Subsidy Design in Privately Provided Social Insurance: Lessons from Medicare Part D

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The efficiency of publicly subsidized, privately provisioned social insurance programs depends on the interaction between strategic insurers and the subsidy mechanism. We study this interaction in the context of Medicare's prescription drug coverage program. We find that the observed mechanism is successful in keeping "raise-the-subsidy" incentives relatively low, acts much like a flat voucher, and obtains a level of welfare close to that for the optimal voucher. Across a range of counterfactuals, we find that more efficient subsidy mechanisms share three features: they retain the marginal elasticity of demand, limit the exercise of market power, and preserve the link between prices and marginal costs. **q1**

I. Introduction

Social insurance programs have traditionally been provided directly by the government. The past two decades, however, have seen an accelerating effort to move these programs to privately provided markets with public

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funding and extensive regulatory oversight (McGuire, Newhouse, and Sinaiko 2011; Gruber 2017). Recent examples in the United States include the use of private managed-care plans in Medicare and Medicaid, private insurers competing for consumers under the Health Insurance Marketplaces of the Affordable Care Act, and, the subject of this paper, the private provision of prescription drug benefits in Medicare Part D. This trend has also extended around the world to, for example, the privatization of social security benefits in Chile and a discussion of privatizing social security, disability, and unemployment insurance systems in many OECD (Organisation for Economic Co-operation and Development) countries. The broad objective of all such programs is to leverage the benefits of competition to provide high-quality services at low cost to both consumers and the government.

One critical issue that arises in such settings is how governments should determine the level and distribution of public funding that flows into these programs. The funding is typically channeled through subsidies that are paid directly to private firms, making the question of how to tailor the subsidy mechanisms central. While answering this question in general is beyond the scope of any single paper, we contribute to the emerging academic and policy discussion of the subsidy mechanism by providing novel evidence from the Medicare Part D prescription drug plan (PDP) program. Part D is an elective prescription drug insurance program available to Medicare beneficiaries that was launched in 2006 and since then has become one of the role models for privately provided, publicly financed social insurance programs in the United States. The PDP market has several features that make it well suited for studying subsidy mechanism design: the program has clear, well-articulated rules that allow us to cleanly model the incentives facing strategic firms; excellent data exist on potential consumers and the set of choices available to them; and a complex mechanism links equilibrium market outcomes to consumer-facing plan prices and public subsidies.

Using this rich environment, we analyze equilibrium allocations, prices, and the incidence of subsidy dollars under the existing subsidization mechanism as well as under an array of counterfactual subsidy mechanisms that resemble a variety of policy proposals in this and related markets. To facilitate this analysis, we proceed in two steps. We posit and estimate a structural model of consumer demand and strategic insurers, respecting the

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many institutional details present in the market. On the demand side, we allow for risk-based selection by allowing preferences and costs to vary across six different consumer types. Allowing for risk-based selection enables us to directly model the key difference between insurance markets and regular product markets: the marginal cost curve is an endogenous function of equilibrium prices. On the supply side, we build a profit function for insurers, accounting for a host of details such as the subsidy mechanism, risk-specific payments, reinsurance, multiple demand types, and the endogenous marginal cost function. We leverage this structural model to estimate demand and cost primitives before turning to counterfactual simulations where we adjust the subsidy mechanism.

We find that equilibrium outcomes—and, by extension, welfare—are driven by four empirical facts. First, we estimate that consumers have relatively low intrinsic willingness to pay for independent PDPs. This is primarily driven by the existence of a highly subsidized close substitute: prescription drug coverage bundled with medical insurance under private Medicare managed-care plans known as Medicare Advantage (hereafter MA-PD [Medicare Advantage prescription drug] plans). **q2** The second, related, result is that the primary driver of welfare is the opportunity cost of government spending. We find that the sign and magnitude of our welfare estimates are dominated by the ability of the government to set subsidies to achieve optimal sorting of consumers, and risks, across different types of prescription drug coverage. Third, the observed subsidy-setting mechanism appears to be successful in keeping plans' margins relatively low, as insurers price near marginal cost. Fourth, we find that, once one distills all of the administrative details of how the Part D market works, the current mechanism acts much like a flat voucher and obtains a level of welfare close to that for the optimal voucher. However, we estimate that a social planner could do substantially better, by adjusting prices to correct our finding that consumers are purchasing too few and too socially expensive plans relative to the social optimum.

While our estimates are specific to the context of Part D, our results suggest several key economic forces that are likely to be important in any setting with publicly subsidized, privately provisioned goods and services. First, it is important to preserve the marginal relationship between the prices that firms set and the prices that consumers pay. This keeps the elasticity of demand relatively high, which results in more intense competition and lower prices in equilibrium. Second, consumer-facing prices should be positively related to the social cost of providing those services. Third, the relationship between subsidies and equilibrium outcomes has to be carefully tempered to prevent strategic pricing by imperfectly competitive firms.

Our paper is related to several distinct literatures in social insurance, design of government transfers, and regulation of private markets. A large theoretical literature has examined the role and motivation for in-kind subsidies in different sectors of the economy, while a substantial theoretical and empirical literature has studied the supply-side effects of government regulation. Laffont and Tirole (1993) give a classic reference on the multitude of theoretical issues. Surprisingly, the has been little empirical analysis at the intersection of these literatures, even though there are a growing number of settings where in-kind subsidies affect the decisions of private strategic firms rather than individual consumers. Our paper contributes to the nascent literature at this intersection, which includes the early work by Cutler and Reber (1998) and Gruber and Washington (2005) on tax and employer subsidies for employer-sponsored insurance plans and conceptually related work on government procurement in health care by Duggan (2004) and Duggan and Scott Morton (2006), as well as the more recent concurrent work on Medicare Advantage and the Affordable Care Act by Enthoven (2011), Frakt (2011), Curto et al. (2014), Decarolis (2015), Tebaldi (2017), Jaffe and Shepard (2018), and Polyakova and Ryan (2018). We contribute to this literature by analyzing the context of Medicare Part D, which in itself is a large market, and move the literature forward by exploring ways of incorporating nonconstant marginal costs into equilibrium pricing analysis with subsidized prices. q3

Our paper contributes to the growing literature that analyzes the Part D program as a prominent example of introducing consumer choice in health insurance. On the demand side, a number of papers have explored the rationality of individual choices, consumer myopia, and inertia.[1] A handful of existing studies on the supply side have considered the quantity and quality of the plan menu offered by Part D insurers and price responses to consumer inertia (Lucarelli, Prince, and Simon 2012; Chorniy, Miller, and Tang 2014; Ho, Hogan, and Scott Morton 2015; Miller and Yeo 2015; Starc and Town 2015; Einav, Finkelstein, and Polyakova 2016; Wu 2016; Fleitas 2017). While studying a different question—the difference in cost-sharing design between independent and integrated drug plans—Starc and Town (2015) is the closest to our work in terms of the modeling approach, including the structural estimation of demand for Part D plans by consumer risk type.

The remainder of the paper proceeds as follows. Section II describes the institutional setting and data. Section III lays out the empirical model of supply and demand, while section IV presents model estimates. Section V

[1] These include Winter et al. (2006); Ketcham and Simon (2008); Heiss, McFadden, and Winter (2010); Abaluck and Gruber (2011, 2016); Ketcham et al. (2012); Kling et al. (2012); Bundorf et al. (2013); Heiss et al. (2013, 2016); Kesternich et al. (2013); Vetter et al. (2013); Ericson (2014); Miller and Yeo (2014); Abaluck, Gruber, and Swanson (2015); Einav, Finkelstein, and Schrimpf (2015); Gowrisankaran, Marsh, and Town (2015); Ho, Hogan, and Scott Morton (2015); Ketcham, Lucarelli, and Powers (2015); Polyakova (2016); and Bundorf, Polyakova, and Tai-Seale (2018).

discusses the economics forces in counterfactual subsidy mechanisms. Section VI concludes.

II. Economic Environment and Data

A. *Medicare Part D Primer*

Medicare is a public health insurance program covering the elderly and the disabled in the United States. Over 50 million individuals benefit from Medicare, which accounts for roughly $500 billion in annual budgetary outlays. The program is administered by the Centers for Medicare and Medicaid Services (CMS). Most beneficiaries become eligible for the program when they turn 65 and are automatically enrolled into insurance for inpatient (Part A) and outpatient (Part B) services under the so-called traditional fee-for-service Medicare. At this point, consumers can make two choices. First, they can decide to purchase coverage for their pharmaceutical expenditures that is not included in Parts A or B. Such coverage is provided by private PDPs under what is known as the Medicare Part D program. Consumers have a choice of more than a dozen PDPs in each of the program's 34 geographic markets. Alternatively, consumers may decide to opt out of traditional Medicare altogether and switch to a private MA-PD plan for bundled inpatient, outpatient, and pharmaceutical coverage. MA-PD plans provide a privately administered, but publicly financed, alternative to government-run Medicare.

Pharmaceutical coverage for Medicare beneficiaries is the empirical context of our analysis. This drug program (launched in 2006) is a large and rapidly growing market that accounts for about a fifth of overall federal spending in Medicare, that is, about $100 billion. Beyond its sheer economic size, this market further plays an important role in policy making, as it has become the role model for private provision of publicly funded social insurance. Consumers in Part D bear only a fraction of the program's cost (in total, ca. 15%) because of extensive premium subsidies and risk-equalization programs. The efficiency of the mechanism by which the government sets the premium subsidy is at the heart of our research question, so we describe it in some detail.

To determine subsidies for pharmaceutical coverage, CMS starts by collecting "bids" from insurers that should reflect the full price that an insurer would charge for an average risk beneficiary. The regulator then takes a weighted (by lagged enrollment shares) average of these bids across all Part D plans across all markets. The consumer-facing premium for each plan is set by CMS as 25% of the national bid average plus the difference between the plan's bid and the national average. In addition to consumer premiums, insurers collect a payment from CMS that varies across consumers, depending on their health risk. CMS assigns consumer i a risk score. To a plan that enrolls this consumer, CMS then pays a subsidy equal to the insurer's bid multiplied by i's risk score net of consumer premium.[2]

For consumers with income under 150% of the federal poverty line (known as "LIS," or low-income-subsidy, consumers), CMS pays the full premium when consumers are enrolled in a qualifying plan. Further, LIS consumers are randomly assigned to qualifying plans, unless they actively enroll in a plan of their choice. Plans in market m qualify for LIS random assignment and full subsidies if their consumer premiums fall below the average consumer premium in market m. As discussed in detail in Decarolis (2015), LIS random assignment generates a discontinuity in market shares that we account for in section III.B.

Table 1 reports key summary statistics for the Part D market. In the years 2007–10, there were, on average, 1.3 million Medicare Part D–eligible individuals per geographic market in the United States. Out of these, about 0.2 million did not purchase any Part D coverage, about 0.25 million chose to buy drug plans bundled with Medicare Advantage, and 0.5 million enrolled in stand-alone PDPs.[3] **q4**

Consumers had, on average, a choice of 49 Part D PDPs in their markets, offered by 16 insurers in 2007–10. We can clearly see the central role of subsidies in this market: the national average bid in the years 2007–10 was $1,001; $648 of that amount was covered in subsidies. Consumers paid the remainder (plus any additional premiums that insurers can collect for coverage enhancements), for an average consumer-facing premium of $505. Consumer premiums varied substantially across geographic markets and time, ranging from $375 to $643 in annual premiums.

In our empirical analysis, we differentiate consumers by their health risk type. The idea is that consumers of different health may have different preferences for pharmaceutical coverage and also generate different costs for insurers. We distinguish six consumer risk types. Among consumers not eligible for low-income support, we construct five risk groups that differentiate across low-risk (relatively healthy) and high-risk (relatively unhealthy) consumers. We treat consumers who are eligible for low-income support as a separate (sixth) risk group. In panel D of table 1, we report the share of each consumer risk type among enrollees in our analytic sample. The shares of risk type 1 (lowest-risk) to 5 (highest-risk) consumers in the market are, on average, respectively 5%, 20%, 39%, 7%, and 1%. The remainder 30% of potential consumers are individuals eligible for LIS.

[2] In addition to premium subsidies, CMS further provides additional payments for especially high-risk consumers. We discuss more details in the appendix, available online.

[3] Detailed Medicare Part D enrollment numbers are recorded in table 14 of the annual Medicare and Medicaid Statistical Supplement published by CMS at www.cms.gov/Research-Statistics-Data-and-Systems/Research/MedicareMedicaidStatSupp/Overview.html.

TABLE 1
Summary Statistics

	Mean (1)	Standard Deviation (2)	Minimum (3)	Maximum (4)
	A. Contracts			
1. No. of PDPs per market	49	5.00	35	64
2. No. of insurers per market	16	.60	14	17
3. Unweighted average PDP premium ($)	505	59	375	643
	B. Subsidies ($)			
4. CMS average national bid	1,001	45	965	1,060
5. CMS base consumer premium	353	26	328	383
6. CMS subsidy for average risk beneficiary	648	20	631	677
7. Low-income benchmark threshold	354	24	333	388
	C. Enrollment (millions)			
8. All Part D eligible	1.32	1.00	.06	4.76
9. PDP enrollment, regular	.26	.18	.01	.70
10. PDP enrollment, low income[a]	.24	.20	.01	1.02
11. MA-PD enrollment, regular	.21	.25	.00	1.38
12. MA-PD enrollment, low income[a]	.05	.06	.00	.25
13. Employer-sponsored coverage	.20	.16	.01	.48
14. Other coverage sources	.17	.11	.01	.48
15. No creditable coverage	.19	.13	.01	.58
	D. Distribution of Risk Types among Enrollees (%)			
16. Risk type 1 consumers	5	2	3	15
17. Risk type 2 consumers	20	5	11	40
18. Risk type 3 consumers	39	5	19	52
19. Risk type 4 consumers	7	2	2	12
20. Risk type 5 consumers	1	0	0	1
21. LIS-eligible consumers	30	6	9	45

Note.—Panel A is based on CMS Part D Landscape files for the years 2007–10. A market is one of 34 Part D "regions" that cover the 50 US States and the District of Columbia. "Insurers" are defined as Part D contracting organizations, which can have common ownership. Panel B is based on data from the annual releases by CMS titled "Annual Release of Part D National Average Bid Amount and Other Part C and D Bid Information." Panels C and D report enrollment statistics across different types of Part D coverage (including not purchasing any coverage) as well as across consumer risk types within the primary types of Part D coverage considered in the paper—PDPs and MA-PD plans. The mean in col. 1 is calculated across 136 region-years (34 geographic markets in the years 2007–10). The enrolment statistics in panel C are based on CMS data on the whole market, not the analytic sample. The statistics in panel D are based on the analytic sample as described in sec. IV.

[a] Counts of regular versus low-income enrollment approximated using plan-level LIS counts enrollment.

B. Data

We combine two primary sources of data. The first data set contains detailed information about plan prices and characteristics for all Part D plans in all markets in the years 2007–10. The data also include information on market-level aggregate enrollment in PDPs and MA-PD as well as other types of Part D programs.[4] The second data set consists of administrative individual-level pharmaceutical claim records for the years 2007–10 for a 20% sample of Medicare beneficiaries.[5] These data contain individual- q5 level information on consumer demographics, including chronic conditions, as well as Part D enrollment status, including plan choice and LIS eligibility. The enrollment data are linked to claim information that records each drug purchase for each consumer in the sample. The purchase records include information about the total cost of a prescription as well as how this cost is split between consumer, insurer, and the government. From the 20% sample we construct our analytic sample by restricting the data to individuals living in the 50 US states and not having special types of pharmaceutical insurance, such as employer-provided coverage. The restrictions (described in more detail in the appendix) decrease the sample size from 38,628,624 individual-years (for 11,266,409 unique individuals) in the raw data to 23,957,330 individual-years (for 7,543,722 unique individuals) in our analytic sample.

III. Model

We propose an empirical model of demand and supply of insurance contracts in Medicare Part D that will help us evaluate the efficiency and allocative properties of the subsidization mechanism in this program. We start with a model of demand for insurance contracts that follows the approach of Berry (1994) and Berry, Levinsohn, and Pakes (1995) before turning q6 to a model of supply that incorporates the many institutional features of this market.

A. Demand

We model consumers in 34 Part D markets in the years 2007–10 as choosing an insurance plan that maximizes their indirect utility as a function of both pecuniary and nonpecuniary plan characteristics. We estimate demand separately for six different risk types of consumers. The underlying utility structure is assumed to be the same across all six consumer groups; for the LIS market, we adjust plan characteristics to reflect the differences in premiums and cost sharing that these consumers face.[6]

[4] These data are publicly available from CMS. CMS tabulates the depository of the data sources at www.cms.gov/Research-Statistics-Data-and-Systems/Research-Statistics-Data-and-Systems.html.

[5] Detailed description of data and data access are available in the online supplementary material, as well as at www.resdac.org.

[6] One empirical challenge specific to the LIS market is that we cannot distinguish between LIS enrollees who are in LIS-eligible plans through random assignment and those enrolled by choice. We address this challenge by aggregating all plans eligible for LIS random

The utility for enrollee i of plan j in market m consists of a deterministic component and an idiosyncratic Type I extreme value–distributed random shock, ϵ_{ijm}:

$$u_{ijm} = -\alpha_i p_{jm} + \beta_i x_{jm} + \xi_{jm} + \epsilon_{ijm}, \tag{1}$$

where p_{jm} is the plan's enrollee-facing premium after subsidies. The observable characteristics, x_{jm}, include the annual deductible, flags for whether the plan has coverage in the donut hole and whether the plan has additional coverage beyond the statutory minimum (i.e., is "enhanced"), and several generosity measures of drug formularies. We also include fixed effects for parent organizations that capture individuals' preferences for brand names of large insurance companies and quality characteristics of plans, such as pharmacy networks. The term ξ_{jm} is a plan-specific fixed **q7** effect that captures unobserved plan quality. We also include the number of years the plan has been on the market as a reduced-form approach to capturing stickiness in consumer decision-making.[7] The utility of the outside option is normalized to zero. For all five risk types of regular consumers, the outside option constitutes buying an MA-PD plan bundled with a medical plan or not buying any drug coverage. For LIS consumers who are randomly assigned to plans when first entering the program, we assume that the outside option constitutes switching to Medicare Advantage.[8]

We model heterogeneity in preferences along two major dimensions. First, for the five risk types of regular enrollees, unobserved consumer heterogeneity enters the model through random coefficients on the premium, coverage in the gap, and overall inside option. The unobserved heterogeneity may capture differences in income, as well as individuals' differences in risk, conditional on risk type, and risk aversion. We choose a lognormal distribution for random coefficients on premiums; it is composed of a common component, α, and an individual-level random shock, $\nu \sim \mathcal{N}(0, 1)$, which is scaled by σ_α:

$$\ln \alpha_i = \alpha + \sigma_\alpha \nu_i \,. \tag{2}$$

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assignment into one choice within the inside option. To do the aggregation, we average the characteristics of these LIS-eligible plans. The idea is to interpret the option of not opting out of the random-assignment plans as one distinct choice that LIS enrollees can make. The potential measurement error introduced by this aggregation is alleviated by the fact that plans eligible for LIS random assignment have many of the same key characteristics for the LIS population, such as zero premiums, zero deductibles, no gap in coverage, and otherwise reduced or eliminated cost sharing.

[7] Additional details and a discussion of the vintage measure may be found in the appendix.

[8] We do not include consumers eligible for other sources of Part D coverage into our model, assuming that their coverage options are always superior to the publicly available Part D contracts. This primarily includes consumers eligible for coverage through Veteran Affairs and employer-sponsored plans.

The parameters governing coverage in the gap, β_{gap} and σ_{gap}, and the inside option, β_{inner} and σ_{inner}, are specified analogously without the logarithmic transformation.

Second, we allow the entire vector of preference parameters to vary on the basis of the observable risk type (and LIS status) of the consumer. This approach allows for risk-based sorting of consumers in the market. We place non-LIS consumers into one of five groups on the basis of a one-dimensional risk score, which we construct from a normalized prediction of individual-level drug expenditures. We predict drug expenditures using a linear link between historical drug expenditures observed in the data and the individual's health status measured with indicators for the presence of more than 50 chronic conditions. We divide individuals into five risk groups, using percentiles of the risk score distribution (5th, 25th, 50th, 75th, and 95th percentiles).[9] **q8**

B. *Supply*

Modeling the supply side in the Medicare Part D market presents a considerable challenge, as the decision-making of insurers is affected by a complex set of regulatory provisions. For brevity, we have relegated the intricate details of the construction of our profit function to the appendix. The resulting profit function for a given firm f with a portfolio of PDPs J_f in a given market is given by

$$\pi_f(b) = \sum_{j\in J_f}\left\{\sum_{t=1}^{5}\left[M_t^{\mathrm{R}} s_{jt}^{\mathrm{R}}(b)(\theta_t^{\mathrm{R}} b_j - \kappa_t^{\mathrm{R}} c_j)\right] + M^{\mathrm{LIS}} s_j^{\mathrm{LIS}}(b)(\theta^{\mathrm{LIS}} b_j - \kappa^{\mathrm{LIS}} c_j)\right\}, \quad (3)$$

where b is the vector of bids set by firms, M is market size, s is a vector of plan shares, and c is a vector of marginal costs; the subscripts j and t refer, respectively, to each plan and each consumer risk type among the five risk types of regular enrollees. The superscripts refer to regular (R) and LIS enrollees.

Several key aspects of this profit function differ from a profit function in a standard product market. First, while firms are required to set one bid per plan, b_j, both per-enrollee revenues and costs are indexed by risk type and LIS eligibility. For a consumer of risk type t, a firm that bid b_j receives $\theta_t b_j$, where θ_t is a risk-adjustment factor based on the enrollees' risk score. The risk-adjustment system is calibrated so that an average enrollee has a risk score of 1, which implies that firms receive more than b_j for higher-risk enrollees and less than b_j for lower-risk enrollees.[10] Further, the firms

[9] The appendix outlines the details of the ordinary least squares prediction, risk score construction, and division into five risk groups.

[10] In the appendix, we discuss the institutional details of the risk-adjustment system as well as why it may imperfectly offset the variance in costs across risk types.

faces a different expected cost for each potential consumer, depending on the consumer's health conditions, pharmaceutical needs, and insurance plan design. To model this aspect of the insurance market, we assume that marginal costs vary multiplicatively by consumer risk type, so that the insurer's marginal costs are given by $\kappa_t^{\mathrm{R}} c_j$, where the scaling factors κ_t^{R} and κ^{LIS} measure differences in average costs across consumer types.[11]

This profit function thus captures the key difference between insurance markets and regular product markets: an insurer's marginal cost curve is a function of all prices in the market due to consumers of different risk types sorting across plans. The slope of the marginal cost curve can be negative (adverse selection) or positive (advantageous selection); our model does not impose a restriction on the direction of selection. Since insurers cannot directly price-discriminate in this market, the pooling of risks leads to cross subsidization across consumer types, with lower-risk types subsidizing higher-risk types.

Second, consumers face subsidized premiums; the premium formula for regular enrollees is

$$p_j^{\mathrm{R}} = \max\{0, b_j - \bar{b} + \zeta\bar{b}\}, \tag{4}$$

where $\bar{b}$ is the enrollment-weighted average bid across all Part D plans in the entire United States—critically, this includes not just PDPs but also MA-PD plans—and ζ is the share of the average bid not covered by the baseline federal subsidy.[12] The adjustment ζ is set every year by CMS and is governed by fiscal considerations and the Part D statutes. For example, in 2010, this number was 0.36. Notably, this premium-subsidy structure distorts both the absolute and relative prices of Part D plans.

Third, the share of LIS enrollees in plan j is complicated by that market segment's random-assignment mechanism: only plans with a consumer premium below the average premium in the region qualify for random assignment of LIS consumers; all other plans receive zero LIS enrollees, unless these enrollees opt out of the random assignment and actively choose these plans. The appendix outlines how we address the resulting nonlinearity in the plan's market share in the LIS market.

We use the profit equation above and the behavioral assumption that insurers in this market engage in Bertrand price competition to infer plan-type-specific marginal costs and to solve for market equilibria under counterfactual subsidy mechanisms.

[11] The construction of these scaling factors is discussed in more detail in the appendix.

[12] Given that $\bar{b}$ is determined by over 1,500 plans, we assume that firms treat it as a fixed constant.

C. Welfare Metrics

In most of our counterfactual exercises, we focus on measuring welfare levels and changes for regular enrollees. For these enrollees, total welfare in the Medicare Part D PDP market consists of three pieces: consumer surplus (CS), insurer profits (Π), and government subsidies (G), including the deadweight loss associated with taxation needed to fund the subsidy payment:

$$W = \mathrm{CS} + \Pi - \lambda G, \tag{5}$$

where λ is the social cost of raising public revenues. All objects in equation (5) account for opportunity cost: consumer surplus is measured against the zero-utility outside option; profits are computed against what the firm could have made selling to consumers in another market, for example, the MA-PD market; and government expenditures reflect the opportunity cost of subsidizing the consumer in another market, such as MA-PD or other public pharmaceutical programs. When solving for a vector of prices that would lead to a socially optimal allocation, we adjust the welfare function by multiplying Π by λ. This captures the idea that under a social planner's allocation, the government directly controls prices and will tax/subsidize firms to achieve a zero-profit condition. Detailed derivations of each component of the welfare function can be found in the appendix.

IV. Model Estimates

A. Demand Parameters

Table 2 reports demand estimates. Columns 1–5 report estimates for regular enrollees from the random-coefficient logit model with a lognormally distributed price coefficient; column 6 reports demand estimates from a Berry (1994) logit model for LIS enrollees.[13] All models are estimated using instrumental variables to account for the possibility that there is an unobserved quality aspect of plans in the error term that is correlated with premiums but that we fail to capture with the observed characteristics. We instrument for plan premiums and assume that other characteristics of the contracts are exogenous in the short run. We motivate this by observing that, while bids for a given plan vary substantially over time, insurers offer a rather stable portfolio of contract types over time (Polyakova 2016). We use Berry, Levinsohn, and Pakes (1995)–style instruments that measure the number of insurance contracts offered by the same insurer in a different market, as well as Hausman-style instruments that measure prices **q9**

[13] We do not estimate random coefficients for the LIS enrollees, as the relevant product characteristics are set to zero for this population.

charged for the similar plans in other geographic markets.[14] These instruments are particularly appealing in our setting because of the regulatory structure of the market, where markets are separated by the CMS. Instrumenting the price in one region with the prices of the same contract in other regions allows us to isolate the variation in prices that is common across these contracts (e.g., because of insurer's price negotiations with pharmaceutical producers) but is not correlated with market-specific unobserved quality (e.g., due to local marketing), over and above average quality captured by insurer fixed effects. The first stage is jointly statistically significant, with an F-statistic of 245 for the market with regular consumers and 23 for the LIS market.

We find intuitive patterns for the price coefficients, with riskier types and LIS consumers having generally lower price sensitivity than other consumers. We do not find evidence of statistically significant dispersion in the price coefficient, which is reasonable, given that we are estimating demand within groups of consumers with similar expected costs and health risks, both likely drivers of price sensitivity. Modal aggregate elasticities of demand by consumer risk group are -12.9, -8.9, -5.5, -5.26, and -5.9, in order of increasing health risk. These are economically reasonable estimates and are similar to the range of elasticities (aggregated across risk types) reported in Lucarelli, Prince, and Simon (2012; -2.0 to -6.0) and Starc and Town (2015; -5.0 to -6.3).

Nonpremium-plan characteristics are estimated to have coefficients with intuitive signs. Consumers dislike higher plan deductibles—more so if they have lower health risk—but enjoy measures of plan generosity: coverage in the gap, broader coverage of common drugs, and more in-network pharmacies all give higher utility. We also note an economically and statistically significant positive coefficient on the vintage of plans, suggesting that plans that entered earlier in the program were able to capture a larger beneficiary pool. We find some evidence of significant dispersion in preferences (among some risk types) for two other variables for which we allow random coefficients: the inner option and the dummy for gap coverage.

To assess whether the estimated willingness to pay is reasonable, consider the following calculation. A typical plan with a nonzero deductible has a deductible that varies from \$265 to \$310. At the average of \$290, removing the deductible has a dollar value of $-\$290 \times (-10.6/23.5) = \$130$ at the median value of the premium coefficient for risk group 1. For risk group 5, the same computation suggests that this group values removing

[14] Specifically, we construct the instrument by including the lagged enrollment-weighted average of prices of plans offered in other regions in the same macro region and in the other macro regions by the same company, where macro regions are defined as three large geographic areas in the United States.

TABLE 2
RESULTS: DEMAND AND MARGINAL COST

	Beneficiaries Not Eligible For LIS					
	Risk Type 1 (1)	Risk Type 2 (2)	Risk Type 3 (3)	Risk Type 4 (4)	Risk Type 5 (5)	LIS (6)
	A. Parameters of the Utility Function					
Premium ($000s):						
Mean	3.16	3.25	2.46	2.56	2.56	−7.93
	(.35)	(.61)	(.33)	(.38)	(.39)	(.56)
Standard deviation	.24	.50	.11	.33	−.07	. . .
	(.50)	(.39)	(.62)	(.67)	(.72)	. . .
Standard deviation, inner option	.67	6.92	−.20	.37	.83	. . .
	(.55)	(.73)	(.35)	(.48)	(.33)	. . .
Annual deductible ($000s)	−10.61	−11.36	−8.00	−7.97	−7.92	. . .
	(2.29)	(1.61)	(1.27)	(1.56)	(1.48)	. . .
Indicator for having any coverage in the gap:						
Mean	3.83	3.75	1.82	3.38	4.62	. . .
	(2.08)	(1.32)	(1.12)	(.86)	(1.14)	. . .
Standard deviation	2.05	−.33	1.97	−.19	.87	. . .
	(.85)	(.98)	(.53)	(.65)	(.72)	. . .
No. of most common drugs covered	47.87	34.03	40.85	43.92	60.00	1.05
	(17.57)	(11.11)	(14.11)	(10.85)	(8.68)	(7.39)
Measure of pharmacy network breadth	.36	.35	.24	.31	.28	.10
	(.02)	(.03)	(.01)	(.10)	(.04)	(.07)
No. of years the plan is on the market	1.09	1.24	1.07	1.05	.92	.48
	(.19)	(.12)	(.10)	(.13)	(.12)	(.04)
F-statistic first stage across all risk types	245	245	245	245	245	23

	B. Marginal Cost Projection for Non-LIS Market				
Annual deductible ($000s)	−.19	−.23	−.29	−.42	−.52
	(.04)	(.05)	(.06)	(.09)	(.11)
No. of most common drugs covered	−.78	−.30	−.11	−2.11	−2.83
	(2.21)	(2.69)	(3.42)	(4.95)	(6.17)
Indicator for having any coverage in the gap	.30	.36	.46	.68	.83
	(.01)	(.01)	(.01)	(.02)	(.03)
Measure of pharmacy network breadth	−.098	−.14	−.18	−.28	−.34
	(.04)	(.05)	(.07)	(.10)	(.12)
No. of years the plan is on the market	.03	.04	.04	.06	.08
	(.00)	(.00)	(.00)	(.01)	(.01)
Mean dependent variable (inverted MC, $000s)	.67	.80	1.00	1.46	1.81
Standard deviation dependent variable	.16	.20	.25	.36	.44
R^2	.77	.76	.76	.76	.76
Observations	756	756	756	756	756

NOTE.—The table reports parameter estimates for demand models as described in sec. III.A (panel A). The parameters are reported separately for risk types 1–5 of regular consumers (cols. 1–5) and consumers eligible for LIS (col. 6). We report standard errors in parentheses. All models include, but do not report, a constant, fixed effects for parent organizations, year fixed effects, geographic market fixed effects, a dummy for an enhanced plan, the number of drugs on the plan's formulary, and the number of drugs placed in tiers 1–2 of the formulary. *F*-statistics are reported for the first-stage regressions of regular (col. 1) and LIS (col. 6) premiums on price instruments as described in sec. IV. Panel B reports the results of a hedonic regression of marginal costs (MC)—for plans not distorted by LIS random-assignment incentives—estimated via the inversion of the first-order conditions on plan characteristics in 2010. The regression includes the same plan characteristics as the demand model for regular consumers.

the deductible at $-\$290 \times (-7.92/12.9) = \$178$. These levels of willingness to pay for a zero deductible seem reasonable. Noting that consumers still, on average, pay Medicare's standard 25% coinsurance for the first \$290 in spending, the expected monetized value of going from \$290 to a zero deductible is $0.8 \times (\$290 - 0.25 \times \$290) = \$174$, which is almost exactly our willingness-to-pay estimate for consumers who are likely to spend through the deductible (i.e., those in risk group 5), and it is lower for consumers who are less likely to spend the whole amount (the deductible level lies roughly at the 20th percentile of the spending distribution; see Einav, Finkelstein, and Polyakova 2016).[15]

Column 6 of table 2 reports two-stage least squares estimates of the Berry logit model for the LIS market. To estimate LIS demand, we adjust premiums to reflect LIS-specific subsidies and remove cost-sharing rules, such as a deductible, that LIS consumers do not face. The estimated price coefficient, at -7.9, suggests that LIS demand is less sensitive to prices than all risk types of regular enrollees. This is intuitive, as prices are about \$400 lower per year for the LIS enrollees, when compared to regular premiums.

B. Marginal Cost Estimates

We address two challenges in constructing the marginal cost estimates. First, plans that are eligible and compete for random assignment of LIS beneficiaries have a nonlinear share function preventing us from using a standard approach of inverting the first-order condition for these "distorted" plans. Second, marginal costs are assumed to not be constant within a plan across enrollees—we allow for marginal costs to vary across five regular-consumer risk types and LIS consumers.

We start with the estimation of marginal costs for plans that we identify as systematically not competing for random assignment of LIS consumers.[16] This set of plans includes 756 out of 1,540 plans available in 2010,

[15] A similar calculation for coverage in the gap gives a valuation of $\$1{,}000 \times 4.62/12.9 = \$358$ for risk group 5 and $\$1{,}000 \times 3.83/23.5 = \$163$. Again, this is reasonable, given that consumers are not very likely to enter the gap. Further, even if offered, gap coverage will not cover 100% of expenditures, making the actual difference between having and not having coverage for the \$3,000 gap roughly 75% of the gap's amount. That is, if individuals spent through the whole gap, they would value the coverage at \$2,250. Assuming that consumers who enter the gap have uniform expenses across the gap, the mean gain in coverage is \$1,125. However, most consumers do not face these costs in the gap; Einav, Finkelstein, and Polyakova (2016) document that about 25% of consumers enter the gap. Assuming that those consumers entering the gap have uniformly distributed expenditures in the gap, the upper bound on the valuation of coverage is \$281. We estimate a value that is substantially above this amount for the riskiest consumers and substantially below for the lowest-risk consumers.

[16] We construct a group of such plans by selecting all contracts of those insurers that within a given market (year-region) were not eligible to enroll randomly assigned LIS

which is the year that our counterfactual analysis focuses on. For these plans, we assume that the pricing incentives are captured by the first-order condition of the profit function in equation (3) with respect to bid b. The first-order condition for prices can be inverted to recover the baseline marginal cost c_j for each plan j (Nevo 2001). Normalizing the marginal cost multipliers κ_t^R (which we estimate from claims data, as described in the appendix) so that the multiplier for risk group 1 of regular enrollees, κ_1^R, is equal to one, the inversion recovers the marginal cost for the least expensive risk group 1 enrollees. We then apply κ_t^R multipliers for risk groups 2–5, as well as the LIS consumers, to compute marginal costs for all enrollees.[17]

We next proceed to estimating the marginal costs for plans that we hypothesize distort their bids to compete for LIS random assignment, since we observe these plans' insurer-market pair qualifying for random assignment at least once in our data. We use a hedonic regression of marginal costs on plan characteristics of "nondistorted" plans and then apply this projection to the distorted plans to get a prediction of marginal costs. The hedonic regression for 756 nonmanipulating plans takes the following form (we estimate a separate regression for each consumer risk type t):

$$\mathrm{MC}_{jt} = X_{jt}\beta_t + \tau_{ft} + \delta_{mt} + \epsilon_{jt}, \qquad (6)$$

where X_{jt} includes the same nonpremium characteristics of plans that we had included in the utility function. We add the unobserved quality estimate for each plan as an additional explanatory variable in X. We condition the regression on firm (τ_{ft}) and market (δ_{mt}) fixed effects to account for inherent differences in marginal costs across insurers and geographic regions. Panel B of table 2 reports the coefficients for the hedonic regression. Intuitively, the most important determinants of marginal costs are estimated to be deductibles (a higher deductible is associated with a lower marginal cost) and coverage in the gap (plans that offer coverage in the gap have higher marginal costs). We use the estimates of how plan characteristics translate into marginal costs to predict marginal costs for all plans that we assume are "distorted" by LIS random assignment. This exercise hinges on the assumption that all plans have a similar "production function." In other words, we assume that the plans that manipulate the LIS threshold manipulate their bids but do not have different marginal costs **q10**

individuals into any of their plans. See Decarolis (2015) for a discussion of factors that are likely to drive plans to compete for low-income beneficiaries.

[17] As the multipliers do not vary by plan, we assume that, on average, consumer-type spending does not change across plans; i.e., we assume no moral hazard. While the literature has documented the presence of some moral hazard in this market (Einav, Finkelstein, and Schrimpf 2015), the (relatively small) estimated magnitudes are concentrated in the coverage in the gap benefit phase, which only few enrollees reach—hence, we would not expect them to affect the average across a large number of enrollees within enrollee types.

conditional on a set of nonprice characteristics. This appears reasonable, as the main source of costs in the insurance market is determined by individual health risk; therefore, it is conceivable to assume that plans with the same financial characteristics and formulary generosity will have similar marginal costs conditional on the same risk pool.

The resulting vector of marginal costs is centered at $663 for the lowest-risk enrollees and ranges from $337 to $1,193 across plans. The scaling for highest-risk regular enrollees (type 5) implies an average marginal cost for this risk group of $1,800, with a range across plans from $809 to $3,220. These estimates of economic marginal costs from the inversion of the first-order conditions appear plausible, given our estimates of plans' accounting costs from the claims data. Our computations suggest that the average PDP liability was $588 for regular consumers of risk type 1, $1,067 for average-risk category 3, $1,977 for risk category 5, and $1,363 for LIS beneficiaries.[18] Our estimates of economic marginal costs imply profit margins of 7% on average (standard deviation of 9%) for regular enrollees. These are fairly low margins, suggesting that the regular-enrollee market is reasonably competitive, which is consistent with the policy analysis of this market (Congressional Budget Office 2014).

C. *Measuring Government Spending*

In the remainder of the paper, we repeatedly calculate welfare, which requires several assumptions about the computation of government spending. There are two types of government expenditures that we compute. First, we compute premium subsidies. The baseline premium subsidy is set at circa 70% (with some minor annual variation) of the average (weighted) bid for basic coverage across all plans offered in the United States in a given year. The consumer premium is computed as the difference between a plan's bid, together with plan's add-on prices for any coverage enhancements, and the baseline subsidy. The baseline subsidy is not actually paid out to the plans. Instead, plans receive a payment that is the difference between their baseline bid, multiplied by the enrollee's risk score, and the consumer premium. As the risk score can be smaller than 1 for relatively healthy enrollees, plans receive subsidy payments that are much lower than 70% of the average (weighted) bid for less risky enrollees while receiving much higher subsidies for higher-risk enrollees. As detailed above and in the appendix, we construct proxies for risk scores from the information about chronic conditions and use the average risk score per consumer type to scale subsidies received by plans.

[18] We define plan liability from the claims data as follows: for each individual we take the difference between the total cost paid for drugs at the point of sale and subtract patient cost-sharing payments, LIS cost-sharing subsidies, and 85% of spending in the catastrophic part of the benefit, as the plan carries only 15% liability in the latter benefit phase.

The second type of government payment to Part D plans is reinsurance. This payment covers 80% of prescription costs for very high-spending beneficiaries. In 2010, beneficiaries had to spend more than $6,440, in total, on drugs for the reinsurance program to start paying out to plans. We compute average differences in reinsurance payments per risk type (most of the payments are concentrated in risk group 5) from observed claims data. We assume that this payment multiplier is fixed and does not change across counterfactuals. We apply these multipliers to plan-level reinsurance statistics reported by CMS.[19] We further compute average premium and reinsurance subsidies in the MA-PD program, as well as additional payments for low-income beneficiaries from the micro-level claims data. The MA-PD computation allows us to estimate the opportunity cost of government expenditures in the PDP program. In our data, most individuals who switch out of PDPs switch to MA-PD plans rather than to no coverage. Hence, in our counterfactuals, we assume that if individuals switch from the inside option of PDPs to the outside option, they switch to the MA-PD program rather than leave drug insurance altogether. Thus, the government is still likely to incur subsidy spending for these individuals through the MA-PD program. The details of these calculations are outlined in the appendix.

D. *Efficiency of the Observed Subsidy Mechanism*

Using demand and marginal cost estimates, we next compute consumer surplus, producer profits, government transfers, and total surplus for the observed market allocation and the observed subsidy mechanism. For expositional clarity, we report results for a single year (2010). The calculations are reported in columns 1 and 2 of table 3 for regular and LIS enrollees, respectively. **q11**

We estimate that the total annual consumer surplus generated by Part D PDPs for regular enrollees was $2.4 billion (row 1), or about $300 for each of 7.8 million enrollees (36% of the potential market size). The majority of enrollees, 59%, were of about average risk, in risk group 3; 6% were in the healthiest category, and only about 1% of enrollees fell into risk type 5. All enrollees paid, on average, $510 in premiums, while firms collected $1,129 in per capita revenue before risk adjustment. Accounting for risk adjustments, but not counting any ex post risk-corridor payments, we compute that insurer profits amounted to $536 million (row 2). The $3 billion of consumer and producer surplus came at a steep price—government expenditures on PDP subsidies (including premium subsidy, risk-adjustment payments, and reinsurance) totaled nearly $5.5 billion

[19] Reported in www.cms.gov/Medicare/Medicare-Advantage/Plan-Payment/Plan-Payment-Data.html.

TABLE 3
Results: Counterfactual Subsidy Mechanisms with Fixed Outside Option

	Observed Allocation		Remove Cross-Market Links		Change Market Power		Subsidies Proportional to Bids			Flat-Voucher Subsidies		
	Regular Enrollees (1)	LIS Enrollees (2)	No LIS Link (3)	No LIS, No MA-PD Link (4)	Independent Plans (5)	Monopoly Ownership (6)	5% of Bid (7)	32% of Bid (8)	95% of Bid (9)	$0 (10)	Optimal: $800 (11)	$1,500 (12)
1. Consumer surplus ($M)	2,298	2,642	2,678	3,028	3,080	2,443	11,032	3,613	974	950	2,955	10,742
2. Insurer profit ($M)	559	. . .	1,062	1,205	1,154	1,923	35,260	3,821	40	27	1,311	2,605
3. Consumer and producer surplus ($M)	2,857	2,642	3,739	4,233	4,235	4,367	46,293	7,434	1,014	977	4,266	13,347
4. Subsidy spending in PDPs ($M)	4,181	14,210	5,686	6,881	6,964	5,885	59,216	11,966	(35)	(56)	6,676	22,094
5. Reinsurance spending in PDPs ($M)	1,264	26,502	1,502	1,692	1,764	1,307	4,551	2,552	52	34	1,707	3,023
6. Total government spending ($M)	5,445	40,712	7,188	8,573	8,728	7,192	63,768	14,518	17	(22)	8,383	25,117
7. Counterfactual subsidy spending if enrolled in MA-PD plan ($M)	4,686	16,469	5,680	6,466	6,548	5,194	10,578	6,880	144	97	6,316	10,739
8. Counterfactual reinsurance spending if enrolled in MA-PD plan ($M)	1,209	17,496	1,455	1,649	1,669	1,339	2,636	1,744	39	26	1,612	2,674
9. Total opportunity cost of government spending ($M)	5,894	33,965	7,135	8,115	8,217	6,533	13,214	8623	183	123	7,927	13,413
10. Total surplus; not accounting for opportunity cost of government spending ($M)	(4,222)	(50,283)	(5,605)	(6,912)	(7,112)	(4,983)	(36,605)	(11,439)	992	1,005	(6,632)	(19,305)
11. Total surplus; accounting for opportunity cost of government spending ($M)	3,441	(6,129)	3,671	3,638	3,570	3,510	(19,426)	(229)	1,230	1,165	3,674	(1,868)

12. Return on nominal dollar of government spending, no DWL of tax ($)	(.48)	(.94)	(.48)	(.51)	(.51)	(.39)	(.27)	(.49)	59.13	(46.29)	(.49)	(.47)
13. Return on nominal dollar of government spending, with DWL of tax ($)	(.60)	(.95)	(.60)	(.62)	(.63)	(.53)	(.44)	(.61)	45.26	(35.84)	(.61)	(.59)
14. Opportunity-cost-adjusted return on dollar of government spending ($)	.63	(.15)	.51	.42	.41	.49	(.30)	(.02)	72.93	(54.00)	0,44	(.07)
15. Characteristics of the allocation												
16. Inside-option enrollment (000s)	7,798	7,700	9,745	11,284	11,425	8,955	19,879	11,856	248	182	10,985	20,450
17. Inside-option enrollment (% of total market)	36	79	45	52	53	42	92	55	1	1	51	95
Share of inside-option enrollment (%):												
18. Risk group 1	6	. . .	6	7	7	7	7	6	0	0	7	7
19. Risk group 2	17	. . .	18	18	17	19	21	15	67	72	18	23
20. Risk group 3	59	. . .	60	61	61	58	62	64	2	1	61	60
21. Risk group 4	16	. . .	14	13	13	15	10	13	31	27	14	9
22. Risk group 5	1	. . .	1	1	1	1	1	1	0	0	1	1
23. Average weighted premium ($)	510	25	474	438	441	450	201	603	1.448	1.531	444	78
24. Average weighted bid ($)	1,129	1,051	1,170	1,174	1,175	1,254	4,011	1,885	1,524	1,531	1,244	1,473

Note.—The table reports the levels of consumer surplus, producer surplus, government spending, and total welfare under the observed allocation (cols. 1 and 2) and under counterfactual allocations with a fixed outside option (cols. 3–12). We compute these objects using estimates of demand and marginal costs (for cols. 1 and 2) as well as simulations of counterfactual equilibria (cols. 3–12). All quantities are computed as discussed in sec. III and app. E. These baseline results assume that the cost of public funds (λ) is equal to 1.3. Negative quantities are reported in parentheses. $M = millions of dollars; DWL = deadweight loss.

(row 7). Taken at face value, the program thus generated negative surplus, with a return of −46 cents on a dollar spent in subsidies (row 13).

To interpret this computation, however, it is important to take into account the opportunity cost of government funds. The outside option in our model includes either purchasing an MA-PD plan or not purchasing any creditable Part D coverage. If all consumers who were to leave PDPs enrolled in MA-PD plans, the government would incur a very similar level of expenditures on these consumers. In rows 8–10, we compute that the government would have spent $5.9 billion if PDP consumers enrolled in MA-PD plans.[20] The difference between rows 7 and 10, which amounts to $450 million, is the extra government spending on pharmaceutical coverage generated by the PDP program. This extra spending, along with our assumption that the deadweight loss of government taxation is 30 cents on the dollar, gives us a social cost of government spending on PDPs of $585 million.[21]

Putting it all together, we estimate that the total surplus generated by the regular Part D PDP market, when the opportunity cost of government funds is accounted for, was about $3.5 billion. In other words, the government generates an extra 65 cents of surplus for each dollar it spends in the PDP program. This positive return on a dollar is one of our primary findings, along with the corollary that the vast majority of this surplus comes from forgone government expenditures. The latter generalizes to many publicly funded settings, where the return on public spending in each program is hard to evaluate in vacuum, as there are almost always substitute programs where the government still incurs expenditures on the same individuals. Without taking into account “competing” programs and the opportunity cost of government funds, one may significantly underestimate the surplus generated by each publicly funded program.

Column 2 of table 3 reports a similar calculation for the LIS market. Consumers in this market enjoyed $2.6 billion in surplus. We do not report the profits associated with this part of the market, as the static Bertrand-Nash model of competition used to recover marginal costs in the regular market does not apply to firms engaged in dynamic competition for LIS enrollees. Computing government subsidies and government opportunity cost for LIS enrollees requires some additional accounting to

[20] This estimate of alternative government spending includes only the subsidies for pharmaceutical coverage in MA-PD plans. The literature on Medicare Advantage has further estimated that there are differences in per capita public spending on medical insurance between enrollees in traditional fee-for-service Medicare and those in Medicare Advantage. We do not take into account this difference, as we do not have the data to compute risk-type-specific differences between traditional Medicare and Medicare Advantage. Since the literature estimates that Medicare Advantage leads to higher government spending (Curto et al. 2014 estimate that the difference was about 3% in 2010 and 11%, on average, in the years 2006–10), our computation is a lower bound of the surplus in the PDP program.

[21] We examine the sensitivity of our results to the value of λ in the appendix.

incorporate LIS-specific payments to insurers that cover the generous reductions in cost sharing that LIS beneficiaries enjoy. We add LIS premium subsidies to the row that counts government premium subsidies in PDPs. For the nonpremium subsidies, we add the per-plan average payments for LIS cost sharing that we compute from the claims data. These generate significant quantitative changes to subsidy levels as compared to regular beneficiaries—we compute the per capita government spending on LIS enrollees in 2010 to be \$5,287, as compared to \$698 for regular enrollees. We do similar accounting adjustments on the MA-PD side, so as to make the opportunity-cost calculation comparable to the calculation of PDP subsidies. After these adjustments and under insurer profits set to zero, total welfare is computed at negative \$6.1 billion. This is driven by two factors. First, LIS beneficiaries face much lower prices—on average \$485 lower annual premiums than regular enrollees—this difference is paid from public funds. Second, given our computation on the level of subsidization of LIS enrollees in both PDP and MA-PD programs, the latter appears modestly less expensive. Hence, the net government spending component of the welfare function for LIS enrollees is negative. The bottom line is that the government spends an enormous amount of money on LIS enrollees in PDPs, where willingness to pay is low and the opportunity cost of government spending is negative.

V. Counterfactual Subsidy Mechanisms

We are interested in understanding how insurer incentives and consumer demand interact with the subsidy mechanism to determine market outcomes. We initially consider a set of counterfactual subsidization mechanisms where the outside option (MA-PD plans) is held constant while we adjust the subsidy mechanism in the PDP market. This conceptual exercise allows us to cleanly illustrate and tease apart the complex economic forces at work. We then turn to a set of counterfactuals where we adjust the outside option to reflect equilibrium changes in the PDP market. The idea is that any changes to subsidies in the PDP market are likely to be mirrored in the MA-PD market—the counterfactuals with adjusted outside option allow us to simulate such parallel changes.

In both settings, we consider two distinct types of subsidy mechanisms. The observed mechanism sets subsidies as a function of the bids submitted by insurers. With a sufficiently competitive product market, the appeal of this approach is that subsidies are linked to the costs of providing the good. This has the advantage of protecting consumers from the risk of cost increases as well as giving policy makers a practical starting point for determining subsidy levels. The downside of such an approach is that strategic firms can internalize the fact that the subsidy is more generous when bids are higher, leading to higher profits at the expense of taxpayers.

To evaluate this approach to subsidy determination, we consider several local alterations of the existing mechanism. We start by investigating the equilibrium effects of cross-market ties—under the observed mechanism, the subsidy in the PDP market depends on insurer bids in the MA-PD and LIS markets; we remove these ties in our counterfactual simulations. We then investigate the role of market power for such bid-based subsidy determination by simulating the allocations under the two extremes where every plan is a firm and where all plans are owned by one firm. Finally, we consider what happens if bid-based proportional subsidies are tied directly to firm bids rather than to a weighted average of such bids as in the observed mechanism.

We then proceed to consider an entirely different type of subsidy—a flat voucher that is not linked to any contemporaneous insurer behavior. Conceptually, this type of subsidy can generate high-powered incentives to lower prices when markets are sufficiently competitive. At the same time, it imposes a greater informational requirement on the government to arrive at a subsidy level and places the incidence of program cost risks onto consumers. Multiple proposals for reforms in Medicare and other publicly subsidized programs envision flat subsidies; hence, evaluating the benefits and drawbacks of such high-powered mechanisms is particularly relevant for understanding the proposed policy making in and outside of Medicare.

Our intent across all counterfactuals is to both understand the specific welfare consequences of different mechanisms in PDPs, which are of independent interest, given their popularity and the large amount of government expenditures flowing through them, and draw out more general **q12** lessons about why different mechanisms generated more or less surplus that may be useful in guiding subsidy mechanism design in more general contexts.

A. *Results with Outside Option Held Fixed*

Table 3 shows the results when the outside option is held fixed. We start with two counterfactuals that remove cross-market links across PDP, MA-PD, and LIS markets in columns 3 and 4. Removing LIS market incentives from the regular market leads to an increase in bids and the generosity of the subsidy relative to the observed allocation. In this counterfactual, the firms have no incentive to compete to be below the average premium in order to be eligible for randomly assigned LIS enrollees. The resulting PDP enrollment of regular enrollees is higher than that under the observed allocation, as is the government spending on both premium and reinsurance subsidies (by $1,743 million). The total surplus that accounts for the opportunity cost of government funds increases ($230 million), despite the fact that additional government spending exceeds the increase in consumer surplus ($380 million) and producer profit ($503 million); the positive difference in total surplus is driven entirely by the slower change in the forgone government spending in the MA-PD program ($1,241 million). Rows 18–22 highlight the role of risk selection in the market. Higher subsidies lead to a very slight increase in the share of enrollment from lower-risk consumers; the direction of this effect is intuitive, and the small magnitude of changes is consistent with the previous literature that has found limited risk screening on prices in this market (Polyakova 2016). Column 4 reports the outcomes when the average bid in the formula for determining the subsidy in the regular market no longer includes MA-PD plans (which tend to have lower bids than PDPs). In this case, the baseline subsidy is set as 68% of the average Part D PDP bid. Given higher PDP bids, this change leads to another increase in the subsidy relative to column 3. As a result, consumer surplus and profits increase again; this increase, however, is offset by the growth in opportunity-cost-adjusted government spending, which leads to a slightly lower total surplus. The results in column 4 give us a benchmark (simulated within the model) for the analysis of alternative subsidy mechanisms for the regular market.

These results illustrate several general economic forces at play in this market. First, with a highly subsidized substitute available (i.e., switching to MA-PD plans that offer both medical and pharmaceutical coverage), consumers' baseline willingness to pay for plans in the PDP market is very low. Column 10 reports results when the premium subsidy is set to zero; PDP enrollment drops to near zero as consumers leave the PDP market.[22]

Second, increasing the generosity of the subsidy bolsters total consumer welfare, but it does so by giving costly transfers to inframarginal consumers (and changing relative prices within the PDP market, which can lead to further allocative distortions) while also attracting marginal consumers with decreasing valuations for the product. This is reflected in consumer surplus per enrollee: under the observed mechanism it is $441; without LIS enrollees this number drops to $377, and without links to the MA-PD market it declines further, to $322.

Third, the sign of welfare outcomes is largely driven by the opportunity cost of government spending. Government expenditures in PDPs per enrollee increase from $698 under the observed allocation to $738 and $760 across the two counterfactuals. Even with producer profits included, these costs substantially exceed the benefits that they generate within the PDP market. Only when the opportunity cost of spending in the MA-PD market is accounted for does the overall welfare of the PDP market become positive.

[22] The idea of low willingness to pay for health insurance coverage in the presence of even more distant substitutes—such as charity care—has been documented in other settings. For example, Finkelstein, Hendren, and Shepard (2017) find low willingness to pay for health insurance among low-income adults in Massachusetts.

Fourth, the government's difficult balancing act on the consumer side of the market—setting premium subsidies to induce the optimal level of sorting across the inside and outside options and across plans within the inside option—is further complicated by possible strategic behavior by insurers. To help assess the degree of market power and strategic markups in this market, columns 5 and 6 report results for two extreme counterfactuals on the supply side: one where all plans are independent firms and one where all plans are owned by a single monopolist. In both cases we let the subsidy rule follow the same mechanism as in column 4. There is a substantial degree of market power possible in this market: the average enrollment-weighted bid under the monopolist is more than $79 higher than that with atomistic firms, an increase of just under 7%. This leads to higher profits and lower consumer surplus. Interestingly, total welfare is nominally lower both under the atomistic firms counterfactual and under a monopolist than in the reference (col. 4). Atomistic plans attract slightly too many consumers to the market, given how much it costs the government to service them, while the monopolist has too few.

The results suggest that, without links to the LIS and MA-PD markets, the current ownership configuration delivers outcomes fairly close to that of a purely competitive ownership structure. This is an interesting result, as one of the motivating reasons for using managed competition to deliver publicly subsidized goods and services was to leverage competition to reduce prices. Our conclusion on this point requires caution, however, as we cannot assess the counterfactual of possible alternatives, such as a standard government-run program or a regulated monopolist, as we do not know anything about the comparative costs of delivering similar insurance plans in such scenarios, and therefore we cannot make any claims about additional efficiencies introduced by competition. Also, while we take the marginal costs of firms as given here, it is possible that a single buyer would be able to exert monopsony power in negotiating with upstream pharmaceutical companies. The combination of the two effects is ambiguous, and we limit our conclusion to the observation that the current ownership structure gives results similar to that if all plans were independent firms.

Fifth, subsidy design matters. We have already shown that linking the level of the subsidy to other markets can have large effects on market outcomes, and we now show that how insurer bids are translated to consumer premiums can have an even more dramatic effect. We solve equilibrium outcomes under two different approaches: a proportional subsidy and a flat subsidy (i.e., a voucher). Columns 7–9 of table 3 show the outcomes for proportional subsidies where consumers pay 5%, 32%, or 95% of the bid submitted by insurers. This subsidy mechanism produces extreme outcomes, primarily because of the exercise of market power by insurers. In the two cases where consumer are largely shielded from bids, insurers increase bids dramatically. The government is left to cover the large gap between the bid and the consumer-facing premium. In the case where consumers pay 5% of the bid, enrollment is nearly universal and government expenditures are nearly a staggering $3,200 per enrollee. Of the increase of $55 billion in government expenditures, firms capture $34 billion, or 62%. Only when the consumers pay 95% of the bid does the mechanism produce positive welfare numbers, although ones far below those from the current mechanism. Notably, the extreme counterfactuals where consumers face almost the full cost of coverage—those in columns 9 and 10—are the only ones that result in positive nominal surplus without accounting for the opportunity cost of government spending. In these counterfactuals, the government spends far less than it generates in consumer and producer valuation, as only consumers with the highest willingness to pay stay in the program.

Inspecting the formula for determining the consumer-facing premium subsidy in equation (4) reveals that the existing mechanism is similar to a lump-sum voucher from a consumer's perspective; there is essentially a fixed payment that is applied to each plan in the marketplace. To assess this intuition empirically, we solve for outcomes with vouchers running from $0 to $1,500 in $100 increments. Columns 10–12 show the outcomes of vouchers with the extremes of $0 and $1,500, along with the voucher that generated the highest amount of surplus ($800). Figure 1 illustrates our estimates of total welfare across the range of vouchers considered.[23] Total surplus under the fixed outside option (marked with a solid line) is positive until $1,300, peaking at $800 at a level of welfare that is slightly higher, although comparable, to that for the existing mechanism. In general, vouchers perform much better than proportional subsidies, largely because they preserve the elasticity of demand on the margin while still allowing the policy maker to influence sorting between PDPs and MA-PD plans. In turn, this leads firms to keep their bids reasonably competitive, minimizing the amount of costly transfers from taxpayers to firms. This is exemplified by the average weighted bid actually being lower at the $800 voucher than at the extremes. We note that the most generous proportional and voucher counterfactuals have very similar enrollments but are achieved at vastly different levels of social cost—proportional subsidies lead to average bids of nearly $4,000 and create an order-of-magnitude-higher social loss.

[23] We note that our model allows for "soft" exit of plans under very low subsidies. We constrain insurers to make weakly positive profits: when subsidies are very low, as in the case of a $0 voucher, insurers may find it profitable to set very high premiums for some of their plans to induce zero enrollment. This is akin to plans exiting the market in an environment where fixed costs accrue primarily at the insurer rather than at the individual plan level.

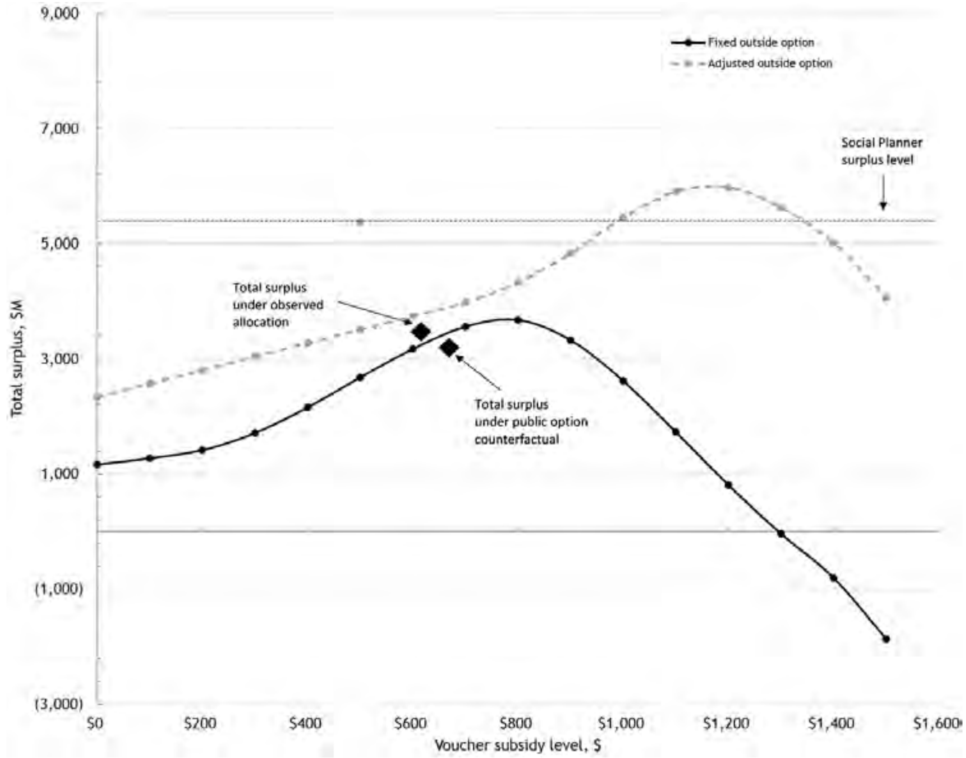

FIG. 1.—Welfare under counterfactual subsidy policies: estimated total welfare (including the accounting for the opportunity cost of government spending) in counterfactuals with flat-voucher subsidies ranging from $0 to $1,500 in $100 increments. The solid line marks the welfare estimates in counterfactuals with a fixed outside option (row 11, cols. 10–12, in table 3). The thick dashed line plots welfare levels for counterfactuals with vouchers when the subsidy in the outside option (MA-PD plans) is adjusted to be the same voucher (row 12, cols. 5–7, of table 5). We also mark the total surplus (at the average subsidy level) for the observed allocation and the public option with subsidy counterfactual, as well as the social planner's surplus level (row 11, col. 1, in table 3; row 12, col. 2, in table 4; and row 2, col. 1, in table 4, respectively).

To put our normative findings into perspective, we perform three benchmark computations of the social optimum in this market. We start by computing the social planner's allocation. We assume that the social planner knows consumer demands and marginal costs (both by type) and can directly set prices but cannot force consumers to purchase certain insurance plans and instead must incentivize their choices through plan prices. The detailed results are reported in column 1 of table 4, while figure 1 shows the level of welfare achieved by the social planner in comparison to market mechanisms. We find the social planner's solution by solving for a set of plan-specific prices in equation (5). The social planner increases welfare to $5.4 billion and sets prices that result in large losses for insurers. To illustrate, figure 2 plots the resulting changes in premiums compared to the observed mechanism, along with changes **q13**

TABLE 4
RESULTS: ALLOCATIONS AND WELFARE UNDER NONMARKET MECHANISMS

		Public Option	
	Social Planner (1)	With Subsidy (2)	Without Subsidy (3)
1. Consumer surplus ($M)	3,258	3,005	970
2. Insurer profit ($M)	(7,088)	. . .	. . .
3. Consumer and producer surplus ($M)	(3,830)	3,005	970
4. Subsidy spending in PDPs ($M)	. . .	6,860	. . .
5. Reinsurance spending in PDPs ($M)	. . .	. . .	. . .
6. Additional subsidy spending in MA-PD plans ($M)	. . .	. . .	. . .
7. Total government spending ($M)	. . .	6,860	. . .
8. Counterfactual subsidy spending if enrolled in MA-PD plan ($M)	6,943	5,599	154
9. Counterfactual reinsurance spending if enrolled in MA-PD plan ($M)	1,770	1,433	41
10. Total opportunity cost of government spending ($M)	8,713	7,032	195
11. Total surplus; not accounting for opportunity cost of government spending ($M)	(3,830)	(5,912)	970
12. Total surplus; accounting for opportunity cost of government spending ($M)	5,371	3,229	1,223
13. Return on nominal dollar of government spending, no DWL of tax ($)	. . .	(.56)	. . .
14. Return on nominal dollar of government spending, with DWL of tax ($)	. . .	(.66)	. . .
15. Opportunity-cost-adjusted return on dollar of government spending ($)	. . .	.47	. . .
16. Characteristics of the allocation			
17. Inside-option enrollment (000s)	12,374	10,237	322
18. Inside-option enrollment (% of total market)	57	47	1
Share of inside-option enrollment (%):			
19. Risk group 1 consumers	7	9	1
20. Risk group 2 consumers	18	19	71
21. Risk group 3 consumers	61	59	10
22. Risk group 4 consumers	13	12	19
23. Risk group 5 consumers	1	1	0
24. Average weighted premium ($)	374	87	728
25. Average weighted bid ($)	374	758	728

NOTE.—The table reports the level of consumer surplus, producer surplus, government spending, and total welfare under counterfactual allocations without market mechanisms. The nonmarket mechanisms are defined in sec. V.A. To compute these objects, we use estimates of demand, marginal costs, and the derivation of the social planner's problem in app. E. All quantities are computed as discussed in sec. III and app. E. These baseline results assume that the cost of public funds (λ) is equal to 1.3. Negative quantities are reported in parentheses. $M = millions of dollars; DWL = deadweight loss.

in market shares by the highest and lowest risk types, in the California market. Plans are ordered from left to right by increasing marginal cost. There are two broad takeaways: first, the social planner adjusts prices to obtain a general shift in market shares to favor less costly plans. The majority of plans losing market share are the most expensive, while the single biggest increase in share occurs at a low-priced plan. The second

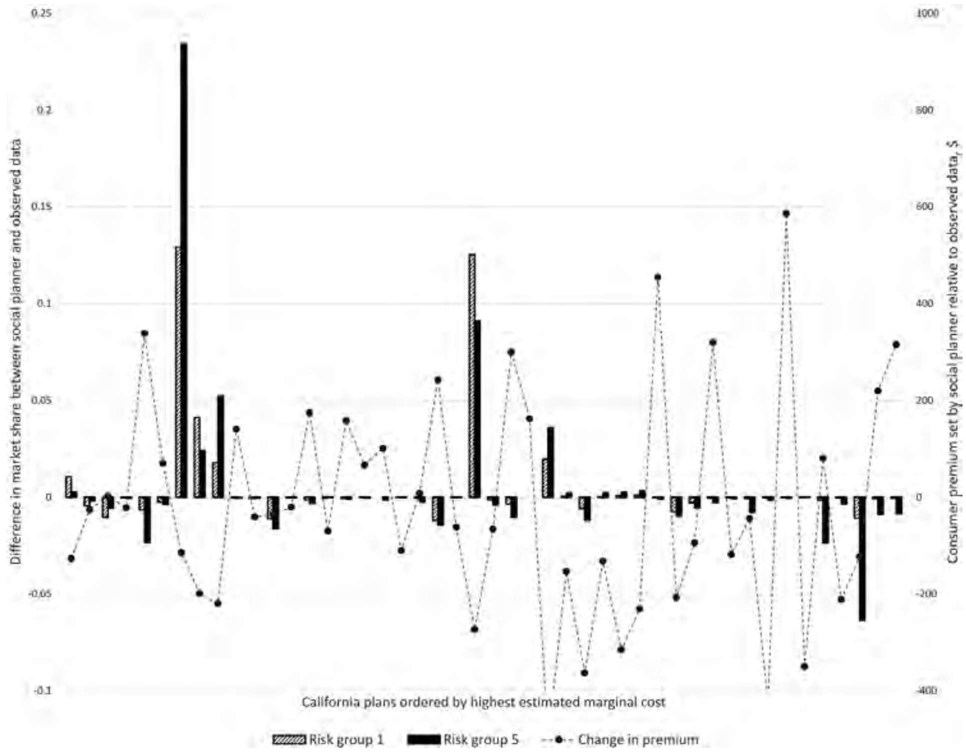

Fig. 2.—Social planner's solution: changes in premiums and market shares: example of the social planner's allocation in one Part D market: California in 2010. The *x*-axis orders 47 PDPs that were available in California in 2010 by increasing—from left to right—estimated marginal cost. On the left-hand-side *y*-axis, we plot the change in the market share of each plan that the social planner induces, relative to the observed allocation. The changes are plotted as bars. Positive changes imply that the social planner allocates a plan a higher market share, while negative bar values imply a lower market share for the plan, relative to the plan's observed market share. We report the changes in market shares separately for the lowest-risk (risk group 1) and the highest-risk (risk group 5) regular consumers. The right-hand-side *y*-axis and the corresponding dashed line plot the changes in premiums for each plan between the premium set by the social planner relative to the observed premium. A positive value of the premium difference for a plan implies that the social planner's solution would increase the premium for this plan.

takeaway is that there are substantial differences in where consumers of different risk types move, with the largest difference being that the social planner puts more of the most expensive consumers into cheaper plans. The social planner's solution illustrates that consumers are systematically choosing plans that are too socially expensive and are doing so differentially by risk type, which leads to inefficient sorting.

We also consider an alternative scenario that captures some of the intuition of the social planner while retaining simplicity. In a counterfactual that simulates the idea of a very generous public option (which can be thought of as, e.g., letting Medicaid administer pharmaceutical coverage), we replace all plans in each market with the characteristics of the plan with the lowest estimated marginal cost.[24] We assign the reinsurance subsidies that the government pays under the existing mechanism to the marginal cost of that plan. The government then pays the same average premium subsidy as under the observed allocation ($676), while setting prices such that the firm makes zero profit. The results are reported in column 2 of table 4. In this simulation of public option coverage, we find that overall surplus is lower than that under the social planner, at $3.2 billion. Consumer surplus, however, is almost as high as that under the social planner, at $3 billion, while producer profit is set to zero by design. This counterfactual manages to achieve a close-to-optimal sorting of consumers between MA-PD plans and PDPs; the total surplus it generates is comparable to the levels of surplus under the optimal voucher and the observed mechanism. This counterfactual is particularly appealing, given its simplicity in theory; in practice, it of course depends on the ability of the government to offer a public plan at the cost of the cheapest private plan observed in this competitive environment. One way in which this kind of semipublic option could arise would be through an auction mechanism, where only one—most efficient—private plan is allowed to serve a geographic market for a given year. The results in column 3 emphasize that the surplus in this environment is still generated by the opportunity cost of government funds, as consumers do not have sufficient willingness to pay even for the least costly plans. In column 3, we simulate a related counterfactual where the government offers a low-cost public option that is, however, not subsidized. This would be closer to traditional Medicare (rather than Medicaid) expanding pharmaceutical coverage and charging the cost of coverage to consumers. In this case, we see similar patterns as in competitive counterfactuals with no subsidies—enrollment drops almost to zero, and only consumers with high enough valuation of coverage enroll in the program, generating positive nominal surplus. q14

We find that most of the mechanisms are very similar in the composition of risk types for enrollees in the inside option. To the extent that risk sorting changes in more extreme counterfactuals, it follows intuitive patterns consistent with the presence of adverse selection in this market. Figure 3 illustrates how the share of high-risk consumers (types 4 and 5) changes in the inside option as voucher-based subsidies get more generous. As vouchers increase, leading to lower prices, the share of high-risk

[24] We keep the number of plans fixed to equalize the role of the idiosyncratic error term in the logit model when comparing outcomes across counterfactuals. For some lowest-cost plans we do not observe positive enrollment for all risk types, which leads to a missing estimate of the plan-risk-type-specific fixed effect ξ. To proceed with the public option counterfactuals, we had to impute the missing ξ estimates. We proceeded by taking the ξ estimates for a given plan for other risk groups; scaling is by the ratio of average differences in ξ's across risk types among all plans for which we were able to estimate ξ's.

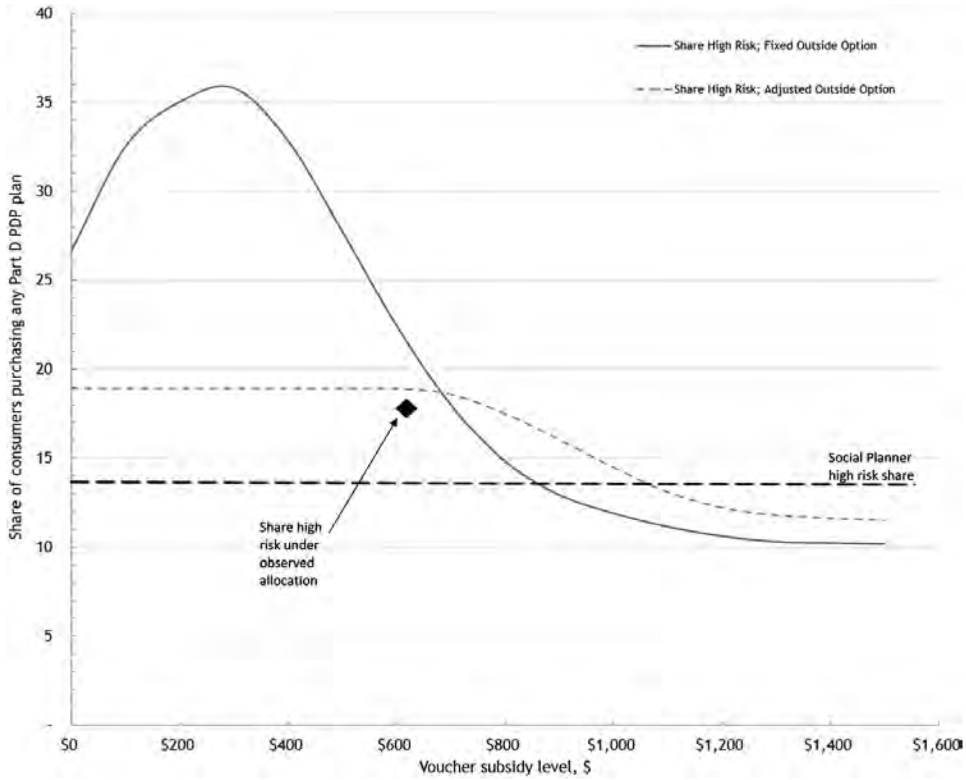

Fig. 3.—Risk sorting under counterfactual subsidy policies: share of high-risk consumers (risk types 4 and 5) among regular consumers who are buying the inside option—a PDP—in counterfactuals with flat voucher subsidies ranging from $0 to $1,500 in $100 increments. The solid line marks the share of high-risk consumers in counterfactuals where the outside option is held fixed. The short-dashed line marks the share of high-risk consumers in counterfactuals that adjust the outside option to have the same level of voucher subsidy as in the inside option. The longer-dashed line demarcates the share of high-risk consumers in the PDP market as simulated under the social planner's allocation. The plotted quantities are also reported in rows 21 and 22, cols. 10–12, of table 3 (for the fixed outside option); rows 22 and 23, cols. 5–7, in table 5 (for the adjusted outside option); and rows 22 and 23, col. 1, in table 4 (for the social planner).

consumers falls as lower-risk consumers start entering the market. This gradient is relatively shallow at very high subsidy levels, suggesting that after a certain threshold, prices are not the first-order drivers of selection. For example, moving from an $800 voucher in column 11 to a $1,500 voucher in column 12 leads to a dramatic change in prices, from $444 to $78—this is associated with the share of inside-option enrollment from risk groups 1 and 2 increasing only from 25% to 30% and the high-risk consumer share decreasing from 15% to 10%. Notably, figure 3 highlights that the optimal voucher of $800 achieves the same share of high-risk consumers among inside-option enrollment as under the social planner. This optimal share of high-risk consumers is about 5 percentage points lower than the observed share, suggesting that too few low-risk consumers are purchasing PDP insurance (a common result in markets with adverse selection).

With the usual caution that our findings are specific to our settings, there are several general themes that can be distilled from our results and may apply to other instances of regulated and subsidized competition. We find that the best mechanisms share three qualities: they preserve the marginal relationship between the prices that the firm sets and the prices that consumers face, they limit how fast the subsidy grows as a function of firm prices, and they link the consumer-facing price to (social) marginal cost. Keeping consumer-facing prices related one-to-one to firms' prices at the margin increases the elasticity of demand and leads to lower prices in equilibrium. Slowing down how fast the subsidy grows relative to the prices that firms set also helps limit firms from exerting market power to increase prices. Finally, as illustrated by the social planner's solution, keeping consumer prices related to marginal cost prevents allocative inefficiency along both the extensive and intensive margins.

The existing Part D mechanism reflects these three qualities in several dimensions. First, linking the equilibrium subsidy with both the LIS and MA-PD markets helps keep the subsidy low. Second, the form of the subsidy, as a percentage of enrollment-weighted average of last year's plans average bid, both limits strategic pricing by insurers and preserves the marginal relationship between bids and consumer prices by acting like a voucher. Third, the size of the subsidy is not so large that all consumer-facing premiums are zero, which in turn helps preserve the link between marginal cost and prices.

B. Results with Adjusted Outside Option

We next examine how the results of the main counterfactual simulations change when the outside option (i.e., MA-PD plans) is adjusted to reflect changes in the generosity of subsidies in Part D PDPs. For each counterfactual, we adjust the subsidy in the outside option by the average value of the change in PDP subsidy. Importantly, this remains a partial equilibrium analysis, as we do not consider possible general equilibrium changes in MA-PD plan prices, in prices of other pharmaceutical insurance options, or in drug prices.[25] We intend for this adjustment to capture the idea that when a government reforms one publicly subsidized program, it is likely to implement similar reforms in related programs. In the case of Medicare Part D, PDPs and MA-PD plans are obviously closely related

[25] In practice, this is implemented by adjusting the utility of choosing the inside option. We discuss the details of the adjustment calculation in the appendix.

TABLE 5

Results: Counterfactual Subsidy Mechanisms with Adjusted Outside Option

	Remove Cross-Market Links		Change Market Power		Flat-Voucher Subsidies		
	No LIS Link (1)	No LIS, No MA-PD Link (2)	Independent Plans (3)	Monopoly Ownership (4)	$0 (5)	Optimal Voucher: $1,200 (6)	$1,500 (7)
1. Consumer surplus ($M)	3,504	4,189	4,227	4,410	(12,460)	9,577	11,327
2. Insurer profit ($M)	873	914	881	1,220	832	1,992	2,173
3. Consumer and producer surplus ($M)	4,378	5,103	5,108	5,630	(11,628)	11,569	13,500
4. Subsidy spending in PDPs ($M)	4,725	5,269	5,366	4,266	(920)	15,596	19,707
5. Reinsurance spending in PDPs ($M)	1,252	1,306	1,368	957	1,152	2,335	2,831
6. Additional subsidy spending in MA-PD plans ($M)	442	802	789	1,415	(10,344)	943	674
7. Total government spending ($M)	6,419	7,377	7,522	6,638	(10,112)	18,874	23,212
8. Counterfactual subsidy spending if enrolled in MA-PD plan ($M)	5,075	5,545	5,649	4,363	(448)	12,297	13,493
9. Counterfactual reinsurance spending if enrolled in MA-PD plan ($M)	1,203	1,257	1,280	962	1,075	2,274	2,456
10. Total opportunity cost of government spending ($M)	6,278	6,802	6,929	5,325	627	14,571	15,949
11. Total surplus; not accounting for opportunity cost of government spending ($M)	(3,967)	(4,487)	(4,671)	(3,000)	1,517	(12,967)	(16,675)
12. Total surplus; accounting for opportunity cost of government spending ($M)	4,194	4,356	4,337	3,922	2,332	5,975	4,058

13. Return on nominal dollar of government spending, no DWL of tax ($)	(.32)	(.31)	(.32)	(.15)	.15	(.39)	(.42)
14. Return on nominal dollar of government spending, with DWL of tax ($)	(.48)	(.47)	(.48)	(.35)	(.12)	(.53)	(.55)
15. Opportunity-cost-adjusted return on dollar of government spending ($)	.65	.59	.58	.59	(.23)	.32	.17
16. Characteristics of the allocation							
17. Inside-option enrollment (000s)	7,769	8,195	8,355	6,016	6,785	16,231	17,774
18. Inside-option enrollment (% of total market)	36	38	39	28	31	75	82
Share of inside-option enrollment (%):							
19. Risk group 1	6	6	6	6	6	7	7
20. Risk group 2	17	17	17	18	17	16	16
21. Risk group 3	59	60	60	56	58	64	65
22. Risk group 4	16	16	16	19	18	11	11
23. Risk group 5	1	1	1	1	1	1	1
24. Average weighted premium ($)	466	427	429	414	1,224	94	86
25. Average weighted bid ($)	1,.162	1,164	1,164	1,219	1,224	1,286	1,461
26. Outside-option adjustment ($)	56	84	84	113	(677)	203	218

NOTE.—The table reports the level of consumer surplus, producer surplus, government spending, and total welfare under counterfactual allocations with an endogenously adjusted outside option. To compute these objects, we use estimates of demand, marginal costs, and simulations of counterfactual equilibria. All quantities are computed as discussed in sec. III and apps. E and F. These baseline results assume that the cost of public funds (λ) is equal to 1.3. Negative quantities are reported in parentheses. $M = millions of dollars; DWL = deadweight loss.

substitutes, but this general idea holds more broadly—few publicly subsidized programs exist in isolation. The results are given in table 5. There are two additional rows (6 and 26) included in the table in comparison to table 3, listing the additional payments that the government makes to the MA-PD plan in each counterfactual relative to the observed subsidy levels in the MA-PD market (row 6) and the dollar amount of the adjustment we make to the outside option (row 26). A positive number in row 26 implies that the outside option becomes more attractive. There are two ways in which MA-PD-related computations change in these results. Row 6 accounts for how much more or less the government has to pay to consumers who purchase the MA-PD (i.e., outside) option. Rows 8 and 9, which measure the opportunity cost of government funds, are also adjusted to reflect a similar change in what the government would have paid for PDP enrollees if they switched to MA-PD plans.

A common thread across all counterfactuals with the adjusted outside option is that sorting between the inside and outside options (and across risk types within the inside option) is very similar to the observed allocation. This is intuitive, as by adjusting the outside option, we are essentially restoring the observed differences between the two enrollment options. In counterfactuals in which we remove the linkages across LIS, MA-PD, and PDP markets or alter the degree of market power, PDP insurer bids and consumer premiums decrease slightly in the face of a more attractive, and hence more competitive, outside option (cols. 1–4). Consumer surplus increases while government payments net of the opportunity-cost decrease, given that we are subsidizing PDPs and MA-PD plans in similar ways. As a result, total surplus accounting for the opportunity cost of government funds in these counterfactuals is roughly \$500 million higher than that computed for the same counterfactuals in table 3.

We observe similarly intuitive changes in the counterfactuals that consider flat subsidies. As figure 1 shows, for voucher levels that are close to the observed subsidy level (up to around \$1,000), the surplus of counterfactuals with the adjusted outside option is reasonably close—only somewhat higher—to that of both the observed allocation and the counterfactuals without the outside-option adjustments. The optimal voucher with adjusted outside option is substantially higher, at \$1,200 versus \$800 in the nonadjusted case. This is again driven by the more attractive outside option creating competition for PDPs leading to lower bids, premiums, and relative subsidies. Figure 3 highlights the stabilization of the market movement when we adjust the outside option—the share of high-risk consumers remains stable at the observed levels until the voucher increases above \$900; at the highest voucher levels, the equilibrium level of high-risk consumers converges to the same level as that under the counterfactuals without outside-option adjustments, remaining somewhat closer to the optimal social planner level. Moreover, as we observe in figure 1, with high vouchers applied to both the inside and outside options, the market achieves the level of surplus that is equal to the social planner's. This effect is generated entirely by significant changes in the opportunity cost of government funds that result when we adjust the outside option that is driven by fixed MA-PD plan prices that do not respond to more generous subsidies. This highlights the general principle that to the extent that the government can control the level of prices in the market (in this case this happens mechanically, as we do not allow MA-PD prices to adjust), higher subsidies can generate substantial consumer surplus. This surplus is still generated at very high nominal government spending. Without accounting for the opportunity cost of government funds, the voucher of $1,200 (col. 6) generates negative $13 billion in surplus, losing 39 cents on each dollar spent.

The general takeaway is twofold. First, the evaluation of subsidized programs is challenging in the presence of possibly subsidized substitutes, which is commonplace in many settings. Whether there is a positive return on a dollar spent in one program depends crucially on how this dollar would have been spent in related programs on the same beneficiaries. This phenomenon is very transparent in markets, such as the PDP and MA-PD markets, with close substitutes, but is likely to still be important, but less obvious, in other programs (e.g., health insurance coverage and charity care as examined in Finkelstein, Hendren, and Shepard 2017). Second, if substitute and related programs are likely to be subject to the same policies as the program of interest, estimating the general equilibrium effects may be necessary to understand the full economic impact of changes in both programs. Without general equilibrium estimates, it is useful to focus on partial equilibrium analysis that holds substitutes fixed to understand the economic forces of, for example, the subsidy design mechanisms, as we do in table 3.

VI. Conclusion

In this paper we have analyzed the welfare effects of the mechanism for determining subsidies for PDPs in Medicare Part D, focusing in particular on the supply side of the market. We draw several conclusions for our specific empirical setting. First, we find that the current PDP program is efficient only if we account for the fact that the government would likely subsidize the same consumers outside of the PDP program as well. Without taking this fact into account, we could conclude that the program generates only a fraction of dollar value that is spent on it from the federal budget. This is due to two related factors. First, demand for PDPs is generated almost exclusively by high subsidies—consumers have very low willingness to pay for unsubsidized plans, driven by the availability of close substitutes. Second, this market is imperfectly competitive, and firms are able to capture some of the rents of the subsidy mechanism.

On the supply side we find, perhaps surprisingly, that the current structure of the program mutes insurers' ability to raise subsidies and hence positively affects total welfare. This is due to the complex way in which prices for distinct parts of the program, such as MA-PD coverage, LIS, and market premiums for regular beneficiaries in PDPs, are all tied together into one mechanism. We find that the current mechanism, which incorporates multiple parts of the program into an average that is used to calculate subsidies, is similar in its incentives to a predetermined optimal voucher mechanism. We find that providing flat vouchers that are optimally set ex ante could increase the total surplus in levels and relative to federal dollars spent, but not by a large amount (although a flat-voucher mechanism could dramatically reduce the cost of administering the program, an effect that we do not include in our calculations). We further find that removing the averaging and setting proportional subsidies would lead to a rapid upward price spiral, as the competitive pressure on the market is not strong enough to mitigate the "raising-the-subsidy" incentives.

Further, our analysis reveals a close connection between Part D PDPs and Medicare Advantage that, although not emphasized in prior literature, proved to be crucial for our findings. We believe that our approach to the quantification of welfare, which gradually removes interlinked parts of the environment—specifically, LIS bidding incentives and the MA-PD part of the bid average—can be useful for the analysis of many other public programs that do not exist in isolation but, instead, are linked to each other through the choices of consumers and producers or through government transfers.

Beyond the Part D context, our setting, which is characterized by the presence of two publicly subsidized programs that are close substitutes, sheds light on the challenges inherent in the analysis of economic returns to any dollar spent on social insurance programs. In many such programs, and especially health care, the government faces a version of the Samaritan's dilemma. If public funds are ultimately used to pay for individuals' health care needs through some channel, then the question the policy maker faces is not whether to subsidize health care use but finding the most efficient way of doing it. This idea lies at the heart of our results—funding the public benefit that we analyze makes economic sense only insofar as there would be some expenditures on the activities related to this benefit in all counterfactual policies that are plausibly available to the government. This insight has broad implications for the empirical analysis of economic returns to many other public policies that is frequently done in isolation of potentially less obvious substitutes.

While our empirical analysis focused on the subsidy mechanism in the Medicare Part D program, our findings have broader implications for market design of privately provisioned and publicly subsidized social insurance programs. As in any setting with the equity-efficiency trade-off, subsidy policies will have efficiency costs for the market. One source of such inefficiencies is market power. Subsidies create incentives for imperfectly competitive insurers to raise markups and pass them through to the price-inelastic government. In the paper, we illustrate that the details of the subsidy mechanism matter dramatically for how these incentives play out. Further, depending on whether the policy is guided by the considerations of consumer surplus, total welfare, or government spending, we demonstrate that different subsidy mechanisms deliver drastically different results across these three measures of surplus. Overall, we argue that the less studied supply-side behavior in the presence of regulatory intervention and subsidization plays a key role in determining the efficiency outcomes of privately provided social insurance programs. Answering the general question about the optimal mechanism design in these increasingly economically relevant settings presents an important avenue for future empirical and theoretical research.

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