Supply Response to Consumer Inertia: Strategic Pricing in Medicare Part D

by

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B.S. Economics and Finance, Tsinghua University (2011)

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Abstract

A growing literature has documented evidence that consumers in health insurance markets are inertial, or behave as though they face substantial switching costs in choosing a health insurance plan. I investigate whether the private firms that provide prescription drug insurance through Medicare Part D exploit this inertia when setting prices. I first document descriptive evidence consistent with insurers initially setting low prices in order to "invest" in future demand before later raising prices to "harvest" inertial consumers. I then apply a two-step estimation approach following Bajari, Benkard and Levin (2007) to explore the implications of these invest and harvest incentives for equilibrium pricing, finding that on net, demand inertia reduces equilibrium prices (i.e. the invest incentive dominates the harvest incentive). Finally, I evaluate welfare consequences of policies that could be used to constrain insurers' ability to conduct such "invest-then-harvest" pricing patterns. I find, for example, that a policy change to cap premium increases would improve consumer welfare by both lowering average premiums and smoothing prices over time.

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0.1 Introduction

A growing literature has documented evidence that consumers in health insurance markets behave as if they face substantial switching costs when choosing health insurance plans. In this paper, I investigate whether private firms exploit this type of consumer inertia when setting prices for health insurance products and analyze the resulting welfare and policy implications. My empirical setting is Medicare Part D, a public program in which private insurers under contract with the government provide outpatient prescription drug insurance to more than 30 million Medicare beneficiaries (Hoadley et al., 2014).

Consumer inertia is a well-recognized feature of Medicare Part D, where standard enrollees only need to actively choose plans when they first join the program and are subsequently defaulted into previous choices unless they choose to switch. Hoadley et al. (2012) document the low frequency of switching despite large changes in plan premiums. Miller and Yeo (2015a) and Polyakova (2015) both identify substantial switching costs among Part D enrollees and estimate significant welfare loss because switching costs tend to prevent consumers from re-optimizing and to lock them into sub-optimal plans.

Building on prior evidence of inertia in consumer demand in the context of Medicare Part D, my paper proceeds in three steps. First, I use administrative micro-data on Medicare beneficiaries and their plan choices to document descriptive facts that are consistent with the theoretical framework outlined by Klemperer (1987). The key idea of Klemperer (1987)'s framework is that, in the presence of demand inertia, insurers initially set low prices in order to "invest" in future demand before raising prices to "harvest" inertial consumers. I start by testing for this "invest-then-harvest" pricing pattern (also known as "bait-and-switch" or "bargains-then-ripoffs" pricing) by using a measure of markup or variable profit margin to eliminate potential confounding variations in cost and subsidy that affect insurers' pricing decisions. I document descriptive evidence consistent with insurers initially setting low prices in order to invest in future demand before later raising prices to harvest inertial consumers. Indeed, insurers charge lower markups when plans first enter and increase markups afterward; even the same insurer charges 148 dollars lower in annual markups for entrant plans than incumbent plans offering similar coverage. This difference in markup is over 30 percent of the average annual premium during the sample period. Such a striking invest-then-harvest pricing pattern rejects the null of no strategic response and provides suggestive evidence that insurers account for inertia when setting prices.

My finding confirms the public suspicion of Part D sponsors' "bait-and-switch" tactic. According to a Boston Globe article by Krasner (2006), the start-up of Medicare Part D was seen as "a once-in-a-lifetime opportunity" to attract new customers for Humana, one of the biggest insurers operating in Medicare Part D. The article notes that Humana tends to introduce plans at low prices, which are subsequently increased by a large margin.[1] One health-care analyst's response to Humana's pricing is very telling: "That's not an acceptable inflationary increase in prices. That's sucker them in and you just start raising the prices." A Humana spokesman blamed the price increase on the government's subsidy formula, but that contention was disputed by an actuary from the Centers for Medicare and Medicaid Services (Krasner, 2006).

Insurers' invest-then-harvest pricing has important welfare implications. On one hand, dynamic choice inefficiency arises as consumers' plan choices tend not to remain optimal after price changes, but switching frictions prevent many from taking advantage of re-optimization. On the other hand, it is an empirical question whether the invest or harvest incentive dominates and whether prices are higher or lower compared with the benchmark with no inertia. To explore the implications of these invest and harvest incentives for equilibrium pricing, I propose and estimate a dynamic model of insurers' pricing decisions that incorporates consumer inertia and adverse selection. Following Bajari et al. (2007)'s two-step estimation approach, I uncover insurers' discount factor, which tells us how much firms value future profits relative to current profits and quantifies their incentive to invest in future demand. As a result, the identification comes from the observed price or markup levels. Intuitively, the more insurers care about the future, the stronger invest incentive they face and the lower they set their premiums. The structural estimation reveals a strong invest incentive for insurers, which is consistent with low markups observed early on.

I apply this dynamic model to answer two important economic questions. First, what is the net effect of strategic pricing in response to inertia on equilibrium prices? In other words, do switching costs toughen or soften competition? It is an empirical question and depends on which of the following incentive dominates – the incentive to price low to invest in future demand, or the incentive to harvest inertial incumbent consumers. To quantify insurers' trade-off between these counteracting incentives, I decompose observed pricing patterns by comparing this dynamic model with a counter-factual benchmark without inertia and with a counter-factual in which insurers are myopic and do not invest in future demand. Comparisons show that on net, demand inertia toughens competition and reduces equilibrium prices in this setting, i.e. the invest incentive dominates the harvest incentive.

[1]For example, premiums of Humana Standard, with over 2 million enrollees, increased by 60 percent on average between 2006 and 2007 and by 466 percent in seven regions (Krasner, 2006).

Finally, I apply the model to understand the potential role of government regulations. What are the price and welfare consequences of policies that could be used to constrain insurers' ability to exploit inertia using the "invest-then-harvest" pricing tactic? Even if there are policies that can effectively reduce the scope of investing and harvesting, the effects of government intervention are not directly intuitive. In fact, the effects are ambiguous ex-ante because pricing response to inertia creates two offsetting effects on consumer welfare. On one hand, price increases create dynamic choice inefficiency in consumer choice in the presence of switching frictions. On the other hand, the structural estimation suggests that inertia reduces prices as insurers face very strong incentives to invest in future profits. The desirability of government intervention depends on how effectively each policy can smooth prices over time without increasing average price levels. In order to assess desirability of government intervention, I first consider the most natural and straightforward policy, which is to cap the rate of annual premium increases at ten percent.[2] A second policy I consider is to offer a public option at a low price to compete with private insurers. An inexpensive public option would not only restrain room for increasing prices later on, but would also reduce the incentive to invest in future demand early on. I also consider the effects of removing risk sharing and fully exposing insurers to excessive losses and gains from their pricing decisions. A caveat with the last two policies is that public options and risk corridors are important policy instruments with many potential effects other than influencing insurer response to inertia, and my analysis here only speaks to one of many aspects of their effects. Among these policies, I find that a policy change to cap premium increases would be the most effective in improving consumer welfare by both lowering average premiums and smoothing prices over time. Offering a low-price public option lowers average prices and increases consumer welfare, but such welfare gains are dominated by the extra social cost of offering the public plan. Removing risk sharing has little impact on welfare but transfers money from the government to insurers because with risk sharing, taxes on excessive gains outweigh subsidies on excessive losses, both in the model and empirically.

My work builds on multiple literatures and contributes to the general understanding of supply in privatized health insurance markets, often with switching frictions. In recent years, we have seen a growing role for non-group insurance over typical employer-based and traditional government-provided insurance. For example, the Affordable Care Act establishes state-based health insurance exchanges where individuals and small business can choose from plans provided by private insurers. Therefore, it is increasingly important to understand how the private supply side operates in health insurance markets with switching frictions. First, my paper builds on the growing literature on consumer inertia and choice frictions in general[3] in insurance markets, including Medicare

[2]This policy experiment is similar in nature to the "Effective Rate Review" policy under the Affordable Care Act, which ensures that "in any State, any proposed rate increase by individual or small group market insurers at or above 10 percent will be scrutinized by independent experts to make sure it is justified". See CMS report: `http://www.cms.gov/CCIIO/Resources/Fact-Sheets-and-FAQs/rate_review_fact_sheet.html`.

[3]This growing body of literature examines inefficiency or sub-optimality of enrollees' plan choices in Medicare Part D (Heiss et al., 2008, 2013; Abaluck and Gruber, 2011, 2013; Kesternich et al., 2013; Kling et al., 2012; Ketcham et al., 2012, 2015).

Part D and other health insurance settings. Polyakova (2015) models inertial consumers facing a switching cost and estimates switching costs to be two to four times as high as annual premiums among Medicare Part D enrollees. Ho et al. (2015) study inattention as a crucial driver of observed inertia and analyze its implications for prices, consumer out-of-pocket costs and government subsidy. Switching friction is a general feature of a variety of insurance markets with defaults, not limited to prescription drugs for the elderly. For example, Nosal (2012) estimates switching cost in Medicare Advantage, while Handel (2014) provides evidence of consumer inertia among a large firm's employees in choosing from employer-provided insurance plans. The contribution of my paper is to build on these studies and develop a structural model of dynamic pricing that allows me to simulate supply-side policy counter-factuals.

Furthermore, my work contributes to recent studies on insurance supply in privatized health insurance markets and its interactions with government regulations. Abaluck and Gruber (2013) conclude that the increased welfare loss from choice inconsistency in Medicare Part D is largely driven by supply-side changes, indicating the importance of understanding insurers' behavior. Ericson (2014) is the first to examine strategic pricing in response to inertia in Medicare Part D, documenting evidence of increasing premiums that is consistent with insurers exploiting inertia in pricing. Miller (2014) studies the role of inertia as well as government subsidy in insurers' plan offering and welfare in Medicare Advantage. Shepard (2015) studies insurers' competition over hospital networks in response to adverse selection. Starc (2014) analyzes the impact of imperfect competition on consumer welfare in Medigap. Decarolis (2015) identifies insurers' strategic response to the low-income subsidy system in their plan offering and pricing. Decarolis et al. (2015) and Miller (2015) study the welfare impacts of the current subsidy policy in Medicare Part D. Ericson and Starc (2015) examine the impacts of pricing regulations in Massachusetts's health insurance exchange. Miller and Yeo (2015b) analyze the effect of introducing a public option alongside private insurers in Medicare Part D. Building on these papers, my study investigates insurers' pricing response to inertia and analyzes policy counter-factuals where such strategic pricing interacts with pricing regulation, additional competition from a public option, etc.

Finally, this study is related to both theory and empirical literatures on firm strategy in the presence of switching costs (Farrell and Klemperer, 2007, provide a review). Klemperer (1987) uses a two-period model to discuss the general intuition for firms' pricing incentives when consumers face switching cost – the incentive to invest in future demand by charging low prices, and the incentive to harvest inertial incumbent enrollees by charging high prices. Beggs and Klemperer (1992) illustrate how these two incentives interact in an infinite-period model with horizontal differentiation and infinite switching costs, and show analytically that the harvest incentive always dominates and switching costs soften competition. My study builds on Dubé et al. (2009) and Arie and Grieco (2014), both of which relax the crucial assumption of infinite switching cost and show that switching costs do not necessarily soften competition and can actually reduce equilibrium prices. Empirical evidence of strategic pricing in response to inertia is established in the bank deposit market (Sharpe, 1997), in the credit card market (Stango, 2002), in electricity markets (Waterson, 2003), in phone services (Knittel, 1997; Shi et al., 2006; Viard, 2007; Park, 2010), in the software market (Larkin, 2008), and recently in insurance markets (Ericson, 2014; Miller, 2014). My paper adds to the recent extension of this literature to the health insurance sector, an important market featuring consumer switching cost.

The rest of this paper is organized as follows. Section 0.2 describes the empirical setting and data. Section 0.3 discusses important intuitions from relevant theory papers. Section 0.4 presents descriptive evidence and discusses alternative explanations. Section 0.5 lays out the structural model. Section 0.6 describes the empirical strategy and presents estimation results. Section 0.7 conducts counter-factual analysis of policy experiments. Section 0.8 concludes.

0.2 Empirical Setting and Data

0.2.1 Institutional Features of Medicare Part D

Medicare is a public health insurance program for the elderly and the disabled in the US. Medicare Parts A and B have covered hospital and physician services since the program's inception in 1965, but prescription drug coverage was not provided until the introduction of Medicare Part D in 2006. Providing outpatient prescription drug insurance to the elderly and the disabled, Medicare Part D is a large program in terms of both enrollment and spending. The Congressional Budget Office reports that in 2014, there were 37 million Medicare beneficiaries enrolled in Part D (Hoadley et al., 2014), and the Congressional Budget Office (CBO) estimates the program cost around 65 billion dollars[4].

Unlike Medicare Parts A and B and other traditional government insurance programs, Part D is not delivered directly by the government, but rather by private insurers under contract with the government. These companies offer Medicare beneficiaries a choice between two types of prescription drug plans: bundled medical insurance and prescription drug benefits through the Medicare Advantage Prescription Drug plans (MA-PDs) that were in place prior to the deployment of Part D under Medicare Advantage[5] and the stand-alone prescription drug coverage-only plans introduced in 2006. These stand-alone prescription drug plans (PDPs) are the focus of the present study.

Of all Medicare beneficiaries who have private prescription drug coverage, about 62 percent were enrolled in stand-alone prescription drug plans in 2012 (Hoadley et al., 2012). Stand-alone plans are offered in 34 geographically-defined markets within the continental United States. Plans in each market are offered by private insurers that are regulated by the government through the Centers for Medicare and Medicaid Services (CMS). In a typical market, approximately 20 firms offer more than 30 plans that are differentiated in terms of coverage. There are two broad types of prescription drug plans: basic plans that provide coverage actuarially equivalent to the required

[4]See Congressional Budget Office's Medicare Baseline Projection Reports in March 2015: `http://www.cbo.gov/publication/44205`.

[5]Medicare Advantage (MA) is a health insurance program of managed health care (preferred provider organization (PPO) or health maintenance organization (HMO)) that serves as a substitute for Medicare Parts A and B Medicare benefits.

minimum coverage as per the defined standard benefit set by the CMS and so-called "enhanced-benefit" plans that offer offer supplemental coverage on top of the minimum required coverage. Supplemental coverage relative to the defined standard benefit includes reduced deductible, partial or full coverage in the donut hole, reduced cost sharing, etc.

There are two types of Medicare beneficiaries, and I conceptualize the demand systems for both types based on the institutional setting in the structural model. Standard beneficiaries become eligible for Medicare at age 65. Enrollment takes place annually during an open enrollment period. After standard enrollees become eligible and first join Part D, they have to actively choose their prescription drug plans. In years after this initial enrollment, standard beneficiaries are defaulted into their previous plans unless they actively switch. Low-income enrollees are eligible through the low-income subsidy (LIS) system. Unlike standard beneficiaries, low-income enrollees do not need to choose their own plans or pay their own premiums and out-of-pocket costs. Instead, the government pays all or part of their premiums and out-of-pocket costs and randomly assigns them to basic plans priced below market average. Within both groups of beneficiaries, a small fraction of beneficiaries leave and a slightly higher fraction of new beneficiaries arrive annually: the annual attrition rate is around eight percent for standard enrollees and around ten percent for low-income enrollees; the annual arrival rate is around ten percent for standard enrollees and around thirteen percent for low-income enrollees.

Insurers can enter any market and offer one or more plans in each market. Within each market, price discrimination is not allowed and the same plan must be offered at the same price to both incumbent enrollees and newcomers. Premiums are set annually in two components – a basic premium for basic coverage, which applies to all plans, and a supplemental premium for supplemental coverage, which applies only to enhanced-benefit plans. Basic and supplemental premiums are set simultaneously, but in different manners. Supplemental premiums are set directly by insurers, while basic premiums are set through a centralized bidding process. Each year before the new enrollment cycle starts, insurers submit bids to the CMS for basic premiums. The CMS then computes the basic premiums for each plan as the insurer's bid minus the national average bid plus some base premium adjustments.[6] This is referred to as a bidding process because basic plans that bid below market average win a share of low-income enrollees.

Insurer revenue is generated by enrollee premiums and three types of government subsidies. The government provides these subsidies to mitigate adverse selection and to partially insure insurers against excessive losses. First, plans are paid risk-adjusted subsidies based on each enrollee's health status or risk in terms of drug spending. Second, individual reinsurance covers 80 percent of catastrophic spending. Finally, risk corridors provide risk sharing between the government and insurers – excessive losses are partially compensated and excessive profits are taxed. Despite the complexity of the subsidy regime, variable profit or markup is still an increasing function of premiums, given any enrollee. In other words, the standard trade-off between a higher markup versus a higher market share still holds in this setting.

[6]Base premium is about one third of the enrollment-weighted national average bid.

0.2.2 Data

I use administrative data provided by the Centers for Medicare and Medicaid Services (CMS) on Medicare beneficiaries (henceforth "beneficiary files") and insurance plans (henceforth "plan files"). The beneficiary files cover a 20 percent random sample of Medicare beneficiaries from 2006 to 2011. For each year, this sample includes on average about 2.2 million standard enrollees and about 2 million low-income enrollees who are enrolled in stand-alone prescription drug plans. These beneficiary files include variables on enrollee demographics such as age, gender and race; on prescription drug plan choices in each year; and details on drug expenditures. The plans files include information on plan premiums and financial characteristics, such as a plan's deductible, gap coverage and tiered cost sharing. The recently released plan bridge files provide a crosswalk to unencrypted insurer and plan names, which allows me to identify the same insurer and plan across markets.

In descriptive evidence, I focus on a measure of markup or variable profit margin among standard enrollees to get rid of potential confounding variations in cost and subsidy that affect insurers' pricing decisions. I construct markups for each plan, averaged across its standard (low-income) enrollees, as the plan's premium plus the average risk-adjusted subsidy minus the expected cost, where the expected cost is defined as expected claims cost adjusted for pharmaceutical rebates, variable administrative cost and individual reinsurance. Details on the construction of expected claims cost will be discussed in Section 0.5.2. This markup measure incorporates the above-mentioned individual reinsurance and risk-adjusted subsidy. Individual reinsurance for catastrophic drug expenditure is computed using information on drug claims. To compute risk-adjusted subsidies in each year, I use the corresponding risk adjustment software from the CMS to compute the "risk score" for each enrollee. The CMS computes this risk score as a comprehensive summary of enrollee risk in terms of predicted drug spending and uses it to determine the amount of direct subsidy to pay insurers for each enrollee.[7]

Table 1 reports market-year level summary statistics. Panel A of Table 1 reports summary statistics on market structure, including numbers of insurers and plans, the Herfindahl index, and enrollment-weighted average premiums. The average number of number of insurers offering stand-alone plans in a market is 21, and there is meaningful variation across markets, ranging from 11 to 29. Most markets have more than 30 stand-alone plans, about half of which are basic plans and the other half of which are enhanced-benefit plans. There is also substantial cross-market variation in these numbers of plans. Part D markets are on average moderately concentrated, with a Herfindahl

[7] The CMS computes risk scores in each year using the corresponding software to predict each beneficiary's prescription drug spending in year t as a function of their inpatient and outpatient diagnoses from year t-1 and demographic information and uses these risk scores to determine risk-adjusted subsidy to insurers for each enrollee. To compute risk-adjusted subsidy in each year between 2006-2011, I use the corresponding RxHCC risk adjustment model from `http://www.cms.gov/Medicare/Health-Plans/MedicareAdvtgSpecRateStats/Risk-Adjustors-Items/Risk2006-2011.html` (retrieved June, 2014; last accessed October, 2015). Einav et al. (forthcoming) also use CMS software to compute risk scores as a proxy for individual predicted drug spending, and they use the 2012 model to compute risk scores for enrollees in 2006-2011 to consistently compare health status across years.

index of 0.22. There is some variation in premium levels across markets and a general increasing trend over time: enrollment-weighted average premium increased from 329 dollars in 2006 to 507 dollars in 2011.

Panels B and C of Table 1 report summary statistics on standard and low-income Medicare beneficiaries at the market level, including population size, annual attrition and arrival rates, and the share choosing stand-alone plans. Numbers of beneficiaries correspond to the 20% random sample, and should be multiplied by 5 to get actual Medicare population sizes. Arrival and attrition rates are relative to one-year lagged population sizes. Shares in stand-alone plans are calculated as out of the entire population of standard or low-income Medicare beneficiaries, including those with stand-alone plans, those with bundled coverage under Medicare Advantage, those with coverage provided by employers or third parties, and those without any prescription drug coverage. For both types of enrollees, the average attrition and arrival rates, as well as the share choosing stand-alone plans, do not vary much over time within each market. Therefore, I take these rates as constant for each market for the structural estimation.

Table 2 reports summary statistics on stand-alone plans, first pooled across years and then by year. The first row summarizes pooled data from 2006 to 2011, and each other row corresponds to a single year. The first column is the total number of plans. There were 1429 plans in 2006, and the decline in the number of plans over time is mostly driven by consolidations rather than exits. The second column reports numbers of plan entries, which were concentrated in 2006 and 2007. There were relatively few entrants overall after 2009. The third column reports numbers of plan exits, which are relatively low compared with the number of plans. Total premium is the annual total premium, which is the combined value of basic premium and supplemental premium.

As a simplification of my analysis, I focus on strategic pricing in this paper and abstract away from a second strategic response to inertia: since price discrimination across new and old enrollees is banned, firms face an incentive to continuously introduce new plans that can be priced low to "invest" in future demand while charging higher premiums to incumbent consumers. Many plans similar in coverage were forced to consolidate to comply with the "meaningful-difference" regulation, which was introduced in 2010 by the CMS to limit strategic entry behavior by requiring new plans to be sufficiently differentiated in coverage from existing plans by the same insurer. Although strategic plan entry is another important margins of firms' strategic behavior[8], I abstract away from it and focus on pricing here – i.e., conditional on the set of plans being offered, withdrawn and consolidated each year, how do firms price their plans? I include all prescription drug plans, including both non-consolidated and consolidated plans for the analysis. In order to link consolidated plans over time and to control for plan fixed effects for regression analysis later, I use each plan's most recent plan ID as its unique identifier.

[8] In a separate project, I document descriptive evidence consistent with such strategic entry and product proliferation.

0.3 Conceptual Framework

Klemperer (1987) discusses the general intuition for two counteracting incentives that firms face in the presence of consumer inertia, or when consumers behave as if they face switching costs. In the benchmark case without switching costs, demand in different periods is independent and so are firms' optimal strategies. However, when consumers face switching costs, demand is sticky over time, which creates two opposing incentives for firms: on one hand, firms want to charge low prices to "invest" in future demand, but on the other hand, firms want to charge higher prices to "harvest" inertial incumbent consumers. In a simple two-period model, firms only face the "invest" incentive in the first period and only face the "harvest" incentive in the second period. As a result, equilibrium price follows an "invest-then-harvest" pattern – firms charge low prices initially and increase prices afterward.

While a two-period model highlights the key trade-off firms face, a more realistic approximation of real markets is an infinite-period model, in which the invest and harvest incentives coexist. Beggs and Klemperer (1992) show how these two incentives interact in an infinite-period model with horizontal-differentiated products and consumers who are subject to switching costs. They solve for the unique Markov Perfect Nash Equilibrium under a critical assumption of perfect lock-in – i.e., consumers never switch because they are subject to infinitely large switching costs. In this equilibrium, prices are higher than the benchmark case without switching costs. This is not likely the case in a real-world context such as Medicare Part D, in which switching costs are not infinite as evidenced by the fact that some consumers do switch plans.

Dubé et al. (2009) relax this crucial assumption of infinite switching costs and examine an infinite-period model with switching costs and vertical differentiation. The authors establish the existence of a Markov Perfect Equilibrium and numerically solve for equilibrium prices as functions of switching costs. Applying this model to the markets of orange juice and margarine and using the empirically estimated level of switching costs in model simulations, they find equilibrium prices to be 18% lower than the case without switching costs, which reflects that the invest incentive dominates because of "the strategic effects of firms lowering their prices to defend themselves against other firms' attempts to steal customers". Moreover, the authors show that depending on the magnitude of switching costs, equilibrium prices can be higher or lower than the case without switching costs. For example, when switching costs are sufficiently large or even infinite, the harvest incentive dominates and prices are higher than the case without switching costs. In other words, with finite switching costs, it is an empirical question whether the invest or harvest incentive dominates. My supply model in Section 0.5 similarly features finite switching costs, and I will investigate this question empirically in the setting of Medicare Part D.

Applying these intuitions to the setting of Medicare Part D, plans only face the invest incentive when they first enter and face both the invest and harvest incentives in subsequent periods. Therefore, prices or markups should be lower when plans initially enter than in subsequent periods, and they should also be lower compared to incumbent plans. Because the invest and harvest incentives coexist every year except for the first, whether inertia leads to higher or lower equilibrium prices is an empirical question.

0.4 Descriptive evidence

0.4.1 Switching Costs

To lay the framework for my analysis of strategic pricing, I first summarize the existing evidence of consumer inertia and present some corroborative evidence. Polyakova (2015) documents evidence of consumer inertia in Medicare Part D, and estimates the magnitude of switching costs to be two to four times as high as average annual premiums. As corroborative evidence of this type of consumer inertia, Table 3 shows, separately for different cohorts of standard beneficiaries, the enrollment shares as of 2011 by plans introduced in each year. Note that most plans were introduced in 2006 and fewer plans were introduced in subsequent years, partly contributing to higher shares in plans introduced in 2006 among all cohorts of enrollees. Interestingly, the percentage enrolled in the oldest plans (introduced in 2006) declines for younger cohorts of beneficiaries (84% among the 2006 cohort of enrollees and 72% among the 2011 cohort). Moreover, new cohorts of consumers are more likely to choose newly introduced plans. For example, the 2007 cohort is more likely to choose plans introduced in 2007 than the 2006 cohort. Similarly, the 2008 cohort is more likely than the 2006 and 2007 cohorts to choose plans introduced in 2008, and so forth. These statistics provide corroborative evidence that consumer inertia matters from the insurers' perspective.

0.4.2 Invest-then-Harvest Pricing

Figure 0-1, which displays enrollment-weighted markups over time for plans introduced in different years, shows two notable patterns. First, there is a general increasing trend: markups tend to increase as plans age. As I will show below, this increasing trend is robust across a variety of specifications. Second, within most years, entrants are priced lower than incumbent plans by a substantial margin. These patterns are consistent with the invest-then-harvest predictions discussed in Section 0.3.

To formalize this invest-then-harvest pricing pattern, I estimate regressions that compare markups between plans that have just entered the market and incumbent plans.

$$Markup_{kjmt} = \alpha + \beta\mathbf{1}\{Entry\}_{kjmt} + Coverage_{kjmt}\gamma + \delta_m + \lambda_t + \xi_k + \epsilon_{kjmt} \tag{1}$$

$Markup_{kjmt}$ is markup averaged across standard enrollees for plan j offered by firm k in market m in year t. $\mathbf{1}\{Entry\}_{kjmt}$ is a dummy indicating whether plan j first entered market m in year t. $Coverage_{kjmt}$ includes plan features, such as deductible level, whether the plan offers gap coverage and tiered cost sharing.

Table 4 reports ordinary least squares estimates of β from four specifications. Column (1) shows the raw correlation between markup and the entry dummy. Column (2) adds market and year fixed effects to account for potential differences across markets and over time that affect both entry and plan pricing. Column (3) adds insurer fixed effects to account for unobserved time-invariant heterogeneity at the insurer level. Column (4), which adds controls for plan coverage, compares plans within insurer and controlling for coverage. Consistent with the prediction in Section 0.3, these regression estimates suggest that the same insurer charges significantly lower markups on new plans than on incumbent plans with the same characteristics. Within the same insurer and year controlling for plan characteristics, markup is 148 dollars lower on entrant plans than incumbent plans, which is high relative to the average annual premium of 372 dollars.

0.4.3 Addressing Alternative Explanations

While the empirical invest-then-harvest pricing patterns documented in Section 0.4.2 are consistent with firms exploiting consumer inertia to maximize profits dynamically, such pricing patterns might also be rationalized by alternative explanations. First, since Medicare Part D is a new market, insurers might not be well-informed about cost, which could cause them to under-price initially and adjust prices upward as they learn about cost over time. Relatedly, in a learning-by-doing story, insurers might set low prices and invest in market shares in order to learn more quickly about cost. Finally, as Decarolis (2015) shows, the low-income-subsidy system also contributes to premium increases over time.

I have no intention of running a horse race to rule out these potential alternative explanations. It seems likely that insurer responses to inertia as well as these alternative stories are all empirically relevant to some extent. However, I argue that these alternative stories seem unlikely to explain the pricing patterns documented in Section 0.4.2. First, in the story of learning about cost, it is not clear why firms would systematically underestimate cost. Moreover, I find that even within the same firm, significantly lower markups are charged for entrant plans than for incumbent plans, contradicting the notion of learning about cost. Such within-firm comparisons also help contradict the learning-by-doing story.

In order to formally assess the robustness of my results to these alternative explanations, I test for evidence of the invest-then-harvest pricing pattern on subsamples of plans for which these alternative explanations are arguably not relevant. Table 5 summarizes these estimates for Equation 1 using subsamples. To address the first alternative explanation that firms learn about cost, the first three columns of Table 5 focus on subsamples of plans offered by insurers who are arguably well-informed about the cost of supplying prescription drug insurance to Medicare beneficiaries. Column (1) restricts the sample to plans offered by insurers that were major sponsors[9] of Medicare Advantage prior to 2006 and that provided prescription drug insurance bundled with medical insurance to Medicare beneficiaries. Column (2) restricts the sample to plans offered by insurers with prior experience in Medicare Advantage. Column (3) restricts the sample to plans offered by insurers with prior experience in providing insurance coverage to Medicare beneficiaries. These three subsamples are not subject to the concern that insurers are not informed about cost. To address the second alternative explanation or the learning-by-doing story, Column (4) reports estimates

[9]Seven biggest sponsors in terms of market shares as of 2005 according to Gold (2006)

using a subsample of plans offered by insurers that are already experienced in Part D. Specifically, I assume that the benefit from such learning diminishes after the insurer serves many enrollees, which motivates restricting the sample of plans to those offered by insurers that have served at least 5000 enrollees before in the same market. Finally, to address potential confounding effects from the low-income-subsidy system, I use the subsample of enhanced-benefit plans, which are not eligible to receive low-income enrollees.

As shown in Table 5, the estimated coefficient–or the difference in annual markup between entrants and incumbent plans, holding the insurer and plan coverage as fixed, ranges from -\$134 to -\$187, which is not much different from the estimate of -\$148 on the full sample of plans. In other words, the result that markups are much lower on entrant plans than incumbent plans is robust to focusing on subsamples of plans where these alternative explanations are less relevant. This suggests that the empirical pricing pattern we observe is largely driven by strategic responses to consumer inertia rather than by these alternative explanations.

0.5 Model

My descriptive evidence in Section 0.4 rejects the null of no strategic response to inertia and is consistent with firms exploiting consumer inertia to maximize profits dynamically. To explore insurers' trade-offs between the invest and harvest incentives, I develop a dynamic model of insurers' pricing decisions that incorporates demand inertia and adverse selection. Structural estimation of this model in Section 0.6 uncovers insurers' discount factor, which quantifies the strength of the invest incentive. In Section 0.7 I further decompose observed pricing patterns to quantify insurers' trade-offs between invest and harvest incentives by comparing this model with a counter-factual benchmark with no inertia and with a counter-factual case where insurers are myopic and face no invest incentive. Finally, in Section 0.7 I simulate the price and welfare consequences of several policy experiments that could be used to constrain insurers' ability to exploit inertia.

0.5.1 Demand

As described in Section 0.2, there are two types of Medicare beneficiaries – standard enrollees and low-income enrollees – and I conceptualize the demand system for each type based on the institutional setting. I start with demand for standard beneficiaries, who make their own plan choices and are defaulted into their previous choices unless they actively switch. Since the focus of this study is on understanding firm pricing, I use the demand model and estimates from Polyakova (2015) for standard enrollees. In her model, standard enrollees are myopic[10] and choose a plan

[10] One concern is that consumers can be forward-looking about changes in plan prices and their own health risk in the future. The latter is allowed by controlling for age, while consumers forward-looking about future price changes will be less likely to start with a cheap plan, which should dampen insurers' incentives to invest in market shares. However, as Handel (2014) argues, consumers make very poor decisions if we consider forward-looking demand. Moreover, dynamic demand adds additional complexity while dynamic supply is already computationally demanding. In fact, in dynamic games literature on durable goods, experience goods and network goods, it is fairly standard to

to maximize current utility, subject to switching costs. Let i denote individual, j plan, k insurer, m market (region) and t year. Individual i's utility[11] from choosing plan j in year t is as follows, where p_{kjt} is annual premium, ϕ_{kjt} is characteristics of the plan, and $\mathbf{1}\{\text{Default}\}_{ikjt}$ is an indicator of whether consumer i is defaulted into plan j at time t. This default dummy is omitted for new enrollees, who are not defaulted into any plans.

$$u_{ikjt} = -\alpha p_{kjt} + \beta_{it}\phi_{kjt} + \gamma_{it}\mathbf{1}\{\text{Default}\}_{ikjt} + \lambda_{it}\mathbf{1}\{\text{Insurer}\}_k + \epsilon_{ikjt} \tag{2}$$

In this logit model, ϵ_{ikjt} is independent and identically distributed with a Type 1 Extreme Value distribution function.[12] ϕ_{kjt} includes the following characteristics that are feasibly observed by beneficiaries when they are making their choices: the deductible, the initial coverage limit, whether the plan offers coverage in the gap, whether the plan uses fixed dollar co-payments or coinsurance percentages, and whether the plan is eligible for getting low-income subsidy enrollees. Preferences over plan coverage β_{it} depend on the individual's demographics and health risk, $D_{it} = \{\text{age}_{it}, \text{gender}_i, \text{race}_i, \text{risk score}_{it}, \text{esrd indicator}_{it}\}$, where risk score is a measure of each beneficiary's health risk in terms of drug spending and esrd indicator is a dummy for end-stage renal disease. There are random coefficients in preferences over deductible, initial coverage limit and gap coverage: $\beta_{it} = \pi^\beta D_{it} + \psi_i^\beta$, where $\psi_i^\beta \sim N(\psi^\beta, \sigma^2)$. Switching costs γ_{it} and preference over insurers λ_{it} also depend on individual demographics and health risk: $\gamma_{it} = \pi^\gamma D_{it} + \psi^\gamma$, and $\lambda_{it} = \pi^\lambda D_{it} + \psi^\lambda$.[13]

Standard consumer i's probability of choosing plan j depends on plan features as well as the default plan l, which I denote as $P_j(p, l)$ and which follows the logit form. Active consumers without default plans face an unconditional choice probability $P_j(p)$. Aggregating individual choice probabilities, the share of standard enrollees choosing plan j in year t $S_{kjt}()$ is derived as follows.

$$S_{kjt}(p, \mathbf{S}_{t-1}) = \frac{1-\lambda}{1-\lambda+\mu} \sum_{l \in J(m)} S_{lt-1} P_j(p, l) + \frac{\mu}{1-\lambda+\mu} P_j(p) \tag{3}$$

$S_{kjt}()$ is a function of prices p, lagged shares S_{t-1}, the attrition rate of standard enrollees λ and

assume myopic demand.

[11]Polyakova (2015) points out "this formulation assumes that individuals choose the option with the highest "perceived" utility, which may not necessarily correspond to the highest "objective" valuation of plans as financial contracts (indeed, Abaluck and Gruber (2011, 2013) suggest that beneficiaries are choosing their plans inconsistently with the objective efficiency frontier)".

[12]Polyakova (2015) models choice among stand-alone prescription plans and does not include the outside option. I use a similar linear regression to predict, separately for incumbent and new beneficiaries, the share choosing to enroll in stand-alone plans instead of bundled coverage or no coverage, based on prices, number of plans, market fixed effects, etc. Estimates show that market fixed effect explains 66 percent for newcomers and 95 percent for incumbent enrollees. Details will be discussed in the Appendix. Alternatively, I can re-estimate the demand model using a nested logit model, in which beneficiaries first choose between not enrolling in prescription coverage, enrolling in bundled coverage and enrolling in stand-alone coverage, and then choose a plan if they choose any coverage in the first step. Since I focus on supply of stand-alone plans, I choose to take the simplistic approach instead to abstract away from the complexity of modeling demand for both bundled and stand-alone coverage.

[13]More specifically, preference over the two biggest insurers depend on D_{it} while preferences over other insurers follow the form of standard fixed effects.

the arrival rate μ. Because attrition and arrival rates do not vary much empirically within each market, I take λ and μ as exogenous and suppress their notations for this share function $S_{kjt}(p, \mathbf{S}_{t-1})$. Let $J(m)$ denote the set of plans in market m. The first component of Equation 3 is the summation of shares across incumbent enrollees defaulted into different plans $(\sum_{l \in J(m)} S_{lt-1} P_j(p,l))$ weighted by the fraction of incumbent beneficiaries $(\frac{1-\lambda}{1-\lambda+\mu})$, while the second component represents the share among new beneficiaries without defaults (or the unconditional choice probability $P_j(p)$) weighted by the fraction of new beneficiaries $(\frac{\mu}{1-\lambda+\mu})$. In other words, other than prices, lagged market shares are important in determining current shares of standard enrollees because incumbent consumers' choice probability $P_j(p,l)$ is biased toward the lagged choice or default plan l. The importance of lagged shares is slightly depreciated by attrition of incumbent enrollees (λ) and arrival of new enrollees (μ): empirically $\frac{1-\lambda}{1-\lambda+\mu}$ is approximately 0.90 in my data.

Although only around 20 percent of Medicare beneficiaries are low-income enrollees, they account for over 40 percent of enrollment in stand-alone prescription plans. Therefore, it is important to include profits from the population of low-income enrollees when modeling insurers' profit maximization problem. Unlike standard beneficiaries, low-income enrollees do not need to choose their own plans. Instead, the Centers for Medicare & Medicaid Services randomly assigns them to eligible plans when they first qualify for the low-income subsidy or when their previous plans are no longer eligible for receiving low-income enrollment. Low-income enrollees are evenly divided into eligible plans – basic plans priced below market average – except that an insurer eligible both in the last period and the current period keeps its incumbent low-income enrollees on top of this random assignment.[14] Based on how low-income enrollees are automatically allocated across plans in reality, I model their discrete and mechanical demand, which depends on lagged low-income shares other than current plan bids for basic premiums.

Let λ^{LIS} denote the attrition rate of low-income enrollees and μ^{LIS} the arrival rate. The share of low-income enrollees assigned to basic plan j in year t $S^{LIS}_{kjt}()$ is computed as follows, where $\omega = \frac{1-\lambda^{LIS}}{1-\lambda^{LIS}+\mu^{LIS}}$ is the share of incumbent enrollees and $1-\omega = \frac{\mu^{LIS}}{1-\lambda^{LIS}+\mu^{LIS}}$ is the share of newcomers. The benchmark $\bar{b}_{mt}$ is the average bid among basic plans weighted by lagged low-income enrollment. $J_B(m)$ is the set of basic plans in market m. $N_{mt} = \sum_{l \in J_B(m)} \mathbf{1}\{b_{lt} \leq \bar{b}_{mt}\}$ is the number of basic plans pricing below benchmark. $S^{Reassign}_{mt}$ is the share of low-income enrollees

[14] In 2006, low income enrollees were randomly assigned to basic plans pricing below market average. In subsequent years, insurers keep previously assigned low-income enrollees conditional on having a basic plan pricing below the benchmark, where the benchmark is weighted by lagged low-income enrollment. Except for these enrollees who stay with a below-benchmark basic plan, low-income enrollees are again randomly assigned to basic plans pricing below benchmark. Low-income enrollees can choose to opt out of their assigned plans and choose a different plan and pay the difference in premiums. Among low-income enrollees choosing stand-alone prescription drug plans, the empirical fraction of "choosers" who have ever opted out increases over time from around 6% in 2006 to around 20% in 2010 (Summer et al., 2010). Such opting out behavior is not flagged in the administrative data, and cannot be identified except for those who choose plans not eligible for low-income enrollees. Decarolis et al. (2015) model the demand for such "choosers" based on the subsample for which opting out is observed in the data. I choose to model only the random assignment and not such opting out behavior because it is not essential to my focus of strategic pricing in response to inertia among standard enrollees.

who need re-assignment because their former insurers lost below-benchmark status.[15]

$$S_{kjt}^{LIS}(p, \mathbf{S}_{t-1}) = \begin{cases} 0 & b_{kjt} > \bar{b}_{mt} \\ (\omega S_{mt}^{Reassign} + 1 - \omega)/N_{mt} & b_{kjt} \leq \bar{b}_{mt}, b_{kj't-1} > \bar{b}_{mt-1} \forall j' \in J_B(k) \\ \omega S_{kj,t-1}^{LIS} + (\omega S_{mt}^{Reassign} + 1 - \omega)/N_{mt} & b_{kjt} \leq \bar{b}_{mt}, b_{kjt-1} \leq \bar{b}_{mt-1} \\ \omega S_{kj',t-1}^{LIS} + (\omega S_{mt}^{Reassign} + 1 - \omega)/N_{mt} & b_{kjt} \leq \bar{b}_{mt}, b_{kjt-1} > \bar{b}_{mt-1}, b_{kj't-1} \leq \bar{b}_{mt-1} \end{cases} \tag{4}$$

In the first case in Equation 4, basic plan j prices above the benchmark and receives no low-income enrollees. In the second case, basic plan j prices below benchmark, and the insurer k had no plans pricing below benchmark in the previous year. In this case, plan j receives an even share of incumbent low-income enrollees who need to be re-assigned ($\omega S_{mt}^{Reassign}$) plus new low-income enrollees ($1 - \omega$). In the third case, basic plan j prices below benchmark, and it also priced below benchmark in the previous year. In this case, plan j receives an even share of randomly assigned enrollees as in the second case, while keeping its incumbent low-income enrollees ($\omega S_{kj,t-1}^{LIS}$). In the final case, basic plan j prices below benchmark, and another plan j' by the same insurer prices above benchmark but priced below benchmark in the previous year. In this case, plan j receives an even share of randomly assigned enrollees as in the second case, plus it keeps incumbent low-income enrollees within the same insurer ($\omega S_{kj',t-1}^{LIS}$).

0.5.2 Cost

Medicare Part D is a health insurance market with the potential for adverse selection. In my setting, health risk correlates with consumer preference as well as switching costs, as suggested by the demand estimates. Moreover, Handel (2014) and Polyakova (2015) both conclude that the interaction between adverse selection and switching costs has important welfare implications, which depend on the specific market setting. In order to account for this well-recognized issue, I follow Starc (2014) to model adverse selection and allow claims cost to be endogenous to price. This complication is a nuance rather than the focus of my model.

Conceptually, in the presence of adverse selection, consumers with different risks in terms of drug expenditure sort into different plans based on coverage and prices. As a result, insurers' claim costs depend on the types of consumers each plan gets, and therefore they are endogenous to price, which affects consumers' sorting behavior. I start with constructing the claims cost measure at the level of individual-plan pairs, before formulating endogenous claims cost at the plan level. For each enrollee's drug expenditure, an insurer is responsible for covering the remaining after subtracting the part paid out-of-pocket by the enrollee, the part covered by the government and the part rebated by the pharmacy and pharmaceutical manufacturers. As described in Section 0.2, the government provides three types of subsidies: risk-adjusted subsidies based on each enrollee's health risk, individual reinsurance for catastrophic drug spending, and risk corridors that partially

[15] This can be computed as $S_{mt}^{Reassign} = \sum_{l \in J_B(m)} \mathbf{1}\{b_{kj't} > \bar{b}_{mt}, \forall j' \in J_B(k)\} S_{klt-1}^{LIS}$.

compensate excessive losses and tax excessive profits. Individual reinsurance lowers insurer claims cost, while risk-adjusted subsidy and risk corridors do not enter claims cost directly but enter the profit function in other ways in Section 0.5.3. As for rebates, the claims data already incorporates rebates from pharmacies but not rebates form pharmaceutical manufacturers, which I will adjust for later using summary statistics from government reports.

Each individual's claims cost is constructed as total drug expenditure net of pharmacy rebates, individual reinsurance from the government and the enrollee's out-of-pocket spending. Intuitively, individual i's claims cost to plan j offered by insurer k is a function of both plan coverage (X_{kjt}) and consumer demographics and health risk (W_{it}). Insurer fixed effects δ_k are included to account for unobserved time-invariant heterogeneity in coverage or quality, such as broadness of pharmacy network, generosity of formularies and quality of customer service, which vary across insurers.

$$c_{ikjt}(X_{kjt}, W_{it}) = \alpha + X_{kjt}\beta + W_{it}\gamma + \delta_k + \xi_{ijt} \tag{5}$$

There are two important identifying assumptions embedded in this individual claims cost function. First, selection only works through observables. This is not a terrible assumption in this setting, as W_{it} includes enrollee risk score, which is a comprehensive risk measure in terms of expected drug spending. Second, this function assumes that there is no plan-individual specific moral hazard: while cost may depend on the plan's characteristics, the unexplained part of an individual's cost does not depend on the plan chosen. To the extent that the variation in plan coverage is well captured by both the detailed plan characteristics X_{kjt} and the insurer fixed effects included in the cost function, this assumption is justified because the notion of moral hazard in insurance markets typically refers to the fact that enrollees utilize more services with more generous coverage as they face a lower marginal price.

Based on this individual cost function and the demand system outlined in Section 0.5.1, I aggregate individual costs to get plan-level expected claims costs as follows. The cost (per enrollee) of plan j offered by insurer k depends on its coverage as well as the average characteristics of its enrollees, which is endogenous to price and the resulting selection.

$$C_{kjt} = \alpha + X_{kjt}\beta + E[W_{it}|\text{Choose Plan j}]\gamma + \delta_k \tag{6}$$

For tractability of the supply model, in which the state space includes lagged market shares by consumer type, I discretize types of standard enrollees based on risk score and gender.[16] In other words, instead of controlling for enrollee characteristics W_{it} continuously in estimating the individual cost function 5, I drop W_{it} and estimate this function separately for each type of consumers. Within each type, consumers are assumed to be homogeneous (up to random coefficients in preferences) with cost realizations drawn from a common distribution. Low-income enrollees are taken

[16] Although the risk score is computed using demographics including gender, an OLS regression shows a small difference in cost by gender even conditional on risk score. To fully capture the cost difference across genders, I group standard consumers by gender in addition to risk score. I do not divide consumers by other demographic variables because they do not appear significant in predicting cost after controlling for risk score.

as homogeneous with a common cost distribution because of the automatic random allocation.

In order to get expected variable cost at the plan level, I adjust for two sources of variable cost other than expected claims cost. First, I take variable administrative cost to be 16% of claims cost based on estimates from other studies on similar markets: Starc (2014) estimates administrative cost to be 16% of premiums on average in Medigap; Ho et al. (2015) use data from the National Health Expenditure Survey to compute administrative cost to be 14-16% of total cost, and 16-19% of non-administrative cost, averaged across Medicare Advantage plans and plans in Medicare Part D. Second, I take rebates from pharmaceutical manufacturers to be 10% of total drug spending based on summary statistics from government reports: Boards of Trustees (2012) reports that the average manufacturer rebate rate, as a percentage of total prescription drug costs, ranged between 8.6 percent and 11.3 percent between 2006 and 2010.[17]

Other than expected variable cost, cost realizations also matter for insurers' dynamic profit maximization because of risk corridors. Risk corridors provide risk sharing between the government and insurers by partially compensating excessive losses and taxing excessive profits. In order to account for this when estimating the supply model, I randomly draw realized cost from normal distributions centered around expected cost and average across these random draws to get expected insurer profit. The standard deviation of this distribution of plan-level cost is calculated using standard deviation of individual cost and plan enrollment.

0.5.3 Supply

My model of insurers' strategic response to inertia in pricing builds on the work of Beggs and Klemperer (1992) and Dubé et al. (2009) and incorporates new features based on my empirical setting. As in Dubé et al. (2009), I consider an overlapping generations model with imperfect lock-in. In this model, both single-product and multi-product insurance firms offer differentiated plans and compete for consumers subject to switching cost. In each period, a fraction of old consumers leave the market and new consumers arrive.

In order to focus on insurers' dynamic pricing decisions in the presence of inertia, I make the following simplifying assumptions. First, I take plan characteristics as given, which is not a bad approximation in my setting, as empirically insurers tend to adjust premiums instead of plan characteristics. Second, I take market structure as given and abstract away from strategic entry. This assumption is less innocuous because entry does happen empirically. Since price discrimination is not allowed, firms face an incentive to continuously introduce new plans that can be priced low to invest in future demand while also charging higher premiums to incumbent consumers. However, the "meaningful-difference" regulation essentially put an end to such strategic entry, and the number of plans remains quite stable afterward. Although the timing of this regulation is close to the end of the sample period, it suffices in confirming that there will not be unobserved entry after the sample period, as the supply model involves forward simulation for many more periods. In other words, entry is less common in recent years and will continue to be less common looking-ahead. Relatedly,

[17]There is no need to adjust for pharmacy rebates, which are already net out in the claims data.

I only model variable profits of insurers and not fixed costs, which are sunk costs and therefore not relevant for pricing decisions. Third, I assume that insurers take the regulation environment as given, without foresight of future policy changes. Finally, I assume pricing decisions are separately made for stand-alone prescription drug plans and Medicare Advantage plans that bundle medical insurance and prescription benefits. Although cannibalization between these two segments is a concern, it is not essential to the invest-then-harvest pricing story, and I focus on the pricing of stand-alone prescription drug plans and abstract away from modeling the demand and supply for MA-PD plans.

0.5.3.1 Value Function

Insurers account for consumer inertia and choose bids and supplemental premiums to maximize discounted profits. As calculated in Equation 7, $V(\sigma_k, \sigma_{-k}, \delta, \mathbf{SV}_{mt_0})$ is the expected present value of profit for firm k in market m in year t_0, where σ denotes pricing strategies, δ denotes insurers' annual discount factor, SV includes the state variables and Π denotes annual variable profit.

$$V(\sigma_k, \sigma_{-k}, \delta, \mathbf{SV}_{mt_0}) = \mathrm{E}[\sum_{t=t_0}^{\infty} \delta^t \Pi_{kt}(\sigma_k, \sigma_{-k}, \mathbf{SV}_{mt})] \tag{7}$$

Since firms account for demand inertia, profits and pricing strategies are state-dependent. Besides exogenous state variables, including plan characteristics and enrollee characteristics, because of inertia (Beggs and Klemperer, 1992), SV_{mt} also includes lagged market shares by consumer type, which evolve deterministically based on the demand system in Section 0.5.1. Insurer profits and pricing strategy depend on lagged market shares among both standard and low-income enrollees. First, lagged standard enrollee shares matter because, intuitively, the harvest incentive depends on how many standard enrollees an insurer has locked in. Second, lagged low-income enrollee shares also matter for insurer profits and pricing strategy due to the way low-income enrollees are assigned as described in Section 0.5.1. In the presence of adverse selection, different types of enrollees differ in cost and demand. Therefore, lagged shares of different types of enrollees arguably affect insurer pricing differently, and I include lagged shares by consumer type to account for this. As a side note, lagged market shares by consumer type pin down expected cost, and therefore there is no explicit cost term in the value function.

Insurer k's pricing strategy σ_k for all its plans ($j \in J(k)$) is a mapping from states $\mathbf{SV}_{mt}$ to bids for basic premiums (b_{jt}) and supplemental premiums (PS_{jt}). More specifically, σ_k includes bids for basic premiums for each plan $b_j(\mathbf{SV}_{mt}, \epsilon_{jt}) = f(\mathbf{SV}_{mt}) + \epsilon_{jt}$ and supplemental premiums for each enhanced-benefit plan $PS_j(\mathbf{SV}_{mt}, \epsilon_{jt}) = h(\mathbf{SV}_{mt}) + \epsilon_{jt}$.[18]

[18]The interpretation for ϵ_{jt} is managerial mistake or specification error, and is assumed to be drawn independently across plans and years from a normal distribution centered around zero.

0.5.3.2 Annual Profit Function

Firm k's annual variable profit consists of profits from all its plans in market m, $j \in J_m(k)$. In other words, multi-product firms jointly maximize profit across all plans. Plan j's total profits include profits from different groups of enrollees Π^{θ}_{kjt}, where θ represents discrete types of standard enrollees and the group of low-income enrollees. $\Gamma(.)$ is a function representing adjustments from the risk corridors, which partially compensate for excessive losses and tax excessive gains.

$$\Pi_{kt}(b, PS, \mathbf{SV}_{mt}) = \sum_{j \in J(k)} \Gamma(\sum_{\theta} \Pi^{\theta}_{kjt}(b, PS, \mathbf{SV}_{mt})) \tag{8}$$

Plan j's (pre-risk-corridor) profit from each enrollee type can be calculated as enrollment times markup.

$$\Pi^{\theta}_{kjt}(b, PS, \mathbf{SV}_{mt}) = M^{\theta}_{mt} S^{\theta}_{kjt}(b, PS, \mathbf{S}_{t-1}) Markup^{\theta}_{kjt}(b, PS, \mathbf{SV}_{mt}) \tag{9}$$

M^{θ}_{mt} denotes the population of each type of enrollee within market m in year t. S^{θ}_{jt} denotes shares of each type of enrollee choosing plan j in year t, which is calculated based on the demand system as shown in Equations 3 and 4. Markup on each enrollee type is equal to total premium minus expected cost plus risk-adjusted subsidy. Expected cost is constructed in Section 0.5.2, while premiums and subsidies are computed following the actual process of setting prices and government subsidy. Each year before enrollment takes place, for each plan $j \in J_m(k)$, insurer k submits a bid b_{jt} for its basic premium and sets directly the supplemental premium PS_{jt} if it is a enhanced-benefit plan. The CMS computes basic premium as $PB_{jt} = b_{jt} -$ (national average bid $-$ base premium), where base premium is a fixed fraction of national average bid. Enrollees face a total premium $p_{jt} = PB_{jt} + PS_{jt}$, where $PS_{jt} = 0$ for basic plans. In order to mitigate adverse selection in this market, the government computes a risk score for each enrollee r_{it}, based on demographics and medical history, and pays risk-adjusted subsidy $r_{it} b_{jt} - PB_{jt}$ to the insurer. For an average enrollee with a risk score of one, the sum of basic premium and risk-adjusted subsidy is equal to the bid for basic premium. In other words, although risk-adjusted subsidy is endogenous to plan bids for basic premiums, insurers still face the standard trade-off between a higher markup (as a result of both a higher enrollee premium and a higher government subsidy) and a higher market share when setting prices.

I restrict insurers' strategies to be Markovian because the full set of dynamic Nash equilibria is unbounded and complicated. The Markov-Perfect Nash Equilibrium requires $V(\sigma_k, \sigma_{-k}, \delta, \mathbf{SV}_{mt}) \geq V(\sigma'_k, \sigma_{-k}, \delta, \mathbf{SV}_{mt})$ given competitors' strategies σ_{-k} for all states and alternative strategies σ'_k, i.e. each insurer's strategy has to be optimal given competitor's strategies.

0.6 Structural Estimation

0.6.1 Demand Estimation

Table 6 reports Polyakova (2015)'s simulated maximum-likelihood estimates on a few important demand parameters. Estimates for the price coefficient and the switching cost dummy are relatively robust across specifications. Besides including a rich set of plan features in all specifications, Columns (3) and (4) include more insurer fixed effects than the first two columns[19] to address the concern with unobserved insurer quality affecting both premiums and demand. Moreover, Columns (2) and (4) use lagged cost as an instrument for plan premium to address the concern with unobserved plan quality affecting both premiums and demand. Both instrumenting and controlling for more insurer fixed effects only increase the magnitude of the premium coefficient slightly, which confirms that including rich plan characteristics leaves little room for unobserved insurer and plan quality to affect both pricing and demand.

Controlling for more insurer fixed effects reduces the magnitude of the intercept for the switching cost term from 5.6 to 5.1, or reduces the implied switching cost for a 75 year-old female enrollee with average risk from $1330 to $1164. This difference suggests that there is unobserved quality at the insurer level that enrollees persistently value over time, and it is important to account for those unobservables with insurer dummies. Therefore, I choose the last specification with instruments for premium and ten insurer fixed effects as input for my supply estimation.

0.6.2 Cost Estimation

Figure 0-2(a) visually summarizes the individual cost estimation results. This figure reports, for each type of enrollee, expected cost to a basic plan offering minimum coverage and to an enhanced-benefit plan with more generous coverage (zero deductible and gap coverage). Standard enrollees are divided into groups with low, medium and high risk scores. In addition to these expected cost measures, Figure 0-2(b) adds switching cost in dollars and willingness-to-pay for more generous coverage. There is a significant correlation between cost and willingness-to-pay for extra coverage across different types of plans. There is also a small positive correlation between cost and switching cost, but this is less strong than the correlation between cost and willingness-to-pay.

Figure 0-2 pools female and male enrollees for simplicity, and Appendix Figure A.1 also breaks down by gender in addition to risk score. The patterns look similar – there is a lot of cost heterogeneity across enrollee types, and cost correlates strongly with preference and weakly with switching cost. More details on the estimation results are reported in Appendix Table A.1.

[19] Columns (1) and (2) include three insurer fixed effects by including dummies for the two biggest insurers (the omitted category consists of all other insurers), while Columns (3) and (4) include three insurer fixed effects by including dummies for the nine biggest insurers (the omitted category consists of all other insurers).

0.6.3 Supply Estimation

Estimating parameters of dynamic games and computing equilibria are computationally demanding (Benkard, 2004; Bajari et al., 2010). The large number of insurers in Part D markets makes it even more difficult computationally. Instead of solving for the equilibrium of the supply model, I follow Bajari et al. (2007)'s two-step approach to uncover insurers' valuation of future profits. Essentially, this approach minimizes the violation of insurer rationality by finding the parameter value or insurers' discount factor such that the observed pricing strategies are closest to equilibrium strategies. This approach is implemented in two steps. In the first step, I empirically estimate how insurers price their plans by regressing premiums on relevant state variables. Such reduced-form estimates empirically correlate insurers' actions to states and characterize insurers' strategies $\sigma(SV)$, which are also referred to as the empirical policy functions.

In the second step, I take competitors' strategies as given by these empirical strategies characterized in the first step and forward simulate to construct insurers' discounted profits $V(\sigma_k, \hat{\sigma}_{-k}, \delta, \mathbf{SV})$ as in Equation 7 given a discount factor. This simulated value function can be constructed using both each insurer's empirical strategy and alternative strategies. Imposing rationality or optimality on insurers' decisions based on the definition of MPNE in Section 0.5.3, I estimate the discount factor δ such that profitable deviations from empirical policies are minimized, i.e. the empirical strategies reflect minimum violation of rationality.

In other words, I assume the insurers solve the dynamic pricing game in Section 0.5.3 and set their pricing strategies accordingly, and I look for parameters of the supply model such that insurers' pricing behavior is optimal. Besides model assumptions in Section 0.5.3 and the following functional form assumption in Section 0.6.3.1, this estimation approach requires that insurers in all markets play the same equilibrium strategies so that data from all markets can be used to jointly characterize empirical pricing strategies in the first step.

0.6.3.1 Step One: Empirical Pricing Policy Function

I let the data reveal insurers' empirical pricing strategies by estimating prices or premiums as functions of shares as well as other determinants of pricing decisions as in equation 10. Premiums p_{jt} include bids for basic premium b_{jt} for basic plans and supplemental premiums PS_{jt} for enhanced-benefit plans. The controls include own lagged shares by enrollee type S^{θ}_{kjt} and shares of other plans offered by the same insurer S_{k-jt}, plan characteristics X_{jt}, and insurer fixed effects to account for unobserved heterogeneity across insurers that affect both shares and pricing decisions. The residual is assumed to be normally distributed, and I use the estimated standard deviation to get random draws for competitors' prices for forward simulations in the second step.

$$p_{kjt} = \alpha + \sum_{\theta} \beta^{\theta} S^{\theta}_{kjt} + \sum_{\theta} \gamma^{\theta} S^{\theta}_{k-jt} + X_{jt}\lambda + \xi_k + \epsilon_{jt} \tag{10}$$

These empirical policy functions condition on a coarser set of state variables than what is required to compute a Markovian strategy and are similar in nature to the notion of oblivious strategy as formalized by Weintraub et al. (2008). As an approximation for Markov perfect equilibria, Weintraub et al. (2008) define oblivious equilibrium as an equilibrium in which each firm is assumed to make decisions based on its own state and knowledge of the long-run average industry state. The rationale for using a coarser set of state variables in my setting is the same as that for computing oblivious equilibrium: realistically it is computationally infeasible to compute Markov perfect equilibria when market sizes are large and the state space explodes even with 20 firms. Such simplifications can actually provide good approximation to firms' equilibrium behavior. In fact, Weintraub et al. (2008) show that the oblivious equilibrium approximates a Markov perfect equilibrium as the number of firms grows.

I estimate empirical pricing strategies separately for three clusters of plans: basic plans offered by single-product firms, basic plans offered by multiple-product firms, and enhanced-benefit plans offered by multiple-product firms. Different factors are relevant for pricing across these clusters of plans – for example, controls are different for single- versus multiple-product firms (shares of other plans within firm are not relevant for the former). Therefore, I estimate the empirical pricing functions separately for these three clusters of plans.

Table 7 summarizes my key coefficient estimates. Not surprisingly, plans with higher coverage are more expensive: premiums decrease with deductible amount and increase with gap coverage. Premiums also depend on lagged shares, but the coefficient varies across clusters of plans and types of enrollees. Finally, the key takeaway is that the adjusted R^2 is reasonably high, meaning that this first step is doing a good job at predicting what firms do based on these observable factors, which is a prerequisite for feeding these empirical policy functions into the second step to estimate firms' discount factor.

0.6.3.2 Step Two: Uncover Insurers' Discount Factor

Given the discount factor and pricing strategies, I can forward simulate to get the empirical value function for insurer k, the empirical counterpart to the value function in Equation 7.

$$\hat{V}(\sigma_k, \sigma_{-k}, \delta, SV_{mt_0}) = \mathrm{E}_n[\sum_{t=t_0}^{\infty} \delta^t \Pi_{kt}(\sigma_k, \sigma_{-k}, \mathbf{SV}_{mt})|\mathbf{SV}_{mt}] \tag{11}$$

I take competitors' strategies σ_{-k} as given by empirical pricing strategies estimated from the first step and consider each insurer's optimization problem separately. In order to compute this simulated value function for each possible σ_k, including the empirical strategy and alternative strategies, I forward simulate 500 times and take the average across simulations to get $\hat{V}$. The discount factor can be estimated using the simulated minimum distance estimator as follows, where N is the number of states times the number of alternative-strategies considered.

$$\hat{\delta} = \mathrm{argmin} \frac{1}{N} \sum_{\tilde{\sigma}_k, \mathbf{SV}_{mt}} (\min\{\hat{V}(\tilde{\sigma}_k, \hat{\sigma}_{-k}, \delta, \mathbf{SV}_{mt}) - \hat{V}(\hat{\sigma}_k, \hat{\sigma}_{-k}, \delta, \mathbf{SV}_{mt}), 0\})$$

Intuitively, the discount factor reflects minimum violation of insurer rationality by minimizing room for profitable deviations. The objective function is the average forgone profit by choosing empirical strategies $\hat{\sigma}_k$, compared with alternative strategies $\tilde{\sigma}_k$. Since MPNE requirement applies to all possible alternative strategies, alternative strategies can be any perturbations of empirical strategies. Therefore, I consider single-period deviations from the empirical policy functions for simplicity and consider 100 alternative strategies for each insurer.

Conceptually, the discount factor tells us how much insurers care about future profits and therefore how strong the invest incentive is. The identification comes from the observed price or markup levels – intuitively, the more insurers care about the future, the stronger invest incentive they face and the lower they set the premiums. Table 8 reports the estimated $\hat{\delta}$ of 0.946[20], which suggests that insurers value future profits strongly and therefore face a strong invest incentive. The standard error is bootstrapped.

0.7 Counter-factual Analysis

Section 0.4 shows a striking invest-then-harvest pricing pattern that is consistent with insurers exploiting consumer inertia. Structural estimation in Section 0.6 uncovers a high discount factor, indicating that insurers have very strong incentives to invest in future demand. Should we worry about such invest-then-harvest pricing among Part D sponsors? On one hand, price increases over time create dynamic choice inefficiency in consumer choice in the presence of inertia. On the other hand, the net effect on consumer welfare also depends on whether switching costs toughen or soften competition. In this section, I apply the dynamic supply model above to answer two important economic questions. First, what is the net effect of strategic pricing in response to inertia on equilibrium prices? This is an empirical question and depends on whether the invest or the harvest incentive dominates. To quantify insurers' trade-off between these counteracting incentives, I decompose the observed pricing patterns into components attributed to invest and harvest incentives in Section 0.7.1. Second, what are consequences of policies that could be used to constrain insurers' ability to exploit inertia using the "invest-then-harvest" pricing tactic? To evaluate the desirability of government intervention, I simulate the effects of three policies on prices and welfare, including two policies implemented or proposed under the Affordable Care Act.

0.7.1 Do Switching Costs Lead to Higher or Lower Prices?

The competitive effect of switching costs is ambiguous and depends on whether the invest incentive or the harvest incentive dominates. While Beggs and Klemperer (1992) show that the harvest

[20]One potential concern is that such a high annual discount rate cannot be reconciled with the fact that many Part D sponsors are publicly traded and have high rates of returns on investment. However, it should be noted that I estimate a common discount rate for all insurers in this market for computational feasibility. While the discount factor or rate of return might vary across insurers empirically, this estimate represents the average discount factor across insurers. Furthermore, even for big insurers such as Humana, the annual rate of return is not much higher than that implied than the estimated discount factor. For example, Humana's recent annual return on investment ranges from 6.37% to 7.91% based on `http://csimarket.com/stocks/HUM-Return-on-Investment-ROI.html`.

incentives always dominates when consumers are perfectly inertia and switching costs are infinite, this is not necessarily true when consumers are subject to finite switching costs. In fact, Dubé et al. (2009) show that depending on the magnitude of switching costs, equilibrium prices can be higher or lower than the case without switching costs. Contrary to conventional wisdom that switching costs soften competition, the authors show examples where inertia reduces equilibrium prices. When switching costs are finite, firms face incentives to price low not only to attract new consumers but also to attract consumers currently attached to competitors. Arie and Grieco (2014) highlight the "compensating" effect, or the incentive to induce competitors' consumers to switch products, as the key contributing factor to lower price levels.

In order to decompose the effects of the invest and harvest incentives on driving prices, I compare prices in the model with inertia with two counter-factual benchmarks, one without inertia and one in which insurers are myopic. In the dynamic model with inertia, insurers are subject to both the invest and harvest incentives when setting prices. In the counter-factual benchmark with no inertia, insurers are subject to neither the invest incentive nor the harvest incentive. In the counter-factual with myopic insurers, insurers face no invest incentive and only the harvest incentive. The comparison between the dynamic model with consumer inertia and these two counter-factual benchmarks helps decompose insurers' trade-off between the invest and harvest incentives.

In the counter-factual benchmark with no inertia, standard enrollees' demand is different from Section 0.5.1 because their utility, which is described below by Equation 12, no longer includes switching costs as in Equation 2.

$$u_{ikjt} = -\alpha p_{kjt} + \beta_{it}\phi_{kjt} + \lambda_{it}\mathbf{1}\{\text{Insurer}\}_k + \epsilon_{ikjt} \tag{12}$$

In the counter-factual with myopic insurers, demand is the same as in Section 0.5.1, but now the discount factor $\delta = 0$ in the supply model, and insurers set prices only to maximize annual variable profits without any consideration for future profits.

Table 9 reports enrollment-weighted equilibrium markups among standard enrollees in a simplified two-period model with inertia corresponding to the actual setting, in the counter-factual benchmark with no switching costs and in the counter-factual with myopic insurers. Consistent with the invest-then-harvest intuition, in the model with inertia we see low prices (small and negative average markup) in the first year but high prices (high average markup) in the second period. Interestingly, average markup is lower than the benchmark with no inertia, which indicates that the invest incentive dominates the harvest incentive and that inertia toughens competition. A comparison between the model with inertia and the counter-factual benchmark without inertia in the first year shows that the invest incentive accounts for a drop of around \$300 in markup. Another comparison between the model with inertia and the counter-factual with myopic insurers in the second year shows that the harvest incentive accounts for an increase of around \$100 in markup. These comparisons show that the invest incentive dominates the harvest incentive and that switching costs make the market more competitive. These findings contradict the conventional wisdom that switching costs soften competition, and confirm the conclusions of Dubé et al. (2009) and Arie and Grieco (2014).

0.7.2 Policy Experiments

The effects of government intervention are not directly intuitive and are in fact ambiguous ex-ante, because pricing response to inertia creates two offsetting effects on consumer welfare. On one hand, price increases create dynamic choice inefficiency in consumer choice in the presence of switching frictions. On the other hand, the structural estimation suggests that inertia reduces prices as insurers face very strong incentives to invest in future profits. The desirability of government intervention depends on how effectively each policy can smooth prices over time without increasing average price levels. In this section, I apply my model to understand the potential role of government intervention by simulating the price and welfare consequences of policy experiments where the government restricts insurers' ability to exploit consumer inertia with the invest-then-harvest pricing tactic.

First, the most straight-forward way to constrain insurers' invest-then-harvest pricing strategy is to cap the annual increase in plan bids and supplemental premiums by a certain percentage. This cap directly curbs insurers' ability to harvest and raise prices later, and therefore also dampens the invest incentive upon entry. In fact, the Affordable Care Act implements an "Effective Rate Review" policy closely resembling a cap on annual premium increase: "any proposed rate increase by individual or small group market insurers at or above 10 percent will be scrutinized by independent experts to make sure it is justified" (U.S. Department of Health and Human Services, 2014). Motivated by this policy, I consider a policy experiment in which firms can only increase bids and supplemental premiums by up to 10 percent each year. The model is set up similarly to that in Section 0.5, except that now there is a constraint that insurers' bids and supplemental premiums cannot exceed 110 percent of those in the previous year.

A second policy I consider is to offer a public option at a low price to compete with private insurers. Widely discussed in privatized insurance markets, public options were proposed as part of the Affordable Care Act but were removed in the final reconciled bill. Intuitively, offering an inexpensive public option increases competition, which restrains room for insurers to harvest consumer inertia or charge high prices later on and, as a result, also weakens the invest incentive early on. I consider a policy experiment in which the government adds a public option to the market, offering the minimum required coverage and priced at $300 in all years. The model is similar to that in Section 0.5, except that now there is additional competition from this public option.

Finally, I also consider the effects of removing risk sharing and fully exposing insurers to excessive losses and gains from their pricing decisions. The risk corridors might have exacerbated insurers' invest-then-harvest pricing tactic by making it less costly for insurers to price low initially to attract consumers. However, risk corridors might also weaken the invest-then-harvest incentives because insurer profits exceeding a threshold are taxed. The net effect is ambiguous and is an empirical question. Given the importance of the risk corridors in this setting, I analyze this counter-factual to understand the effect of this regulation (or its removal) on insurer pricing and consumer welfare. The supply model remains the same as in Section 0.5, except that risk corridor adjustment Γ is removed from the profit function in Equation 8. A caveat with the last two policy experiments is that public options and risk corridors are big policy instruments with many potential effects other than influencing insurer response to inertia, and my analysis here only speaks to one of many aspects of their effects.

0.7.3 Implementation

The empirical policy functions estimated in Section 0.6.3.1 only characterize equilibrium strategies in the empirical setting and can no longer be used as competitors' strategies in the counter-factuals. Instead, I need to solve for the Markov Perfect Nash Equilibrium in each counter-factual. It is computationally difficult to solve for the equilibrium in each game, given the large number of insurers and the large number of parameters to solve for in the equilibrium strategy. For computational feasibility, I restrict the set of strategies to follow the functional form of the empirical policy function. I assume that in each counter-factual, equilibrium pricing strategies (bids for basic premiums and supplemental premiums) take the functions form of the following, where I constrain the coefficients on shares to change by the same proportion relative to the empirical coefficients and constrain the coefficients on plan characteristics to change by the same proportion relative to the empirical coefficients.

$$\tilde{p}_{kjt} = \tilde{\alpha} + \tilde{\xi}_k + \sum_{\theta} \tilde{\beta}^{\theta} S^{\theta}_{kjt} + \sum_{\theta} \tilde{\gamma}^{\theta} S^{\theta}_{k-jt} + X_{jt}\tilde{\lambda} + \epsilon_{jt} \tag{13}$$

With this simplification, I forward simulate to get the expected value functions given the price vector in the first year P_0 and the coefficients that guide pricing strategies in subsequent periods. I then iterate over insurers' optimal choices of initial prices and these parameters using the simulated value functions until a fixed point is reached, which provides the equilibrium pricing strategies. Given the solved equilibrium strategies, I move on to Section 0.7.4 and compute welfare.

For computational feasibility, I conduct counter-factual analysis on one representative market with around a quarter of a million enrollees annually choosing stand-alone plans.[21] The population sizes of both standard and low-income enrollees are close to cross-market averages as reported in Table 1. In addition, for computational feasibility given the large number of insurers, I report results from simplified two-period models. Although the price levels would be more comparable to the data in the model with a longer time horizon, two-period models already highlight intuitions for the key economic forces, and the following qualitative interpretations are not an artifact of the two-period set up.[22] As a benchmark for comparison, I also solve for the equilibrium in a two-period

[21] Although I only perform the simulations on one representative market, I assume the same policy experiment is implemented throughout all markets and the national-average bid (used to transform bids to premiums and subsidies) changes by the same proportion as in this market.

[22] While the two-period models suffice in illustrating the key insights, I am working on models with a longer time horizon in order to verify the robustness of the conclusions and to provide a more realistic comparison with the data.

game with the current setting, i.e. with consumer inertia, no cap on price increase, no public option and with the current risk corridor set up.

0.7.4 Welfare Metrics

I evaluate effects of three policy experiments on prices as measured by enrollment-weighted premiums and markup levels, as well as on social welfare, including consumer welfare, insurer profit and government subsidy. I compute consumer welfare, insurer profit and government subsidy as relevant to standard enrollees because the automatic allocation of low-income enrollees makes it difficult to infer their preferences and to compute their welfare. In order to consistently compare static and dynamic counter-factuals, I define these welfare measures on a per-period basis. Total surplus W on a per-period basis can be calculated as follows, where CS denotes consumer surplus in money metrics, Π denotes total insurer profits, $Subsidy$ denotes government subsidy, and λ is the social cost of raising public funds. I take $\lambda = 1.3$, based on estimates in Hausman and Poterba (1987).

$$W = CS + \Pi - \lambda Subsidy \tag{14}$$

Whether consumer surplus should include switching costs depends on the underlying causes for observed inertia (Handel, 2014, provides a detailed discussion). Such distinction is not crucial for welfare analysis in my policy experiments, which all directly influence the supply side rather than the demand side. Here I take switching costs as welfare-neutral, but when evaluating the robustness of my results, I plan to consider switching costs as partly or fully welfare-relevant. When treated as welfare neutral, switching costs do not count towards actual utility but do affect choice probabilities. I simulate individual utilities and choices to compute consumer welfare in monetary terms after the normalization over the absolute value of the price coefficient.

Insurer profits are calculated based on individual choice simulations above and using the relevant profit functions. I compute pre-risk-corridor profits because risk corridor payments will be reported separately as part of government subsidy. There are three types of subsidies relevant to standard enrollees – risk-adjusted direct subsidy for each enrollee to insurers; risk corridor payments to insurers in cases of excessive losses (but the payment can go the other way if the insurer earns excessive profits); and individual reinsurance to insurers, which covers 80 percent of catastrophic drug expenditures. In the counter-factuals, I focus on direct subsidy and risk corridor payments, which are endogenous to firms' pricing strategies. These subsidies can be computed similarly to the profit term above on an per-year basis. The other subsidy, individual reinsurance, is not likely to change much across counter-factuals and therefore is less interesting for the counter-factual exercise. Following Decarolis et al. (2015), I compute government subsidy as relative to what would have been spent subsidizing the same individuals in MA-PD instead, assuming that in the absence of stand-alone plans, an enrollee would get prescription drug coverage through MA-PD plans instead.

0.7.5 Policy Experiment Results

Table 10 reports enrollment-weighted equilibrium markups among standard enrollees, first predicted by the model with inertia corresponding to the actual setting as the benchmark for comparison, then from three policy experiments: setting a cap on the percentage of annual premium increase, providing a public option at a low price, and removing risk sharing between the government and insurers. All three policies dampen the invest incentive in the first year and lead to higher markups on average, to different degrees. All three policies also dampen the harvest incentive in the second period and lead to lower markups on average, to different degrees.

In the counter-factual with a 10 percent cap on annual bid and supplemental premium increase, average markup is higher relative to the benchmark case in the first year, but is lower in the second year, which is consistent with the intuition that such a policy dampens the invest-then-harvest incentives. The average price level is slightly lower than the benchmark without any policy experiment. In the counter-factual where a public option is offered at a fixed price of $300, markups in both periods are lower compared to the benchmark, but price in the second year is still much higher than that in the first year. In the last counter-factual, where the risk corridor is removed, prices are only slightly different from the benchmark, if noticeable. To sum up, capping annual premium rise is the most effective in terms of both smoothing prices over time and constraining average price levels. Offering a low-price public option constrains markup rise in the second year but not by much. Removing the risk corridors has little impact on markups.

The prediction that the cap on annual premium increase rate can lower average prices is not as intuitive as the other prediction on smoothing pricing dynamics. On one hand, capping the annual premium increase constrains insurers' ability to raise premiums and harvest inertial incumbent enrollees, which therefore tends to decrease price levels. On the other hand, given the reduced room for harvesting, insurers now face weaker incentives to set low prices to invest in future demand. The net impact on average price levels depends on the interactions of these two channels. Because there is strong competition among Part D sponsors, the invest incentive turns out to be less sensitive to this policy change than the harvest incentive, leading to a lower price level on average. One caveat with this prediction is that it might be specific to the market structure of Part D, and therefore it needs to be re-evaluated in other market settings.

Table 11 reports simulated per-period consumer surplus for the benchmark model as well as the three policy counter-factuals. For consumer surplus, I also show the difference between each counter-factual and the benchmark and decompose this difference into the component driven by changes in the share of standard enrollees choosing stand-alone prescription drug plans, the component driven by changes in prices and the component driven by changes in choice efficiency. Capping annual price increase results in the highest consumer welfare, which is largely due to the direct effect of lower average prices and the resulting increase in enrollment, but there is also a noticeable reduction in dynamic choice inefficiency. Offering a low-price public option increases consumer surplus, which works mostly through enrollment in the public option, but there is also a small reduction in dynamic choice inefficiency. Removing the risk corridors has little impact on all margins.

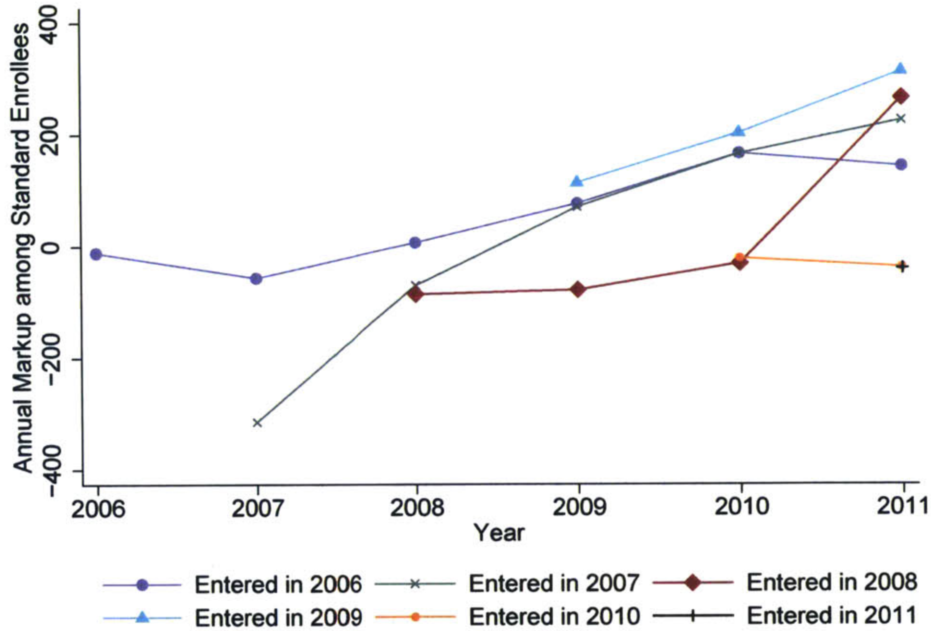
Table 12 reports results on social welfare, including consumer surplus, insurer profit, subsidy and social surplus. Capping premium increase is the most desirable in terms of both consumer and social welfare. Offering a low-price public option improves consumer welfare, but such welfare gains are dominated by the extra social cost of providing the public option. Removing the risk corridors has little impact on consumer and social welfare but transfers money from the government to insurers because with risk sharing, taxes on excessive gains outweigh subsidies on excessive losses both in the model and empirically.

These policy experiments are informative about the desirability of each policy in terms of restricting invest-then-harvest pricing and in terms of improving consumer welfare. Among the policies I consider, a policy change to cap premium increases would be the most effective in improving consumer welfare. This welfare increase comes from both smoother price dynamics and lower average premiums. There are two important next steps to check the robustness of the policy implications. First, I am working on models with a longer time horizon to evaluate the robustness of my conclusions. While key insights from these policy experiments are intuitive and the qualitative interpretations are not an artifact of the current two-period set up, some numbers might be different when we consider a longer time horizon. For example, prices in the second year in the model with inertia are higher than the counter-factual without inertia, which will change after allowing for a longer and more realistic time horizon. Second, the timing of policy intervention matters and I plan to evaluate effects of introducing the cap on annual premium increases at different points of time.

0.8 Conclusion

A growing literature has documented evidence that consumers in health insurance markets behave as if they face substantial switching costs when choosing health insurance plans. In this paper, I investigate whether private insurers in Medicare Part D exploit this type of consumer inertia when setting prices for insurance plans. I first document descriptive evidence consistent with insurers initially setting low prices in order to invest in future demand before later raising prices to harvest inertial consumers. To explore the implications of these invest and harvest incentives for equilibrium pricing, I develop and estimate a dynamic model of insurers' pricing decisions that incorporates demand inertia and adverse selection. I estimate a high discount factor among insurers, which is indicative of a strong incentive to invest in future demand and is consistent with low prices observed early on. I also find that on net, demand inertia reduces equilibrium prices, i.e. the invest incentive dominates the harvest incentive. Finally, I evaluate welfare consequences of policies that could be used to constrain insurers' ability to conduct such invest-then-harvest pricing patterns. Among the policies that I analyze, I find that a policy change to cap premium increases would be the most effective in improving consumer welfare by both lowering average premiums and smoothing prices over time.

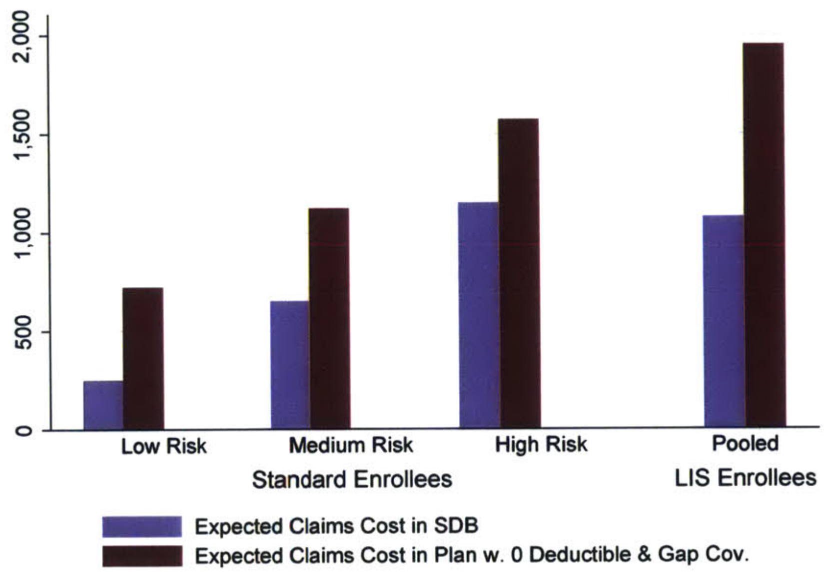
Figure 0-1: Markup By Year of Entry



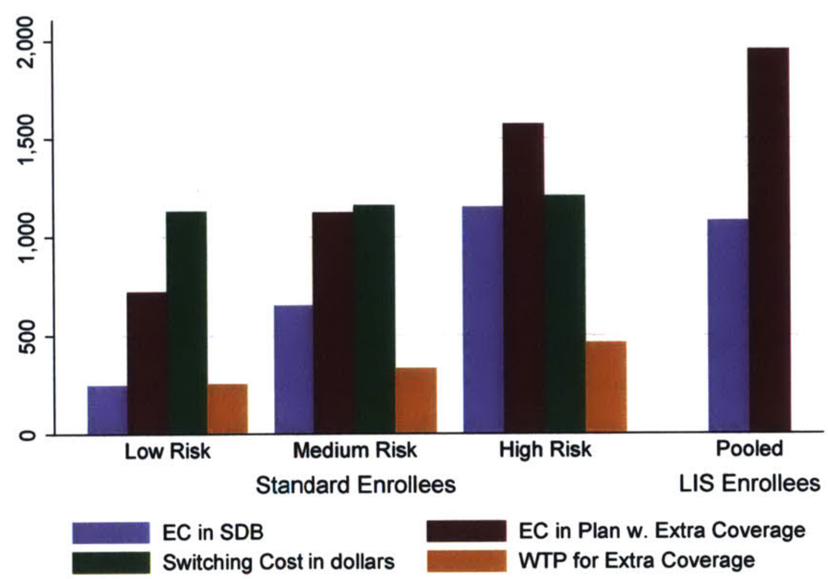
Notes: This figure shows trends in average annual markup for plans introduced in each year. The horizontal axis is year and the vertical axis is annual markup among standard enrollees. Each data point represents the enrollment-weighted average markup for a given cohort of plans in a given year. Each line shows the trend in average annual markup for plans introduced in a specific year.

Figure 0-2: Expected Claims Cost, Switching Cost and Preference by Consumer Type

(a) Expected claims cost by consumer type: low, medium, and high risk scores



(b) Expected claims cost, switching cost and preference by consumer type



Notes: Panel (a) reports, for each type of enrollee, their expected claims cost to a basic plan providing the required minimum coverage or standard defined benefit (SDB) and to an enhanced-benefit plan offering zero deductible and gap coverage on top of basic coverage. Standard enrollees are divided into low-, medium- and high-risk groups based on their risk scores. Panel (b) reports, for each type of enrollee, the expected claims cost as in Panel (a), switching cost in dollars, and willingness-to-pay for extra coverage (zero deductible and gap coverage) relative to basic coverage.

Table 1: Summary Statistics

	Mean	SD	Min	Max
Panel A: Stand-alone Prescription Drug Plans				
# Insurers	21	2.5	11	29
# Plans	47	8.2	27	66
# Basic Plans	24	4.0	15	36
# Enhanced-Benefit Plans	23	4.9	12	31
Herfindahl index	0.22	0.06	0.13	0.48
Average Annual Premium, 2006	329	36.5	270	413
Average Annual Premium, 2011	507	46.6	393	583
Panel B: Standard Medicare Beneficiaries				
# Beneficiaries	217,794	160,446	8,635	762,538
Annual Rival Rate	0.10	0.015	0.078	0.150
Annual Attrition Rate	0.08	0.007	0.061	0.098
Share in Stand-alone Plans, 2006	0.24	0.081	0.042	0.43
Share in Stand-alone Plans, 2011	0.26	0.063	0.18	0.42
Panel C: Low-income Medicare Beneficiaries				
# Beneficiaries	59,738	51,148	2,822	267,848
Annual Rival Rate	0.13	0.022	0.092	0.25
Annual Attrition Rate	0.10	0.012	0.073	0.15
Share in Stand-alone Plans, 2006	0.88	0.098	0.52	1
Share in Stand-alone Plans, 2011	0.80	0.11	0.46	0.99

Notes: Panel A reports summary statistics for stand-alone plans across markets. The Herfindahl Index is computed using enrollment of standard enrollees. Average premiums are weighted by standard enrollment. Panels B and C report summary statistics on standard and low-income Medicare beneficiaries at the market level. Numbers of beneficiaries correspond to the 20% random sample and should be multiplied by 5 to get actual Medicare population size. Arrival and attrition rates are relative to lagged population size. Shares in stand-alone plans are calculated as out of the entire population of standard or low-income Medicare beneficiaries, including those with stand-alone plans, those with bundled coverage under Medicare Advantage, those with coverage provided by employers or third parties, and those without any prescription drug coverage.

Table 2: Summary Statistics on Plans by Year

	# Plans	# Entries	# Exits	Total Premium	Markup
Pooled	9490			371.9	47.5
2006	1429	1429	NA	329.0	-5.5
2007	1865	594	3	362.7	-55.4
2008	1824	201	86	408.1	4.2
2009	1687	53	83	476.6	71.9
2010	1576	107	24	503.3	148.8
2011	1109	22	95	507.1	121.3

Notes: The table reports summary statistics for all stand-alone prescription drug plans, first pooled across years and then by year. Total premium is the total of annual basic premium and annual supplemental premium. Premiums and markups are reported in enrollment-weighted averages. Markup is defined in Section 0.2.2.

Table 3: Enrollment Shares as of 2011 by Beneficiary Cohort

Beneficiary Cohort	2006	2007	2008	2009	2010	2011
# Standard Beneficiaries in PDPs	1,412,073	126,234	121,569	111,783	109,327	118,387
Share in plans introduced in 06 (%)	83.68	79.14	76.79	71.90	71.67	71.67
Share in plans introduced in 07 (%)	7.15	8.10	9.22	10.42	8.42	7.06
Share in plans introduced in 08 (%)	2.60	2.79	3.09	3.97	3.32	2.03
Share in plans introduced in 09 (%)	1.22	1.78	2.16	3.23	2.34	0.97
Share in plans introduced in 10 (%)	3.13	4.76	5.15	6.30	8.85	9.44
Share in plans introduced in 11 (%)	2.23	3.43	3.58	4.18	5.41	8.83

Notes: This table reports shares of standard enrollees choosing stand-alone plans by cohort of beneficiaries (the columns) and by year of plan entry (the rows). Beneficiary cohort is the year that the beneficiary first enrolls in a stand-alone prescription drug plan. Each cell reports the share of the corresponding enrollee cohort choosing plans introduced in a certain year. The enrollment shares in this table are computed as of 2011. For example, the first column shows that there were about 1.4 million standard Medicare beneficiaries who first enrolled in stand-alone prescription drug plans as standard enrollees in 2006. In 2011, among these standard beneficiaries, 83 percent were enrolled in plans introduced in 2006, 7 percent were enrolled in plans introduced in 2007, and so forth.

Table 4: Comparing Markups Between Entrant Plans and Incumbent Plans

Markup	(1)	(2)	(3)	(4)
1{Entry}, =1 for entrants	-82.7	-182.8	-158.1	-147.7
	(64.9)	(42.8)	(30.8)	(27.9)
Market FE		x	x	x
Year FE		x	x	x
Insurer FE			x	x
Plan Features				x
N	9312	9312	9312	9312
Adjusted R^2	0.024	0.173	0.268	0.688

Notes: The table reports the regression results for equation 1, using plan-year level observations for all plans in the sample period 2006-2011. The regressor of interest is a dummy variable equal to one if the plan enters in that year. All standard errors are clustered at the plan level. Column (1) reports estimates without any controls. Column (2) controls for market and year fixed effects. Column (3) also controls for insurer-fixed effects in addition to market and year fixed effects. Column (4) adds controls for plan coverage, including deductible amount, whether the plan offers gap coverage and tiered cost sharing. Standard errors are clustered at the insurer level.

Table 5: Comparing Markups Between Entrant Plans and Incumbent Plans on Subsamples

	Experienced Prior to Part D			(4) Experienced in Part D	(5) Enhanced benefit plans
	(1) Major MA sponsors	(2) MA sponsors	(3) Medicare Sponsors		
1{Entry}, =1 for entrants	-186.6	-168.9	-168.6	-192.0	-134.3
	(29.6)	(25.1)	(24.9)	(30.5)	(62.1)
N	2881	5339	5657	2918	4573
Adjusted R^2	0.732	0.707	0.706	0.567	0.766

Notes: The table reports the regression results for equation 1, using plan-year level observations for subsamples of plans in 2006-2011. The regressor of interest is a dummy variable equal to one if the plan enters in that year. Controls include plan coverage, and market, insurer and year fixed effects. Column (1) reports estimates using the subsample of plans offered by insurers that were major sponsors in Medicare Advantage prior to 2006 and offered prescription drug coverage bundled with medical coverage to the Medicare population. Column (2) reports estimates using the subsample of plans offered by insurers with some experience in Medicare Advantage prior to 2006. Column (3) reports estimates using the subsample of plans offered by insurers that provided insurance to the Medicare population prior to 2006. Column (4) reports estimates using the subsample of plans offered by insurers that have served at least 5000 Part D enrollees in the same market before. Column (5) reports estimates using the subsample of enhanced-benefit plans only, which are not eligible for random assignment of low-income beneficiaries. Standard errors are clustered at the insurer level.

Table 6: Polyakova (2015)'s Demand Estimates for Standard Enrollees

	(1)	(2)	(3)	(4)
Annual Premium, $100	-0.39	-0.45	-0.41	-0.50
	(0.01)	(0.01)	(0.01)	(0.01)
Default plan, 1/0	5.45	5.61	5.07	5.09
	(0.25)	(0.26)	(0.26)	(0.26)
x Health Risk Score	0.23	0.22	0.36	0.37
	(0.06)	(0.07)	(0.07)	(0.07)
Number of insurer FE	3	3	10	10
Use lagged cost as IV for Premium	No	Yes	No	Yes
Implied SC for 75yo female, av. risk	$1506	$1330	$1392	$1164

Notes: The table reports estimation results for a few key coefficients from Polyakova (2015)'s simulated maximum likelihood estimation – coefficients on plan premium, on the default dummy, and on the interaction of the default dummy and enrollee risk score. Columns 1 and 3 do not instrument for annual premium, while columns 2 and 4 use lagged cost as an instrument for premium. Columns 1 and 2 control for insurer dummies for the 2 biggest insurers in each market (the omitted category consists of all other insurers), while columns 3 and 4 control for insurer dummies for the 9 biggest insurers in each market (the omitted category consists of all other insurers).

Table 7: Empirical Pricing Strategies

	Single-plan Insurers	Multi-plan Insurers		
	Basic Plans	Basic Plans	Enhanced-Benefit Plans	
	Bid for P_{basic}	Bid for P_{basic}	Bid for P_{basic}	$P_{supplemental}$
Intercept	231.4	1065.5	1244.7	66.7
	(133.9)	(679.2)	(238.91)	(268.0)
Plan Coverage (%)				
Deductible (in \$100)			-56.1	-18.9
			(17.3)	(16.5)
1{Gap coverage}			146.5	95.5
			(29.3)	(18.0)
Lagged Shares By Type of Standard Enrollees (%)				
Low risk share	4.1	-4.2	-16.6	3.2
	(3.3)	(3.9)	(6.7)	(3.2)
Female low risk	-10.6	7.2	3.1	-1.1
	(3.9)	(6.1)	(4.0)	(2.5)
Male medium risk	3.2	0.8	-5.1	-0.5
	(5.9)	(2.7)	(10.9)	(5.7)
Female medium risk	-10.2	-11.8	-9.8	-16.9
	(5.3)	(4.7)	(7.3)	(6.9)
Male high risk	-1.2	-1.7	11.5	20.5
	(8.7)	(4.2)	(8.8)	(6.7)
Female high risk	15.3	10.7	1.9	-5.5
	(6.4)	(4.1)	(9.5)	(8.9)
Number of obs.	677	2804	3265	3278
Adjusted R^2	0.78	0.56	0.72	0.69

Notes: The table reports key coefficient estimates from empirical pricing policy function estimation for three clusters of plans, controlling for plan coverage and insurer fixed effects. All standard errors are clustered at the insurer level.

Table 8: Structural Parameter Estimate

	Coefficient	Standard Error
Discount Factor (β)	0.946	0.073

Notes: The table reports the minimum-distance estimate for the discount factor and the bootstrapped standard error.

Table 9: Decomposition Results: Equilibrium Markup Levels

Average Markup	Model w. Inertia	Restrict Insurers' Ability to Exploit Inertia		
		Cap Annual Price Rise	Add Public Option	Remove Risk Corridors
2006	-8	157	45	7
2007	403	164	346	398

Notes: The table reports enrollment-weighted average markups (among standard enrollees) in the two-period model with consumer inertia, in the counter-factual benchmark without inertia and in the counter-factual with myopic insurers.

Table 10: Counter-factual Policy Experiments: Equilibrium Markup Levels

Average Markup	Model w. Inertia	Restrict Insurers' Ability to Exploit Inertia		
		Cap Annual Price Rise	Add Public Option	Remove Risk Corridors
2006	-8	157	45	7
2007	403	164	346	398

Notes: The table reports enrollment-weighted average markups (among standard enrollees) in the two-period model with consumer inertia and in the counter-factual policy simulations.

Table 11: Counter-factual Policy Experiments: Consumer Welfare

Consumer Surplus ($Millions)	Model w. Inertia	Restrict Insurers' Ability to Exploit Inertia		
		Cap Annual Price Rise	Add Public Option	Remove Risk Corridors
Consumer Surplus	78.68	109.23	93.24	78.88
ΔCS		30.54	14.56	0.20
ΔCS due to ΔP		11.30	0.48	-1.42
ΔCS due to Δchoice efficiency		6.87	3.60	1.52
ΔCS due to ΔPDP share		12.37	10.48	0.10

Notes: The table reports consumer welfare estimates for the actual policy setting (as the benchmark for comparison) and for policy counter-factuals (relative to the benchmark), all with a simplified two-period setting. Consumer Surplus is as defined in Section 5.3 and is converted to a per-year value so that it can be consistently compared across counter-factuals. The change in consumer surplus resulting from each counter-factual policy is decomposed into three components – the difference due to enrollees opting in and out of stand-alone plans, the difference due to the resulting equilibrium price changes, and the difference due to changes in consumers' plan choices.

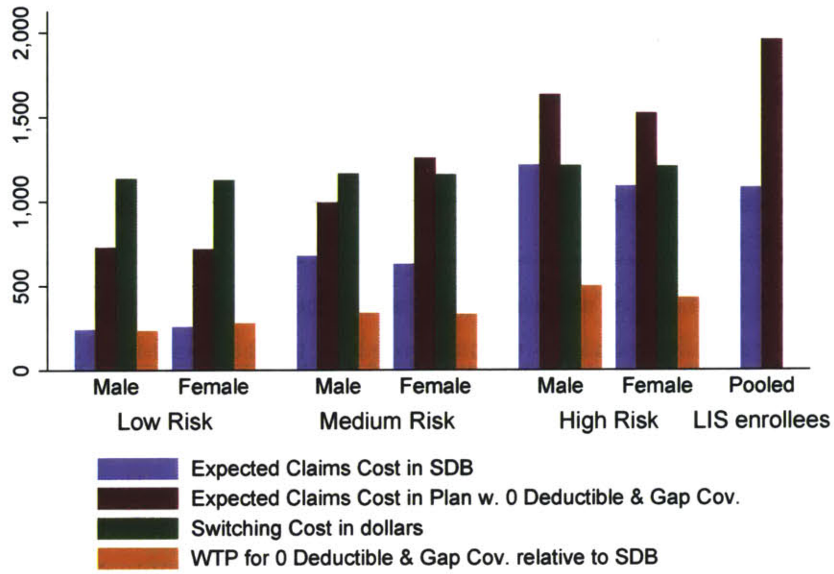
Table 12: Counter-factual Policy Experiments: Social Welfare

Social Welfare ($Millions)	Model w. Inertia	Restrict Insurers' Ability to Exploit Inertia		
		Cap Annual Price Rise	Add Public Option	Remove Risk Corridors
Consumer Surplus	78.68	109.23	93.24	78.88
Insurer Profit	14.43	16.01	9.98	46.60
Direct Subsidy	182.81	165.64	157.06	183.60
Subsidy for Public Option	NA	NA	13.75	NA
Total Direct Subsidy, rt MA-PD	2.88	-19.01	5.82	2.88
Risk Corridor Payments to insurers	-30.34	-27.17	-31.30	0.00
Total Surplus	119.71	177.12	109.09	121.74
Public Option Share	NA	NA	0.08	NA

Notes: The table reports welfare estimates for the actual policy setting (as the benchmark for comparison) and for policy counter-factuals, all with a simplified two-period setting. Consumer Surplus, Insurer Profit, Direct Subsidy and Risk Corridor Payments are as defined in Section 5.3 and are all converted to a per-year value so that they can be consistently compared across counter-factuals. Positive risk corridor payments mean that the government pays insurers in aggregate while negative risk corridor payments mean that insurers pay the government in aggregate.

0.8.1 Appendix

Figure A.1: Expected claims cost, switching cost and preference by consumer type



Notes: This figure reports, for each type of enrollees, their expected cost, switching cost in dollars, and willingness-to-pay for extra coverage: zero deductible and gap coverage, relative to basic coverage. In addition to the division into low-, medium- and high-risk groups based on their risk scores as in Figure 0-2, standard enrollees are also grouped by gender, which makes a small difference in terms of expected cost.

Table A.1: Individual Cost Estimation

	Low Risk-score		Medium Risk-score		High Risk-score		Low-income
	Male	Female	Male	Female	Male	Female	Enrollees
Intercept	383.4	383.2	750.2	706.9	1145.2	1078.6	1018.4
	(5.11)	(4.44)	(4.91)	(3.50)	(9.04)	(4.85)	(3.35)
Deductible	-0.585	-0.451	-0.297	-0.234	0	0.056	0.248
	(0.015)	(0.013)	(0.014)	(-0.010)	(0.02)	(0.013)	(0.009)
Partial Gap Cov.	206.2	204.5	192.2	226.8	266.4	344.1	594.2
	(9.3)	(7.8)	(6.5)	(5.0)	(10.0)	(6.0)	(14.2)
Full Gap Cov.	637.3	653.9	716.8	694.3	1051.8	1032.8	1490.0
	(19.4)	(15.2)	(12.1)	(8.8)	(15.6)	(8.9)	(26.4)
Number of obs.	568,117	670,788	1,195,847	1,856,589	1,160,410	2,451,539	9,928,135
Adjusted R^2	0.08	0.09	0.07	0.08	0.05	0.07	0.02

Notes: The table reports some key coefficients from the individual cost estimation for Equation 5. Insurer fixed effects are included. Standard errors are clustered at the insurer level.

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