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CONSUMER INERTIA AND FIRM PRICING IN THE MEDICARE PART D PRESCRIPTION DRUG INSURANCE EXCHANGE

Keith M. Marzilli Ericson

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ABSTRACT

I use the Medicare Part D prescription drug insurance market to examine the dynamics of firm interaction with consumers on an insurance exchange. Enrollment data show that consumers face switching frictions leading to inertia in plan choice, and a regression discontinuity design indicates initial defaults have persistent effects. In the absence of commitment to future prices, theory predicts firms respond to inertia by raising prices on existing enrollees, while introducing cheaper alternative plans. The complete set of enrollment and price data from 2006 through 2010 confirms this prediction: older plans have approximately 10% higher premiums than comparable new plans.

Keith M. Marzilli Ericson
Boston University School of Management
595 Commonwealth Avenue
Boston, MA 02115
and NBER
kericson@bu.edu

An online appendix is available at:
http://www.nber.org/data-appendix/w18359

1 Introduction

I examine the dynamics of firm interaction with consumers on the Medicare Part D prescription drug insurance exchange, a large and controversial program that receives government subsidies of about $40 billion annually and covers over 24 million people (Duggan, Healy, and Scott Morton 2008). Medicare Part D is the largest change to the Medicare program since its inception. Unlike Medicare's classic fee-for-service components, Medicare Part D established a marketplace in which firms compete to provide prescription drug insurance plans: a competitive insurance exchange. It is therefore a model for the insurance exchanges envisioned in the 2010 federal health reform. It began providing coverage in 2006, allowing us to see the market's first year and subsequent evolution. While program costs were initially below expectations, premium growth in recent years has outpaced growth in drug costs (Duggan and Scott Morton 2011). Strategic firm responses to inertia can explain this pattern.

In many markets, individuals are subject to switching costs and other frictions that lead to inertia.[1] Rational firms should respond to inertia when setting prices, initially pricing low to acquire market share and then raising prices on consumers when they are less responsive to price. However, market design decisions determine the form this response takes. For instance, while firms would like to use introductory offers to price separately to new versus repeat enrollees, such offers are legally prohibited in the Medicare Part D market. Firms have an incentive to replicate this pricing pattern in other ways. In this context, theory predicts firms should initially offer plans at low prices to attract first-time enrollees. In later periods, firms should raise prices when their plans have a base of enrollees "stuck in place", while new plans are introduced at low prices to attract new individuals entering the market. I show empirically that Medicare Part D enrollees display inertia in their choice of plan, and that prices in this market display the pattern predicted by the theory.

Existing literature shows that health insurance choices display inertia that can have substantial consequences. Handel (2009) examined insurance choice the year following a large price change and found that individuals may have forgone gains of over $1500 that year to stay in their current plan.[2] Inertia in enrollees' choice of plan results from switching

[1] Carroll et al. (2009) find that employees typically stay with arbitrary 401(k) savings defaults, but make substantially different decisions when forced to make an explicit choice for themselves. Jones (forthcoming) argues that inertia explains the pattern of over-withholding of income taxes. Chetty et al. (2011) examine labor supply elasticities, and show that observed responses match the pattern predicted by an adjustment cost model: larger tax changes lead to larger estimated elasticities.

[2] In addition, Samuelson and Zeckhauser (1988) discussed health insurance decisions as an example of status quo bias, though they recognized that inertia might be accounted for by classical explanations such as switching costs. Strombom, Buchmueller and Feldstein (2002) examine plan share sensitivity to health plan premiums at the University of California. They find that new hires have higher premium elasticities

frictions, including both switching costs (the time and effort costs that result from moving between plans), and psychological factors that lead to inaction. If individuals do not make an active decision, they take the default option, which for standard enrollees is to stay in the same plan from year-to-year, regardless of firm price changes.[3] Crucially, switching frictions lead enrollees to be less responsive to price once they have already enrolled in a plan.

Even though switching prescription drug coverage is arguably easier than switching an entire health insurance plan, changing plans may still be difficult if individuals find it costly to evaluate their options. Abaluck and Gruber (2011) argue that Medicare Part D enrollees have difficulty in making their initial plan choices, while Kling et al. (2011) show that enrollees may not be paying attention to their options in subsequent years. Switching is low in this market, which is consistent with either inertia or preference heterogeneity. While Medicare Part D enrollees have the opportunity to switch plans each year during open enrollment without regard to their health status, only about 10% of enrollees switched between 2006 and 2007 (Heiss, McFadden and Winter 2007). Yet at least some enrollees are attentive: Ketcham, Lucarelli, Miravete, and Roebuck (forthcoming) found that the probability of an enrollee switching plans increased with their potential gain to doing so.

In the presence of inertia, random variations in initial conditions will have persistent effects. I first show suggestive evidence of inertia: higher prices in a plan's first year are associated with lower enrollment in subsequent years, even conditional on subsequent years' prices. I then use a regression discontinuity design in Medicare Part D's low-income subsidy (LIS) program to more credibly identify inertia. LIS recipients, which comprise about half the market, faced an automatic enrollment program set up by policy makers who were concerned they would fail to enroll. Individuals identified as being eligible for the subsidy were automatically defaulted into plans selected at random from the set of plans below a price benchmark. Because the precise level of the benchmark is unknown to firms in advance, a regression discontinuity design can estimate the causal effect of pricing below the benchmark. Pricing below the benchmark in the first year had a strong effect on enrollment: plans priced just below the benchmark had more than twice the market share of plans priced just above. Plans that randomly priced below the benchmark in the market's first year continued to have higher enrollment in later years, indicating that the LIS program's initial assignment of enrollees to plans had persistent effects on later choices.

A large theoretical literature examines the response of firms to switching costs (see

than incumbent employees, as predicted by models of inertia. This work has not examined firms' strategic responses to inertia in setting premiums, in part because it has typically examined employer-based health insurance, where firm behavior is constrained by an employer gatekeeper.

[3] Ericson (2012) considers alternative default rules and provides a framework for setting optimal dynamic defaults.

Farrell and Klemperer 2007), and predicts an "invest-then-harvest" pricing pattern: products are offered at low prices and then subsequently at high prices. (This pattern is widely, albeit pejoratively, known as "bargains-then-ripoffs" pricing.) One firm provides a stark example of this strategy. In the first year of Medicare Part D, Humana priced its basic plans as loss leaders: about $10 per month on average, substantially below the market's average of $30. Both management and analysts agreed Humana was setting low prices to gain market share in the market's first year.[4] Over the next three years, Humana raised its price on these plans by more than 40% each year, until by 2009 and 2010, the average price was over $40 per month, now above the market average.

While Humana is a particularly extreme example, pricing data confirms the market as a whole displays the pattern predicted by invest-then-harvest pricing. I show that firms initially set relatively low prices for newly introduced plans, but then raise prices as plans age while new, low-cost plans are introduced each year. In a given year, plans that have existed for a longer period of time have annual premiums that are 10%, or $50, higher than newly introduced plans. The higher prices of existing firms suggest that many consumers either have switching costs of this amount or face other switching frictions (e.g. procrastination, forgetting) with costs in this range.[5]

The paper is organized as follows. Section 2 describes the structure of the Medicare Part D market. Section 3 discusses the theory of firm pricing when individuals are subject to switching frictions. Section 4 describes the data used in the empirical portions of the paper and shows that past prices predict market share. Section 5 uses a regression discontinuity design to test for inertia among LIS recipients. Section 6 then tests the predictions of the theory for firm pricing. Finally, Section 7 discusses the implications of the results and concludes.

[4] For instance, referring to the market's first year, Humana VP Steve Brueckner said: "If you don't get your fair share, you're going to be in trouble later on." (see "New Medicare Drug Benefit Sparks an Industry Land Grab" *Wall Street Journal*. Jan. 25, 2006)

[5] Optimization frictions of this magnitude have implications for what economists can learn from individuals' responses to changes in their environment. Chetty (2011) shows that in the presence of switching costs or other optimization frictions, a range of structural elasticities (i.e. long-run elasticities) is consistent with the observed response to a price change. For policy changes to the Medicare Part D market, such as increased subsidies for more generous coverage, the switching frictions found here would imply that the elasticities estimated from the stock of enrollees would be essentially uninformative about the true long-run elasticity.

2 Basic Structure of the Medicare Part D Market

2.1 Standalone PDPs

Medicare Part D began offering prescription drug insurance in 2006 for seniors over the age of 65 and other Medicare beneficiaries. I focus on the core portion of the program–standalone prescription drug plans (PDPs), which are distinct from other sources of coverage (e.g. Medicare Advantage HMOs or employer/union sponsored PDPs). As in health insurance exchanges, there is a menu of plans available for purchase at listed prices. Firms must accept all individuals who choose a given plan at a fixed price: the premium enrollees pay does not vary by age or health status. Firms are free to enter the market, so long as they satisfy CMS regulations. Many firms compete: from 2006-2010, 92 unique firms offered coverage.

Plan design is constrained by Medicare regulation. Each plan is required to offer at least "basic" coverage, as defined by the Centers for Medicare & Medicaid Services (CMS). Basic plans can come in three different forms: Basic Alternative, Actuarially Equivalent Standard, or Defined Standard Benefit. Each type of basic plan must offer coverage that is actuarially equivalent to the Defined Standard Benefit,[6] with a formulary that covers each therapeutic class of drug.[7] However, "enhanced" plans may offer coverage that is actuarially more generous (e.g. lower deductibles or coverage in the "doughnut hole"). I focus analyses on basic plans, which have fewer unobserved characteristics.

Contracts are annual, with firms committing to a price and formulary for that year.[8] Each year, firms simultaneously submit plan price bids. Then, during an open enrollment period (Nov. to Dec.), individuals observe the new prices and can switch plans. Standard enrollees must initially make an active choice to enroll in Medicare Part D. However, once they are enrolled, they stay with their current plan by default if they take no action. Pricing and plans offered vary by PDP region: each of the 34 PDP regions[9] is either a state or group of states (plus Washington D.C.), and I refer to these regions as "states" throughout.

[6] Defined Standard plans have a fixed format: in 2010, the standard benefit has a \$310 deductible, 25 percent coinsurance up to an initial coverage limit of \$2,830 in total drug spending, a coverage gap (the “doughnut hole”), and catastrophic coverage when enrollee out-of-pocket spending exceeds \$4,550. Actuarially Equivalent Standard plans have the same deductible, but may use copayments instead of coinsurance and tiered copayments for brand-name and specialty drugs. Basic Alternative allows plans to vary the amount of the deductible.

[7] Formulary variation may be a source of switching costs. Even if drugs within a therapeutic class are close substitutes, individuals face costs of changing their prescription.

[8] While firms can make mid-year changes to the formulary, they must be approved by CMS. Most changes are beneficial from the enrollees’ perspective. Approved negative changes most often take the form of swapping a newly-available generic drug for the identical branded drug. See Levinson (2009).

[9] I limit the analysis to plans in 50 United States proper and exclude those in its territories and possessions.

The prices that enrollees face are a result of firm bids and government subsidies. The subsidies are designed so that enrollees pay the full marginal cost of a more expensive plan; an increase in a firm's bid translates one-for-one into an increase in enrollee premiums. For basic plans and standard enrollees, plan premiums are equal to the plan bid minus a fixed dollar subsidy, which is calculated by CMS based on the national average bid.[10]

Because premiums are community-rated (all enrollees pay the same price) and guaranteed-issue (plans must take all comers), a risk adjustment scheme was designed to reduce the incentives for firms to select a healthier or lower-cost population. Firms receive higher payments from CMS for enrollees with higher expected costs. The risk adjustment system is designed so that firms should determine their prices/bids based on the cost of providing coverage to an average individual in the population. The payments firms actually receive are equal to their bid multiplied by enrollees' risk adjustment factors.These factors are based on demographic characteristics and diagnostic history, with additional adjustment made for low-income subsidy status and institutionalization status. For more detail, see Robst, Levy and Ingber (2007) and Appendix Section A.3.

Section 6.2 evaluates the risk adjustment model for standard enrollees and finds that payments compensate firms for enrollees' higher expected costs as they age. However, risk adjustment for LIS recipients is insufficient. When designing the risk adjustment scheme, CMS had limited data on the relative costs of LIS recipients. Hsu et al. (2010) show that while CMS risk adjustment scheme assumes that full-subsidy LIS recipients are only 8% more expensive than comparable standard enrollees, they are in fact 21% more expensive. LIS recipients are therefore less profitable for firms than standard enrollees.

Firms might wish to continually introduce virtually identical cheap plans. However, there are both formal and informal restrictions that make this difficult. CMS requires that firms offering multiple plans demonstrate that there are significant differences among the plans; this regulation only formally applied beginning in 2009, but CMS negotiated with firms to enforce this provision earlier. Moreover, for a firm to offer a plan, CMS must approve its bid submission. This bid is required to be tied to the firm's estimate of the revenue it needs to provide the benefit. Thus, firms may not wish to introduce variations in plan prices that they cannot plausibly link to variations in cost of benefit provision. CMS has been progressively increasing the standards that firm bids must meet (see Levinson 2008).

[10] To calculate the subsidy, CMS calculates the national average bid $\bar{p}$. Each plan receives a fixed dollar subsidy, equal to $\frac{0.745-r}{1-r}\bar{p}$, where r is an adjustment factor for the cost of catastrophic reinsurance. The program costs for individuals without the LIS are subsidized 74.5% by the federal government. The premium subsidy is less than 25.5% of a plan's bid, since the government also subsidizes the plans by providing catastrophic reinsurance for expenses above a certain threshold. The next section describes the additional subsidy given to LIS recipients. Heiss, McFadden, and Winter (2007) provide more details on the bidding process and the subsidy calculation for enhanced plans.

2.2 The Low-Income Subsidy (LIS) Program

Low-income subsidy recipients comprise a large share of the market (52% of PDP enrollees in 2006).[11] LIS recipients enroll in the same plans as standard enrollees, but receive additional premium subsidies and reduced cost-sharing. Medicare beneficiaries become eligible for at least a partial form of the LIS if their incomes are below 150 percent of the federal poverty level and pass an asset test; the exact amount of assistance varies with income and assets. Individuals receiving the full LIS benefit receive a premium subsidy equal to that of the LIS "benchmark" b in that state; if they choose a plan with a premium below the benchmark, they pay no premiums. In a plan with premiums of p, an LIS recipient thus pays $\max\{p-b,0\}$. The benchmark differs in each state and is recalculated each year based on the state's average plan bid; it is not known ex ante to firms.[12] In 2006, the average state's benchmark was about $32 per month.

The LIS program applies defaults in two ways: automatic initial enrollment and automatic switching. First, due to concern about inertia in enrollment behavior, individuals who meet certain eligibility criteria[13] for the full LIS are automatically enrolled into Medicare Part D. They are defaulted into a randomly selected basic PDP with a premium below the benchmark premium. LIS recipients may actively elect to choose another plan; they may do so at any time and are not limited to switching during the open enrollment period.

The mix of plans that price below the benchmark varies between years, as plans change their prices and the benchmark adjusts. The second default–"automatic switching"– is applied if a plan moves from being below the benchmark in one year to above the benchmark in the next. If an auto-enrolled LIS recipient in such a plan had never made an active choice, they are automatically switched to a different plan below the price benchmark, unless they take action to stay in their current plan. LIS recipients who actively enrolled themselves, or who were auto-enrolled but then chose to move from their default plan, are notified that they will pay a higher premium if they do not switch, but they are not re-defaulted into a new plan.

[11] Many individuals not eligible for the LIS do not choose a standalone PDP, but instead choose Medicare Advantage HMOs with prescription drug coverage or receive an employer-sponsored plan.

[12] In 2006-2007, the benchmark was the average bid in that state, with PDPs equal weighted and Medicare Advantage prescription drug (MA-PD) portions enrollment weighted. In subsequent years, the benchmark transitioned to enrollment weighted PDP and MA-PD bids. Appendix Section A.3 gives more detail on the calculation of the benchmark and its evolution over time.

[13] Approximately 84% of LIS recipients in 2010 were deemed automatically eligible for the full LIS by their Medicaid, Supplemental Security Income (SSI), or Medicare Savings Program (MSP) status. Other potential LIS recipients must apply for the subsidy. CMS reserves the term "automatic enrollment" for Medicare and Medicaid dual-eligibles, and uses a similar "facilitated enrollment" process for individuals who were not dual-eligible but otherwise deemed eligible for the full LIS. Since the processes are virtually identical, I use the term "automatically eligible" to refer to both groups.

Concerned with the difficulties of switching LIS recipients away from plans that previously priced below the benchmark, CMS instituted a "de minimis" policy for LIS recipients for 2007 and 2008. De minimis plans were those whose premium exceeded the benchmark by less than \$2 (2007) or \$1 (2008) per month. Under the policy, LIS enrollees in de minimis plans would not be automatically switched by default. However, no new LIS enrollees would be defaulted into such plans, and de minimis plans would not receive any additional premiums over the benchmark amount from any of their LIS recipients.[14] While this policy reduced the need to switch LIS recipients between plans, it also had the effect of making LIS recipients less profitable for firms, as they could yield \$12-\$24 less per year in revenue than a standard enrollee.

3 Theory: Inertia and Firm Responses

Switching frictions lead to inertia in individuals' choice of plan, and so individuals will be more sensitive to price when they initially enroll than in later periods. As a baseline model, we can simply assume that individuals choose optimally when they initially enroll.[15] However, in later periods, they only switch if the gain do doing so is larger enough to outweigh their switching friction. The probability of switching for a gain of ΔU is thus some function $F(\Delta U)$ that increases in the gain to doing so. There are a variety of types of switching frictions, including both switching costs that result from moving between plans and reduce welfare, and psychological frictions that affect whether an individual acts, but not their welfare conditional on the action taken. For instance, when an individual switches plans, they need to learn the rules of the new insurance plan, may need to do paperwork at their pharmacy, and may experience disutility from negative emotions (e.g. confusion, loss aversion)– these are real switching costs that reduce welfare. On the other hand, an individual may wish to switch plans but forget (Ericson 2011) or procrastinate (O'Donoghue and Rabin 2001)– these are psychological frictions that lead them not to act and simply take the default option.

If consumers display inertia in their health insurance choices, firms will rationally respond. In setting prices, firms have two motives: an investment motive, to acquire market share for the future, and a harvesting motive, to maximize profits this period on new and existing customers. Farrell and Klemperer (2007) review the theoretical literature on how inertia affects equilibrium under imperfect competition. In a wide variety of contexts, theory predicts an invest-then-harvest (a.k.a. "bargains-then-ripoffs") pricing pattern, in which

[14] That is, all LIS recipients who were eligible for the full subsidy. Partial subsidy recipients were not automatically enrolled or switched, and so the de minimis policy did not apply to them.

[15] They may in fact make some mistakes, as argued by Abaluck and Gruber (2011).

products are initially sold at low (perhaps below marginal) cost, but sold at higher prices in later periods.

I model insurer behavior in the Medicare Part D market, which is regulated as described in Section 2. Insurers must issue a policy to anyone who requests it, and must charge all enrollees the same price for a given plan. Risk adjustment implies that individuals do not vary in cost by age. I make the simplifying assumption that the form of the insurance contract (e.g. copays, drugs covered) is fixed, which is a good approximation to government regulation of basic plans. Keeping with the way Medicare Part D and other insurance markets are regulated, firms offer policies for one period, without the possibility for commitment to future premium levels.

Each firm j offers one plan,[16] and sets its price p_{jt} in each period. Quantity sold this period s_{jt} is a function of this price and past market share.[17] The expected cost of each enrollee, net of risk adjustment, to the firm is c_j. Firms are infinitely lived with discount factor δ, and seek to maximize the expected discounted present value of profits V_{jt}. The value of the firm V_{jt} is given by flow profits and future profits in the recursive equation:

$$V_{jt} = (p_{jt} - c_{jt})\, s_{jt} + \delta V_{jt+1}(s_{jt})$$

where the second term captures that future firm value may depend on its current market share.[18] The firm's first order condition for optimal pricing is thus:

$$p_{jt} - c_{jt} = \frac{s_{jt}}{-ds_{jt}/dp_{jt}} - \delta \frac{dV_{jt+1}(s_{jt})}{ds_{jt}} \tag{1}$$

where ds_{jt}/dp_{jt} is the firm's demand curve. Factors that make demand more inelastic, such as switching frictions, raise markups. The demand curve ds_{jt}/dp_{jt} that a firm j faces when setting prices is the sum of the demand curves for three different types of individuals: 1) potential repeat customers, 2) potential switchers from other plans, and 3) new enrollees entering the market unattached to any plan. Potential repeat customers likely have relatively inelastic demand, compared to the other groups, since new choosers and potential switchers

[16] While firms may offer more than one plan so long as they are sufficiently distinct, for clarity, I examine the case where one plan only is offered. The Theory Appendix shows that the same incentives face firms that offer multiple plans.

[17] The demand of sophisticated consumers for a plan will depend on both its price and its market share, as market share may predict firm's future behavior. In this discussion, I ignore this effect, which is equivalent to assuming individuals cannot observe market share or are myopic. Equilibrium models with sophisticated consumers give similar results (see Ericson 2012 and Farrell and Klemperer 2007).

[18] This model could be generalized in a number of ways. Switching costs or attachment to the firm could depend on the length of time an enrollee has been in a plan. Furthermore, type of consumer might matter: older individuals may be less valuable since they will not live as long.

can choose from many close substitutes. In such a case, older plans will face more inelastic demand and optimally set prices higher than comparable newer plans, since newer plans have fewer potential repeat customers.[19]

A simple example illustrates the intuition behind invest-then-harvest pricing. Let all plans be perfect substitutes, and take the case where $\delta = 0$ (e.g. as though it were the market's last period.[20]) Then, new plans would set price equal to marginal cost, and all new enrollees would choose one of these new plans. Existing plans with potential repeat customers would set price equal to marginal cost plus a markup term $\frac{s_{jt}}{-ds_{jt}/dp_{jt}}$that depends on the elasticity of repeat demand. New entrants will therefore have lower prices than comparable existing plans. Some enrollees in existing plans would switch to cheaper, newly introduced plans, while others remain stuck in place at their previously chosen plan.

4 Describing the Medicare Part D Market

4.1 Data Source

Data from the Medicare Part D market show both that individuals display inertia and that firm prices display the pattern predicted by the model above. I use data from CMS on plan premiums, characteristics, and aggregate enrollment. Data on PDP premiums and characteristics for each year are available from 2006 (the first year of the market) through 2010. I divide the 2,464 plans into cohorts based on the year they were first offered. Enrollment data is available for July 1 of each calendar year from the monthly enrollment reports. The Data Appendix provides more details.

For each plan, I observe its premium, deductible, and benefit type,[21] along with the firm and plan name. Table 1 gives descriptive statistics of the Medicare Part D plans, by year of plan introduction (cohort).[22] States vary in the number of plans offered and average premiums. Moreover, a given firm may price essentially the same plan quite differently in different states. For example, in 2006 Humana offered the "Humana PDP Complete" plan for $767 per year in Ohio and only $575 in New York.

There is substantial variation in premiums, even for basic plans. Figure 1 shows the distribution of premiums in 2010 for basic plans, split between older cohorts of plans (plans introduced in 2006 and 2007) and newer cohorts (plans introduced 2008 and later). Though

[19] In this general model, switching frictions and previous market share s_{jt-1} can have an ambiguous effect on optimal prices, depending on the relative elasticities of these three groups.

[20] While this example assumes $\delta = 0$, Ericson (2012) shows that a invest-then-harvest pricing pattern is the equilibrium of this environment when $\delta > 0$ as well, consistent with the predictions of other models of equilibrium under imperfect competition (Farrell 1986; Farrell and Klemperer 2007).

[21] Basic alternative, actuarially equivalent standard, defined standard benefit, or enhanced.

[22] Table A.1 gives descriptive statistics, limiting the sample to basic plans only.

the peaks of the distributions are similar (around \$400/year), the older cohorts have a larger tail of high premium plans, consistent with the predictions of Section 3 that plans raise premiums as they age. However, the variance in prices indicates that there is heterogeneity in firm strategies or costs. Variation in pricing can come from firm-specific costs of providing coverage, price strategies (e.g. firm estimates of demand elasticity, or whether firms recognize the investment value of acquiring market share), and perceived quality of firms (firm-specific demand shocks).

New plans come from one of three sources: existing firms offering sufficiently distinct plans, existing firms expanding into different geographical regions, or new firms entering the market. Table 1 indicates that for the first five years of the market, it was primarily existing firms expanding in both ways. Most new plans were offered by firms who already offered plans somewhere else in the country, while about two-thirds were introduced by firms already offering a plan in the same state.

The number of individuals choosing plans for the first time was largest in 2006, since this was the first year Medicare Part D offered coverage, and the stock of all people eligible for Medicare could choose in that year. The initial enrollment period ended May 15, 2006, after which individuals faced a late enrollment penalty fee if they did not have a qualifying form of prescription drug coverage. Immediate enrollment was optimal for most seniors, and most seniors did in fact enroll: by May 2006, Medicare had met its target that 90% of the eligible population have some form of prescription drug coverage (Heiss, McFadden, and Winter 2007). In subsequent years, new entrants to the PDP market come from individuals newly eligible for Medicare and from individuals leaving another source of coverage (e.g. Medicare Advantage plans).

Figure 2 shows total enrollment over time, broken down by plan cohort (the year in which a plan was introduced). The 2006 cohort of plans captured most of the market, as most of the inflow into the PDP market took place in the market's first year; inertia implies that enrollees are likely to stay with their initial plan. This cohort has an aggregate enrollment[23] of 15.4 million in 2006, a number that drops over time, as enrollees leave these plans (by death or switching) or as plans attrit from the sample. Subsequent cohorts of plans have much lower enrollment, consistent with the predictions of the model in Section 3: there are fewer new enrollees after the first year of the market.[24] After 2006, the number of

[23]These numbers differ from the aggregate numbers released by Medicare by about 1 million, as my numbers exclude Employer/Union Only Direct Contract PDPs and PDP enrollment outside the 50 U.S. states.

[24]Other factors could also contribute to the observed pattern of lower enrollment in subsequent cohorts. For instance, fewer plans are introduced in later years. Yet this is unlikely to explain the full story: the number of plans introduced in 2007 was over half the number introduced in 2006, but the 2007 cohort's enrollment is substantially below half of that in the 2006 cohort.

new choosers is small relative to the size of market: I estimate that newly eligible individuals comprise less than 10% of new PDP enrollees in each year.[25]

I examine the behavior of standard choosers (non-LIS enrollees) separately from that of LIS recipients, since LIS recipients face different prices and are not necessarily making an active choice even when they first enroll. I subtract estimates of LIS enrollment from total enrollment to get estimates of standard enrollment.[26] I construct plan market shares of total enrollment in each state, and then market shares of standard enrollees: a plan's non-LIS enrollment over the state's total non-LIS enrollment. Plan shares of total enrollment in 2006 range from less than $\frac{1}{1000}$% to 38%; the median plan share is 0.4%. The median plan's share of standard enrollment is also 0.4%. Appendix Figures A.1 and A.2 plot LIS enrollment and standard enrollment by cohort of plan. The fraction of enrollees receiving the LIS among the 2006 cohort is initially high (52%), but falls to 41% by 2009. Newer plans have a higher fraction of LIS enrollment in 2009 (70% to 89% depending on cohort), which is expected, since new plans have lower prices.

4.2 Correlation between Enrollment and Past Prices

I begin with standard enrollees and provide suggestive evidence that this half of the market displays inertial behavior. Using aggregate enrollment data, I test whether past prices predict market share (conditional on present prices and characteristics). I estimate regressions of the following form:

$$\ln s_{jtm} = x_{jtm}\beta_1 + \alpha_1 p_{jtm} + x_{jt-1m}\beta_2 + \alpha_2 p_{jt-1m} + v_{tm}$$

where $\ln s_{jtm}$ is plan j's log market share in market m at time t, p_{jtm} is the plan's premium, and x_{jtm} contains its observed characteristics. State fixed effects v_{tm} capture factors that vary among states, including the number of plans offered. Of course, firms set prices endogenously to unobserved quality, with the expectation of price increasing in quality in most models. If firm price-setting is subject to random noise (e.g. information shocks), then even conditional on present prices, the expectation of quality should increase in lagged price p_{jt-1m}, giving $\alpha_2 > 0$ in the absence of inertia.[27] Inertia predicts that $\alpha_2 < 0$: higher past prices induce lower enrollment which persists into later periods.

[25] From 2007 to 2010, about 2 million Americans turned 65 each year and become eligible for Medicare; less than half of them chose a standalone PDP.

[26] Since CMS has not released LIS enrollment figures regularly, I have LIS enrollment data from July of 2006 and 2007, but from February of 2008 and 2009; they were unavailable for 2010. Hence, these data slightly underestimate the share of LIS enrollees in later years. The Data Appendix gives more details.

[27] Other models of unobserved heterogeneity can lead to biases in either direction; hence this evidence is only suggestive.

I estimate this regression using standard (non-LIS) enrollment,[28] limiting the sample to basic plans: these plans offer similar actuarial value and have little flexibility in plan design, reducing unobserved heterogeneity.[29] I run regressions both with and without firm fixed effects. Each specification is useful: using variation in pricing among firms is valuable because such variation may be less endogenous to market conditions (e.g. if firms are subject to information shocks), but controlling for firm fixed effects reduces unobserved heterogeneity.

Table 2 examines the association between 2007 enrollment and 2006 prices for the cohort of plans introduced in 2006. It shows that past prices strongly and negatively predict enrollment. Column 1 regresses 2007 log plan shares on 2006 and 2007 prices. It finds that premiums in 2006 still predict enrollment in 2007, with a coefficient on past premiums nearly as large as that on current premiums. Column 2 runs the "naive" regression of 2007 log plan shares on 2007 prices only and shows that the coefficient on 2007 premiums is 50% larger in magnitude when lagged prices are omitted, due to the correlation of past and present prices. For comparison, column 3 examines initial choices in 2006, regressing log plan shares on price for the same sample. The coefficient on contemporaneous price is larger in magnitude for the first year of the market (column 3) than for 2007 (column 1): premiums that are $1 higher predict a plan share that is 14 percent lower in 2006. (Thus, for a plan with a 2% market share, a $1 higher premium would predict a 1.7% market share.) In contrast, the same $1 decrease predicts that market share is only 9.7 percent lower in 2007. Columns 4-6 present analogous regressions with firm fixed effects included and show that the results are similar.

The association between enrollment and past prices is a robust phenomenon. Similar regressions for 2009 data shows that even three years later, premium in 2006 is still negatively associated with enrollment (Appendix Table A.2). Moreover, in 2009, there is a series of previous prices that can be included as controls. Of all the past prices, the 2006 premiums should have the largest effect, since that was when the largest cohort of individuals made its initial choices. Indeed, Appendix Table A.3 shows that premiums in the year of introduction have the largest association with enrollment when all the lags of premiums and plan characteristics are included.

[28] LIS recipients face different defaults and prices. I include controls for whether the plan is below the benchmark to capture any effect of the LIS program on the plan.

[29] Ideally, I would like to separate out new enrollees from existing enrollees, but this is not possible using aggregate data.

5 Low-Income Subsidy: Defaults and Inertia

5.1 Regression Discontinuity Design

While the above analysis suggests standard enrollees display inertia, this section provides more precisely identified evidence on inertia from the other half of the market: LIS recipients. The LIS program only automatically enrolls individuals into plans that set their price below a price benchmark. Because the benchmark is not known ex ante, but is a random variable, firms cannot precisely choose whether to set prices above or below the benchmark.[30] Hence, a regression discontinuity strategy can identify the causal effect of being randomly assigned LIS enrollees. I compare the subsequent enrollment and pricing strategies of plans that randomly fell just above the benchmark in 2006 to those that fell just below. The identification assumption is that pricing directly above or below the benchmark is as good as random, so that plan characteristics do not change discontinuously around the benchmark.

The regression discontinuity approach is particularly credible in 2006, as it was the first year of the Medicare Part D market. Because the benchmark in 2006 is an equal-weighted average of PDP bids in each state, even a large number of firms colluding could not precisely predict the benchmark level. Define the variable "relative premiums" to be a plan's premiums minus that state's benchmark level; this is the forcing variable. Appendix Table A.4 supports the identification assumption that there are no discontinuous changes in covariates at the benchmark. The observed characteristics of PDPs (type of basic plan, and deductible level) are similar on either side of the benchmark for the bandwidths used here, though in some bandwidths, the mix of basic plans differs slightly. I show regressions with and without controls for these characteristics; results are similar.[31]

Plans attrit from the sample overtime. Attrition can occur because firms cease offering a plan, or if they merge with or are acquired by another firm. Attrition, of course, has no

[30] This is particularly true in 2006, since plan bids were all equally weighted in the construction of the benchmark, and firms did not know all competitors' bids. However, Decarolis (2012) shows that in later years, when the LIS benchmark is enrollment weighted, some firms will have the ability to manipulate the benchmark. This potential manipulation does not affect the regression discontinuity presented here, which relies on 2006 pricing.

[31] Although it is not necessarily for the validity of the design, McCrary (2008) suggests testing for discontinuities in the density of the forcing variable. A discontinuous density at the cutoff may suggest firms were able to manipulate whether they are above or below the benchmark. In the absence of collusion with CMS, this seems implausible. Applying the test suggests there may be a discontinuity in the density at the cutoff, but these seems to be a result of the density not being smooth in general. Appendix Figure A.3 graphically displays the result of the density discontinuity test at the cutoff, which finds a log difference in density height at the cutoff of 0.317 (standard error 0.14), giving a t-statistic of 2.21. Yet rather than firms sorting around the cutoff, further tests suggest the density is not smooth: testing for discontinuities at one dollar intervals around the cutoff gives t-statistics above 1.6 at four of ten locations. Appendix Figure A.4 displays the histogram of relative premiums and shows that there are spikes at a number of points in the histogram, including one near zero.

effect on the estimates of 2006 enrollment, but may affect estimates of enrollment and price responses in subsequent years. Attrition between 2006 and 2007 is negligible: Appendix Table A.5 shows that less than 5% of plans attrit by 2007 in the regression discontinuity windows used here. Attrition by 2008 is similarly small. Yet by 2009 and 2010, more than 20% of plans in the regression discontinuity windows have attrited, and plans that price below the benchmark in 2006 are more likely to attrit. I present estimates for 2009 and 2010, but they should be viewed as conditional on remaining in the data.

5.2 Effect of Pricing Below Benchmark on Enrollment

Figure 3 confirms that pricing below the benchmark leads to a substantial increase in enrollment. This figure plots 2006 premiums relative to the LIS subsidy amount against 2006 log enrollment share, and plots predicted enrollment, controlling for premiums relative to the benchmark in linear and quartic polynomial specifications. The first two panels in Table 3 confirm the visual effect: Panel 1 shows a regression that controls for relative premiums linearly, while Panel 2 uses a quadratic polynomial of relative premiums, plus plan characteristic controls. The Imbens and Kalyanaraman (2009) optimal bandwidth for log plan shares is approximately $4,[32] but the effect is robust to the use of other bandwidths. Regardless of specification, the coefficient in column 1 for being below the benchmark indicates that pricing just below the benchmark leads to market shares that are approximately 200 log-points (150%) higher than other plans. Average plan market shares in the $4 window above the benchmark are just under 1%, while below the benchmark the average is about 5.5%. A placebo test using only the enrollment of non-LIS individuals finds effects that are small in magnitude and not significantly different than zero, supporting the identification strategy: the benchmark does not appear to affect non-LIS enrollment.

Pricing below the benchmark in 2006 has a persistent effect on subsequent enrollment. The effect of pricing below the benchmark on 2006 enrollment can be due in part to LIS recipients accepting the default, and in part to price sensitivity (plans below the benchmark are free); most LIS recipients do not make an active choice.[33] The effect of pricing below the benchmark in 2006 on enrollment in 2007 and beyond is evidence of inertia, as random variation in initial conditions has persistent effects Additional columns in Table 3 show that pricing below the benchmark in 2006 predicts enrollment not only in 2006, but in later years as well: plans below the benchmark in 2006 have market shares that are 130 log points higher in 2007. The effect decays over time, but is still substantial in 2008. Appendix Figure

[32] The optimal bandwidth varies slightly by year; I use a consistent cutoff for each year.

[33] While the exact number of LIS recipients who made an active choice cannot be determined from the aggregate data, the Medicare Payment Advisory Commission (2010) puts the number of LIS recipients who ever made an active choice by 2010 at 2.5 million, or about a third of LIS recipients.

A.5 shows this visually for 2008 enrollment. For 2009 and 2010, the local linear regressions indicate a large effect, but not the polynomial regressions. The estimated effect on enrollment in these later years is conditional on not attriting from the data.

The persistent effect of random variation in initial conditions comes from two sources: plans that continue to price below the benchmark hold on to the enrollees they have acquired by default, and individuals make active choices to stay with plans that subsequently price above the benchmark. Panel 3 of Table 3 regresses log plan shares in each year on indicators for being a benchmark plan in 2006 interacted with being a benchmark or de minimis plan in the current year. Focus on 2007, in which the three indicator variables control for each possible history of pricing below the benchmark: below the benchmark in both years, below in 2006 only, or below in 2007 only, compared to never having been a benchmark plan. The first row indicates that plans that priced below the benchmark both years had market shares that were 209 log points higher than plans that were below the benchmark in neither year. The coefficient in third row shows that pricing below the benchmark in 2007 alone leads to market shares that were only 15 log points higher than plans never below the benchmark. Comparing these two coefficients shows that pricing below the benchmark has a larger effect on enrollment if the plan was previously a benchmark plan, as such plans keep their previously acquired LIS recipients by default.[34]

Thus, inertia in LIS enrollment comes both from the effect of defaults as well as from active choices to avoid switching costs. Being below the benchmark in 2006 is associated with higher enrollment in 2007 even if the plan is not a benchmark plan in 2007: such plans have market shares that are 62 log points higher than plans that were never below the benchmark. These estimates indicate that about a quarter to one half of LIS recipients chose to stay with their plan even after it priced above the benchmark.

5.3 Effect of Pricing Below Benchmark on Subsequent Pricing

Firms that receive LIS recipients have a relatively larger base of existing enrollees, which may affect firms' pricing in later periods. However, LIS recipients behave differently from standard enrollees, as they are automatically switched if the plan raises its price over the benchmark. Because they face different defaults and prices, Appendix Section A.1.2 shows that the effect of acquiring LIS recipients on a plan's future prices is theoretically ambiguous.

To examine whether falling above or below the benchmark in 2006 had any effect on average premiums in the subsequent year, Figure 4 plots monthly relative premiums in 2007 against relative premiums in 2006 (horizontal axis). In contrast to the enrollment results,

[34] Appendix Table A.6 shows that results are similar if controls are included, including premium in the current year.

visual inspection indicates no obvious discontinuity in average firm behavior above or below the cutoff. This is confirmed in Appendix Table A.7, which finds that being below the benchmark had an insignificant effect on 2007 pricing using a bandwidth of $6 (approximately the optimal bandwidth for premiums). Similarly, for later years (2008 - 2010) the effect is noisily estimated, never significantly different from zero. The sign of the point estimate is not stable across years or specifications.

Even if acquiring LIS recipients did not have an effect on average prices, the desire to hold on to auto-enrollees could create an incentive to keep prices below the benchmark or the de minimis amount in subsequent years. Average prices could remain the same, even as firms were more likely to price below the benchmark. Yet Appendix Figure A.6 shows that plans that were below the benchmark in 2006 are no more likely to be below the benchmark or to be a de minimis plan in 2007. The absence of an effect is confirmed by Appendix Table A.8, which shows that the point estimate is insignificant and in fact negative in most specifications: the point estimates indicate plans are slightly less likely to fall below the benchmark in subsequent years if they did so in the first year, with the local linear regressions indicating a 6 percentage point decrease. Thus the evidence suggests little effect on firm pricing behavior of having acquired LIS recipients.

6 Invest-then-Harvest Pricing Behavior

6.1 Pricing Evidence

The core prediction of switching frictions for firm behavior is that older plans should charge higher prices. Figure 5 confirms graphically that prices follow the pattern predicted by invest-then-harvest pricing. It plots the average premium charged by each basic plan in each year, separating out plans by cohort. As predicted, we see that premiums in each cohort rise over time. Plans are introduced each year, with new plans generally having lower premiums than existing plans. The pattern is not perfect, as premiums for the 2006 cohort declined slightly from 2006 to 2007; afterwards, the 2006 and 2007 cohorts appear to act similarly. CMS, along with other commentators, noted the drop in premiums from 2006 to 2007 and suggested it was the result of lower than expected prescription drug costs, more substitution into generic drugs than anticipated, and higher than expected competitive pressures. It is likely that substantial firm learning occurred between 2006 and 2007; for the 2006 cohort, the standard deviation of premiums for basic plans dropped from about $10 in 2006 to about $6 in 2007. Because aspects of the market are changing over time, including regulation, pharmaceutical prices, and firm information, I do not identify the effect of plan age off the time-series of plan prices.

I first compare the distribution of premiums between older plans and newer plans in a given year: recall that Figure 1 compares the distribution of basic plan premiums in year 2010, for the earlier cohorts (2006 and 2007) and later cohorts (2008+) of plans. It shows that the higher premiums of older cohorts are not due to a few outliers, but to the behavior of many plans. Moreover, in addition to having a higher mean, the 2010 distribution of premiums in the older cohorts is more right skewed than the distribution of premiums for the newer cohorts. This suggests heterogeneity in the extent to which firms are raising prices on existing plans.

To identify the relative prices of older versus newer cohorts of plans, Table 4 regresses log premiums on plan age with various controls for observable plan characteristics.[35] It includes year fixed effects (interacted with state fixed effects) in all specifications and so identifies the effect of plan age on price by comparing plans of different ages in a given year, removing any market specific shock. As a result, the 2006 prices do not contribute to the identification of the effect of plan age. The regressions cluster standard errors at the firm level, to account for the fact that premiums are serially correlated at the plan level and to allow for the possibility that plans offered by the same firm experience common shocks. These analyses show that the observed association between plan age and premiums is not merely due to changes in composition of plans toward cheaper plan types.

Column 1 gives the association between plan age and premiums, confirming the visual results of Figure 5 among basic plans when controlling for state by year fixed effects. Older plans have higher premiums than new plans, about 6% higher in their fourth year and 18% higher in their fifth year.[36] Column 2 adds controls for the form of the basic benefit type, interacted with year fixed effects. These regressions indicate that plans in their fourth year cost 12% more than comparable newly introduced plans, while five-year-old plans cost 15% more than comparable new plans. This column also includes an indicator for whether the firm offering the plan also offered a Medicare Advantage (M.A.) plan, as firms may strategically attract Part D enrollees in an attempt to also enroll them in a Medicare Advantage plan.[37] Firms that offer a Medicare Advantage plan are cheaper, by about 15% per year, suggesting firms may be using PDPs as loss leaders. The invest-then-harvest pricing pattern can result from both new firms entering and existing firms introducing new plans. Column 3 includes

[35] Individual plan fixed effects regressions are not estimated due to the well-known inability to separately identify cohort, age (i.e. year of plan existence), and year fixed effects.

[36] The gradual price increases may result from a number of factors. Sharp raises may draw unwelcome publicity and attention from policy makers; Humana was criticized for its extreme strategy. Switching costs may also develop over time: if a person joins a plan in November and has the opportunity to switch beginning in January, he may not have learned enough about his current plan to make learning about another plan more costly.

[37] Because this variable is collinear with firm, it must be dropped in regressions that use firm fixed effects.

firm fixed effects and identifies the effect of plan age on price using variation within firms over time. The pattern persists, indicating that the observed effect is not due to new firms entering at lower prices but not raising them; the pattern persists even controlling for firm quality. Although I do not observe the detailed formulary characteristics of each plan, controlling for firm fixed effects should remove most of the variation in plan formularies.

While the regressions in Columns 1-3 equally weight all plans and therefore describe the experience of the average plan, enrollment-weighted regressions provide a better description of the experience of the average enrollee. Columns 4-6 weight each plan observation by its total enrollment in that year. The estimated effect of offering a Medicare Advantage plan shrinks, but the age effects become somewhat larger in magnitude when regressions are enrollment-weighted. Compared to new plans, premiums are statistically significantly higher for all plans at least three years old. Because the strategy of introducing plans at lower prices is successful at attracting higher enrollment, the price increase experienced by the average enrollee is larger than the average plan's price increase.

The enrollment-weighted regressions also indicate that the results are not being driven by attrition of plans from the sample. Plans can leave the sample either because the firm discontinues the plan or because the plan is merged with another plan (e.g. when firms merge). Relatively few plans are discontinued (less than 8%; see Appendix Table A.9). Dropping such plans from the regressions does not affect the results. An additional 28% of plans leave the sample because they merge with another plan. The new, larger plan receives additional weight in the enrollment-weighted regressions. These regressions indicate the age effect remains robust.

Appendix Tables A.10 and A.11 show that these results are robust to a number of changes in the regression specification. When regressions include firm interacted with year fixed effects, they identify the effect of age on pricing using variation in a given year at a particular firm. Similarly large effects of plan age on pricing are found using equally weighted regressions. An enrollment-weighted regression find noisy to zero effects within firms, suggesting that larger firms do not vary their prices within a given year based on plan age, consistent with the potential regulatory constraints described in Section 4. The age effect also persists when enhanced plans are included in the sample: the percentage increase with age is larger, albeit measured with more noise. (Recall, we do not capture all the features of enhanced plans). The results are also similar when the regressions are run separately when the sample is split into plans that were ever below the LIS benchmark and plans that were never below that benchmark. Finally, when the dependent variable is the absolute premium in dollars rather than logs, the results are similar and show that plans that are five years older cost about $50 more than comparable newly introduced plans.

6.2 Interpretation: Invest-then-Harvest Pricing or Alternative Stories

These regressions show that there is in fact a price difference between younger and older plans, consistent with the predictions of invest-then-harvest pricing theory. Plans in their fifth year charge an additional 10%, or about \$50, per year than equivalent, newly introduced plans. The price difference Δp between young and old plans can be decomposed into a difference in average costs and markups between cohorts: $\Delta p = \Delta c + \Delta m$. How much of this price differential is attributable to differences in markups, as implied by invest-then-harvest pricing, and how much to differences in costs? If risk adjustment compensates firms fully for differences in costs, then Δp would be driven differences in markup. In the absence of firm cost data, we cannot directly estimate Δc. However, we can evaluate the risk adjustment model and other sources of variation in cost.

The existence of this pricing pattern is itself relevant, regardless of whether the explanation is invest-then-harvest pricing or imperfect risk adjustment: it implies that enrollees will have an incentive to switch between otherwise identical products, either to take advantage of introductory prices (the invest-then-harvest explanation) or a better risk pool (a failure of risk adjustment explanation). Some enrollees will switch, inefficiently expending real resources to do so.

Cost Variation Due to Risk Adjustment Failures.—There are two ways risk adjustment could fail for standard enrollees, and lead to $\Delta c > 0$. First, risk adjustment may not sufficiently account for the increase in a firm's costs as a representative sample of the population ages. Second, risk adjustment may not sufficiently account for the selection of enrollees who choose to stay in older plans: if enrollees whose cost is higher than their risk adjustment payments (that is, enrollees for whom the risk adjustment model fails more) were less likely to switch, older cohorts of plans would have higher costs.[38]

First, risk adjustment does seem to account for the age-related increase in drug spending. Older cohorts of plans will have an older enrollee base, as a result of inertia and the low rate of switching. Thus, effective risk adjustment requires that as an enrollee ages, they do not become more costly to a firm. Risk adjustment payments are based on diagnostic history,

[38] For instance, Brown, Duggan, Kuziemko, and Woolston (2011) show that plans in the Medicare Advantage market engage in risk selection on dimensions not covered by the risk adjustment formula—specifically, that the private Medicare Advantage plans disproportionally enroll low cost individuals, compared to Traditional Medicare. However, the threat of selection is much less severe in Part D than in Medicare Advantage. While Medicare Advantage plans are competing with an essentially non-strategic actor (Traditional Medicare), Part D plans are competing with other strategic Part D plans attempting to select profitable enrollees. The pricing regressions in Table 4 compare different cohorts of Part D plans to each another, and so a selection story must rely not on firms merely attempting to select, but on older firms being less able to select a profitable population than younger firms. However, that is inconsistent with the effects of expertise (older firms have more knowledge) or with the switching results described in this section.

but when that information is unavailable, a simpler model based on age and sex is used. I evaluate the simpler model, as I do not have enrollee claim history; the more detailed model should do even better in modeling costs. Consider when a representative sample of the population 65 and above is aged five years. The change in drug spending for this population matches the change in firm risk adjustment payments. Using the 2007 Medical Expenditure Panel Survey, average prescription drug spending would rise by 2.6% as this population ages five years. Using the age-based risk adjustment factors, a firm's risk adjustment payments would increase by 3.1%. Appendix Section A.3 gives more detail on the construction of these figures.

Second, we can examine how switching behavior varies by observable factors. While we do not know the people for whom the risk adjustment model underpredicts cost (as we do not have data on firm costs), we can infer they likely to be older and sicker enrollees– the enrollees with the highest costs. So if cohort composition is driving the pricing results, we would expect older and sicker enrollees to be more likely to stay with older cohorts of plans. However, we see the opposite pattern: Ketcham, Lucarelli, Miravete, and Roebuck (forthcoming) examine who switches Part D plans using proprietary data on a subset of the market. They find that the probability of switching to an alternative plan is higher for 1) older individuals, and 2) individuals with a higher risk score, and 3) individuals with a changed risk score. Thus, there is no evidence that enrollees who stay behind in older plans are the type for whom risk adjustment is likely to fail.

Moreover, while the primary dimension within the market on which we would expect differential selection is basic versus enhanced plans, the relative costs of these types of plans do not drive the results. The preferred analyses in Table 4 are limited to basic plans alone, as these plans have fewer unobserved characteristics. Nonetheless, the pricing pattern is robust to including enhanced plans in the sample or solely looking at enhanced plans (Appendix Tables A.10 and A.11).

Cost Variation Due to the LIS Program.—While the LIS program has the potential to affect firm pricing strategy, the observed pricing pattern is not attributable to the LIS program. The results in Section 5 indicate that there is no consistent effect of acquiring a large number of LIS recipients on subsequent premiums; the preferred specification finds a negligible negative effect (about 68 cents per month). Moreover, risk-adjustment for LIS recipients is insufficient to cover their higher costs (Hsu et al. 2010), potentially creating an incentive to raise premiums among plans that disproportionately attract LIS recipients. Yet it is the new cohorts of plans that have a higher fraction of their enrollees receive the LIS, a result of their lower prices. In 2009, 40% of enrollees in the 2006 cohort of plans receive the LIS, compared to 70-89% of later cohorts (Appendix Figures A.1 and A.2). Hence, incomplete risk adjustment for LIS recipients implies that the estimated effects of plan age actually underestimate the increases in prices that would occur if risk adjustment were perfect. Finally, Appendix Table A.11 shows that the observed pricing pattern is similar when the sample is split between plans that were ever below, verus were never below, the LIS benchmark.[39]

Cost Variation Due to Negotiated Prices.—Even if the average utilization of enrollees were the same across two firms, firm costs could vary because that the prices firms pay for a given bundle of drugs varies. Yet this potential cost difference should bias us *against* finding the invest-then-harvest pattern. Older cohorts have higher enrollment, and so have greater bargaining power for pharmaceutical prices. Thus, we should expect older cohorts to have lower costs than new entrants, suggesting the markup would be even higher than the observed Δp. (See Lakdawalla and Yin 2012 for evidence that Part D increased the bargaining power of insurers.)

Variation in Markups: Invest-then-Harvest Pricing.—The model of Section 3 predicts that firms are sophisticated and vary prices in response to variation in the price elasticity of demand they face. The pricing behavior is consistent with the invest-then-harvest pricing pattern predicted by Section 3. Plans in their fifth year charge an additional 10%, or about $50, per year than equivalent, newly introduced plans– and this difference is unlikely to be driven by cost differences between firms. Although we do not know the full distribution of switching frictions, these results are quantitatively consistent with the model as well: it seems reasonable that seniors may not switch for gains as small as $50.[40]

7 Discussion and Conclusion

Inertia and firms' responses to it have implications for researchers and policy makers. Since firms predictably raise prices on plans in later years, analysis of this market should consider the lifecycle price of an insurance product. Under perfect competition, firms do not make positive profits: in the first period, they compete away the rents they will later earn (see Ericson 2012 for more detail). Under imperfect competition, switching frictions have an ambiguous effect on firm profits.[41] In either case, total premiums paid will depend on

[39] Decarolis (2012) shows that in later years of the market, some large firms may have had the ability to manipulate the LIS benchmark, and identifies Aetna, CVS, and Medco as displaying suspicious behavior. Manipulation does not drive the pricing results, since 1) only a few large firms have this incentive and 2) Appendix Table A.11 runs the pricing regressions excluding the three suspicious firms and finds no substantive change in the results.

[40] This is a pure utility gain if plans have perfect substitutes; to the extent plans are imperfect substitutes, the utility gain from switching would be attenuated.

[41] For models of imperfect competition, there is an active debate about whether switching costs raise or lower the average level of markups: compare Farrell and Klemperer (2007) and Dubé, Hitsch & Rossi (2009),

an enrollee's ability and willingness to switch plans, which may raise equity concerns: more sophisticated enrollees who can switch to inexpensive plans will effectively be cross-subsidized by enrollees stuck in place at relatively expensive plans.

Inertia limits how enrollees will respond to changes in their environment, and so enrollees who face switching frictions will respond to a policy change differently than individuals making initial decisions. Even moderate switching frictions can limit what can be learned about long-run population responses from existing enrollees. The results in Table 4 suggest an approximate magnitude of switching frictions: \$50, or about 10% of annual premiums.

Chetty (2011) shows that in the presence of switching costs or other optimization frictions, a range of structural elasticities (i.e. long-run elasticities) is consistent with the observed response to a price change. Consider a hypothetical large policy change that puts a 50% subsidy on premiums paid, replacing the current arrangement in which individuals pay the full marginal cost of choosing a more expensive plan. How would this subsidy affect total expenditure on premiums? Suppose a researcher examined existing enrollees and precisely identified the change in their premium spending that resulted from the policy, estimating a price elasticity of spending of -0.07 (similar to that measured in other contexts.)[42] Appendix Section A.4 uses the results of Chetty (2011) to show that with switching frictions of 10% of premiums, an observed elasticity of -0.07 would be consistent with long-run elasticities that range from virtually zero (-9.0×10^{-4}) to very large (-5.0), a rather uninformative range.

Compared to a situation in which firms could commit to future prices or simply charged the same price each period (lifetime average cost), this equilibrium is inefficient: with invest-then-harvest pricing, some individuals switch to get better deals, and expend some real resources in the process.[43] The current contracting structure makes it difficult for firms to commit to future prices, but commitment to future prices (e.g. by allowing multi-year bids) could reduce inefficient switching.[44] Some rough calculations give a sense of the potential

who find that the effect of switching costs on average markups are non-monotonic and depend on the setting. Markups are transfers from enrollees to firms and so affect the distribution of income. Higher markups would also lead to added deadweight loss for the increased taxes to pay for higher premiums (consumers only pay about 25% of the premiums), and from individuals substituting out of the market.

[42] The response of interest here is the percentage change in total spending for a percentage change in price. This differs from the plan share elasticity estimated in Section 4.2, which measures substitutability among plans. Gruber and Washington (2005) observe an elasticity of total premiums spent on health insurance of about -0.07 for employer provided health insurance.

[43] A similar welfare loss would result if there were imperfect risk adjustment, leading to costs varying by cohort of plan. In such a case, enrollees would expend resources switching plans merely to join a better risk pool.

[44] Firms submit annual bids. Because final prices are determined by a subsidy amount that is unknown to firms when submitting their bid, firms cannot easily communicate future pricing intentions to enrollees (e.g. a firm cannot advertise that their plan will cost \$30 month for the next five years). Other barriers to commitment include uncertainty about future costs and inability to commit to unobserved quality.

welfare gain to flat pricing. Heiss, McFadden and Winter (2007) find that 10% of enrollees switch between 2006 and 2007. We do not know how much of this switching is induced by price changes, as opposed to consumer learning or preference change. Suppose that only half of the observed switching would have occurred if firms had set constant prices, so there are about 0.8 million excess switches per year. If the average switching cost borne, conditional on actually switching, is \$25 (recall, switchers can save about \$50), then about \$20 million per year in real costs are expended on switching that would not have occurred if firms committed to constant prices.

Contract restrictions play a major role in determining the form equilibrium takes. Under current regulations, plans must charge all enrollees the same price. If firms were instead allowed to charge "introductory prices" for first-time enrollees, they would choose to do so (see Taylor 2003). Such a policy would still lead to inefficient switching between plans. However, it would weaken incentives for firm entry, since existing firms could simultaneously offer attractive prices to new enrollees while charging enrollees stuck in place a higher price.[45]

Market design decisions can affect the extent to which individuals are inert. The default for standard enrollees is automatic reenrollment in the same plan, regardless of firm price increases. In contrast, LIS recipients face an automatic switching default, which can raise the elasticity of repeat demand and limit price increases in later periods. Ericson (2012) considers how to set these dynamic defaults, and shows that they depend crucially on source of switching frictions (real costs or psychological factors) and the pricing response of firms.

Medicare Part D is a large, functioning exchange that is important to study in its own right, and also gives insights into the design of health insurance exchanges. Yet firms' strategic responses to inertia are relevant for market design in domains other than health insurance: for instance, governments organize school voucher programs and private social security accounts. Market design decisions in these and similar domains should take into account the inertial behavior of individuals, real switching costs individuals face, and the strategic responses of firms to both.

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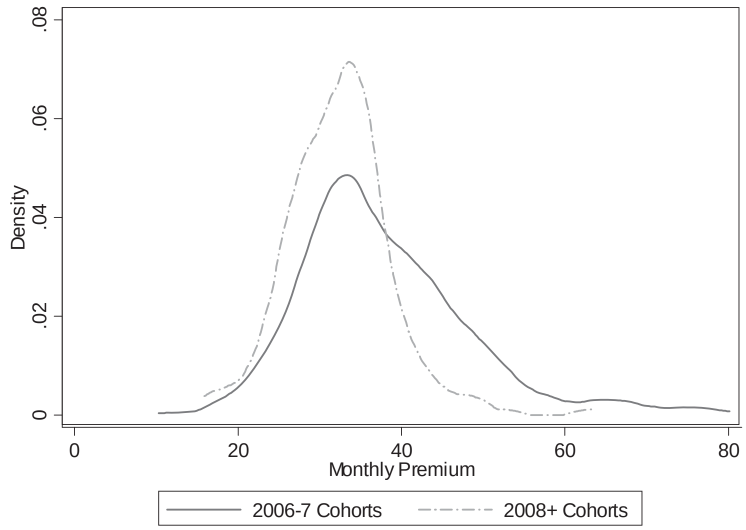

Figure 1: Distribution of Basic PDP Plan Premiums in 2010, by Year of Plan Introduction. Epanechnikov kernel density.

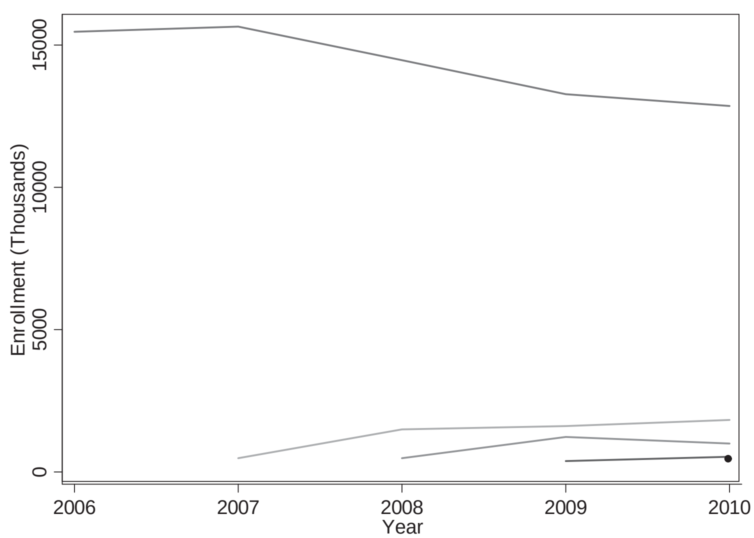

Figure 2: Total PDP Enrollment, by Year and Cohort of Plan. Each line traces the total enrollment of each cohort of plans over time. The enrollment of the 2010 cohort is indicated by a circular marker. Total enrollment includes both standard enrollees and LIS recipients, and is taken as of July 1 of each year. See Appendix Section A.2 for details on data construction.

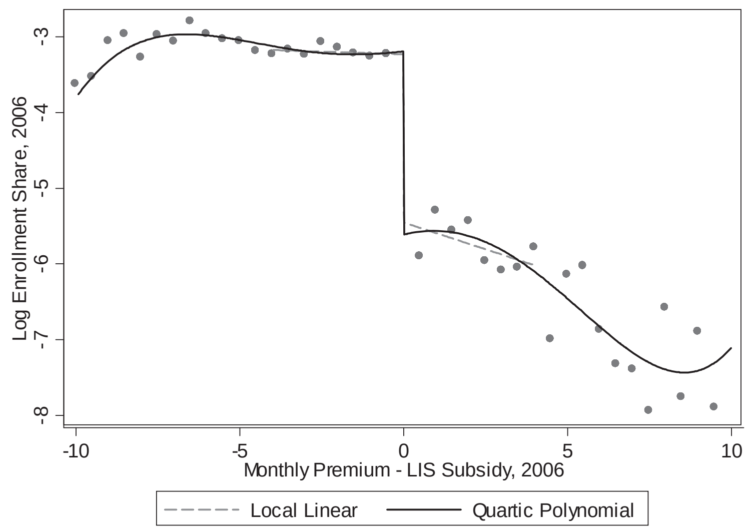

Figure 3: The Effect of 2006 Benchmark Status on 2006 Enrollment. Dots are local averages with a binsize of \$0.50. Dashed lines are predictions from local linear regressions with bandwidth of \$4. Solid lines are predictions from regressions with a quartic polynomial with a bandwidth of \$10.

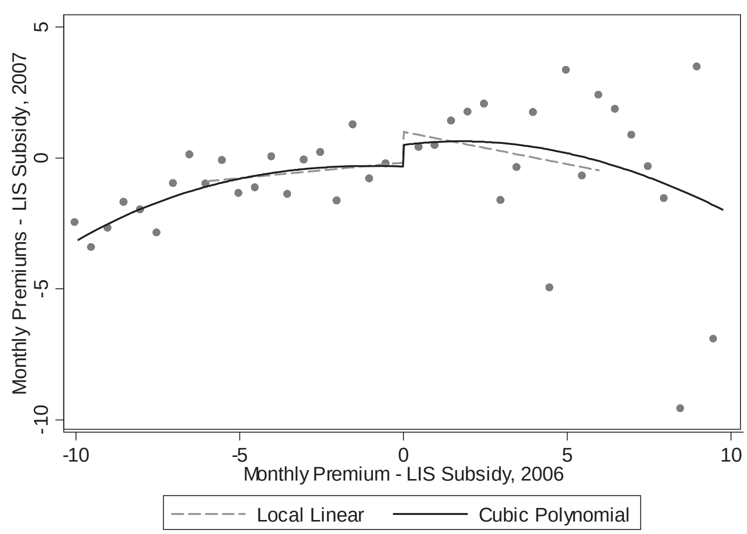

Figure 4: The Effect of 2006 Benchmark Status on 2007 Premiums. Dots are local averages with a binsize of \$0.50. Dashed lines are predictions from local linear regressions with bandwidth of \$6. Solid lines are predictions from regressions with a cubic polynomial with a bandwidth of \$10.

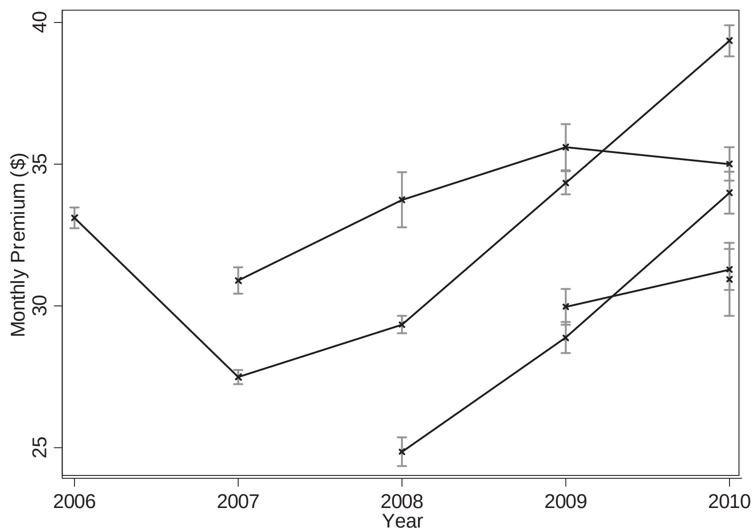

Figure 5: Evolution of Cohort Premiums over Time. Average monthly premiums for basic PDP plans, by plan cohort and year. Each line traces gives the annual premium over time of a given cohort. Standard errors are in grey.

Table 1: Descriptive Statistics of Medicare Part D Plans

	Cohort (Year of Plan Introduction)				
	2006	2007	2008	2009	2010
Mean monthly premium	\$ 37	\$ 40	\$ 36	\$ 30	\$ 33
	(13)	(17)	(20)	(5)	(9)
Mean deductible	\$ 92	\$ 114	\$ 146	\$ 253	\$ 118
	(116)	(128)	(125)	(102)	(139)
Fraction enhanced benefit	0.43	0.43	0.58	0.03	0.69
Fraction of plans offered by firms already offering a plan...					
...in the U.S.	0.00	0.76	0.98	1.00	0.97
...in the same state	0.00	0.53	0.91	0.68	0.86
N Unique Firms	51	38	16	5	6
N Plans	1429	658	202	68	107

Source: Author's calculations from CMS Landscape Source Files. Plan characteristics are taken from the year the plan was introduced (e.g. premium in plan's first year). Standard deviations in parentheses.

Table 2: Response of Enrollment to Contemporaneous and Past Prices: 2007

	(1)	(2)	(3)	(4)	(5)	(6)
	$\ln s_{2007}$	$\ln s_{2007}$	$\ln s_{2006}$	$\ln s_{2007}$	$\ln s_{2007}$	$\ln s_{2006}$
Premium in 2007	-0.0971***	-0.146***		-0.0899***	-0.105***	
	(0.0308)	(0.0447)		(0.0285)	(0.0335)	
Premium in 2006	-0.0773***		-0.140***	-0.0694***		-0.173***
	(0.0185)		(0.0281)	(0.0222)		(0.0254)
Type of Basic Plan	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	No	No	No	Yes	Yes	Yes
N	560	560	553	560	560	553
R^2	0.648	0.484	0.552	0.827	0.800	0.757

OLS regression. Dependent variable: log of plan market share for non-LIS enrollees in a year. Sample: basic PDP plans that were introduced in 2006, and that do not attrit or switch to or from enhanced benefit type before 2007. Plans are dropped from the regression if they have fewer than 10 total enrollees or if estimated enrollment net of LIS is negative. See Appendix Section A.2 for more details. In all columns, state fixed effects and benefit type indicators (Defined Standard, Actuarially Equivalent Standard, or Basic Alternative) are included, and for Basic Alternative plans, deductible bins of \$0, \$1 to \$50,\$51 to \$100 ..., are included. In columns 1 and 4, controls are included separately for type of basic plan and deductible in both 2006 and 2007. Indicators for pricing below the LIS benchmark are also included, separately for 2006 and 2007. Heteroskedasticity robust standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Effect of LIS Benchmark Status in 2006 on Plan Enrollment

$\ln s_t$	2006	2007	2008	2009	2010
	Panel 1: Local linear, bandwidth \$4				
Below Benchmark, 2006	2.224***	1.332***	0.902***	0.803**	0.677
	(0.283)	(0.267)	(0.248)	(0.362)	(0.481)
Premium - Subsidy, 2006					
... Below Benchmark	-0.0141	-0.0774	-0.0731	-0.170	-0.215**
	(0.0322)	(0.0882)	(0.116)	(0.105)	(0.0878)
... Above Benchmark	-0.142*	-0.0331	0.0494	0.0737	0.0488
	(0.0783)	(0.110)	(0.163)	(0.170)	(0.202)
N	306	299	298	246	212
R^2	0.576	0.325	0.131	0.141	0.124
	Panel 2: Polynomial with controls, bandwidth \$4				
Below Benchmark, 2006	2.464***	1.364***	0.872***	0.351	-0.277
	(0.222)	(0.321)	(0.246)	(0.324)	(0.301)
Premium - Subsidy, 2006	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
N	306	299	298	246	212
R^2	0.794	0.576	0.472	0.535	0.685
	Panel 3: Past interactions, local linear, bandwidth \$4				
Below Benchmark or de minimis in:					
...2006 and current year	2.224***	2.089***	2.377***	2.633***	2.443***
	(0.283)	(0.364)	(0.275)	(0.257)	(0.309)
...2006 but not current year		0.628**	0.892**	1.068**	0.967
		(0.293)	(0.329)	(0.446)	(0.625)
...current year but not 2006		0.148	1.356***	2.107***	2.281***
		(0.290)	(0.293)	(0.242)	(0.259)
Premium - Subsidy, 2006	Linear	Linear	Linear	Linear	Linear
N	306	299	298	246	212
R^2	0.576	0.480	0.426	0.498	0.467

Each panel is a separate regression. Dependent variable: log of total plan market share (including LIS enrollees) in a year. Sample: basic PDP plans with premiums within the bandwidth window (\$4 on either side of the benchmark) in 2006. In "Polynomial with controls", regressions include state and firm fixed effects, and benefit type indicators (Defined Standard, Actuarially Equivalent Standard, or Basic Alternative). For Basic Alternative plans, deductible bins of \$0, \$1 to \$50, \$51 to \$100 ..., are included. Premium minus subsidy is included as a polynomial separately above and below the benchmark. Heteroskedasticity robust standard errors, clustered at the firm level, are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Medicare Part D Premiums by Plan Age

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Monthly Premium)					
	Equal Weighted			Enrollment Weighted		
Year of Plan Existence						
...2nd Year	-0.0167	-0.0103	0.0129	0.0183	-0.0229	0.0139
	(0.0508)	(0.0597)	(0.0511)	(0.0478)	(0.0446)	(0.0593)
...3rd Year	0.0290	0.0585	0.0785	0.128**	0.0795**	0.133***
	(0.0808)	(0.0699)	(0.0519)	(0.0528)	(0.0326)	(0.0358)
...4th Year	0.0690	0.117*	0.148***	0.199***	0.112**	0.191***
	(0.0660)	(0.0617)	(0.0496)	(0.0647)	(0.0522)	(0.0684)
...5th Year	0.177**	0.147**	0.0960*	0.320***	0.154***	0.152*
	(0.0871)	(0.0593)	(0.0551)	(0.0861)	(0.0530)	(0.0764)
Firm Offers M.A. Plan		-0.145**			-0.0390	
		(0.0653)			(0.0350)	
Type of Basic Plan	No	Yes	Yes	No	Yes	Yes
Firm Fixed Effects	No	No	Yes	No	No	Yes
N	4,276	4,276	4,276	4,123	4,123	4,123
R^2	0.189	0.396	0.405	0.364	0.632	0.683

Dependent variable: log monthly PDP premium or monthly premium. Sample: basic PDP plans. All regressions include state fixed effects interacted with year fixed effects. Controls for type of basic plan include benefit type indicators (Defined Standard, Actuarially Equivalent Standard, or Basic Alternative) interacted with year fixed effects. For Basic Alternative plans, deductible bins of \$0, \$1 to \$50,\$51 to \$100 ..., are also included and interacted with year fixed effects. Enrollment weighted regressions are weighted using the plan's total enrollment in July of each year. Plans with fewer than 10 enrollees are dropped from weighted regressions. See Appendix Section A.2 for more details. Heteroskedasticity robust standard errors, clustered at the firm level, are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.