characteristics, and for unobserved heterogeneity of plans and beneficiaries.

There are several studies in the literature that examine seniors' demand for Part D plans using models that address some of these limitations. Most of these studies adapt discrete choice models to market level data using the approach introduced by Berry (1994). This approach was used previously in the health economics literature to study demand for Medicare HMOs (Town and Liu (2003), Dowd et al. (2003),

Maruyama (2006)) . Berry remarked that the logit and nested-logit models used to analyze discrete choices of individuals could be log-transformed into linear models of product demand where probability of a choice could be interpreted as its market share. This insight permitted researchers to use these models to study demand using market level data. In addition, Berry's linear transformation allowed for the use of instruments for price, which is difficult to do in non-linear models.

Three papers have applied this approach to study demand for Medicare Part D plans. The first is by Keating (2007), who studies demand for Medicare Part D in 2006 and 2007 using logit, nested-logit, and random utility models. He used demand estimates from these models to quantify switching costs for consumers, which he finds to be substantial and exceeding, on average, premiums paid by beneficiaries. In particular, he finds that consumers are significantly less elastic in 2007 compared to 2006, with elasticity estimates of -1.6 and -2.5, respectively. He proposes that the difference is due to consumers finding it difficult to switch plans once enrolled. The assumption he maintains is that the substantial changes in the behavior of beneficiaries and firms between the first and second years of the program are rationalizable. In particular, Keating interprets differences in price sensitivity estimates between the two years as evidence of change in preferences that indicate the presence of switching costs. An alternative explanation, however, is the possibility of beneficiaries and firms learning more over time about each other and the market conditions in general. This would mean that the later preference estimates are more likely to uncover the true preference parameters.

The second paper is by Lucarelli et al. (2008). The authors of this paper use a nested-logit model to estimate demand for Part D plans in 2006. They used demand estimates and a Bertrand-Nash equilibrium concept to derive insurer's marginal costs. They then used both demand and supply estimates to conduct policy experiments examining the implications of simplifying choice by reducing the number of plans

available to beneficiaries. They find that search costs should be at least two thirds of the average monthly premium in order to justify a regulation that allows only two plans per firm, and that this number would be substantially lower if the limitation in the number of plans is coupled with a decrease in product differentiation, for instance, by removing plans with gap coverage.

The main drawback of these two studies is the use of plan enrollment data that includes both low-income subsidy (LIS) beneficiaries and non-LIS enrollees. The design of Part D benefit for LIS beneficiaries is considerably different from the benefit for non-LIS enrollees. LIS beneficiaries do not pay premiums or deductibles, and have coverage in the doughnut hole. They also pay small copayments. Lastly, and most importantly for demand analysis purposes, the government facilitates their enrollments by automatically and randomly assigning them to Part D plans with premiums below a region-specific benchmark. Many beneficiaries remain in their assigned plans, although they are entitled to switch to a different plan if they prefer. This random assignment means that observable enrollment patterns for LIS beneficiaries do not purely represent their active choices, and, as such, do not reflect their underlying preferences. Therefore, the inclusion of these enrollment patterns in an overall analysis of demand by Medicare Part D enrollees will result in estimates that do not reflect the preferences of the average enrollee.

The third paper, by Frakt and Pizer (2010), attempts to avoid this problem by restricting analysis to enrollments by non-LIS beneficiaries. The authors use data from 2008 for state-level LIS enrollments, and impose multiple assumptions to estimate plan-level LIS enrollment for the year 2007. They then excluded this enrollment to generate enrollment by non-LIS enrollees. The aim of their analysis is to estimate beneficiary price sensitivity in the Medicare Part D market, focusing on the market for stand alone plans (PDPs). Their estimate of the elasticity of enrollment with respect to premium is -1.45, which is significantly higher than the [-0.33, -0.12]

range of estimates from previous studies calculating premium elasticity of demand for Medicare HMOs (Dowd et al. (2003), Town and Liu (2003), Atherly (2002)).

There are few issues with this study, however, apart from the fact that the data are generated based on a set of assumptions. First, their specification includes organization dummies but not regional dummies or other regional control variables, which leaves unaccounted for several demand factors that are potentially correlated with the instruments they chose. In addition, their model includes a potentially endogenous variable that is not instrumented for. The variable is an indicator for LIS plans, which are plans with premiums below a weighted average of their region. Therefore, the indicator is a function of premium, and consequently endogenous in their specification.

Of the these three papers, only Keating (2007) extended the analysis to account for heterogeneity in consumer preferences. He estimated a random utility model using the approach introduced by Berry et al. (1995) (BLP). The results are in line with those from his nested-logit model, with elasticity significantly lower in 2007 compared to 2006 (-1.3 and -2.6, respectively). His model included interactions between plan characteristics and consumer demographics that are useful in explaining parameter heterogeneity. For instance, enrollees with higher medical expenditures are found to be less sensitive to premium. On the other hand, the random component of heterogeneity was not statistically significant.

Abaluck and Gruber (2009) also use a random utility approach to estimate demand for Part D plans. The authors used a large dataset obtained from Wolters Kluwer that included information on drug utilization and insurer choices by millions of Part D enrollees. They limit their analysis to non-LIS enrollees and estimate a multinomial conditional logit model to examine enrollees' plan choices in 2006. The objective of their analysis is to test if enrollees' choices are consistent with optimization. They find that Part D enrollees make choices that are inconsistent with

utility maximization under perfect information. For instance, enrollees place higher emphasis on premiums compared to expected out-of-pocket costs, and over-value certain financial plan features, such as gap coverage, beyond any impact of these features on their out-of-pocket spending. They used models of parameter heterogeneity to test the robustness of these findings. They only include random heterogeneity and find significant heterogeneity in the coefficients on premium, deductible, and gap coverage. Their initial results, however, obtained even after accounting for heterogeneity.

Chapter 4
Econometric Model

4.1 Demand

Following previous literature (Abaluck and Gruber (2009), Town and Liu (2003), Keating (2007), Lucarelli et al. (2008)), I model the utility U of beneficiary i from choosing a prescription drug plan p in region r as a linear function of the plan's premium, deductible, and measures of plan generosity.

$$U_{ipr} = -\alpha_i p_{pr} + X_p'\beta_i + \eta_{pr} + \varepsilon_{ipr} \tag{4.1}$$

where p_{pr} is the plan's premium, X_p is a $k \times 1$ vector of plan features including annual deductible and measures of plan generosity, and α_i and β_i are individual specific taste parameters. The error term in (4.1) has two components; η_{pr} is a plan-level error term which captures common valuation of plan features that are not captured by premium and X, such as reputation, customer service, and the structure of pharmacy network. ε_{ipr} is an idiosyncratic error assumed to be iid with Type-1 extreme value distribution across individuals and plans. Note that X's are assumed to be constant for plan p in year y across all regions in which it is offerred. This is not a requirement of the program, but holds true for the vast majority of part D plans, and provides a rational for the exogeniety of plan features.

The utility specification in (4.1) is of the random coefficient (mixed) logit form, which could be estimated using the approach introduced by Berry, Levinsohn, and Pakes (1995), henceforth labeled BLP. The individual parameters are modeled as

functions of observed and unobserved individual characteristics. Following Nevo (2001), I specify the parameters as follows:

$$(\alpha_i) = (\alpha) + \Pi_p D_i + \Sigma_p \nu_{ip}, \qquad \nu_{ip} \sim P_{\nu p}, \qquad D_i \sim \hat{P}_D \tag{4.2}$$

$$(\beta_i) = (\beta) + \Pi_x D_i + \Sigma_x \nu_{ix}, \qquad \nu_{ix} \sim P_{\nu x}, \qquad D_i \sim \hat{P}_D \tag{4.3}$$

Where α and β are population averages of the individual specific parameters, D_i is a $d \times 1$ vector of demographic variables, ν_{ip} and ν_{ix} are, respectively, 1×1 and $k \times 1$ vectors of unobserved individual characteristics determining preferences to premiums and plan generosity and assumed to have a parametric distributions given by $P_{\nu p}$ and $P_{\nu x}$; P_D is the nonparametric distribution of demographic characteristics derived from data sources described below, Π_α and Π_β are, respectively, a $1 \times d$ vector and a $k \times d$ matrix of coefficients that measure how taste characteristics vary with demographics; and Σ_p and σ_x are variance-covariance matrices of the multivariate normal distribution of the unobserved individual characteristics ν_{ip} and ν_{ix}.

To complete the specification of the demand system, I need to model the outside option. The outside option comprises all the other options, besides stand-alone part D plans, that are available to Medicare beneficiaries. These include fee-for-service (FFS) Medicare with no drug coverage, Medicare Advantage plans with or without drug coverage, and FFS Medicare with employer or union supplemental drug coverage, including VA, FEHB, and TRICARE. The indirect utility from this outside option is given by

$$u_{i0r} = \eta_{0r} + \Pi_0 D_i + \sigma_0 \nu_{i0} + \varepsilon_{i0r} \tag{4.4}$$

The mean utility from the outside option, η_{0r}, and the coefficients Π_0 and σ_O

are not identified separately from the coefficients on individual characteristics in (4.2). I set these coefficients to equal zero, which normalizes the indirect utility from the outside option to equal the idiosyncratic error term ε_{i0r}. Let $\theta = (\theta_1, \theta_2)$ refer to the vector of all the model parameters, where $\theta_1 = (\alpha, \beta)$, and $\theta_2 = (\Pi_p, \Pi_x, \Sigma_p, \Sigma_x)$. Combining equations (4.1) and (4.2), we have

$$u_{ipr} = \delta_{pr}(p_{pr}, X_p, \eta_{pr}; \theta_1) + \mu_{ipr}(p_{pr}, X_p; \theta_2) + \varepsilon_{ipr} \tag{4.5}$$

where

$$\delta_{pr} = \alpha p_{pr} + X_p'\beta + \eta_{pr}$$

and

$$\mu_{ipr} = [p_{pr}](\Pi_p D_i + \Sigma_p \nu_{ip}) + [X_p'](\Pi_x D_i + \Sigma_x \nu_{ix})$$

The term δ_{pr} is the mean utility from plan p in region r, and is common to all beneficiaries in that region. Deviations from the population mean are subsumed in the term $\mu_{ipr} + \varepsilon_{ipr}$, which is a mean-zero heteroskedastic deviation that captures the effect of individual characteristics.

Beneficiaries choose the option that gives them highest utility. This defines the set of unobserved consumer characteristics that lead to the choice of a particular plan:

$$A_{pr}(X_{.r}, p_{.r}, \delta_{.r}; \theta_2) = \{D_i, \nu_{ip}, \nu_{ix}, \varepsilon_{i0}, ..., \varepsilon_{iPr} | u_{ipr} \geq u_{ip'r}\}$$

The expected market share for each plan is given by

$$S_{pr}(p_{.r}, \delta_{.r}; \theta_2) = \int_{A_{pr}} dP(\varepsilon, \nu, D) \tag{4.6}$$

If ε_{ipr} is type-1 extreme value distributed, then the expected shares take the

following form

$$S_{pr}(p_{.r}, \delta_{.r}; \theta_2) = \int S_{ipr} dP(\nu) dP(D) \tag{4.7}$$

$$= \int \frac{\exp(\alpha_i p_{pr} + X'_p \beta_i + \eta_{pr})}{1 + \sum_{p'} \exp(\alpha_i p_{p'r} + X'_{p'y} \beta_i + \eta_{p'r})} dP(\nu) dP(D) \tag{4.8}$$

Computing the integral in equation (4.8) requires specifying the probability distributions $P(\nu)$ and $P(D)$. If one assumes that individual heterogeneity enters only through the idiosyncratic error term ε_{ipr} which is iid across individuals and products and is distributed type-1 extreme value, then the standard *multinomial logit* demand model is obtained. However, the multinomial logit model is known to give rise to unrealistic own- and cross-price elasticities resulting from its implied independence of irrelevant alternatives assumption (IIA) (McFadden et al. (1998), BLP, Nevo (2000)). In particular, the model restricts elasticities to be a function of market share, regardless of characteristics. Two products with the same market share are predicted to have the same cross price elasticity with a third product, even if the characteristics of that product are closer to one than the other. Models that introduce correlations in the structure of the error term ε_{ipr}, such as the *generalized extreme value* model (McFadden 1978), are less restrictive but require predetermined grouping of products assumed by the modeler. The *nested logit* model is an example of this type of models. Here the products are grouped into predetermined exclusive and exhaustive sets, and ε_{ipr} is decomposed into an iid shock plus a group-specific component (Nevo (2000)).

The full model described above accommodates a richer form of consumer heterogeneity. Consumers differ not only in the additive error term ε_i but also in their tastes for plan characteristics, including premiums. Correlation between product choices is introduced through the term μ_{ipr}, which is a function of both product and consumer characteristics, and ε_{ipr} is again assumed to be iid across consumers and

products.

The advantage of more realistic price elasticities comes at the cost of computational difficulty. The integral in equation (4.7) does not have a closed form solution, and will have to be computed numerically. This difficulty is largely overcome using simulation methods; a technique introduced by Pakes (1986). The distribution of personal characteristics can be obtained by sampling from available surveys of Medicare beneficiaries with regional coverage, such as the Medicare Current Beneficiary Survey (MCBS).

After obtaining the predicted market shares given by (4.8), one could, in principle, proceed by estimating the model parameters using a minimum distance approach. The estimated parameters will be those that minimize the difference between observed and predicted market shares. However, such an approach does not take into account the potential correlation between premium and unobserved product characteristics, η_{pr}, and consequently will generate inconsistent estimates. The methods introduced by Berry (1994) and BLP are designed to deal with this endogeneity problem through linearizing the model and using appropriate instruments for premium. An alternative method was recently suggested by Petrin and Train (2010), and involves using a control function approach to account for the unobserved plan features. Petrin and Train compared their approach to that of BLP and found that, at least in their particular application, the two methods give similar estimates (Petrin and Train (2010)).

4.2 Supply

Let $\mathscr{J}_{ry}$ be the set of plans offered by insurer j in region r. The profit function for insurer j is given by

$$\pi_{jr} = \sum_{p \in \mathscr{J}_r} \pi_{pjr} \tag{4.9}$$

$$\pi_{jr} = \sum_{p \in \mathscr{J}_r} \left(\int S_{ipjr}(sb_i + p_{pjr} - mc_{ipjr}) dP(\nu) dP(D) \right) \times M_r - FC_{pjr} \tag{4.10}$$

where sb_i is premium subsidy paid by CMS, mc_{ipjr} is the expenditure on prescription drugs that i is expected to cost plan pr, M_r is the number of part D eligible Medicare beneficiaries in region r and FC_{pjr} refers to fixed costs of operating part D plan(s) in region r, including setting up pharmacy networks, establishing relations with wholesalers and pharmaceutical companies, etc.

Insurers compete by setting premiums and features in a four-stage game. In the first stage, insurers choose the regions to enter and the number of plans to offer in each region. In the second stage, insurers choose plan features, which are the same for any plan in all the regions in which it is offered. In the third stage, insurers choose premiums for plans on a region-by-region basis. Therefore, the same plan could have different premiums in different regions. In the final stage, consumers choose plans that maximize their expected utility and costs and profits are realized. A Nash equilibrium is assumed to exist for this strategic game between insurers. I will only model the third and fourth stages of this game, assuming that market structure and plan characteristics are exogenous.

Using backward induction, insurers solve for optimal premiums given any choice of plan features. The first-order condition for premium is given by:

$$\frac{\partial \pi_{jr}}{\partial p_{pjr}} = \sum_{p' \in \mathscr{J}_r} \int \left[\frac{\partial S_{ip'jr}}{\partial p_{pjr}} (sb_i + p_{pjr} - mc_{ipjr}) + S_{ip'jr} \right] dP(\nu) dP(D) = 0 \tag{4.11}$$

I assume that beneficiaries and plans play a static game; that is, their payoff functions do not include any dynamic effects of current decisions. This is an obvious simplification, but one that has been widely used in the literature (Town and Liu (2003), Abaluck and Gruber (2009), Lucarelli et al. (2008), Lustig (2007)).

4.3 Identification

Identification in the model above comes from variation in premiums, characteristics, and enrollment across plans, and regions, as well as from variation in the choice sets and demographics across regions. The coefficient on premium is identified by observing how demand for a plan varies with premium, fixing all plan features. Similarly, the coefficients on plan features are identified by observing how enrollment changes with features, holding everything else the same. Identification of the distribution of taste parameters comes from differences in choice sets available to beneficiaries in different regions, and from the variation in consumer characteristics across regions. Having a large number of plans with positive market shares indicates that a region has a higher level of consumer heterogeneity compared to regions with only limited choice sets.

The main challenge in estimating the proposed model is to deal with the likely endogeneity of premium in a non-linear system. I will follow the approach developed by BLP, which linearizes the demand model and instruments for endogenous variables in a GMM framework. To linearize the model, I use Berry's contraction mapping to derive a value for δ_{pr} for any given θ_2 that equates predicted shares to the actual market share of plan pr (Berry (1994)). I then use the derived δ_{pr} to construct the structural error to be used in the GMM objective function. The structural error is η_{pr}, which could be written as

$$\eta_{pr} = \delta_{pr} - \alpha p_{pr} - X_p'\beta \tag{4.12}$$

Similar to Keating (2007) and Lucarelli et al (2008), I used instruments that are functions of the characteristics of competing firms in the same region. The instruments are based on an approach similar to that used by BLP and Bresnahan et al. (1997). They include observed characteristics for each plan, counts of characteristics of other plans in the region in the same nest, and counts of characteristics of plans offered by the same insurer in the region. These instruments are assumed to be uncorrelated with omitted and unobservable plan characteristics, but correlated with premium. The exogeneity of this set of instruments is predicated on assuming the exogeneity of observed characteristics, of which they are functions. This is a standard assumption in most of the discrete choice literature (Berry (1994), Berry et al. (1995), Nevo (2000)), and is especially feasible given the design of Medicare Part D program. Plans offered in multiple regions may have different premiums, but they share the same deductible, gap coverage, and formulary. This means that the choice of deductible, gap coverage, and formulary is taken at a supra-regional level and could be considered exogenous to demand in a specific region.

However, observed plan characteristics could be correlated with other unobserved characteristics that are shared between regions. For instance, insurers with experience in offering plans to Medicare beneficiaries are likely to have developed a better understanding of their preferences and health status, compared to those with limited or no such experience. They are also more likely to have developed more efficient marketing strategies that are specifically tailored to this segment of the market. This would result in a correlation between the observed design features and the unobserved marketing strategies. I guard against this possibility by including insurer-level fixed effects that capture unobserved insurer characteristics. The correlation of the proposed instruments with premium stems from the relationship, in a differentiated oligopoly market, between the characteristics of competing products and demand elasticity and markup. Demand in such a market is more elastic if

competitors offer products that are less differentiated, and vice versa.

The demand moments using this set of instruments are:

$$E[(\delta_{pr} - \alpha p_{pr} - X_p'\beta)Z_{pr})] = 0 \tag{4.13}$$

where Z is a matrix of instruments. The GMM objective function to be minimized is

$$Q(\theta) = M(\theta)'AM(\theta) \tag{4.14}$$

where $M(\theta)$ is a vector of the sample versions of the moments defined in (4.13)

$$M(\theta) = \frac{1}{N}\sum_{p,r}(\delta_{pr} - \alpha p_{pr} - X_{py}'\beta)Z_{pr}) \tag{4.15}$$

and A is a weighting matrix:

$$A = (Z'Z)^{-1}$$

4.4 Estimation

4.4.1 Logit and Nested Logit Model

The logit and nested-logit specifications are simple demand models that would provide a valuable first look at the data before embarking on the more complicated task of estimating the full random utility model. In addition, estimating these models allows us to compare our results with those from previous studies using the two models. Their estimation is based on Berry's linearization approach. We can write the indirect utility from plan p and the outside option in region r as

$$u_{ipr} = \alpha p_{pr} + X_p'\beta + \eta_{pr} + \varepsilon_{ipr} \tag{4.16}$$

$$u_{i0r} = \varepsilon_{i0r} \tag{4.17}$$

where η_{pr} is the mean unobserved quality of plan p in region r. The logit model assumes that ε_{ipr} is iid and type-1-extreme-value distributed, which gives the following closed-form solution for expected shares:

$$s_{pr} = \frac{\exp(\alpha_i p_{pr} + X'_{py}\beta_i + \eta_{pr})}{1 + \sum_{p'} \exp(\alpha_i p_{p'r} + X'_{p'}\beta_i + \eta_{p'r})} \tag{4.18}$$

Taking logs and rewriting (4.18) we get

$$\log(s_{pr}) - \log(s_{0r}) = \alpha p_{pr} + x'_p\beta + \eta_{pr} \tag{4.19}$$

Similarly, the nested logit model could be written as

$$\log(s_{pr}) - \log(s_{0r}) = \alpha p_{pr} + x'_p\beta + \sigma \log(s_{pr|Gr}) + \eta_{pr} \tag{4.20}$$

where $s_{pry|Gr}$ is the market share of plan pr within its group, and groups are defined by benefit type (basic vs. enhanced). Consistent coefficient estimates are obtained by running two-stage-least-square regressions using equations (4.18) and (4.19) and the instruments described in section (4.3).

The nested logit model relaxes the iid assumption of the error term in the logit model by introducing group-specific correlations. This is one way to account for the interaction between plan features and consumer characteristics by assuming that consumer valuations for products within each group are correlated. The logit model should be rejected in favor of the nested logit model if the estimation of (4.20) results in an estimate of σ that is statistically significant.

4.4.2 The Full Model

The estimation procedure of the full model is composed of an inner and an outer loop. The inner loop uses Berry's contraction mapping to find, for each value of θ_2, the vector of mean utility $\delta_{\cdot r}$ for all plans in the region that equates expected shares with actual market shares. Expected shares are computed using a simulation

technique similar to BLP. The distribution of demographics, $P(D)$ is simulated by sampling from MCBS 2006. The vector of mean utility is then used to compute the structural error in equation (4.12).

The outer loop uses numerical optimization to minimize the objective function in (4.13) over the set of Θ. I use a quasi-Newton optimization algorithm from the Matlab optimization toolbox. To increase the chances of arriving at a global minimum, I use 50 vectors of starting points generated from a standard normal distribution. The tolerance levels for the internal and external loops are set to 10^{-12} and 10^{-5}, respectively.

Chapter 5
Data

5.1 Data Sources

I use several data sources for the analysis of premium determinants and the demand for Part D plans. For the analysis of premium determinants, I use data for the years 2007 to 2009, along with the corresponding simulations described below. For analysis of demand for Part D plans, I only use data from 2009 as plan-level enrollment numbers for low-income-subsidy (LIS) beneficiaries are not available for earlier years.

CMS provides annual plan landscape files that list all the plans offered in the particular year with their basic features, such as premium, deductible, benefit type, and gap coverage. The landscape files are available for the years 2006-2010. CMS enrollment files provide enrollment in each plan by region and county. They also provide the number of Medicare beneficiaries who are eligible for Part D in each Part D region. Enrollment files are available for the years 2006-2009.

Plans' formulary data come from CMS formulary and pharmacy network files. The files provide a list of all the drugs included in each plan's formulary, together with their tier placement and copayment or co-insurance. The files use national drug code (NDC) to identify each drug. The formulary files are available for the years 2006-2009. The 2009 formulary files include pricing data for each NDC included in a plan's formulary. Specifically, the file contains the average cost to enrollees of a 30-day supply of each NDC. Drug prices are needed for the out-of-pocket costs and

plan costs simulations described below. This information, however, is not available for previous years. To overcome that, I deflated 2009 prices using Consumer Price Index (CPI) to generate average prices for the years 2007 and 2008.

I use data from the The Medicare Current Beneficiary Survey (MCBS) to simulate out-of-pocket costs and plan costs, and to draw from the empirical distribution of demographics for the estimation of the full model. MCBS is a comprehensive annual survey of a nationally representative sample of Medicare beneficiaries. It includes detailed information on demographic characteristics, health status, health insurance, and healthcare utilization. The Cost and Use files of the data release validate survey responses related to utilization and link them to the corresponding claims in CMS's administrative data (Adler (1994)). I use MCBS 2006 Cost and Use files for the analysis, which is the latest release of these files. For each respondent, the files provide detailed information on their drug utilization, including drug name, dosage, and quantity. This information enables me to simulate each respondent's expected out-of-pocket costs if they join a plan by matching their drugs to those on the plan's formulary.

5.2 Simulating Out of Pocket Costs and Plan Costs

The objective of these simulations is to generate an index of plan generosity using the distribution of expected beneficiaries' out-of-pocket costs. I used drug utilization data from MCBS 2006 Cost and Use files, together with plan formulary data from CMS. The same MCBS 2006 data was used to simulate expected out of pocket costs for the plans offered in the years 2007, 2008, and 2009. A necessary assumption for this exercise is that drug utilization by beneficiaries remains the same; that is, on expectation, beneficiaries's use of medications is the same a year later, regardless of their choice of prescription drug plan. This is not an ideal assumption, but is reasonable enough given the evidence that medication use is highly correlated over

time (Ellis and McGuire (2007)). In addition, Levy and Weir (2008), using data from the Health and Retirement Survey, found no evidence of moral hazard after joining part D (Levy and Weir (2008)). Moreover, even if the absolute levels of these simulated costs are not accurate, what matters for the purposes of this study is their usefulness as a measure of a plan's generosity relative to competing plans.

MCBS 2006 Cost and Use files contain the Prescription Medicine Events (PME) file that lists, for every sampled beneficiary, details of each incident of medication purchase. The details include the name of the drug, its strength, quantity, total amount paid for that purchase, the amount paid out-of-pocket, and the amount(s) paid by private and public insurance sources.

The first step in the simulation process is to clean drug names in MCBS PME files to match the names in formulary files. This was done manually. Some of the medications in the MCBS files had no names. For some of those, there were associated NDCs that were used to find the name using the National Drug Code directory maintained by the Food and Drug Administration (FDA). For others, it was possible to reasonably guess the name of the drug using other events that were likely refills of the same medication (judging from the details of the event, such as total cost, medication strength, quantity, etc). I dropped those events that remained with no names.

The second step is to obtain prices for these drug events. Plans compete to secure lower drug costs to their enrollees, which allows them to offer generous coverage at lower premiums. The simulations should ideally capture this aspect of plan differentiation. However, plan-specific pricing data is only available for 2009. For the years 2007 and 2008, I used average prices, derived by deflating the averages of plan-specific prices in 2009, and applied those prices to all plans. As a result, simulations for these two years only capture differentiation along plans' benefit design, but not their ability to obtain lower drug prices.

Thirdly, I cleaned the days-supply data in MCBS files to match those in formulary files. Formulary files have either a 30-day supply or a 90-day supply option, whereas MCBS files have a range of days-supply entries. I considered any days-supply entry in MCBS that is less than 30 days as a 30-day supply, and any thing above 30 days as a 90-day supply.

Fourthly, I created refill episodes using data on the number of times a particular medication was refilled, and grouped those medications with refill times that are close enough.

And lastly, I matched prescription drug events to plan formulary files using drug name and days-supply. This allowed me to calculate the required copay for that event, taking into account features of the plan, including the tier of the drug and level of coverage under which the event took place (initial coverage period, doughnut hole, or catastrophic coverage zone).

Chapter 6
Results and Discussion

6.1 Premium Determinants

Studying the factors that influence the setting of premiums by insurers is of interest in and of itself and deserves a separate and detailed investigation (Simon and Lucarelli (2006)). That is not the ultimate objective of this study. Instead, this analysis of premium determinants is done in the context of studying demand for Part D plans and is undertaken primarily for assessment purposes. The simulations of plan costs and out-of-pocket expenditures described in chapter (5) are computationally complex and involve assumptions and simplifications that could affect their validity as measures to be used in demand estimation. Examining a simple model of premium setting provides a reasonable test of such validity.

Table (6.1) shows the estimates from three specifications regressing premium on a list of variables that are likely to influence insurers' pricing decisions. The estimates were obtained using data from the years 2007 to 2009. Deductible is expected to be negatively correlated with premium. Plans with higher deductible, holding other features constant, expose enrollees to higher out-of-pocket payments, which decreases plans' costs and reduces the overall value of the plan. Gap coverage and average plan costs are measures of a plan's generosity and its cost to the insurer. Average-plan-cost is a derived variable created by simulating expected plan expenditures using each plan's benefit design and formulary structure and the medication profiles of 2006 MCBS respondents in the plans' region. This variable

could be used as a measure of the generosity of a plan's benefit. It summarizes the various aspects of a plan's benefit, including its formulary design, tier structure, and cost-sharing arrangement. I use simulated average plan cost instead of simulated average out-of-pocket spending, to be used later in demand estimation, primarily because it is easier to interpret in a model of premium setting. The two variables, however, are generated using the same procedure and are highly correlated.

Plans providing gap coverage and assuming higher costs, on average, provide superior actuarial value to their enrollees and will need to charge higher premiums to cover their costs. Gap coverage could also differentiate a plan from its competitors allowing it to charge a higher markup. The positive association between premium and measures of generosity reflects standard price-cost relationship for a profit-maximizing firm (reflecting demand elasticity and the nature and level of competition). In addition, it reflects firms' expectations of the effect of increased generosity on the extent of moral hazard and adverse selection. If firms expect significant levels of moral hazard and adverse selection, then their markups will be a complex function of expected demand elasticity, expected level of competition, and the anticipated levels of moral hazard and adverse selection.

Specification (1) includes the variable national, indicating whether a plan is offered in all of the 34 Part D regions. Such plans are offered mostly by large insurers, such as Aetna, United Health, and Humana. The correlation between premium and the national indicator could go either way. Large insurers enjoy economies of scale and are in a better position to negotiate better terms with drug manufacturers and pharmacy networks (Lakdawalla and Yin (2009), Duggan and Morton (2010)), which would allow them to charge premiums lower than competition. On the other hand, most beneficiaries recognize the names of large insurers and may have used one of their Medigap or Medicare Advantage products. This brand recognition and prior beneficiary experience may allow large insurers to exact a higher markup. A

negative coefficient on the indicator would suggest the former effect, while a positive coefficient would suggest the latter.

Specification (1) also includes region-level variables that are expected to affect premiums in the region. The number of insurers offering Part D plans in a region ranges from 20-27 in the period 2007-2009, with most of the regions having 22-25 insurers. The number of insurers operating in a region indicates the potential level of competition for enrollees in that regions. Regions with more insurers are likely to witness higher levels of competition and lower premiums as a result. The percentage of Medicare beneficiaries who are also eligible for Medicaid was computed using MCBS 2007 Access to Care module. Low-income subsidy recipients pay no premium if they enroll in qualified plans. To be qualified, plans are required to charge premiums lower than a region-specific benchmark determined by CMS using plan bids. A larger fraction of dual eligibles in a region is expected to lead to more plans trying to qualify to enroll them, lowering average premium in the region.

There are other variables that remain unaccounted for in specification (1) (Simon and Lucarelli (2006), Keating (2007)). Some of those variables are at the regional level, while others are at the level of the insurer and the plan. For instance, plans use regional measures of health status and utilization of prescription drugs to estimate actuarial costs of different benefit designs. Prior experience in providing insurance products to Medicare beneficiaries, either in Medicare Advantage or Medigap markets, may allow insurers to utilize their brand name value and charge higher premiums for their Part D products. Insurers with better marketing channels may use those to differentiate their product from competition, allowing them to charge higher premiums. Specification (2) adds a region fixed effect to capture the effect of those region-level variables that are time invariant. We are then left with other insurer-level and plan-level variables that are not included in the model. I account for the time-invariant component of unmeasured insurer-level variables by adding a

fixed effect for parent organization in specification (3) .

Accounting for unmeasured plan-level variables is more complicated. Plans offered in different regions with the same name share most of the features, including deductible, gap coverage, formulary design, and cost-sharing structure. Those features change from year to year, so it is possible to include a plan-level fixed effect in the model to account for unobservable plan features. However, this would limit the model to explaining premium variation within the same plan over the years, which is limited compared to premium variation between plans in each year. Therefore, no plan-level fixed effects are included. The aim of this analysis, however, is not to examine hypotheses of causal relations, but rather to examine how premium is correlated with average plan cost and other variables to be used in demand estimation.

Most of the estimates from the preferred specification (3) are significant and have the expected signs. The coefficient on the deductible is negative and significant. The magnitude of the coefficient means that for a one dollar increase in annual deductible, ceteris paribus, leads to a 24 cent reduction in annual premium. Simon and Lucarelli (2006) and Keating (2007), using different sets of determinants in their analyses, report estimates of 12 cents and 36 cents, respectively.

It is not immediately evident what the magnitude of this coefficient is expected to be. For instance, if a plan has a zero deductible and all enrollees expect to utilize prescription drugs, and the market is perfectly competitive with no moral hazard or adverse selection, then an increase in deductible by one dollar should lower annual premium by the same amount. On the other hand, if a plan has a high deductible, and a large proportion of its enrollees do not expect to spend that much on prescription drugs, then an increase in deductible affects these enrollees only to the extent that they become less insured against the risk of a bad health shock leading to higher utilization. Therefore, in this case, the plan could get a way

with a small reduction in premium since raising deductible affects only slightly the expected out-of-pocket payments for the majority of its enrollees. The effect for a more realistic plan, with mixed enrollment and a small to moderate deductible, is expected to be somewhere in the middle of these two extremes. Moreover, deductible is likely to be correlated with plan features that are omitted from the model, which complicates the interpretation of the estimated coefficient.

The coefficient on the indicator for national plans is negative but statistically insignificant. The point estimate means that large insurers, on average, use their low-cost advantage to charge lower premiums. The positive and significant coefficient on average plan cost is a good indication that this simulated index is capturing what it is intended to capture. However, the positive and significant coefficient on the gap coverage indicator suggests that some of the features of plans with gap coverage are not captured by a linear term of simulated plan cost. Nonetheless, specifications with quadratic and logarithmic terms (not shown) have similar results. The gap coverage indicator may be reflecting, in addition to generosity, a degree of differentiation that allows plans to charge higher premiums.

The coefficient on average plan cost means that, holding deductible and gap coverage constant, an increase in monthly average costs by one dollar increases monthly premium by only 13 cents. Attenuation bias due to omitted variables and measurement error in this simulated variable are possible reasons for this low estimate. The correlation between gap coverage and average plan costs complicates the interpretation of the magnitude of the coefficient on gap coverage. The estimate of this coefficient means that, holding deductible and average cost constant, providing coverage in the gap increases premium by $22 on average. However, gap coverage is invariably associated with an increase in average plan cost, which means that gap coverage is priced at more than $22 (see section 6.2). The year fixed effects are positive and significant, reflecting the upward trend in premiums over the period

2007-2009.

The determinants considered in specification (1) of this analysis explain around 60% of the variation in premiums within each region over the years 2007 to 2009. Including fixed effects for the parent organization in specification (2) increases the explanatory power of the model to around 74%, indicating the presence of an idiosyncratic component of the pricing decision. Table (6.2) shows that this idiosyncratic component is particularly large in 2006 and it gets smaller over the years. This is consistent with evidence in the literature that insurers in 2006 were testing the waters and using different approaches to price their plans (Simon and Lucarelli (2006)), reflecting the significant levels of uncertainty surrounding the conditions of the market in the early years. The gradual reduction in the importance of this idiosyncratic component suggests that insurers' pricing strategies are converging over time, which in turn suggests the presence of a common process of market learning.

Table 6.1: Premium Determinants

Variable	**1**	**2**	**3**
Deductible	-0.016^{*}	-0.013	-0.019^{**}
	(0.007)	(0.007)	(0.004)
Gap Coverage	23.70^{**}	22.15^{**}	22.40^{**}
	(3.62)	(3.70)	(3.08)
Avg Plan Cost	0.09^{**}	0.14^{**}	0.13^{**}
	(0.03)	(0.03)	(0.01)
National	-1.07	-1.06	
	(2.30)	(2.35)	
Number of Insurers	-0.66^{**}		
	(0.15)		
% Medicaid	-0.13^{**}		
	(0.06)		
2008	2.03	3.42^{**}	1.64
	(1.50)	(1.46)	(1.70)
2009	10.61^{**}	12.12^{**}	13.03^{**}
	(1.78)	(1.82)	(1.93)
Intercept	35.95^{**}	21.97^{**}	20.61^{**}
	(3.48)	(3.25)	(3.93)
Fixed Effects	None	Region	Region, Organization
R^2	0.59	0.602	0.74

[a] Data for years 2007 to 2009. Standard errors clustered by plan. Number of Insurers and % Medicaid variables are at the regional level. Significance levels: $*$: 5% $**$: 1%

Table 6.2: R^2 from Regressions of Premium on Determinants

Year	**1**	**2**
2006	.23	0.66
2007	.50	0.74
2008	.57	0.85
2009	.66	0.79
Fixed Effects	Region,Year	Organization, Region, Year

[a] Data for years 2006 to 2009. From regression of premium on deductible, and indicators for gap coverage and national plans.

6.2 The Logit and Nested Logit Models

I estimate the linearized logit and nested-logit models specified in equations (4.19) and (4.20) using plan characteristics that are observable to beneficiaries at the time of enrollment. The models regress the difference between the log of plan share and the log of the share of the outside option on premium, deductible, gap coverage, and simulated average out-of-pocket spending. This simulated measure of generosity resembles what Medicare provides to enrollees through its Plan Finder tool. Medicare encourages beneficiaries to use this tool during open enrollment to choose plans that best match their needs. Medicare beneficiaries can enter their current medications into the Plan Finder to get an estimate of how much they should expect to pay out-of-pocket if they joined a particular plan in their region. The average out-of-pocket spending variable I use is generated by averaging similar simulated plan estimates for all 2006 MCBS respondents. The outside option is composed of traditional fee-for-service Medicare with no drug coverage, Medicare Advantage Part D plans (MAPD), and other sources of prescription drug coverage, such as employer sponsored plans and federal employee plans.

I also include fixed effects to account for unobservable region-level and insurer-level demand factors. Important region-level demand factors include the size of the market, the level of demand for prescription drugs, and the characteristics of the outside option in the region, such as the size of the MAPD market, and uptake of retiree drug subsidy by employers in the region. Insurer-level demand factors include its size and ability to bargain with drug manufacturers and pharmacy networks, its marketing approach, and its experience in serving Medicare beneficiaries through Medicare Advantage plans and Meigap plans.

I use aggregate and LIS plan-level enrollment data to compute enrollment by non-LIS beneficiaries in 2009. Limiting demand estimation to non-LIS beneficiaries is crucial for the validity of our revealed preference estimates. The majority of

LIS beneficiaries are randomly assigned to qualified plans in their region. Hence, enrollment patterns resulting from this assignment do not reflect the choices of these beneficiaries. Excluding their enrollment ensures that the derived demand estimates reflect actual consumer choices and are not contaminated by administrative decisions taken on their behalf.

Table (6.3) shows demand estimates for non-LIS enrollees from the logit and nested logit models described in equations (4.19) and (4.20). The coefficients obtained from the logit and nested-logit specifications reflect structural estimates of parameters of the utility from enrolling in a Part D plan. Gap coverage is expected to increase enrollees' utility, while higher deductible and out-of-pocket spending are expected to lower utility.

Deductible, gap coverage, and average out-of-pocket spending are correlated by design. Average out-of-pocket spending incorporates amounts paid towards the deductible, and coverage during the gap reduces out-of-pocket spending in the doughnut hole. Nevertheless, the model includes all three variables, instead of only average out-of-pocket spending, for two reasons. First, as shown in section (6.1), deductible and gap coverage are significant premium determinants, even in the presence of the simulated plan cost variable. This suggests that deductible and gap coverage variables have hedonic valuations that are independent of the simulated generosity measure. In addition, there is evidence in the literature that Part D enrollees are more responsive to plan features that are simple and easy to observe, compared to measures that are complex but more objective (Abaluck and Gruber (2009)).

The average out-of-pocket spending measure reflects drug pricing behavior by the plan along with the design features of its formulary, such as the list of medications covered, the tier structure, and cost-sharing arrangement. Plans negotiate with pharmacies the prices their enrollees pay for covered medications before reaching

the deductible and while in the doughnut hole. Those prices also determine the amount to be paid as co-insurance. Two plans with the exact same formulary can have different average out-of-pocket spending if they charge different drug prices. The plan charging lower prices will have lower out-of-pocket costs. The capturing of this drug-pricing dimension of generosity is an important advantage of using the simulated out-of-pocket spending measure, as it can not be captured using measures that only account for formulary design features.

Out-of-pocket spending can be viewed as a component of the overall price that an enrollee expects to pay by joining a plan. This would suggest restricting its coefficient (β_{oop}) to be equal to the coefficient on premium (α), since both reflect the same marginal utility of income. This is a reasonable restriction if the model estimated is based on individual-level data. In our model, however, the out-of-pocket spending measure is a plan-level variable that reflects the average expected spending for a standardized population. Some of the enrollees may expect to have out-of-pocket spending that is lower or higher than this average. For such enrollees, an additional dollar in average out-of-pocket costs does not translate into an additional dollar in expected spending for them. Enrollees healthier than average should expect to pay less than the marginal increase in average out-of-pocket spending, whereas sick enrollees should expect to pay more. On the other hand, an additional dollar in a plan's premium means an additional dollar in spending for any enrollee joining that plan.

The coefficients on the two variables, therefore, reflect different economic quantities. The coefficient on premium reflects the average marginal utility of income for Part D enrollees. The coefficient on average out-of-pocket, on the other hand, reflects the average of the interaction between an enrollee's marginal utility of income (α_i) and her marginal increase in expected out-of-pocket spending resulting from a one-dollar increase in the average out-of-pocket spending (γ_i). The distribution

of this interaction term need not have the same mean as that of the distribution of (α_i). In fact, if we assume that α_i and γ_i are normally and jointly distributed, with means α and γ and standard deviations σ_α and σ_γ and correlation parameter ρ, then Aroian (1947) shows that the mean of the product of the random variables is given by:

$$\beta_{oop} = \mu_{\alpha\gamma} = \alpha * \gamma + \rho * \sigma_\alpha * \sigma_\gamma \tag{6.1}$$

If we assume that γ is 1 and ρ is positive, meaning that health and wealth are positively correlated, then β_{oop} should be smaller than α in absolute value. Therefore, the marginal effects of premium and average out-of-pocket spending should not be restricted to be equal.

The characteristics included in the logit and nested-logit models of table (6.3) constitute an incomplete list of the features that enrollees consider when choosing among available Part D plans. There are additional characteristics that are observed by the econometrician but are omitted for the sake of simplicity and tractability, e.g. details of a plan's network of pharmacies. Other plan features are not observed by the econometrician, such as the quality of marketing and customer service. If these omitted and unobserved features are the same for all the plans offered by a certain insurer in all the regions, then the inclusion of an insurer fixed effect will be enough to capture those variables.

However, it is likely that features of plans offered by one insurer will vary from region to region and from plan to plan within the same region. For instance, many insurers use different formularies for their basic and enhanced plans, and may use different pharmacy networks for the same plan in different regions. The error term in the logit and nested-logit specifications, therefore, incorporate plan-region deviations from the mean valuation captured by the insurer fixed effect. In an oligopolistic market, such as that of Part D, price is a function of marginal cost and a markup

term that is a function of demand elasticity (Berry (1994)). Thus, premium is correlated with any product characteristic that influences demand, making premium potentially endogenous in any specification with omitted and unobserved demand factors. The linearized nested-logit model includes log of within-nest share defined as the share of a plan among other plans with the same benefit type. This variable is also endogenous, as it is simultaneously determined with the log of plan share, which is part of the dependent variable. To obtain consistent estimates, therefore, we need to overcome the endogeneity problem of these two variables through the use of valid and relevant instruments.

Specifications (2-4) in table (6.3) use instruments for premium and the log of within-nest share that are similar to those used by Lucarelli et al. (2008) (see chapter (4). The first-stage specification tests for the instruments are shown in Table (6.3). The minimum eigen value test is the test of choice for instrument weakness when the model has multiple endogenous variables and there are more than one first-stage F statistic (Stock and Yogo (2005)). The test provides the minimum eigen value of a matrix analog of the first-stage F statistic, and is equivalent to the F statistic when there is only one endogenous variable. Stock and Yogo (2005) provide critical values based on the tolerance for estimation bias resulting from the use of instruments relative to the bias resulting from the use of the endogenous variables. A test statistic larger than the critical value corresponding to a certain tolerance level indicates that relative bias is smaller than that level of tolerance. The minimum eigen value statistics for both the IV logit and IV nested-logit models are larger than the critical values for a 10% level of relative bias, indicating that the instruments are reasonably strong.

The use of instruments is expected to increase the absolute value of the coefficient on premium. The omitted and unobserved variables described above are mostly quality indicators that are positively correlated with premium. Without instruments,

the marginal change in premium reflects not only an increment in price but also a corresponding increase in quality, resulting in estimate of price sensitivity that are biased towards zero. The other variables in the model are correlated with premium. Hence, instrumenting for premium is expected to correct the bias in their coefficients that results from the endogeneity of premium. The direction of this correction, however, is difficult to predict.

The estimates in table (6.3) are in line with expectations. The coefficient on premium is larger, in absolute value, in both specifications (2) and (3). The increase is greater in specification (3) which includes region fixed effects. This effect of controlling for region indicates the importance of controlling for region demographics, and is one of the motivators of using the full model described in chapter (4). The coefficient on gap coverage also increases in magnitude and becomes statistically significant.

The coefficient on average out-of-pocket spending is negative and significant and does not change much with the use of instruments. The magnitude of this coefficient is significantly smaller in absolute value than that of the coefficient on premium. For Part D enrollees, a $1 increase in a plan's premium is equivalent, on average, to $2.6 increase in this plan's average out-of-pocket spending. This estimate is consistent with the result in equation (6.1).

The significance of the coefficients on deductible and gap coverage, while accounting for average out-of-pocket spending, could be interpreted as evidence that beneficiaries pay disproportionate attention to plan features that are familiar and easy to understand, compared to features that are more difficult to obtain and interpret (Abaluck and Gruber (2009), Heiss et al. (2010)).

Specification (4) is a nested-logit model where plans are grouped according to type of benefit into basic plans and enhanced plans. Sigma, the coefficient on the log of within-nest share, is significant, indicating that the logit specification should

be rejected in favor of the nested-logit specification. The value of sigma indicates a high level of correlation among the idiosyncratic taste shocks for plans of the same benefit type. This correlation reflects the appeal of plans within the same nest to consumers with similar characteristics, which motivates the use of demand models that incorporate interactions between consumer and plan characteristics. The coefficients on plan features from this IV nested-logit model are qualitatively and quantitatively similar to those from the IV logit model.

A good proportion of the fixed effects for regions and contracts are statistically significant. There are 71 contracts in the dataset, 28 of which have fixed effects that are significantly different from the reference contract. This indicates that Part D plans are differentiated along dimensions beyond those considered in the model. Of the 34 PDP regions, 23 had fixed effects that are significantly different from the reference region. This suggests that alternative coverage options do vary from region to region.

To give an economic interpretation to the magnitudes of coefficients, I use the estimates from specification 4 to quantify the value of different plan features to Part D enrollees. I compute willingness-to-pay (WTP) measures by dividing parameter estimates by the estimate of the marginal utility of income. The model uses monthly premium; therefore, the coefficient on premium reflects the marginal utility from a dollar in a month. To get an estimate of the willingness to pay for a year of a particular benefit we need to multiply this monthly willingness-pay measure by 12. Including average out-of-pocket spending in the model complicates the derivation of the value of lower deductible and gap coverage, because the three measures are correlated. To compute the correct willingness-to-pay, we need to use the marginal effect of deductible and gap coverage, instead of coefficient estimates. However, estimating marginal effects requires the knowledge of the exact mathematical relation between these variables and average out-of-pocket spending, which does not

exist since the benefit design and generosity vary widely from one plan to the other. Instead, we could use, as an approximation, the statistical relation that exists in the data between deductible, gap coverage, and average out-of-pocket spending. To that end, I use an OLS model regressing average out-of-pocket spending on deductible and gap coverage, controling for premium, organization, and PDP region. A one dollar increase in deductible increases out-of-pocket spending by 54 cents in a year, and gap coverage reduces out-of-pocket spending by around $25, controlling for all the other variables included in the demand model.

Using these estimates of marginal effects, I find that non-LIS enrollees are willing to pay around $139 (in 2009 dollars) per year to go from a deductible of $295 to no deductible. This is a surprisingly low estimate given that the majority of Medicare beneficiaries are likely to have annual drug expenditures that are higher than $295. Moeller et al. (2004) estimate that the average Medicare beneficiary spent $113 per month on prescription drugs. The overwhelming majority (88%) of the sample I use have simulated annual out-of-pocket spending that is greater than $295. The reduction should be worth at least $295 to such enrollees, since it will reduce their expected out-of-pocket spending by at least as much. Frakt and Pizer (2010) demand estimates entail a higher value of $230 (in 2007 dollars, equivalent to $239 in 2009 dollars) for a $295 dollar reduction in premium. Their model, however, instruments only for premium while including an indicator for low-income-subsidy plans, which is a function of premium. The potential endogeneity of this indicator variable could affect the consistency of all the other coefficients. Both estimates, nevertheless, are significantly higher than the one provided by Lucarelli et al. (2008), who report a valuation of $46 (in 2006 dollars, equivalent to $49 in 2009 dollars) per year for the elimination of a $250 deductible. This is not surprising given their model's inclusion of LIS beneficiaries who should have a willingness-to-pay of zero since the subsidy covers their deductible payments.

Gap coverage is valued by non-LIS Part D enrollees at around $259 per year. To gauge the reasonableness of this estimate, I compare it to an estimate of the average savings from gap coverage using simulations of out-of-pocket spending. For each Medicare beneficiary in the simulation sample, I compute her average out-of-pocket spending for plans providing gap coverage in her region and compare that to her average out-of-pocket spending for plans with no gap coverage. On average, gap coverage results in $286 of savings for Medicare beneficiaries. This is close to the WTP estimate, as well as to the $250 rebate amount that beneficiaries will receive in 2010 for expenditures in the gap as part of the new health reform legislation.

I also compare the estimate of WTP for gap coverage to the average market price of gap coverage, adjusted for other plan features and insurer and region dummies. To compute the adjusted average price for gap coverage, I run a hedonic regression similar to the one in table 6.1 using 2009 data. The average annual price for gap coverage using this measure is around $348, which is significantly higher than what the average non-LIS enrollees is willing to pay for this feature. Heiss et al. (2010) find hedonic prices for plan features in 2006 that approximate consumers' willingness to pay. The discrepancy I find using 2009 data could be related to what appears to be a death spiral involving plans with generous benefits. There has been a gradual disappearance over the first 4 years of the program of plans offering coverage in the doughnut hole. Winter et al. (2006) report evidence of significant adverse selection into generous plans, and Heiss et al. (2008) estimated that the government will have to increase its subsidy to plans by 16% to preserve consumer choice in plan generosity. If this disappearance is due to adverse selection, with sick enrollees selecting into plans with gap coverage, then plans will have to charge a price for this feature that is higher than its average valuation.

Table (6.3) also shows estimates of the median price elasticity of demand for each specification. Premium elasticity of demand for the nested-logit model is given

by:

$$\varepsilon_{pr} = \frac{\hat{\alpha}}{(1-\hat{\sigma})}\left(1 - \hat{\sigma}\, share_{pr/G} - (1-\hat{\sigma})\, share_{pr}\right) P_{pr} \tag{6.2}$$

where $\hat{\alpha}$ and $\hat{\sigma}$ are the estimates of the coefficients on premium and the log of within-nest share, respectively. The use of instrumental variables increases the estimate of elasticity from -1.47 to -2.39. The 95% confidence interval for the estimate from the IV nested-logit model is [-3.04,-1.42]. The standard error for median elasticity is computed using a parametric bootstrap approach (Horowitz (2001)). I use the estimated variance-covariance matrix of the nested-logit coefficients to draw a large sample from the asymptotic distribution of the coefficients. For each draw, I obtain premium elasticity of demand for each plan and computed the median elasticity for the draw. I then compute the mean and standard deviation of the resulting distribution of median elasticity.

My elasticity estimates are considerably larger than estimates reported in the literature for the elasticity of demand for Medicare HMOs, and are on the higher side of the range reported in previous studies of demand for Part D plans (see chapter 3). All the elasticity estimates for Part D plans reported in the literature are significantly larger compared to those for Medicare HMOs. Frakt and Pizer (2010) discuss two potential reasons for this. First, Part D plans are easier to establish compared to Medicare HMOs, which require the development of a network of hospitals and physicians in addition to the arrangements with drug manufacturers and pharmacy networks for the prescription drug benefit. The smaller fixed costs stimulate entry into the market, leading to the availability to beneficiaries of more substitutes, and consequently to larger premium elasticity of demand. Second, unlike Medicare HMOs which have been offered for more than two decades, Part D plans have been around for only a few years. To the extent that beneficiaries become attached to the plans they enroll-in and face switching costs, the impact of premiums on plan choice

will be less the more significant such attachment is.

There are two potential reasons why the elasticity estimates I report in this research are higher than those reported in previous studies of demand for Part D plans. First, previous studies used data from 2006 or 2007, while I use 2009 data. This time difference is likely to be of significance. There is evidence of significant learning by consumers early in the program in terms of how to navigate the market maze and choose plans that best suit their needs (Ketcham et al. (2010)). The early few years have also seen considerable changes in the number, type, and price of Part D plan offerings, which suggests that insurers were also learning about this new market. To the extent that this learning enables market actors to make more optimal choices, then studies imposing a rational model of behavior would be less mistaken if applied to later years. In addition to this model validity issue, learning by consumers is bound to affect their actual choices. In particular, as consumers become more adept at comparing plans' premiums and features, their demand will become more elastic with regards to these characteristics, especially to premiums which are the most salient and easy to understand of all plan features. This is what the estimates in this study suggest.

We can use our elasticity estimate to compute the probability of plan switching given an increase in premium. The probability of switching associated with a change in the premium is the change in the plans market share due to the change in premium, divided by the original market share (Dowd et al. (2003)):

$$\frac{\delta \text{Probability of Switching}}{\delta \text{Premium}} = -\frac{\delta MS_{pr}/\delta \text{Premium}}{MS_{pr}} \tag{6.3}$$

the right hand side of (6.3) could be derived using our elasticity estimate:

$$\frac{\delta MS_{pr}/\delta \text{Premium}}{MS_{pr}} = -\frac{\varepsilon_{pr}}{\text{Premium}} \tag{6.4}$$

The probability of a non-LIS part D enrollee switching plans increases by 5.8%

for each dollar increase in premium. Similar to elasticity, this estimate is significantly higher than 0.002 and 0.016 reported for Medicare HMOs by Buchmueller (2000) and Dowd et al. (2003), respectively.

Table 6.3: Logit and Nested Logit Demand Estimates for Non-LIS Enrollees

Variable	1	2	3	4
Intercept	-1.5	0.59	2.30	-0.88
	(0.82)	(1.26)	(1.20)	(0.42)
Premium	-0.033^{**}	-0.063^{**}	-0.081^{**}	-0.02^{**}
	(0.003)	(0.012)	(0.01)	(0.004)
Deductible	-0.0018^{**}	-0.0026^{**}	-0.0031^{**}	-0.0004
	(0.0004)	(0.005)	(0.0004)	(0.0002)
Gap Coverage	-0.1	0.86^{*}	1.44^{**}	0.23^{*}
	(0.13)	(0.39)	(0.36)	(0.11)
Avg OOP	-0.019^{**}	-0.024^{**}	-0.028^{**}	-0.008^{**}
	(0.004)	(0.004)	(0.004)	(0.001)
Sigma				0.63^{**}
				(0.04)
Median Elasticity	-1.28	-1.8	-2.39	-2.25
	(0.13)	(0.34)	(0.34)	(0.44)
Fixed Effects	Contract	Contract	Contract, Region	Contract, Region
Instruments	None	BLP	BLP	BLP
Minimum Eigen Value		18.6	19.2	12.8
CV for 10% 2SLS Relative Bias		11.1	11.1	9.5
Over Identification Test		40.6	31.5	66.6

[a] Based on 1612 observations. Dependent variable is $\ln(S_{jt}) - \ln(S_{0t})$. Includes region and organization fixed effects. Robust standard errors in parentheses. Standard errors for median elasticity derived using parametric bootstrap with 1000 draws.

Significance levels: $*$: 5% $**$: 1%

6.3 The Full Model

The estimates of the full model are based on equation (4.2) and were derived using the procedure described in chapter (**??**). I use the empirical distribution of demographics to compute predicted market shares, along with draws from a standard normal distribution for unobserved individual heterogeneity. For each PDP region, I simulate 120 individuals and compute predicted market shares as the numerical approximation of the integral in equation (4.8). The instruments for premium are the same as those used in the IV logit and IV nested-logit models. The number of instruments exceeds the number of exclusion restrictions required to identify the model, leading to an over-identified GMM system that is solved by minimizing the weighted sum of moments specified in equation (4.14).

Table (6.4) shows the full model demand estimates for non-LIS enrollees. Plan features used in the model include premium, deductible, gap coverage, and average out-of-pocket spending. The demographic variable used in the model is medical expenditures, measured by how much Medicare paid on behalf of the individual for inpatient and outpatient care. The measure is obtained from MCBS 2006 and 2007 Access to Care modules, and is adjusted to account for the influence of supplementary health insurance (Atherly (2002)). I excluded expenditures on prescription drugs because they reflect choices beneficiaries made with regards to prescription drug coverage.

The model also includes organization fixed effects to account for unobserved insurer-level features. Unlike the IV logit and IV nested-logit specifications presented above, however, the full model does not include region fixed effects. Interaction parameters are identified by between-market variation in the distribution of demographics and by variation in choice sets (Nevo (2001)). The inclusion of region fixed-effects will capture most of that variation, limiting the identifiability of interaction terms.

Interactions with medical expenditures in the preferred specification of the model are limited to those with the intercept, premium, deductible, and average out-of-pocket variables. The restrictions were chosen to minimize the effect of correlation between the various measures of plan generosity. Such correlation would limit identification of interaction parameters, especially given the limited variation in the distribution of demographics between regions in a single year.

The mean coefficient on premium is larger in absolute value compared to the IV logit and IV nested-logit models, resulting in the higher elasticity estimate of -5.04. This is due to the fact that the full model controls for variables that the linearized logit and nested-logit models cannot incorporate because they assume homogenous parameters. The full model controls for interactions between plan characteristics and demographics, and it accounts for unobserved plan characteristics. The inclusion of these variables in the full model corrects the missing variable bias in the IV logit and nested-logit estimates, and resolves the Independence of Irrelevant Alternatives problem of the logit model in manner that is richer and more flexible than the nested-logit model. The mean coefficients on the other variables are also larger in absolute value, reflecting the correction of the attenuation bias in the logit and nested-logit estimates.

I compute willingness-to-pay estimates based on the results in table (6.4) using the same approach discussed in section (6.2). The magnitude of the mean coefficient on deductible suggests that, on average, Part D enrollees value a reduction in annual deductible from $295 to $0 at approximately $334. This is significantly higher, and more reasonable, compared to the nested-logit estimate. The value of gap coverage also increases to $273 per year, which is still significantly smaller than the $348 implicit price of this feature.

Estimates of the interaction parameters are significant and of the expected sign. Beneficiaries with high inpatient and outpatient expenditures are likely to have

higher drug expenditures as well. The estimates suggest that they are less sensitive to plan premium and deductible than those with good health. This is an intuitive result, since for any benefit package, enrollees with poor health expect to receive more benefits, in absolute dollar amounts, compared to those with good health, and would, as a result, be willing to pay more. Controlling for premium and deductible, enrollees with high medical expenditures are more sensitive to plan generosity, as measured by average-out-of-pocket spending, reflecting their higher drug expenditures. Interactions with unobserved individual tastes are not significant, controlling for interactions with medical expenditures. The limited variation in the distribution of demographics in addition to the similarities in choice sets in different PDP regions makes it difficult to identify all of these parameters using data from a single year.

Interactions of premium and deductible with medical expenditures are positive despite the potential correlation between bad health and low income. It is possible that the random heterogeneity controls for the distribution of income in the region. If this is not the case, then controlling for income directly would probably make the estimates of these interactions even more positive.

Table (6.5) shows the distribution of parameter heterogeneity implied by the full model estimates. The distributions are driven by the empirical distribution of medical expenditures of non-LIS beneficiaries, which is heavily skewed to the left. More than 95% of non-LIS beneficiaries are predicted to have premium coefficients that are less than zero. The positive premium coefficients belong to individuals in the sample with medical expenditures that are extraordinarily high. Corresponding drug expenditures are likely to be in the catastrophic coverage zone, of which the enrollee pays only 5%. The model does not account for this non-linear nature of the interaction, resulting in unrealistic predictions away from the center of the distribution. The same could be said about the distribution of the parameters on deductible and average out-of-pocket spending.

For instance, sensitivity to a marginal increase in deductible should go down as drug expenditures increase towards the maximum deductible offered in the market. If expected out-of-pocket spending is more than this maximum deductible then the marginal sensitivity should go to zero, as any increase in deductible that does not exceed the maximum do not affect such enrollees. Therefore, the mean estimate in table (6.4) probably reflects more the preferences of those on the left side of the distribution of medical expenditures, and less those in its right tail.

Table 6.4: Full Model Estimates for Non-LIS Enrollees

Variable	**Means**	**Standard Deviations**	**Medical Expenditure**
	β	σ	π
Intercept	0.98	2.29	-0.81
	(2.29)	(1.30)	(1.66)
Premium	-0.13^{**}	0.016	0.050^{**}
	(0.02)	(0.023)	(0.016)
Deductible	-0.011^{**}	0.002	0.013^{**}
	(0.001)	(0.004)	(0.005)
Gap Coverage	2.21^{**}	0	0
	(0.65)	0	0
Avg OOP	-0.025^{**}	0.002	-0.016^{**}
	(0.007)	(0.005)	(0.006)
Objective Function	61.1		
Median Elasticity	-5.04		
	0.85		

[a] Based on 1269 observations. Medical expenditures in thousands per month. Robust standard errors in parentheses. Standard errors for median elasticity derived using parametric bootstrap with 1000 draws. Significance levels: $*$: 5% $**$: 1%

Table 6.5: Parameter Heterogeneity

	α_i	$\beta_{Deduct-i}$	β_{oop-i}	Medical Expenditure ($ per month)
Mean	-0.11	-0.005	-0.032	460
Median	-0.12	-0.009	-0.026	80
95%	-0.008	0.02	-0.64	$2,400$
Max	0.96	0.27	-0.37	$21,800$

[a] Based on a combined sample of 15532 of non-LIS beneficiaries from MCBS 2006 and 2007 Access to Care modules. Ranking in terms of absolute value. The numbers do not account for uncertainty of full model estimates or for correlation between these estimates.

Chapter 7

Low Income Beneficiaries

7.1 Low Income Subsidy Recepients and Preferences for Part D Plans

Medicare Part D provides substantial assistance to enrollees with low income. This subsidy is vital component of the program, providing coverage to millions of seniors with limited financial resources. More than 9.5 million beneficiaries received the low-income subsidy (LIS) in 2009, 8.1 million of whom were dual eligibles and other beneficiaries who were automatically deemed eligible for the subsidy (The Henry J. Kaiser Family Foundation (2009)). The remaining 1.5 million applied and qualified for the subsidy. The subsidy pays for the premium, the deductible, and for coverage in the doughnut hole, while beneficiaries pay only small copayments for generic and brand drugs covered by the plan. In addition to copayments, LIS recipients have to pay for medications that are not on their plan's formulary. The premium subsidy is limited to a benchmark determined by a weighted average of premiums in the region. If the beneficiary chooses to enroll in a plan with a premium above the benchmark, she would have to pay the balance.

CMS auto-enrolls beneficiaries who qualify for LIS into plans that charge premiums below the region benchmark. The purpose of this auto-enrollment is to guarantee continuity of coverage for this vulnerable population. There is widespread belief among policy makers and advocacy groups that a significant proportion of this population will fail to sign up for Part D coverage, in a timely fashion, if not assisted

(Kaiser Commission on Medicaid and the Uninsured (2007)). This is especially true for new dual eligibles who qualify for Medicare after turning 65 and loosing Medicaid coverage as a result. LIS beneficiaries, however, can choose a different plan if they are not satisfied with their assignment. In fact, open enrollment for LIS beneficiaries continues throughout the year, and they can switch plans whenever they desire. This is another protective arrangement, to give beneficiaries the chance to change plans if the formulary or pricing in their current plan changes or if they require new drugs that are not covered by their current plan.

Data on plan choices by LIS beneficiaries are limited, but there is evidence from surveys of beneficiaries and advocates working with seniors that many LIS enrollees remain in the plans to which they were initially assigned. For instance, in a survey of individuals who assist Medicare beneficiaries, Summer et al. (2008) report that three quarters of respondents said that few or none of the dual eligible beneficiaries they see were aware that they had the right to switch plans anytime. Around 35% of respondents to that survey said that, very often or often, those who were auto-enrolled had difficulty switching plans.

There is also an indirect evidence from CMS reports on the number of LIS beneficiaries who are reassigned to new plans each year. LIS enrollees in plans that raise premiums above the benchmark in a subsequent year are automatically reassigned to another LIS plan in their region. This is true for those who did not switch plans after the initial assignment. Enrollees who have switched previously receive notification by their plan and by CMS that they have to choose another benchmark plan if they want to avoid paying any premium. CMS reports that 1.2 million LIS beneficiaries were reassigned to new plans in 2010, while 2.2 million were notified to choose a new plan. This means that 3.4 million LIS beneficiaries were enrolled in plans that raised premiums above the benchmark in 2010 (The Henry J. Kaiser Family Foundation (2009)). Out of those, 2.2 million have switched plans previously,

otherwise they would have been reassigned and not just notified. If we assume that those 3.4 million beneficiaries are representative of the other LIS enrollees, then it is reasonable to conclude that at least 30% of LIS beneficiaries end up staying in their assigned plans for the entirety of the year. A higher percentage would have spent some time during the year in the assigned plan, especially given the reports on the difficulty of switching plans and the lack of awareness on the part of beneficiaries of the option to switch.

Therefore, at least some LIS beneficiaries do exercise their option to switch to a different Part D plan. In principle, we could use enrollment patterns corresponding to such active choosers to estimate preferences of LIS beneficiaries. However, plan-level LIS enrollment data do not distinguish between LIS beneficiaries making active plan choices and those randomly assigned. Nonetheless, random assignment is limited to plans that qualify to enroll LIS beneficiaries. Therefore, those LIS beneficiaries enrolled in non-LIS plans are, by definition, active choosers. The full subsidy for those beneficiaries covers the benchmark premium, deductible, and the cost sharing corresponding to the basic part of the plan's benefit. The LIS enrollee is responsible for the share of the premium above the benchmark level, and for any cost-sharing corresponding to the enhanced part of the benefit.

It is possible, therefore, to use LIS enrollment in non-LIS plans to estimate preferences for LIS beneficiaries who are active choosers. Choosing a non-benchmark plan entails extra out-of-pocket spending. Hence it is reasonable to expect that the population of LIS beneficiaries who choose to enroll in such plans are probably more well-to-do compared to those that choose a benchmark plan. Nevertheless, the differences are unlikely to be significant since both groups have incomes close to or below the poverty line.

Reviewing trends in plan enrollment over the period 2008-2009 reveals another issue that could be of concern. There is significant stickiness in enrollment by LIS

beneficiaries into LIS plans, such that when plans cease to be LIS plans they still retain a significant LIS enrollment. This stickiness may be considered a sign of a passive enrollment as opposed to active choice by LIS enrollees that remain enrolled in these plans. However, CMS automatically reassigns beneficiaries auto-enrolled in such plans to other LIS plans. Therefore, those that remain in LIS plans after they lost their benchmark status must have actively chosen to remain enrolled. The exception are those LIS beneficiaries that actively chose to enroll in the plan initially. CMS does not reassign such active choosers automatically. They are informed of the change in the status of their plan, and encouraged to consider switching to another plan if they want to pay no premium. But those have at least shown preference to the plan at some point.

Since I have no data on active choosers enrolling in LIS plans, I consider PDP LIS plans as part of the outside option (together with LIS MAPD plans) and model only the choice of non-LIS PDP plans by LIS beneficiaries. I use the model described in section (6.2) with the same variables and instruments. Table (7.1) presents results from IV logit estimation of this model, and compares those to the IV logit demand estimates for non-LIS enrollees. The premium for LIS enrollees is computed as the difference between a plan's premium and the region's benchmark level. The model does not include the deductible because the subsidy covers the deductible for LIS enrollees even in non-benchmark plans.

The coefficient on premium is larger in absolute value for LIS enrollees, reflecting their lower income which is associated with larger marginal utility of income. Median elasticity, however, is similar for both groups. This is primarily because of the lower premiums paid by LIS enrollees. These elasticity estimates are in effect taken at different points along the demand curve of each group. Therefore, given our assumed linear utility representation, if both groups had the same coefficient on premium, LIS beneficiaries would have had a smaller elasticity estimate. LIS

beneficiaries are also significantly more responsive to measures of plan generosity.

Table 7.1: IV Logit Estimates for Non-LIS and LIS Enrollees

Variable	**NON LIS**	**LIS**
Premium	-0.081^{**}	-0.14^{**}
	(0.01)	(0.02)
Gap	1.44^{**}	2.43^{**}
	(0.36)	(0.74)
Avg OOP	-0.028^{**}	-0.050^{**}
	(0.005)	(0.007)
N	1522	1335
Median Elasticity	-2.98	-2.80
	(0.38)	(0.47)
Minimum Eigen Value	19.2	10.76
CV for 10% 2SLS Relative Bias	11.1	10.27
Over Identification Test	31.5	14.04

[a] Dependent variable is $\ln(S_{jt}) - \ln(S_{0t})$. Robust standard errors in parentheses. Standard errors for median elasticity derived using parametric bootstrap with 1000 draws.

Significance levels: $*$: 5% $**$: 1%

7.2 Potential Savings and Welfare Gains from Strategic Enrollment

Medicare beneficiaries eligible for full low-income subsidy are randomly assigned by CMS to an LIS plan in their region. This random assignment, however, does not take into account each beneficiary's medication profile. This is potentially problematic for these beneficiaries, especially given the degree of variation between plans in the drugs they cover. In a 2006 survey conducted by the office of the inspector general of the U.S. Department of Health and Human Services (DHHS), only half of the drugs commonly used by Medicaid eligible enrollees were included by all the formularies of Part D plans surveyed (Office of the Inspector General (2006)). Summer et al. (2008) report that more than one-third of beneficiary contacts they surveyed reported that, often and very often, drugs needed by their clients were not on their plans' formularies.

LIS recipients assigned to plans that do not cover their drugs will have to pay for those drugs out-of-pocket. This imposes significant financial hardship on these enrollees. LIS beneficiaries, however, have two potential remedies for this unfortunate situation. They could switch to a different Part D plan that covers their medication any time during the year. Alternatively, they could file a request with their plan to cover their medication. Both options require significant awareness and familiarity with the workings of the program that many LIS enrollees may not have (Summer et al. (2008)).

The indirect evidence we have on the proportion of LIS beneficiaries who switch plans indicate that at least 30% of beneficiaries stay in their assigned plans for the whole year. Those could well be the beneficiaries for whom random assignment resulted in a plan that matches their needs. However, reports from the field suggest that a significant number of assigned beneficiaries lack coverage for at least some of their medications, and have difficulty switching to another plan. But even if

these enrollees eventually switched plans, the process can potentially take weeks or months to complete, during which they had to pay for their uncovered drugs out-of-pocket or forgo taking them altogether (Kaiser Commission on Medicaid and the Uninsured (2007)).

Many analysts and beneficiary advocates, therefore, recommended reconsidering the random assignment process. An intuitive alternative suggested by many is for CMS to use claims data to match each LIS enrollee to the plan that best fits her need (Summer et al. (2008), Kaiser Commission on Medicaid and the Uninsured (2007)). For those with no prior data, such as MSP beneficiaries or recent Medicaid eligibles, random assignment will need to be used for the first several months.

CMS has recently undertaken a study to analyze this strategic assignment proposal and to measure its value relative to random assignment (Center for Medicaid and Medicare Services (2009)). Random assignment was found to result in an optimal match for two thirds of reassigned enrollees. A plan is considered optimal if it covers the maximum number of enrollees' drugs compared to other benchmark plans in the region. The remaining one third would benefit from strategic reassignment. Strategic assignment was found to be especially useful to those using drugs that are not in a protected class. Their analysis, however, relies on estimating drug match rates, and does not quantify the consequences of mismatches in terms of out-of-pocket spending.

The analysis in this section evaluates the benefit from strategic assignment using two different approaches. First, I use plan drug pricing data, in addition to plan formularies and drug profiles for a representative sample of LIS enrollees from 2006 MCBS Cost and Use module, to simulate enrollees' expected out-of-pocket spending associated with each benchmark plan in their region. I then use the out-of-pocket simulations to quantify the potential savings from strategic assignments. Second, I use parameter estimates from the analysis of demand by LIS beneficiaries in section

(7.1), and a modified version of the parameter estimates from the full model of demand by non-LIS beneficiaries, to estimate potential welfare gains from strategic assignment. Both evaluations are reported for a period of one month, which is arguably the minimum period a beneficiary would stay in an assigned plan before switching to their optimal plan.

Table (7.2) shows estimates of the potential savings from assigning LIS beneficiaries to plans that minimize their out-of-pocket spending, compared to assignment to plans with average out-of-pocket spending, representing random assignment. On average, LIS beneficiaries stand to save around $122 per month if they were assigned to a plan that best covers their medication, with total potential savings of around $0.6 billion per month. The range of potential savings is quite large, with some LIS beneficiaries saving up to $954. Table (7.3) shows the effect of health status on potential savings from strategic assignment. As expected, potential savings increase as health status worsens.

Savings, however, do not capture all sources of utility for consumers. Enrollees have tastes for other plan attributes, besides proxies for out-of-pocket expenditures, such as the quality of customer service, the structure of pharmacy networks, and the nature of utilization management practices. Therefore, using utility estimates to evaluate strategic assignment is perhaps more informative than using potential savings. The utility from plan characteristics could be estimated using demand models similar to the one presented in section (7.1). In such models, the utility from non-monetary features is captured by insurer fixed effects. However, this model of demand does not allow for interaction between plan features and individual characteristics. Therefore, the estimates from the model cannot be used alone to evaluate a beneficiary's utility from each available benchmark plan in order to determine her optimal choice.

I attempt to overcome this problem by making use of the estimates from section (6.3) for non-LIS enrollees, combined with the sensible conclusion from section

(7.1) that LIS beneficiaries are more sensitive than their non-LIS counterparts to out-of-pocket costs. I use demand estimates for LIS enrollees from section (7.1), including insurer fixed effects, to estimate mean utility for each plan. For the interaction between plan features and medical expenditures, I use estimates from the full model for non-LIS enrollees. Premiums and deductibles of all benchmark plans are effectively zero for all enrollees. Therefore, the only interaction left is that between average out-of-pocket spending and medical expenditures.

The use of estimates for interaction parameters from the non-LIS model will not generate an accurate point estimate. However, it can conceivably provide a lower-bound estimate of the welfare gains to LIS enrollees from strategic assignments. If LIS beneficiaries are more sensitive to out-of-pocket costs, then LIS beneficiaries with high medical and drug expenditures should be more sensitive to a plan's average out-of-pocket spending than non-LIS enrollees with similar levels of expenditures.

Nonetheless, combining coefficients from two different models to generate an estimate may raise concerns. In particular, evaluating the uncertainty of the estimate using standard error from two separate models is problematic. For the parametric bootstrap, for instance, I draw from the asymptotic joint distribution of all the parameters used to generate the estimate of interest. The joint distribution, however, entails covariances between parameter estimates that could not be assessed when these estimates come from different models. To address this concern, I restrict to zero all covariances between parameters. This should have the effect of increasing the uncertainty around my welfare estimate, resulting in conservative standard errors.

Table (7.4) shows results from this estimation exercise. Welfare gain for an LIS beneficiary is computed as the difference in expected utility between his maximum plan utility and average plan utility, divided by average marginal utility of income for LIS beneficiaries. Strategic assignment is estimated to lead to an average monthly

welfare gain of $58, with a total welfare gain of $0.47 billion in one month. The estimates are lower than the estimates of potential savings. This is probably a result of using interaction coefficient from the model for non-LIS enrollees. In addition, savings reflect primarily the listing of beneficiaries' drugs on plan's formularies. Plans with expansive formularies result in bigger savings. However, many such plans use utilization management to limit use of those medications, which can limit utility from joining them.

The estimated savings and welfare gains from strategic enrollment are potentially significant. The analysis in this section suggests that LIS beneficiaries stand to gain at least $58 worth of welfare each month if they were assigned to a plan that best matches their needs. This is approximately equivalent to 30% of the average monthly amount the government pays Part D plans to cover LIS beneficiaries (2.9).

Two caveats are in order, however. First, I assume that medication use is constant over the period of comparison, which is a reasonable assumption for a one month period, but is unlikely to be true for extended periods of time. For instance, Domino et al. (2008) investigate the effect of changes in the use of medications by the end of the year on out-of-pocket spending, conditional on the choice of the lowest cost plan at the beginning of the year. They find that choosing a plan based on current medications is associated with increases in annual out-of-pocket spending of around $556 for 43% of their sample. The increases in out-of-pocket spending is due to changes in the use of medications that were not considered for the initial choice. They conclude that beneficiaries should consider the global generosity of plans, instead of only focusing on coverage of the medications they currently use.

This is a valuable insight that needs to be incorporated in any attempt to improve assignments of LIS beneficiaries. It is important to keep in mind, however, that the comparison made by Domino et al. (2008) is different from the one made in this analysis. The authors compare the ex post savings from strategic assignment to

those from assignment to a plan that is ex post efficient, while this analysis compares strategic assignment to random assignment. An ideal comparison, perhaps, would be to compare the outcomes of both strategic assignment and random assignment to the ex post efficient outcome.

Second, the analysis in this section is a partial equilibrium analysis that does not consider the long-term outcomes of the strategic assignment process. In particular, the analysis is based on static demand analysis that does not incorporate dynamics or the supply side. Strategic assignment is likely to increase the potential for adverse selection. LIS plans providing relatively generous coverage will attract LIS beneficiaries with above average costs. In return, plans will either try to limit their coverage to select against costly enrollees, leading to a race to the bottom, or raise premium and lose their benchmark status. The potential long-run outcome, in either case, is not favorable to LIS beneficiaries. In the short and medium terms, any savings for LIS beneficiaries will translate into higher government spending, which needs to be considered in any analysis on the effect of the policy on overall societal welfare.

Table 7.2: Potential Monthly Savings from Strategic Enrollment

Average Savings	$122
	(4.1)
Range	($0-$954)
Total Savings (billions)	$0.6

[a] Based on 2817 respondents from 2006 MCBS Access to Care module who are LIS recipients and/or dual eligibles. Sampling standard errors in parentheses. Total savings computed using MCBS sampling weights.

Table 7.3: Potential Monthly Savings from Strategic Enrollment by Health Status

Health Status	**Coefficient**	**Std. Error**
Very Good	10.1	13.2
Good	41.0**	12.1
Fair	54.3**	12.2
Poor	102.0**	13.2
Intercept	73.4**	11.04

[a] Based on 2523 respondents from 2006 MCBS Access to Care module who are LIS recipients and/or dual eligibles. Excellent health is the reference category. Significance levels: $*$: 5% $**$: 1%

Table 7.4: Potential Monthly Welfare Gains from Strategic Enrollment

Average Welfare Gain	$58.8
Std. Err	(18.1)
Total Welfare Gain (billions)	$0.473
Std. Err	(0.003)

[a] Based on 2523 respondents from 2006 MCBS Access to Care module who are LIS recipients. Total welfare gain computed using MCBS sampling weights. Standard Errors computed using parametric bootstrap with 1000 draws.

Chapter 8
Conclusion

This study adds to previous literature by estimating separate structural demand systems for LIS beneficiaries and non-LIS enrollees. Several important results are obtained. First, non-LIS enrollees are significantly more sensitive to premiums than previously recognized. The estimate of elasticity of demand for non-LIS enrollees is at least twice that reported in studies using earlier data. The difference could be explained, at least partially, by the nature of the data used for the estimation. However, this finding could also be interpreted as evidence that consumers are becoming more adept over time at choosing plans and navigating the market. Evidence from recent studies in the literature supports this learning hypothesis (Ketcham et al. (2010)).

The analysis also shows that the average valuation of gap coverage by consumers is below the implicit price of this coverage. I interpret this finding as evidence of adverse selection into plans providing generous coverage. The number of plans providing benefits in the doughnut hole has been falling consistently since 2007, and many analysts attribute this gradual disappearance to adverse selection. If such plans are disproportionately selected by enrollees with above-average costs, their pricing will have to go up to match the high costs. This will lead at a certain point to prices exceeding the benefit that an average beneficiary gets from the gap coverage, which is what I find in this analysis.

However, the phasing in of coverage in the doughnut hole staring 2010 is likely to reverse this dynamic. This new subsidy reduces costs to plans of providing com-

prehensive coverage in the gap, and will encourage more beneficiaries to enroll in plans providing such coverage. The resulting reduction in adverse selection, along with the reduction in plan costs, will likely lead to lower prices for comprehensive gap coverage in the future.

Examining parameter heterogeneity revealed a significant relationship between sensitivity to out-of-pocket spending and level of medical care cost. Beneficiaries with high inpatient and outpatient expenditures are likely to have higher drug expenditures as well. The estimates suggest that they are less sensitive to plan premium and deductible than those with good health. This is an intuitive result, since for any benefit package, enrollees with poor health expect to receive more benefits, in absolute dollar amounts, compared to those with good health, and would, as a result, be willing to pay more. On the other hand, enrollees with high medical expenditures are more sensitive to plan generosity (as measured by average-out-of-pocket spending), reflecting their higher drug expenditures.

In addition to estimating demand for non-LIS beneficiaries, I utilize the data on plan-level enrollment by LIS beneficiaries to estimate a demand system for LIS beneficiaries who are active choosers. Specifically, I use the subset of LIS beneficiaries that chose to enroll, or remain enrolled, in a non-LIS plan. I find that LIS beneficiaries are significantly more sensitive to out-of-pocket expenditures compared to non-LIS enrollees. This is likely due to their lower income and the corresponding higher marginal utility of money. My sample is composed of LIS recipients who are willing to pay a premium to join a non-LIS plan, which suggests that the average LIS beneficiary who enrolls in an LIS plan is likely to be even more sensitive to out-of-pocket spending.

The analysis finally examined the welfare gains to LIS beneficiaries from a policy of strategic assignment compared to the current process of random assignment to benchmark plans. I find evidence of significant welfare gains for LIS beneficiaries

from assigning them to plans that best cover their medications. The lower bound estimate of this gain is approximately equivalent to 30% of the average monthly amount the government pays Part D plans to cover LIS beneficiaries. The long term effects of such policy, however, could be unfavorable to LIS beneficiaries. Strategic assignment is likely to increase the potential of adverse selection for LIS plans and lead to a race to the bottom or exit of benchmark plans. Policy makers and regulators will have to carefully weigh the significant short-term gains against the potential long-run costs.

There are several limitations to the analysis that I hope to be able to address in future research. First, the analysis is a partial equilibrium analysis that includes only the demand side and does not model the behavior of insurers. This limits the usefulness of the model in predicting the impact of policy changes that may elicit significant firm responses, such as the implementation of a strategic assignment policy.

Second, the use of market-level data to estimate individual heterogeneity requires significant variation between markets in demographics and choice sets. Unfortunately, both variations are limited if one uses data for Part D from a single year. The incorporation of additional years of aggregate data, or combining aggregate data with individual level data from the new Part D claims release, will significantly add to the precision of the estimates and allow for a richer modeling of consumer heterogeneity.

Finally, the estimation of welfare gains from strategic assignment focused on finding a lower bound instead of a point estimate. The availability of additional data on plan-level LIS enrollment in the future will allow for the estimation of a separate random utility model for LIS beneficiaries.

Bibliography

Abaluck, J. T. and Gruber, J. (2009). Choice inconsistencies among the elderly: Evidence from plan choice in the medicare part d program. Working Paper 14759, National Bureau of Economic Research.

Adler, G. S. (1994). A profile of the medicare current beneficiary survey. *Health Care Financing Review*, 15(4):153–163.

Aroian, L. (1947). The probability function of the product of two normally distributed variables. *Annals of Mathematical Statistics*, 18:265–271.

Atherly, A. (2002). The effect of medicare supplemental insurance on medicare expenditures. *International Journal of Health Care Finance and Economics*, 2:137–162.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *Rand Journal of Economics*, 25:242–262.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 63:841–890.

Boards of Trustees (2009). 2009 annual report. Technical report, Board of Trustees of the Federal Hospital Insurance and Federal Supplementary Medical Insurance Trust Funds.

Bresnahan, T., Stern, S., and Trajtenberg, M. (1997). Market segmentation and the sources of rents from innovation: Personal computers in the late 1980's. *RAND Journal of Economics*, 28:S17–S44.

Buchmueller, T. (2000). The health plan choices of retirees under managed competition. *Health Services Research*, 35(5):94976.

Center for Medicaid and Medicare Services (2009). Medicare part d strategic reassignment enrollment analysis. Technical report, U.S. Department of Health and Human Services.

CMS (2007). 2008 medicare part d call letter. Technical report, Center for Medicaid and Medicare Services.

Congressional Budget Office (2002). Issues in designing a prescription drug benefit for medicare. Technical report.

Congressional Budget Office (2004). A detailed description of cbo's cost estimates for the medicare prescription drug benefit. Technical report.

Cubanski, J. and Neuman, P. (2007). Status Report On Medicare Part D Enrollment In 2006: Analysis Of Plan-Specific Market Share And Coverage. *Health Affairs*, 26(1):w1–12.

Cubanski, J., Neuman, T., Damico, A., and Huang, J. (2009). Examining sources of coverage among medicare beneficiaries: Supplemental insurance, medicare advantage, and prescription drug coverage. findings from the medicare current beneficiary survey, 2007. Technical report, The Henry J. Kaiser Family Foundation.

Cutler, D. M. and Reber, S. J. (1998). Paying for health insurance: The trade-off between competition and adverse selection. *Quarterly Journal of Economics*, 113(2):433–466.

Dafny, L., Duggan, M., and Ramanarayanan, S. (2009). Paying a premium on your premium? consolidation in the u.s. health insurance industry. Working Paper 15434, National Bureau of Economic Research.

DOJ and FTC (2007). Horizontal merger guidelines. Technical report.

Domino, M., Stevens, S., Norton, E., and Yeh, W.-S. (2008). Why using current medications to select a medicare part d plan may lead to higher out-of-pocket payments. *Medical Care Research and Review*, 65(1):114–126.

Dowd, B., Feldman, R., and Coulam, R. (2003). The effect of health plan characteristics on medicare+choice enrollment. *Health Services Research*, 38(1):113–135.

Duggan, M., Healy, P., and Morton, F. S. (2008). Providing prescription drug coverage to the elderly: America's experiment with medicare part d. *Journal of Economic Perspectives*, 22(4):69–92.

Duggan, M. and Morton, F. S. (2010). The effect of medicare part d on pharmaceutical prices and utilization. *American Economic Review*, 100(1):590–607.

Ellis, R. and McGuire, T. (2007). Predictability and predictiveness in health care spending. *Journal of Health Economics*, 26:2548.

Frakt, A. and Pizer, S. (2010). Beneficiary price sensitivity in the medicare prescription drug plan market. *Health Economics*, 19:88–100.

Goldman, D. P. and Joyce, G. F. (2009). Medicare part d: A successful start with room for improvement. *JAMA*, 299(16):1954–1955.

Hall, A. (2007). The value of medicare managed care plans and their prescription drug benefits. Working Paper 2007-19, Federal Reserve Board of Governors.

Hargrave, E., Hoadley, J., Cubanski, J., and Neuman, T. (2009a). Medicare part d plans in 2009 and key changes since 2006. Technical report, The Henry J. Kaiser Family Foundation.

Hargrave, E., Hoadley, J., Cubanski, J., and Neuman, T. (2009b). Medicare prescription drug plans in 2009 and key changes since 2006: Summary of findings. Technical report, The Henry J. Kaiser Family Foundation.

Heiss, F., McFadden, D., and Winter, J. (2006). Who failed to enroll in medicare part d, and why? early results. *Health Affairs*, 25(5).

Heiss, F., McFadden, D., and Winter, J. (2008). The workings of a private health insurance market: Enrollment decisions, plan choice, and adverse selection in medicare part d. Working paper, University of Munich.

Heiss, F., McFadden, D., and Winter, J. (2010). Mind the gap! consumer perceptions and choices of medicare part d prescription drug plans. In Wise, D. A., editor, *Research Findings in the Economics of Aging*. University of Chicago Press.

Horowitz, J. (2001). The bootstrap. In Heckman, J. and Leamer, E., editors, *Handbook of Econometrics, Volume V*, volume 5, pages 3159–3228. Elsevier.

Kaiser Commission on Medicaid and the Uninsured (2007). Perspectives on medicare part d and dual eligibles: Key informants' views from three states. Technical report, The Henry J. Kaiser Family Foundation.

Kaiser Family Foundation (2006). Seniors and the medicare prescription drug benefit. Chartpack, The Kaiser Family Foundation and Harvard School of Public Health.

Kaiser Family Foundation (2009). The medicare prescription drug benefit. Fact sheet.

Keating, B. (2007). *Essays in Industrial Organization: Switching Costs in an Evolving Industry and Price Structure in Two Sided Markets*. PhD thesis, Stanford.

Ketcham, J., Lucarelli, C., Miravete, E., and Roebuck, M. C. (2010). Sinking, swimming, or learning to swim in medicare part d. Working paper, Arizona State University.

Lakdawalla, D. and Yin, W. (2009). Insurer bargaining and negotiated drug prices in medicare part d. Working Paper 15330, National Bureau of Economic Research.

Levy, H. and Weir, D. (2008). The impact of medicare part d on drug utilization and out-of-pocket spending: Evidence from the health and retirement study. Working paper, University of Michigan.

Lucarelli, C. (2006). An analysis of the medicare prescription drug benefit. Working Paper 06-09, Population Aging Research Center, University of Pennsylvania.

Lucarelli, C., Prince, J., and Simon, K. (2008). Measuring welfare and the effects of regulation in a government-created market: The case of medicare part d plans. Working Paper 14296, National Bureau of Economic Research.

Lustig, J. (2007). The welfare effects of adverse selection in privatized medicare. Job market paper, Yale University.

Maruyama, S. (2006). Welfare analysis incorporating a structural entry-exit model: A case study of medicare hmos. Discussion Paper 166, Institute of Economic Research, Hitotsubashi University.

McAdams, D. and Schwarz, M. (2007). Perverse incentives in the medicare prescription drug benefit. *Inquiry*, 44(2):157166.

McFadden, D., , and K.Train (1998). Mixed mnl models for discrete response. mimeo, University of California at Berkeley.

McFadden, D. (2006). Free markets and fettered consumers. *American Economic Review*, 96(1):5–29.

Merlis, M. (2007). Medicare payments and beneficiary costs for prescription drug coverage. Report 7620, The Henry J. Kaiser Family Foundation.

Moeller, J., Miller, G., and Banthin, J. S. (2004). Looking inside the nations medicine cabinet: Trends in outpatient drug spending by medicare beneficiaries, 1997 and 2001. *Health Affairs*, 23(3):217–225.

Nevo, A. (2000). A practitioner's guide to estimation of random coefficients logit models of demand. *Journal of Economics and Management Strategy*, 9:513–548.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, 69(2):307–342.

Office of the Inspector General (2006). Dual eligibles' transition: Part d formularies' inclusion of commonly used drugs. Technical report, Department of Health and Human Services.

Pauly, M. V. and Zeng, Y. (2004). Adverse selection and the challenges to stand-alone prescription drug insurance. In ??, editor, *Frontiers in Health Policy Research 7*.

Petrin, A. and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research*, XLVII:3–13.

Pizer, S. D., Frakt, A. B., and Feldman, R. (2008). Predicting risk selection following major changes in medicare. *??*, ??(??):??

Robinson, J. C. (2004). Consolidation and the transformation of competition in health insurance. *Health Affairs*, 23(6):11–24.

Robst, J., Levy, J., and Ingber, M. (2007). Diagnosis-based risk adjustment for medicare prescription drug plan payments. *Health Care Financing Review*, 28:15–30.

Rothschild, M. and Stiglitz, J. (1976). Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The Quarterly Journal of Economics*, 90(4):629–649.

Safran, D., Neuman, P., Schoen, C., Kitchman, M., Wilson, I., Cooper, B., Li, A., Chang, H., and Rogers, W. (2005). Prescription drug coverage and seniors: Findings from a 2003 national survey. *Health Affairs*.

Schneeweiss, S., Patrick, A. R., Padan, A., Varasteh, L., Levin, R., Liu, N., and Shank, W. (2009). The effect of medicare part d coverage on drug use and cost sharing among seniors without prior drug benefits. *Health Affairs*, 28(2):w305–w316.

Simon, K. I. and Lucarelli, C. (2006). What drove first year premiums in stand-alone medicare drug plans? Working Paper 12595, National Bureau of Economic Research.

Stagnitti, M. N. (2006). Population characteristics of medicare beneficiaries in the u.s. civilian noninstitutionalized population, by level of annual prescribed medicines expenses, 2003. Statistical Brief 138, Agency for Healthcare Research and Quality, Medical Expenditure Panel Survey.

Stock, J. and Yogo, M. (2005). Testing for weak instruments in linear iv regression. In Andrews, D. and Stock, J., editors, *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rotenberg*, pages 80–108. Cambridge University Press.

Summer, L., Nemore, P., and Finberg, J. (2008). Medicare part d: How do vulnerable beneficiaries fare. Issue brief, The Commonwealth Fund.

The Henry J. Kaiser Family Foundation (2009). Low-income assistance under the medicare drug benefit. Fact sheet, The Henry J. Kaiser Family Foundation.

The Henry Kaiser Family Foundation (2010). Summary of key changes to medicare in 2010 health reform law. Issue breif.

Town, R. and Liu, S. (2003). The welfare impact of medicare hmos. *RAND Journal of Economics*, 34(4).

Winter, J., Balza, R., Caro, F., Heiss, F., Jun, B., Matzkin, R., and McFadden, D. (2006). Medicare prescription drug coverage: Consumer information and preferences. *Proceedings of the National Academy of Sciences of the United States of America*, 103(20):7929–7934.

Yang, Z., Gilleskie, D. B., and Norton, E. C. (2009). Health insurance, medical care, and health outcomes: A model of elderly health dynamics. *The Journal of Human Resources*, 44(1):47–114.