Government Payments and Insurer Benefit Design in Medicare Part D

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Abstract

This paper demonstrates health insurers' incentives to design benefits that differentially appeal to profitable enrollees and deter unprofitable enrollees in Medicare Part D. A system of diagnosis-specific payments was meant to neutralize insurer benefit design incentives by paying insurers more for the sick than for the healthy. These diagnosis-specific payments were held steady even as treatment costs for diagnoses rose or fell with the entry of new drugs or the onset of generic competition. As a result, some diagnoses were clearly profitable for insurers, while others were clearly unprofitable. I show that Part D insurers covered drugs that treat the profitable at higher rates and lower copayments than drugs that treat the unprofitable.

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1 Introduction

Recent publicly-financed health insurance expansions have enshrined a requirement that health insurers accept all applicants, both the sick and the healthy, at the same price. Shortly after the passage of the Affordable Care Act, President Barack Obama celebrated that "discrimination against Americans with preexisting conditions will be banned for good." In order to make insurers willing to enroll the sick at the same price as the healthy, the government pays insurers more for a sick enrollee than a healthy one. In the absence of such payments, economic theory shows that insurers will design benefits – i.e., choose covered services and set copayment rates – to differentially attract the profitable and deter the unprofitable. This paper assesses the success of government payments in neutralizing insurer benefit design incentives in Medicare Part D, a publicly-funded prescription drug insurance program.

I find that government payments in Part D failed to neutralize insurer benefit design incentives. In Part D, the government pays insurers on the basis of enrollee diagnoses. The payment for each diagnosis was held steady while new drug entry and the onset of generic competition changed the cost of treatment for many diagnoses. As a result, some diagnoses were clearly profitable, because their payments exceeded average treatment costs, while others were unprofitable. Economic theory has long shown that, in such a setting, insurers will design benefits that are more favorable for profitable individuals. Empirical evidence for the theory, however, has been rare due to several econometric challenges. This paper overcomes the econometric challenges to show that insurers in Part D designed more favorable benefits – i.e., higher rates of coverage and lower copays – for drugs that treat profitable diagnoses, and less favorable benefits for drugs that treat unprofitable diagnoses. Because they paid higher copays, Part D enrollees with diagnoses that were unprofitable under the payment system transferred at least $1.5 billion to enrollees with profitable diagnoses.

Several features of Medicare Part D make insurer benefit design incentives strong and observable to the econometrician. Most importantly, the diagnosis-specific payments in Part D diverged from treatment costs because the government calibrated them based on data from the early 2000s and held them steady until 2011. Due to new drug entry and the onset of generic competition, payments to insurers exceeded treatment costs for certain diagnoses (making them profitable) and were exceeded by treatment costs for other diagnoses (making them unprofitable). In addition, Part D enrollees are responsive to coverage and copays of specific drugs, both because Part D enrollees tend to know their diagnoses and because drugs tend to treat a single diagnosis. Furthermore, Part D insurers have a significant degree of control over coverage and copays for specific drugs, even though they are subject to substantial regulation. Finally, because most drugs are closely linked to a particular diagnosis, an insurer can attract beneficiaries with profitable diagnoses by covering

many drugs for that diagnosis and setting low copayments for them. In Section 2, I explain these aspects of Medicare Part D in more detail.

This paper continues a prior theoretical literature demonstrating insurers' benefit design incentives when insurers cannot discriminate among applicants but know what services attract profitable and unprofitable enrollees. Prior models focus on a "managed care" setting where insurers control utilization through administrative rationing rather than through coverage and copay. Consequently, insurers do not use copays to directly attract and deter beneficiaries, but rather set administrative hurdles that induce lower levels of utilization and deter enrollment (Frank, Glazer, and McGuire, 2000). This paper also furthers a recent literature on diagnosis-specific payment systems in Medicare. Brown, Duggan, Kuziemko, and Woolston (2011) demonstrate that insurers in a Medicare program similar to Part D (Medicare Advantage) differentially enrolled individuals who cost less than their diagnosis-specific payment and successfully deterred the enrollment of unprofitable individuals. I review these two strands of literature in Section 3.

I then develop a model of insurer's choice of copay and coverage when diagnosis-specific payments diverge from average treatment costs. Beneficiaries choose enrollment and drug quantities on the basis of copay, and insurers set profit-maximizing copays taking diagnosis-specific payments into account. An insurer's decision to cover a given drug is modeled as an entry decision: an insurer who covers a drug has entered the market for enrollees who value that drug. Insurers receive an exogenous diagnosis-specific payment that is unrelated to treatment costs. The model predicts that more insurers will cover drugs that treat profitable diagnoses and will choose low copays for them; drugs that treat unprofitable diagnoses are covered at low rates and high copays. Details of the model are provided in Section 4.

An empirical strategy to test the relationship between benefit design and Part D's diagnosis-specific payments is described in Section 5. I first compare diagnosis-specific payments in the payment system with actual diagnosis-specific treatment costs in the prescription drug claims of a large sample of Part D enrollees. Diagnoses with high payments relative to treatment costs are defined as profitable, while diagnoses with low payments relative to treatment costs are unprofitable. The empirical analogue of my theoretical model is that coverage and copay for a given drug should depend on the profitability of the diagnosis the drug treats. However, my measure of profitability is endogenous because unobserved drug quality affects both my profitability measure and my benefit design outcomes. I instrument for profitability with exogenous "technological change", meaning the exposure of each diagnosis to new molecules and new generics entering upon patent expiries. Due to the weakness of new molecules and new generics as instruments, I also develop a "Hausman" instrument that, by excluding a given drug from the profitability calculation, removes the unobserved drug quality that is the primary pathway for endogeneity.

Implementing the empirical strategy (Section 6) shows that the payment system failed to neutralize

insurer benefit design incentives. Instead, consistent with the theory, insurers set more favorable benefits for drugs that treat profitable diagnoses compared to drugs that treat unprofitable diagnoses. I first establish that diagnosis-specific payments diverged from actual treatment costs, such that many diagnoses were clearly profitable or unprofitable. Applying my technological change instrument in a first stage regression, I find that each new molecule entering after payment system calibration lowers profitability by about $35; each new generic raises profitability by $25.

Finally, I show Part D insurers cover drugs that treat the profitable at higher rates and lower copays than drugs that treat the unprofitable. The results are broadly similar across three models: directly measuring profitability, instrumenting for it with technological change, and applying the Hausman instrument. If a given diagnosis-specific payment had been set higher by $10, rates of coverage for drugs for that diagnosis would have been very slightly higher, and copayments would have been more than $7 less. If diagnosis-specific payments had been set equal to average treatment costs, enrollees with unprofitable diagnoses under the original system would have paid less in copays while enrollees with profitable diagnoses would have paid more; the size of the transfer is at least $1.5 billion, or 9% of total enrollee expenditures. Finally, my results suggest an improvement in Part D regulation that would reduce the effect of payment system inaccuracies on benefit design by recognizing that the diagnosis-specific payment system will have diagnosis-specific effects on incentives.

Payment systems like the one used in Part D are integral to recent public health insurance expansions such as the Affordable Care Act exchanges. This paper raises questions about the ability of diagnosis-specific payments to neutralize insurer benefit design incentives. In particular, the government generally announces such payment systems before the market begins, and leaves them in place for several years. When changes in medical technology, such as new drug entry or the onset of generic competition, cause treatment costs and payment levels to diverge, insurer benefit design incentives will persist.

2 How Part D Works

In this section, I explain why there are strong benefit design incentives in Medicare Part D and why it is possible to detect them. I first review evidence suggesting that Medicare beneficiaries have private information on drug needs. Because of this private information, beneficiaries' enrollment decisions respond to the coverage and copays insurers set for specific drugs. While program rules constrain their actions, insurers can use coverage and copay to attract the profitable and deter the unprofitable. Finally, I describe the Part D payment system, which pays insurers a set amount, calibrated on inappropriate data, for each of a beneficiary's diagnoses. I consider each aspect of Part D in turn.

2.1 Beneficiaries Respond to Benefit Design

Beneficiaries appear to have private information on both their level of drug utilization and the exact drugs they will purchase. The presence of beneficiary private information can be inferred from three types of evidence. Firstly, there was no private market prior to Part D's implementation in 2006. Secondly, those who benefit most from Part D were most likely to enroll. Finally, direct evidence on drug utilization shows that both total spending and exact drug purchases are highly correlated across years.

Part D was created because the private market did not provide a product that protected seniors and the disabled from the risk of high prescription drug expenses. When the Medicare program began offering universal coverage to the elderly in 1965, prescription drugs were excluded from the benefit. Beginning in the mid-1980s, prescription drugs became a larger component of medical care (their share of national health expenditures doubled between 1983 and 2003), especially for the chronic diseases common among the Medicare population. Some Medicare beneficiaries obtained coverage through a retiree benefit; others purchased partial coverage through special Medicare-related products (Medigap and Medicare Advantage managed care plans); while those with low assets and income obtained prescription drugs through the Medicaid program. However, prior to Medicare Part D about a quarter of Medicare beneficiaries bore the full risk of drug costs themselves (Levy and Weir, 2009). Economic research on drug utilization among the elderly suggests that the threat of adverse selection inhibited the development of a fully private market (Pauly and Zeng, 2004; Goldman, Joyce, Karaca-Mandic, and Sood, 2006; Cline and Mott, 2003).

Most beneficiaries without alternative insurance chose to enroll in Part D, but those who did not appear to be positively selected. Because of significant government funding – Medicare pays 75% of total Part D costs – and means-tested out-of-pocket payments, enrollment was optimal for most market participants (Heiss, McFadden, and Winter, 2010; Heiss, Winter, and McFadden, 2009). In 2008, about half of Medicare's 44 million beneficiaries were in the market for Part D (i.e., no retiree benefit or Medicare Advantage), and of those about 80% were enrolled (Kaiser Family Foundation, 2008). Enrollment in 2006 was higher among those with high drug utilization prior to Part D (Yin et al., 2008; Pizer, Frakt, and Feldman, 2008; Levy and Weir, 2009). Surveys of those who chose to remain uninsured find that the uninsured fall into two groups (Neuman et al., 2007; Heiss, McFadden, and Winter, 2006). The first group are chronically ill, low-income, and often cognitively impaired. Many of these individuals can enroll in Part D at zero premium, and may have done so as awareness and outreach improved (Ketcham, Lucarelli, Miravete, and Roebuck (2012) show the enrollment decisions of Part D enrollees improved rapidly after 2006, especially for the very old and cognitively impaired). The second group, however, are relatively healthy beneficiaries: almost a quarter of eligible beneficiaries with no chronic conditions chose not to enroll in Part D when it first became available.

Direct evidence shows that among Medicare beneficiaries, prescription drug utilization in one year is a very good predictor of prescription drug utilization in the next year. Most prescription drug spending in the Medicare population is associated with chronic diseases, with nearly half the total on diabetes, cholesterol, or cardiovascular drugs alone (Soni, 2008). Hsu et al. (2009) estimated the Spearman's correlation between decile of total drug spending in consecutive years to be 0.83. Finally, within the setting of Part D, Heiss, Leive, McFadden, and Winter (2012) show that individuals choosing a plan based purely on current year prescriptions choose the *ex-post* optimal plan more often than any of a number of rational expectations models they test, a result that follows from a high degree of persistence of exact drug purchases.[1]

Taken together, this evidence suggests that beneficiaries know what drugs they need and can choose an insurance plan based on the coverage and copay of drugs they expect to take. Copays paid by enrollees vary over the course of the year as their spending levels hit certain thresholds. In this paper, I focus on copays in the "initial coverage zone", where insurers have the largest latitude in copay setting. The initial coverage zone starts after a deductible ($295 in 2009) and continues until total drug expenditure is $2,700, when a "coverage gap", a.k.a. "doughnut hole", begins. Beneficiaries then pay all costs until their year-to-date copays total $4,350, when a "catastrophic zone" of coverage begins. In 2009, nearly two-thirds of beneficiaries only purchased drugs in the initial coverage zone and copays for purchases in the initial coverage zone represented 54% of total copays.

2.2 Insurers Control Benefit Design

Insurers seek to design a benefit that is profitable when marketed to the beneficiaries described above. Two decisions characterize an insurer's benefit design. Firstly, the insurer chooses, within program rules, what drugs to cover. Beneficiaries pay the full amount for drugs that are not "covered", while insurers pay all but the copay for drugs that are. Because coverage is an obvious way for an insurer to deter sick beneficiaries, Part D insurers have to comply with certain regulations. Firstly, insurers had to cover all the drugs in six "protected" therapeutic classes: antiretrovirals, antineoplastics (anti-cancer drugs), antidepressants, antipsychotics, anticonvulsants, and immune suppressants. In addition, plans were required to cover two drugs in each United States Pharmacoepia "therapeutic class". However, plans still vary considerably in their rates of coverage, as documented by Goldman, Joyce, and Vogt (2011). Using a sample of 152 commonly-prescribed drugs (both brands and generics), Hoadley, Hargrave, Cubanski, and Neuman (2006) shows that some plans cover fewer than two-thirds, while others cover nearly all. Hoadley also documents that drugs in different therapeutic classes are covered at very different rates; such a finding is consistent with the relationship between drug coverage and diagnosis-specific profitability I document in this

[1] Medicare encourages beneficiaries to base enrollment on current year prescriptions through the Plan Finder tool on its website, which computes total premiums plus copays across plans for a list of drugs supplied by the beneficiary.

paper.

In addition to choosing drug coverage, the insurer sets drug copays, again constrained by program rules. The Part D legislation defined a "basic benefit": plans pay 75% of drug costs in the initial coverage, 0% in the coverage gap, and 15% in the catastrophic zone. Plans could choose to deviate from the 25% copays in the initial coverage zone prescribed by the basic benefit, although they had to show that, for the type of Medicare beneficiaries they expect to attract, total copays equaled 25% of total drug costs.[2] In practice, this constraint means that plans can raise copays for certain drugs as long as they lower them for others.

Coverage and copays in the initial coverage zone are insurers' major strategic variables. Firstly, purchases in the initial coverage zone account for over two-thirds of total insurer liability. Secondly, while insurers can choose to lower copays in the coverage gap or throughout the benefit, they must finance the lower copays fully through higher premiums. In practice, copays outside the initial coverage zone are close to the levels prescribed by the basic benefit, while as we will see in Table 2, copays in the initial coverage zone show substantial variation across drugs.

Drug coverage and copays determine premium, which is not a strategic variable in Part D. Instead, each plan submits its benefit design to a Medicare-designed application that finds the cost of providing the basic benefit to a "typical" beneficiary (not the beneficiary the plan expects to attract). The cost of providing the basic benefit to a typical beneficiary in insurance plan i is the plan's *bid*. Then the premium for insurer i is set to

$$prem_i = (bid_i - \overline{bid}) + \gamma\overline{bid}$$

where $\overline{bid}$ is the national average bid (weighted by prior-year enrollment), and γ is a fixed percentage (36% in 2009). Then plans with overall generous benefit designs (many covered drugs, low copays) collect dollar-for-dollar higher premiums, while those with low costs can charge low premiums (subject to a zero lower bound).

2.3 Diagnoses Correspond to Profitability Due to Diagnosis-Specific Payments

Recall that Medicare pays insurers approximately 75% of total Part D costs. These payments differ based on enrollee diagnoses. Diagnosis-specific payments can, in theory, offset insurers' incentives to distort benefits. Larger payments for unprofitable types can equalize profitability across all beneficiaries, so that insurers are indifferent among applicants. The practice of conditioning payments to insurers on type is known as *risk adjustment*. Medicare created a system of diagnosis- and demographic-specific payments for Part D that, in

[2]To be specific, insurers first assumed the basic benefit and estimated resulting enrollment and drug utilization. Holding enrollment fixed, they then reestimate drug utilization under the alternative copays. Insurers offering "enhanced" benefits reduce copays by paying more than 75%, 0%, or 15% in each zone of coverage; enhanced plans collect the same government payments and finance the additional benefits through a supplemental premium.

theory, compensated insurers for the expected cost of enrolling a given beneficiary. In this section, I describe those diagnosis-specific payments and what makes them inaccurate.

Medicare had to calibrate the payment system before Part D began and therefore before the appropriate data was available. The payment system designers, Robst, Levy, and Ingber (2007), took advantage of medical claims and prescription drug spending from a sample of federal retirees in 2002 and Medicaid beneficiaries in 2000. Working from a list of diagnoses used to pay Medicare Advantage plans, they identified a set of 86 diagnoses that significantly raised total drug spending in their sample. They defined demographic categories of age × gender and gender × originally disabled.[3] They reduced each individual's total drug spending by 19%, which was an estimate from the official Medicare Office of the Actuary of the reduction in spending expected to result from the fact that federal retirees and Medicaid beneficiaries pay much lower copays than Part D enrollees. Finally, they computed plan liability $\mathcal{L}$ for each individual j by applying the Part D standard benefit. To find the amount of plan liability attributable to each diagnosis and demographic category, they estimated the following linear model on individuals in the calibration data:

$$\mathcal{L}_j = \sum_x D_{jx}\widehat{W_x} + \sum_g D_{jg}\widehat{W_g} + \varepsilon_j$$

D_{jx} and D_{jg} are dummies for the 86 diagnoses (indexed by x) and the demographic categories (indexed by g). $\widehat{W_x}$ and $\widehat{W_g}$ represent the treatment costs associated with each diagnosis or demographic category for this population. In addition, the payment system includes multiplicative factors (separate for the aged and disabled subpopulation) that express the degree to which spending is higher for low-income individuals and those who are long-term institutionalized. The coefficient for each diagnosis is expressed as a weight $W_x = \widehat{W_x}/\overline{\mathcal{L}}$, or the treatment costs associated with each diagnosis divided by the average plan liability in their data. For each beneficiary, Part D plans receive the product of the weights and the plan's bid.

To see how diagnosis-specific payments work, suppose an insurance plan enrolled a 66-year-old man (never disabled, noninstitutionalized, and not low-income) whose 2007 medical claims show an infectious disease. The weight for this man is simply the W_x for Infectious Diseases 0.073 and his demographic weight 0.355. Plan payments are a multiple of plan bids, so that a plan that bids the national average bid ($1011.96 in 2009) would receive $433.12 (= $(0.073 + 0.355)1011.96$) for this man. If that same man enrolled in a plan with lower copays such that its bid was $1500, that plan would receive $642.00.

New molecules and new generics entering upon patent expiry can dramatically change the cost of treating a given diagnosis, but the payment system makes no provision for such changes. The calibration data for the payment system was from 2000 and 2002, but the levels in the payment system were held steady until 2011,

[3]Individuals who are "originally disabled" are those over 65 who were entitled to Medicare prior to age 65 due to disability.

when the payment system was updated (Kautter, Ingber, Pope, and Freeman, 2012). Payment levels were insensitive to new drug entry or patent expiry between these years. For example, the popular cholesterol drug Zocor (simvastatin) began to face generic competition in September 2006. Expenditures on Zocor by elderly Americans totaled $2.3 billion in 2002; presumably at least some of these purchases appear in the data used by Robst, Levy, and Ingber (2007). Inasmuch as generic simvastatin costs less than brand name Zocor, this patent expiration lowered the average treatment costs of High Cholesterol. The payment for High Cholesterol, however, was held steady. At the other end of the spectrum, the treatment of multiple sclerosis (as opposed to simply symptom management) became widespread in in the first decade of the new millenium due to the introduction and expansion of several expensive immunological drugs (Miller, 2011; Cohen, 2009). As we will see in Section 6.2, treatment costs for Multiple Sclerosis greatly exceed its payment.

This payment system was in effect for the first five program years (2006 to 2010, inclusive). In the year studied in this paper, 2010, at least eight years had passed since the expenditures used to calibrate the diagnosis-specific weights were incurred. In addition, insurers were encountering this system for the fifth year, allowing plenty of time for insurers' internal analysis to detect the difference between diagnosis-specific payments and average treatment costs.

We have seen that in Part D benefit design incentives are strong due to beneficiary private information, that insurers have control over benefit design, and that the Part D payment system could fail to neutralize insurer benefit design incentives. In the next section, I review two related literatures: theoretical models of similar settings that predict how insurers might react and empirical evaluations of Medicare's payment systems.

3 Related Literature: Insurer Incentives and Medicare Payments

A relatively robust theoretical literature analyzes insurer incentives in a setting similar to Part D. These models, reviewed in Ellis (2008), assume that (1) individuals have private information on their profitability, (2) insurers cannot deny enrollment or charge premiums based on profitability, and (3) beneficiaries of different types vary (in a known way) in their preference for different medical services. These theoretical models date from the "managed care" era in health insurance; approximating the managed care environment, insurers control the quantity of medical services administratively rather than through copayments and coverage. Insurers set a "shadow price" for each service that beneficiaries pay in time and hassle, but coverage and copays are not set directly. In the first model of "shadow price", Frank, Glazer, and McGuire (2000) define it as "a device to capture the myriad of strategies a plan uses to ration care, other than by demand-side cost sharing (literal prices)." The authors show that the shadow price should be inversely proportional to expected profit from an individual: if the plan expects positive profits from a given type, the shadow

price for services demanded by that type should be lowered. Jack (2006) places the model in a traditional Rothschild-Stiglitz framework, but the basic conclusions do not change. Insurers' benefit design incentives can be neutralized in these models if an omniscient social planner pays each insurer the expected cost of each individual (Glazer and McGuire, 2002, 2000).

A later iteration of this model demonstrates that a medical service's *predictability* and *predictiveness* both increase insurers' incentives to distort benefit design (Ellis and McGuire, 2007). A service's *predictability* is the degree to which individuals can anticipate needing it. As discussed in the previous section, Part D is a particularly good setting for empirically assessing benefit design incentives since the high autocorrelation of drug spending makes it predictable to the individual. A service's *predictiveness* is the degree to which it predicts overall medical spending. In the Part D setting, a diagnosis with a payment equal to its treatment costs that tends to co-occur with an unprofitable diagnosis will be *predictive* of overall unprofitability. In Section 6.5, I interpret my results in light of diagnoses' *predictiveness*.

The literature on benefit design incentives is not accompanied by empirical evidence, presumably because in the absence of something akin to the Part D payment system it is difficult to identify individuals' profitability as well as the services that attract and deter them. However, a small literature assesses the impact of Medicare's diagnosis- and demographic-specific payment system. Brown, Duggan, Kuziemko, and Woolston (2011) study Medicare Advantage plans, which are paid under a system similar to Part D's. Exploiting the transition to diagnosis-specific payments in 2004, the authors show that Medicare Advantage plans successfully select for individuals who are inexpensive relative to the payment plans receive for them (i.e., individuals with milder forms of each diagnosis). This paper begins from the same premise – that inaccuracies in the payment system affect insurer behavior. In their case, the payment system is inaccurate because multiple "types" (i.e., mild and severe forms of a diagnosis) are associated with a single payment. In my case, it is inaccurate due to the lack of appropriate data prior to Part D and the speed of industrial change in the drug industry. Brown et al. demonstrate that insurers differentially select for those who are inexpensive relative to their associated payment. I demonstrate *how* insurers accomplish this selection: by covering at low copays the drugs taken by those with high relative diagnosis-specific payments.

In the next section, I develop a model of copay and coverage in the setting like Medicare Part D where payments are unrelated to actual treatment costs.

4 A Model of Insurer Benefit Design

In this section, I develop a simple model of insurer incentives in a setting like Part D, starting from a version of Frank, Glazer, and McGuire's (2000) model of benefit design incentives (hereafter FGM00). In the model, beneficiaries are characterized by types that determine their valuation of different drugs. Beneficiaries

evaluate insurance plans on the basis of copays and enroll in the plan that allows them highest utility. There are two stages of insurer decision-making. Firstly, each insurer decides whether to enter the market for a given drug by covering it, which involves a constant fixed cost of entry. Secondly, each entering insurer sets copays to maximize profits given drug prices, type-specific payments, and other insurers' copays. Type-specific payments are unrelated to actual treatment costs.

The analysis begins at the second step: the insurers who entered the market set profit-maximizing copays. I examine the copays within a symmetric equilibrium. Then, a zero-profit condition determines the number of entrants. The objects of interest are the reaction of copays and the number of entrants to type-specific payments. As long as parameter values are such that an exogenously higher number of entrants induces lower copays, then the copays fall in type-specific payments and the number of entrants rises. An example using logit demand for plans and log utility for drugs leads to the same conclusions.

The model differs from FGM00 in two ways. The major addition is that the model incorporates an entry decision that represents insurers' choice of what services to cover. In addition, as in Part D insurers set an explicit copay for services instead of a "shadow price".

4.1 Preliminaries: Beneficiary Demand

Beneficiaries are characterized by types denoted by x. Different types of beneficiaries have different preferences for drugs. For simplicity, suppose each type corresponds to exactly one medical service, e.g., a drug. Then a beneficiary of type x values a quantity q of drug x according to $V_x(q_x)$. The same beneficiary's valuation of any other drug is zero: $V_x(q_{-x}) = 0$. Beneficiaries know their type and both beneficiaries and insurers know what service treats each type. Marginal utility is positive, declining, and convex ($V_x' > 0$, $V_x'' < 0, V_x''' > 0$).

Beneficiaries choose among insurance plans based on copays. Suppose a plan i sets copays $c_i = \{c_{i1}, c_{i2}, ...c_{iX}\}$. A utility-maximizing beneficiary of type x enrolled in insurance plan i will choose q_{ix} determined by

$$V_x'(q_{ix}) = c_{ix}$$

This equation implies a demand function $q_{ix} = q_x(c_{ix})$. The shape of utility V_x implies that demand is decreasing and convex in copays. The shape of demand may vary across types x but for each type depends only on a plan's copays c_{ix} and not the plan itself. Indirect utility for an individual of type x facing copays c_{ix} is the utility of the drugs purchased at copay c_{ix} less the individual's cost for them: $v_x(c_{ix}) \equiv V_x(q_x(c_{ix})) - c_{ix}q_x(c_{ix})$.

A beneficiary's valuation of an insurance plan is based on its copays and an idiosyncratic plan-specific

preference taken from a known distribution.

$$U_x(c_{ix}) = v_x(c_{ix}) + \mu_{ix} \quad \mu_{ix} \sim \phi_x(\mu_{ix})$$

The beneficiary enrolls in the plan with highest utility; all beneficiaries enroll in insurance. Let $\widehat{u}_x$ represent the utility of the beneficiary's most-preferred plan when insurance plan i is excluded from the choice set. Following FGM00, insurer i takes other insurers' behavior as given, meaning that $\widehat{u_x}$ is fixed.

$$\widehat{u}_x = v_x(\widehat{c}_x) + \widehat{\mu}_x = \max_{-i} v_x(c_{ix}) + \mu_{ix}$$

The beneficiary enrolls in i if its utility exceeds $\widehat{u}_x$: $v_x(c_{ix}) + \mu_{ix} > \widehat{u}_x$. The probability that type x enrolls in insurance plan i with copay c_{ix} for drug x is expressed by $\widetilde{n}_x$.

$$\widetilde{n}_x = 1 - \phi_x(\widehat{u}_x - v_x(c_{ix}))$$

Example. *Suppose* $V_x(q_x) = \ln q_x$ *and* $\phi_x(\mu_{ix})$ *is the Type I Extreme Value distribution. Then* $q_x(c_{ix}) = 1/c_{ix}$*, and* $v_x(c_{ix}) = -\ln c_{ix} - 1$*. The probability that an individual of type* x *enrolls in insurer* i *becomes* $\widetilde{n}_x = e^{-(\widehat{u}_x - v_x(c_{ix}))} = e^{(-\widehat{u}_x - \ln c_{ix} - 1)}$.

4.2 Step 2: Insurer Copay Decision

Suppose that in the Step 1 entry decision described below N_x insurers chose to enter the market for type x. In Step 2, each insurer chooses profit-maximizing copays, taking other insurers' behavior as given. The insurer's profit on an enrollee of type x depends on two exogenous inputs: drug price p_x and a type-specific per-enrollee payment to the insurer $r_x > 0$. Each insurer must purchase drugs for its enrollees from a drug firm at price p_x.[4] Following FGM00, the type-specific per-enrollee payment r_x does not affect a beneficiary's enrollment decision, either because it is paid by a third party (i.e., the government) or because it is paid by the beneficiary but does not vary across plans. In addition, the type-specific payment is unrelated to actual treatment costs.

When an insurer i setting copay of c_{ix} enrolls an individual of type x, the insurer receives r_x and then buys $q_x(c_{ix})$ of drug x at price p_x, partially offset by copay c_{ix}. Let $\pi_x(c_{ix})$ represent insurer i's profit on an individual of type x.

$$\pi_x(c_{ix}) = r_x - (p_x - c_{ix})q_x(c_{ix})$$

At copay c_{ix}, the insurer's market share is the expected value of the enrollment probability for type x.

[4]Future work sets drug prices through insurer-drug firm bargaining. Firms that make drugs for types with high r_x demand high prices while firms that make drugs for types with low r_x accept lower prices. When drug firm bargaining power is high, the reaction of drug price to r_x is strong, whereas weak drug firms lead to a weaker relationship between r_x and drug price.

Market share depends on other insurers' copays through $\widehat{u}_x$.

$$n_x(c_{ix}, c_{-ix}) = E[\widetilde{n}_x] = 1 - E[\phi_x(\widehat{u}_x - v_x(c_{ix}))]$$

When insurer i sets $c_i = \{c_{i1}, c_{i2}, ...c_{iX}\}$, its total profit is given by

$$\Pi(c_i) = \sum_x [n_x(c_{ix}, c_{-ix})\pi_x(c_{ix}) - \kappa] = \sum_x [n_x(c_{ix}, c_{-ix})(r_x - (p_x - c_{ix})q_x(c_{ix})) - \kappa]$$

where κ, discussed in more detail below, is a fixed cost of entry to the market for drug x. Profit maximization with respect to copay c_{ix} requires the following first- and second-order conditions:

$$\begin{aligned}
\text{FOC} \quad & F(c_{ix}, n_x(c_{ix}, c_{-ix}), r_x, p_x) = n'_{ix}\pi_{ix} + n_{ix}\pi'_{ix} \\
& = n'_{ix}(r_x - (p_x - c_{ix})q_{ix}) + n_{ix}(q_{ix} - (p_x - c_{ix})q'_{ix}) = 0 \\
\text{SOC} \quad & S(c_{ix}, n_x(c_{ix}, c_{-ix}), r_x, p_x) = n''_{ix}\pi_{ix} + 2n'_{ix}\pi'_{ix} + n_{ix}\pi''_{ix} \\
& = n''_{ix}(r_x - (p_x - c_{ix})q_{ix}) + 2n'_{ix}(q_{ix} - (p_x - c_{ix})q'_{ix}) + n_{ix}(2q'_{ix} - (p_x - c_{ix})q''_{ix}) < 0
\end{aligned}$$

where n'_{ix},n''_{ix}, q'_{ix}, and q''_{ix} represent the first and second derivatives with respect to copay c_{ix}.

In the second-order condition, the second two terms are negative but the first term has the sign of n''_{ix}, which depends on the exact distribution of idiosyncratic preferences ϕ_x. If market shares are concave in copays, the second-order condition always holds. If market shares are convex in copays, the second-order condition holds as long as market shares are not "too convex". A sufficient (but not necessary) condition is log-concavity of $n_x(c_{ix}, c_{-ix})$ and $q_x(c_{ix})n_x(c_{ix}, c_{-ix})$ in c_{ix}. The economic intuition is explored further in Carey (2013).

The first-order condition implicitly defines insurer i's best response c^*_{ix} to other insurers' copays. The best response only implicitly defines c^*_{ix} because n_{ix}, q_{ix}, n'_{ix}, and q'_{ix} must be evaluated at the profit-maximizing c^*_{ix}. However, since q_{ix} and q'_{ix} do not depend on other insurer's copays, we can define $q^*_{ix} \equiv q_x(c^*_{ix})$ and $q'^*_{ix} \equiv q'_x(c^*_{ix})$.

Rearranging the first-order condition, the best response c^*_{ix} can be stated analogously to FGM00:

$$c^*_{ix} = p_x - \frac{r_x n'_x(c^*_{ix}, c_{-ix}) + q^*_{ix} n_x(c^*_{ix}, c_{-ix})}{q^*_{ix} n'_x(c^*_{ix}, c_{-ix}) + q'^*_{ix} n_x(c^*_{ix}, c_{-ix})} \tag{1}$$

Because the denominator and n'_x are always negative, copays are always lower than prices for sufficiently large r_x. We assume in this research that r_x always fulfills this condition.

Equation 1 demonstrates insurer i's incentives in choice of copay. Copay is a type-specific discount off of price. Most importantly for this research, the discount is higher when the exogenous type-specific payment r_x is high. FGM00 focus on the possibility that r_x is high because premiums are not type-specific ($r_x = r$) and the cost of providing treatment to type x is low. Alternatively, a type-specific payment may be high

due to an inaccurate payment system, as in this paper.

Example. *Using the same assumptions of log utility for drugs and the TIEV distribution for plan-specific preferences, insurer i's market share takes the familiar logit form. Insurer i's profit on a set of copays c_i is*

$$\Pi(c_i) = \sum_x [n_x(c_{ix}, c_{-ix})(r_x - (p_x - c_{ix})q_x(c_{ix})) - \kappa] = \sum_x \left[\frac{e^{v_x(c_{ix})}}{\sum_i e^{v_x(c_{ix})}} (r_x - p_x/c_{ix} + 1) - \kappa \right]$$

and profit-maximization with respect to c_{ix} requires the following first-order condition.

$$FOC \quad F(c_{ix}, n_x(c_{ix}, c_{-ix}), r_x, p_x) = \frac{e^{v_x(c_{ix})}}{\sum_i e^{v_x(c_{ix})}} \left(\frac{\sum_{-i} e^{v_x(c_{ix})}}{\sum_i e^{v_x(c_{ix})}} (\tfrac{-1}{c_{ix}})(r_x - p_x/c_x + 1) + (p_x/c_{ix}^2) \right) = 0$$

The second-order condition holds without further assumptions. Rearranging the first-order condition, the best-response copay is

$$c_{ix}^* = p_x \frac{2 - n_x(c_{ix}^*, c_{-ix})}{(1 + r_x)(1 - n_x(c_{ix}^*, c_{-ix}))}$$

4.3 Symmetric Equilibrium in Copays

Consider a symmetric equilibrium in copays, such that $c_{ix}^* = c_x^*$ for all insurers. When all insurers set c_x^*, only idiosyncratic preference terms affect plan enrollment:

$$n_x(c_{ix}, c_{-ix}) = n_x(c_x^*, c_x^*) = 1 - E[\phi_x(\widehat{u}_x - v_x(c_x^*))] = 1 - E[\phi_x(v_x(\widehat{c}_x) + \widehat{\mu}_x - v_x(c_x^*))] = 1 - E[\phi_x(\widehat{\mu}_x)]$$

Recall the definition of $\widehat{u}_x = v_x(\widehat{c}_x) + \widehat{\mu}_x$: the utility of the plan that is most preferred when plan i is ignored. Since $\widehat{c}_x = c_{ix} = c_x^*$, $\widehat{\mu}_x$ must be the highest of $N_x - 1$ idiosyncratic preference terms drawn from ϕ_x. Since $\phi_x(\widehat{\mu}_x) \sim U[0, 1]$, its expected value is the expectation of the maximum of $N_x - 1$ draws from the standard uniform: $(N_x - 1)/N_x$.

$$n_x(c_x^*, N_x) = 1 - E[\phi_x(\widehat{\mu}_x)] = 1 - \frac{N_x - 1}{N_x} = \frac{1}{N_x}$$

Imposing the symmetric equilibrium, Equation 1 becomes

$$c_x^* = p_x - \frac{r_x n_x'(c_x^*, N_x) + q_x^*/N_x}{q_x^* n_x'(c_x^*, N_x) + q_x'^*/N_x} \tag{2}$$

Without a distributional assumption, however, there is no closed-form expression for $n_x'(c_x^*, N_x)$.

$$n_x'(c_x^*, N_x) = v_x'(c_x^*) E[\phi_x'(\widehat{\mu}_x)]$$

We are now in a position to consider the reaction of equilibrium copays to the number of market participants N_x. We expect that, other things equal, more entrants leads to lower copays. Letting $\frac{\partial n_x^2}{\partial c_x^* \partial N_x}$ represent the cross-partial derivative of market shares with respect to copay and number of entrants, $\partial c_x^*/\partial N_x$ can be obtained from implicitly differentiating the first-order condition.

$$\text{FOC} \quad F(c_x^*, N_x, r_x, p_x) = n_x'(c_x^*, N_x)\pi(c_x^*) + \pi'(c_x^*)/N_x^* = 0$$

$$\frac{\partial c_x^*}{\partial N_x} = -\frac{\frac{\partial n_x^2}{\partial c_x^* \partial N_x}\pi_x^* - \pi_x'^*/N_x^{*2}}{\text{second-order condition}} = -\left(\frac{\partial n_x^2}{\partial c_x^* \partial N_x} + \frac{n_x'(c_x^*, N_x^*)}{N_x}\right)\frac{\pi_x}{\text{second-order condition}}$$

The expression has the sign of $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} + \frac{n_x'(c_x^*, N_x^*)}{N_x}$. In order to ensure that more entrants leads to lower copays, we require $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} + \frac{n_x'(c_x^*, N_x^*)}{N_x} < 0$. This condition always holds if more entrants make enrollment more sensitive to copays ($\frac{\partial n_x^2}{\partial c_x^* \partial N_x} < 0$). Alternatively, $\frac{\partial n_x^2}{\partial c_x^* \partial N_x}$ may be positive as long as an $a\%$ increase in the number of entrants leads to a decrease in the sensitivity of enrollment to copays of less than $a\%$. If idiosyncratic preferences are distributed TIEV, $\frac{\partial n_x^2}{\partial c_x^* \partial N_x}$ is positive but $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} + \frac{n_x'(c_x^*, N_x^*)}{N_x}$ is negative. Intuitively, if an increase in entrants greatly reduces the sensitivity of enrollment to copays, an insurer's enrollment penalty from higher copays is outweighed by its increase in revenue, and a larger number of entrants leads to higher copays. I assume in this research that $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} + \frac{n_x'(c_x^*, N_x^*)}{N_x} < 0$.

Example. *Under the previous functional form and distributional assumptions, when all insurers set c_x^*, market shares simplify to $1/N_x$.*

$$n_x(c_x^*) = \frac{e^{v_x(c_x^*)}}{\sum_i e^{v_x(c_x^*)}} = \frac{1}{N_x}$$

Equilibrium copays and per-enrollee profits at these copays are

$$c_x^* = p_x \frac{2N_x - 1}{(1 + r_x)(N_x - 1)} \qquad \pi_x(c_x^*) = \frac{N_x(1 + r_x)}{2N_x - 1}$$

Note that $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} > 0$ when N_x exceeds two but $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} N_x + n_x'(c_x^*, N_x^*) < 0$ such that $\partial c_x^*/\partial N_x$ is negative.

$$\frac{\partial n_x^2}{\partial c_x^* \partial N_x} = \frac{N_x - 2}{c_x^*(N_x^3)} \qquad \frac{\partial c_x^*}{\partial N_x} = -\frac{p_x}{(1 + r_x)(N_x - 1)^2}$$

4.4 Step 1: Insurer Entry Decision

In settings like Medicare Part D, insurers commonly provide only a subset of services. I model the decision of what services to provide as an entry problem. If insurer i offers drug x, it pays a fixed cost κ. The fixed cost of entry can be motivated by the cost of negotiating a contract with the maker of drug x. When insurers price at c_x^*, the resultant per-enrollee profits are always positive:

$$\pi_x(c_x^*, N_x) = \frac{r_x q_x'^* - q_x^{*2}}{N_x q_x^* n_x'(c_x^*, N_x) + q_x'^*}$$

but an insurer only enters the market for drug x if its equilibrium market share times these per-enrollee profits will cover the fixed cost. Therefore we find N_x^* such that total profits $\Pi_x(c_x^*, N_x^*) = 0$; we ignore in this model the fact that N_x^* may not be an integer.

$$\Pi_x(c_x^*, N_x^*) = \frac{r_x q_x'^* - q_x^{*2}}{N_x^*(N_x q_x^* n_x'(c_x^*, N_x^*) + q_x'^*)} - \kappa = 0$$

Π_x is quadratic in N_x, but both roots exist and only one is positive.

$$N_x^* = \frac{-\kappa q_x'^* - \sqrt{(\kappa q_x'^*)^2 + 4\kappa q_x^*(r_x q_x'^* - q_x^{*2})n_x'(c_x^*, N_x^*)}}{2\kappa q_x'^*}$$

Example. *Under the above functional forms, the entry problem can be written*

$$\Pi_x(c_x^*, N_x^*) = \frac{1 + r_x}{2N_x - 1} - \kappa = 0$$

and the solution is a function of fixed costs and type-specific payments.

$$N_x^* = \frac{1 + r_x + \kappa}{2\kappa}$$

4.5 Analysis: Effects of Type-Specific Payments r_x in Equilibrium

I now proceed to analyze the effect of type-specific payments on equilibrium copays and entry. I show that, when the second-order condition for profit maximization holds, copays rise with type-specific payments while coverage declines.

The first-order and zero-profit conditions together define c_x^* and N_x^* in terms of p_x, κ, and r_x.

$$F(c_x^*, N_x^*, r_x, \kappa, p_x) = n_x'(c_x^*, N_x^*)(r_x - (p_x - c_x^*)q_x^*) + (q_x^* - (p_x - c_x^*)q_x'^*)/N_x^* = 0$$

$$G(c_x^*, N_x^*, r_x, \kappa, p_x) = r_x q_x'^* - q_x^{*2} - \kappa N_x^{*2}(q_x^* n_x'(c_x^*, N_x^*) + q_x'^*/N_x^*) = 0$$

The derivatives can be found by applying Cramer's rule to the total derivatives of F and G with respect to parameter r_x. Below, the component partial derivatives of F and G are displayed as well as the expressions for the effect of r_x. If the second-order condition holds, then $\partial G/\partial c_x^* > 0$ (see Appendix A.2). The assumption that $\frac{\partial n_x^2}{\partial c_x^* \partial N_x} N_x + n_x'(c_x^*, N_x^*) < 0$ is required if a higher number of entering insurers is to lead to lower

equilibrium copays; the same condition provides signs for the partial derivatives with respect to N_x^*.

$$\frac{\partial F}{\partial c_x^*} = \underbrace{\text{second-order condition for profit-maximization}}_{-\text{ if } c_x^* \text{ is a local maximum}}$$

$$\frac{\partial G}{\partial c_x^*} = \underbrace{r_x q_x''^* - 2q_x^* q_x'^* - \kappa N_x^{*2}(q_x^* n_x''(c_x^*, N_x^*) - 2N_x^* q_x^* [n_x'(c_x^*, N_x^*)]^2 + q_x''^*/N_x^*)}_{+\text{ if SOC holds}}$$

$$\frac{\partial F}{\partial N_x^*} = \underbrace{\frac{\partial n_x^2}{\partial c_x^* \partial N_x}(\pi_x^*) - \pi_x'^*/N_x^{*2}}_{-\text{ from assumption on } \frac{\partial n_x^2}{\partial c_x^* \partial N_x}} \qquad \frac{\partial G}{\partial N_x^*} = \underbrace{-\kappa(N_x^{*2} q_x^* \frac{\partial n_x^2}{\partial c_x^* \partial N_x} + 2N_x^* q_x^* n_x'(c_x^*, N_x^*) + q_x'^*)}_{+\text{ from assumption on } \frac{\partial n_x^2}{\partial c_x^* \partial N_x}}$$

$$\frac{\partial F}{\partial r_x} = \underbrace{n_x'(c_x^*, N_x^*)}_{-} \qquad \frac{\partial G}{\partial r_x} = \underbrace{q_x'^*}_{-}$$

$$\frac{dc_x^*}{dr_x} = -\frac{\overbrace{\frac{\partial F}{\partial r_x}\frac{\partial G}{\partial N_x^*} - \frac{\partial F}{\partial N_x^*}\frac{\partial G}{\partial r_x}}^{-}}{\underbrace{\frac{\partial F}{\partial c_x^*}\frac{\partial G}{\partial N_x^*} - \frac{\partial F}{\partial N_x^*}\frac{\partial G}{\partial c_x^*}}_{-}} < 0 \qquad \frac{dN_x^*}{dr_x} = \frac{\overbrace{\frac{\partial F}{\partial r_x}\frac{\partial G}{\partial c_x^*} - \frac{\partial F}{\partial c_x^*}\frac{\partial G}{\partial r_x}}^{-}}{\underbrace{\frac{\partial F}{\partial c_x^*}\frac{\partial G}{\partial N_x^*} - \frac{\partial F}{\partial N_x^*}\frac{\partial G}{\partial c_x^*}}_{-}} > 0$$

These derivatives show that copay falls in type-specific payments r_x while the number of entrants rises. The sign of the denominator of the derivatives is potentially ambiguous, but I show in Appendix A.3 that it is negative if the second-order condition for profit-maximization with respect to c_x^* holds.

Example. *Under our functional form and distributional assumptions,.*

$$\frac{dN_x^*}{dr_x} = \frac{1}{2\kappa} > 0$$

$$c_x^* = \frac{2p_x}{1 + r_x - \kappa} \qquad \frac{dc_x^*}{dr_x} = -\frac{2p_x}{(1 + r_x - \kappa)^2} < 0$$

Figure 1 depicts the equilibrium c_x^* and N_x^* when $p_x = 100$, $\kappa = 5$, and r_x varies between 10 and 110.

In this simple theoretical model, insurers will disproportionately cover drugs made profitable by a high type-specific payment; copays for these drugs will also be lower. In the next section, I show how to use Medicare Part D to demonstrate these patterns.

5 Empirically Testing Insurer Incentives

In this section, I describe a strategy that deploys features of Part D to verify the patterns predicted by the theory. The first step in the strategy is to identify profitable and unprofitable diagnoses within Part D. To do so, I compare diagnosis-specific payments with the actual treatment costs for each diagnosis. A high

payment relative to average treatment costs implies the diagnosis is profitable. Next, I propose a method of determining what drugs treat each diagnosis. My research question seeks to assess the impact of a diagnosis's profitability on the benefit design (coverage and copays) of drugs treating that diagnosis. Due to endogeneity concerns for my profitability measure, I propose an instrumental variables strategy. Firstly, I instrument for a diagnosis's profitability using the number of new molecules and first generics entering since payment system calibration. Secondly, I develop a "Hausman" instrument: for each drug, the Hausman instrument is the profitability computed only from the *other* drugs treating the same diagnosis. The Hausman instrument removes the drug-specific fixed effect which is the primary endogeneity pathway.

5.1 Measuring Profitability Through Diagnosis-Specific Payments

I create a measure of profitability by comparing diagnosis-specific payments with each diagnosis's actual treatment costs. In order to make the comparison, I adjust each insurer's total treatment costs for other payments that insurers receive that are not diagnosis-specific (including premium). I then estimate the average treatment costs associated with each diagnosis. If new drug entry and the onset of generic competition have caused average treatment costs to diverge from diagnosis-specific payment levels, the diagnosis is *profitable* (if treatment costs are lower) or *unprofitable* (if treatment costs are higher).

The diagnosis-specific payments are meant to make an insurer indifferent among beneficiaries by balancing a Part D insurer's receipts with its liabilities. There are four types of receipts: diagnosis-specific payments, demographic-specific payments, premiums, and government reinsurance payments. An insurer's total liability is what it pays for drugs: the difference between price and copay for each drug purchased in the insurance plan. The payments received by plan i for beneficiary j balance its liabilities when

$$\underbrace{(DP_{ij} + GP_{ij} - prem_i)}_{\text{Direct Subsidy}} + prem_i + RI_{ij} = L_{ij}$$

where
- DP_{ij} is the diagnosis-specific government payment
- GP_{ij} is the demographic-specific government payment
- $prem_i$ is insurer i's premium paid by each beneficiary
- RI_{ij} is the government reinsurance payment
- L_{ij} is insurer i's total liability for beneficiary j

The diagnosis-specific payments I aim to isolate are part of a beneficiary-specific payment known formally in Part D as the Direct Subsidy. The diagnosis-specific payment depends on the insurer's *bid*: its expected liability for a typical beneficiary given its copays and coverage (see Section 2.2). Let x index diagnoses.

Then DP_{ij} is computed according to the following function:

$$DP_{ij} = bid_i \sum_x W_x D_{jx}$$

W_x are the preset diagnosis-specific weights described in Section 2.3 and D_{jx} is 1 if beneficiary j has diagnosis x. Demographic-specific government payments GP_{ij} are computed in the same way for the demographic categories described in Section 2.3.

Insurance plans also receive premiums and reinsurance payments. Insurer i's premium $prem_i$ is removed from the Direct Subsidy and therefore drops out of the payment equation.[5] Reinsurance payments reimburse plans directly for 80% of plan liabilities in the catastrophic zone. The government makes two other payments to insurers that I ignore in my empirical strategy. Firstly, because low-income beneficiaries pay reduced co-pays, the Low-Income Cost-Sharing Subsidy reimburses plans directly for the difference between the reduced copay and the insurer's stated copay. This payment does not affect insurer liability because insurers pay the same amount regardless of a beneficiary's low-income status. Secondly, a Risk Corridor payment partially offsets the losses of any insurer whose total liability exceeds its total receipts by five percent. If instead an insurer's total receipts exceed its liability by 5%, the insurer remits part of its profits to the government under the rules of the Risk Corridor. There is no publicly available information about the frequency or size of Risk Corridor payments.

I adjust plan's total liability for reinsurance payments, demographic-specific payments, and plan bids. The adjusted plan liability $\widetilde{L_{ij}}$ represents what demographic-specific payments were on average meant to cover.

$$(DP_{ij} + GP_{ij} - prem_i) + prem_i + RI_{ij} = L_{ij}$$

$$bid_i \sum_x W_x D_{jx} + bid_i \sum_g W_g D_{jg} + RI_{ij} = L_{ij}$$

$$\sum_x W_x D_{jx} = \frac{L_{ij} - RI_{ij}}{bid_i} - \sum_g W_g D_{jg} = \widetilde{L_{ij}}$$

I now estimate new weights ω_x for each diagnosis to compare to the diagnosis-specific weight W_x.

$$\widetilde{L_{ij}} = \sum_x \omega_x D_{jx} + \varepsilon_j \tag{3}$$

I estimate the above equation using OLS. If the diagnosis-specific payments are accurate, W_x and ω_x, will be approximately equivalent. The results of estimation are discussed in Section 6.2.

[5]Insurers offering enhanced benefits (see Section 2.2) collect a supplemental premium which I also subtract from plan liabilities.

5.2 Linking Drugs and Diagnoses

Among the reasons that Part D is well-suited to the empirical analysis in this paper is that drugs are relatively closely linked to diagnoses, and diagnoses in turn are associated with profitability through inaccurate diagnosis-specific payments. Unfortunately, no reference work links drugs to the 86 diagnoses in the payment system. Instead, I use the empirical association between drugs and diagnoses, made possible by my very large sample of Medicare beneficiaries. An advantage of linking drugs and diagnoses using actual Part D data (rather than a reference work) is that I account for diagnosis-specific *undercoding*. A diagnosis is *undercoded* if health professionals do not tend to report it in medical claims. If the diagnosis is not coded in medical claims, Part D plans do not receive the diagnosis-specific payment for it, even if the beneficiary takes drugs for the diagnosis. In the extreme case, if a diagnosis is never recorded, coverage and copay of a drug that treats it should not be affected by the diagnosis's payment level. Research suggests that undercoding varies by diagnosis and is particularly common for mental diagnoses such as depression (Townsend et al., 2012). In other settings, insurers sometimes encourage physicians to *upcode* individuals by reporting diagnoses the individuals do not have in order to activate diagnosis-specific payments from the government. In those settings (e.g., Medicare Advantage), insurers have a contract with physicians to provide services to their enrolles; an advantage of Part D is that no such contracts exist, making it harder for insurers to communicate with or influence physicians.

In order to abstract from differences in strength or drug form (tablet, capsule, ointment), I link diagnoses to ingredients or ingredient combinations. Then individuals who take (branded) Prozac Weekly are considered to take the same drug ingredient as individuals who take (generic) 10mg fluoxetine tablets or 15mg fluoxetine capsules.

I run a probit model that predicts whether each beneficiary takes a given ingredient combination based on his or her diagnoses. Each coefficient gives the increase in the probability of taking the given ingredient combination associated with having the given diagnosis. For each ingredient combination, I define it as "treating" the diagnosis with the largest coefficient in the probit.

5.3 Assessing the Impact of Profitability

Finally, I predict insurers' choice of coverage and copay using the profitability implied by the payment system. For each insurance plan, I use an insurer-specific measure of profitability: specifically, $R_{xi} = bid_i(W_x - \omega_x)$. R_{xi} is the difference in dollars between what an insurer receives for a beneficiary with diagnosis x and the average treatment costs for this diagnosis. I refer to R_{xi} as the *profitability* of diagnosis x for insurer i. When R_{xi} is positive, the diagnosis-specific payment for x exceeds the average treatment costs for x, and

enrollees in insurer i with x are profitable on average; conversely, when R_{xi} is negative, insurers pay more on average to treat diagnosis x than they receive in diagnosis-specific payments. To note, a given diagnosis is either profitable or unprofitable; however, the magnitude is insurer-specific depending on the insurer's bid.[6]

I use simple linear methods to test the empirical association of profitability R_{xi} with insurer i's benefit design for drugs that treat diagnosis x. I consider three benefit design outcomes Y_{di} for each drug d and insurer i: coverage (1/0), copay in dollars, and copay as a percent of list price. Drug d (specifically, its ingredients) treats diagnosis x. My main estimation equation is:

$$\text{Estimation Model: } Y_{di} = \alpha R_{xi} + \delta_i + \underbrace{\beta TC_d}_{\text{when Y=coverage}} + \nu_{di} \tag{4}$$

A full set of insurer fixed effects δ_i net out all insurer-level patterns in benefit design such as overall generosity. Recall from Section 2.2 that insurers must cover at least two drugs in each "therapeutic class." When Y_{di} is coverage, I include dummies for each therapeutic class, TC_d, to control for the insurer's choice set.

I weight each observation by the total expenditure for the drug among Medicare Advantage enrollees. Weighting is used because drugs vary in their total expenditure by a factor of hundreds of millions. If insurers and beneficiaries have limited resources, they will base their decision (benefit design or enrollment) on drugs accounting for more expenditure. In the framework of Solon, Haider, and Wooldridge (2013), the use of expenditure weights recovers the average partial effect of profitability in the presence of unmodeled heterogeneity across total expenditure levels in how strongly Part D agents respond to incentives.[7] Drug-specific expenditures in Medicare Advantage are a good proxy for drug-specific expenditures in Part D because the populations are similar in disease burden; these weights are largely unaffected by the Part D payment system because Medicare Advantage insurers receive the majority of their payments through a different system.

5.4 Addressing Profitability's Endogeneity

An ordinary least squares approach to assessing the impact of profitability on benefit design includes a omitted variables problem. The empirical framework for Part D treatment costs and benefit design can be summarized in three equations.

$$\underbrace{\omega_x}_{\substack{\text{treatment}\\ \text{costs}}} = f(\underbrace{\delta_d}_{\text{quality}}) = g(\underbrace{Y_{di}(\delta_d)}_{\substack{\text{Part D}\\ \text{benefit}\\ \text{design}}}, \delta_d) \text{ for } d \in D_x, \forall i$$

[6] Scaling $W_x - \omega_x$ by the national average bid instead of each plan's bid does not change the results.

[7] The authors demonstrate that, while ordinary least squares is always inconsistent in the presence of heterogeneous effects, weighted least squares only completely relieves the inconsistency when standard errors are homoscedastic. Note that my analyses cluster standard errors on drugs.

$$\text{True Model: } \underbrace{Y_{di}}_{\substack{\text{Part D}\\ \text{benefit}\\ \text{design}}} = \alpha \underbrace{bid_i(W_x - \omega_x)}_{\text{profitability}} + \underbrace{\delta_d}_{\substack{\text{Part D}\\ \text{quality}}} + \underbrace{\delta_i}_{\substack{\text{insurer}\\ \text{f.e.}}} + \underbrace{\beta TC_d}_{\substack{\text{when}\\ \text{Y=coverage}}} + \eta_{di} \text{ for } d \in D_x, \forall i$$

$$\text{Estimation Model: } \underbrace{Y_{di}}_{\substack{\text{Part D}\\ \text{benefit}\\ \text{design}}} = \alpha \underbrace{bid_i(W_x - \omega_x)}_{\text{profitability}} + \underbrace{\delta_i}_{\substack{\text{insurer}\\ \text{f.e.}}} + \underbrace{\beta TC_d}_{\substack{\text{when}\\ \text{Y=coverage}}} + \nu_{di} \text{ for } d \in D_x, \forall i$$

Each drug comes with a fundamental unobserved "quality" that determines (1) how insurers choose benefit design for it and (2) levels of utilization given a particular benefit design. Drug-specific quality affects Part D benefit design because insurers need to offer high-quality drugs on favorable terms to attract enrollees. Drug-specific quality affects profitability because high-quality drugs are taken more often at any copay, raising treatment costs for insurers. When I estimate Equation 3, the treatment costs ω_x that I recover are a function of unobserved drug quality.

Ideally I could estimate the True Model given in the second equation and explicitly account for unobserved drug quality. For example, if the payment system randomly assigned higher payments for diagnosis x to certain insurers, we would have a situation where drug d is more profitable for certain insurers than for others. Patterns in their benefit design would identify unobserved drug quality separately from the reaction to profitability. Instead, each drug has the profitability of the diagnosis it treats, and I cannot separately identify a drug-specific fixed effect. In the Estimation Model in the third equation, the drug-specific quality term is now contained in the error term, affecting both profitability (through ω_x) and benefit design. I propose two strategies to address the endogeneity of profitability.

Firstly, I instrument for profitability using each diagnosis's exposure to technological change after 2002 (calibration data) but before 2009 (Part D claims data used to measure profitability). In pharmaceutical markets, there are two types of technological change. Firstly, new molecules enter the market after approval by the Food and Drug Administration. Secondly, older molecules lose their patent-protected monopoly and begin to face generic competition (which I style "technological change" because current technology can now be purchased at significantly lower prices). Over the period 2003-2008, 55 new molecules entered the market. 144 ingredients (or ingredient combinations) began to face generic competition; I refer to these as "new generics". Technological change is plausibly exogenous to the Part D payment system. Firstly, Part D represents only a small share of global pharmaceutical demand so entry of new molecules or new generics is not likely to be driven by the Part D payment system. Secondly, because new molecules take many years to develop, any redirection of research and development efforts toward profitable diagnoses would not result in new molecules in the short period between the payment system's announcement (April 2005) and the claims data used to measure profitability (2009).

Secondly, I develop a "Hausman" instrument that computes profitability using only the other drugs treating a given diagnosis.[8] That is to say, when predicting the benefit design for drug d, I instrument for profitability using a measure that excludes claims for drug d from the estimation of Equation 3.

$$\widetilde{L_{ij}} - \widetilde{L_{ijd}} = \sum_x \omega_{xd}^{\mathrm{H}} D_{jx} + \varepsilon_j$$

I subtract plan liabilities for drug d[9] from the left hand side of Equation 3. The new coefficients ω_{xd}^{H} on the diagnosis dummies D_{jx} are the treatment costs for diagnosis x excluding the impact of drug d. The Hausman instrument is $R_{id}^{H} = bid_i(W_x - \omega_{xd}^{\mathrm{H}})$. In terms of the above framework, the Hausman instrument excludes the drug-specific quality term δ_d whose appearance in both the profitability variable and the error term is the source of endogeneity.

5.5 Data: Medicare Claims and Part D Benefit Designs

My paper relies on two principle datasets. The first dataset provides medical and prescription drug claims for a 5% random sample of Medicare beneficiares for the years 2007 to 2009. Each row in the data is a medical service or prescription drug. In the same manner as Medicare, I assign diagnoses to individuals based on the presence of medical codes in their Inpatient, Outpatient, or Carrier (Physician) claims. The Part D claims report each plan's liability directly, and its bid can be inferred from its premium. Several steps in the above empirical strategy rely on this dataset's large size. To estimate average treatment costs for each diagnosis, I use nearly 850,000 beneficiaries enrolled in Part D in 2009. Nearly three million beneficiary-years are used to estimate the empirical association of drugs and diagnoses.

The second dataset used in this paper is the publicly-available Prescription Drug Plan Formulary files for 2009 and 2010. For each insurance plan, the files contain the list of drugs covered by the plan. If a drug is covered, the copay is also available. I again infer bids from premiums.

There are four accessory datasets. I gather data on new molecules and new generics from the Food and Drug Administration.[10] I collect Wholesaler Acquisition Cost (WAC) or "list price" from the Thomson Reuters Historical Pricing File. Wholesaler Acquisition Cost is "the cost at which brand manufacturers

[8] The instrument name is adopted, with apologies, due to its kinship to the instruments in Hausman (1997) which predict endogenous price in a given market from average price in other markets.

[9] As in Section 5.2, I abstract from drug strength by defining drug d by its ingredient or ingredient combination.

[10] While FDA data on new molecules is straightforward, there are two sources of measurement error in my identification of new generics. Firstly, FDA approval of new generics is not synonymous with market entry. Generic manufacturers frequently apply for FDA approval while relevant patents are still in effect. The patent-holding pharmaceutical firm then sues the generic manufacturer to stave off market entry. I counter this by dropping ingredient combinations that the FDA reports as "new generics" that do not appear as generics in the 2009 Part D claims data. The second source of measurement error is introduced by the fact that drugs with the same ingredients vary in strength. The FDA reports approval of a new strength as a "new generic" even if the ingredients have previously been available as generics in other strengths. But the most dramatic price decreases occur when the most popular strengths are introduced right after patent expiry. I counter this by using FDA "new generics" data from 2001 and 2002 (FDA data on new generics is not available for earlier years) to help remove new generics from 2003 to 2008 that were introduced in other strengths earlier. However, I probably classify some ingredients as "new generics" that were introduced in a new strength between 2003 and 2008 but were in fact available before 2001 as generics in the most common strengths.

sell to wholesalers and chain warehouses" (Berndt and Newhouse, 2010). I obtain each drug's ingredients with the help of the RxNORM drug database. Finally, I check my ingredients-diagnosis linkage against the Prescription Drug Morbidity Groups (RxMGs) of the Johns Hopkins Adjusted Clinical Groups Case-Mix System, a commercial product used by insurers to model expected liabilities. The ACG Case-Mix System predicts the "morbidity groups" an individual is likely to have based on prescription drug claims. The "morbidity groups" do not correspond perfectly to payment system diagnoses, but many are very similar.

The empirical strategy described in this section tests the hypothesis that Part D insurers use choice of coverage and copays to attract the profitable and deter the unprofitable. I now proceed to estimation.

6 Results: Profitability and Benefit Design in Medicare Part D

In this section, I first provide basic information about the insurers, beneficiaries, and drugs in my analysis. I then report each diagnosis' profitability, as implied by the Part D payment system. I describe the results of my method for linking each drug to the diagnosis it treats. I assess the instruments I will apply in estimation. I then proceed to estimate the relationship between profitability as defined by the payment system and coverage and copay in Part D plans. Profitability is measured directly and instrumented by technological change and a Hausman instrument that removes the drug in question from the profitability measure.

6.1 Summary Statistics on Insurers, Beneficiaries, and Drugs

I focus on the benefit design of 1550 Part D insurance plans operating in 2010. Each market (states or groups of states) has on average 46 insurance plans, and the largest plan in each market accounts for 20% of enrollment. Plans receive equal weight in the analyses even though plan enrollment is heavily concentrated.

Table 1 reports the characteristics of the beneficiaries used in estimating Equation 3 (top panel) and linking drugs and diagnoses (bottom panel). In the top panel, I describe 848,780 beneficiaries enrolled in traditional Medicare (not Medicare Advantage) in 2008 and Part D in 2009. The first row of Table 1 reports the number of diagnoses appearing on each beneficiary's medical claims. The next rows show the distribution of payments received by these beneficiaries' insurers. Consistent with the large dispersion in costs, payments to insurers vary greatly. Diagnosis-specific payments average just over half of total payments to Part D insurers (less at the extremes). Other payments (demographic-specific and reinsurance) payments are a large proportion of payments for the very healthy and the very sick.

The next rows of this table describe insurer's adjusted liability for each beneficiary. Adjusted liability ($\widetilde{L_{ij}}$) is the portion of plan liabilities that diagnosis-specific payments are meant to cover and is the left hand side of Equation 3. For individuals with very low utilization, demographic-specific payments make adjusted

liability negative. In the next line, I describe the distribution of diagnosis-specific payments minus adjusted liability, which varies widely. When this difference is negative, this beneficiary was (*ex post*) unprofitable and conversely when this difference is positive this beneficiary was (*ex post*) profitable. One explanation for the large disparity in profitability among beneficiaries is that the diagnosis-specific payments were wrong.

The second panel contains basic information about the nearly three million beneficiaries used to link ingredients and diagnoses.

Turning to drugs, Table 2 summarizes the 3921 drugs studied in this analysis, averaged across all Part D plans. The table is structured to compare drugs within quintiles of list price. The first panel describes drugs in the lowest quintile of list price, reporting four characteristics averaged across all Part D plans: coverage, copay, copay as a percentage of negotiated price, and total expenditure in a 5 % sample of Medicare Advantage enrollees. At the median, these inexpensive drugs are covered by virtually all insurers at an average copay of $6. When expressed as a percentage of price, the median copay is a bit under half the total price. Among drugs in this quintile of list price, total expenditure in Medicare Advantage on the median drug was about $21,000; the massive skewness of total expenditures is apparent in this row.

Two patterns emerge from this table. Firstly, copays are commonly far above or below 25% of negotiated prices. Differences in diagnosis-specific payments are not the only potential explanation, but clearly insurers are taking advantage of benefit design latitude. Secondly, while drugs with higher list prices are covered more often and at higher copays, coverage and copay are surprisingly similar across quintiles, suggesting that list price is not the primary factor in benefit design.

Taken together, these data suggest that the potential rewards to benefit design are great (some beneficiaries cost much less or more than plans receive in payments for them), and that insurers are engaging in some degree of it (copays are not 25%). In the next section I show how comparing diagnosis-specific payments to each diagnosis's treatment costs defines each diagnosis as profitable or unprofitable.

6.2 Results: Measuring Profitability Through Diagnosis-Specific Payments

I estimate Equation 3 on the 848,780 beneficiaries described in the top panel of Table 1. The independent variables are beneficiaries' diagnoses from 2008 and the dependent variable is adjusted plan liability from 2009. I exclude two diagnoses, Cystic Fibrosis and Cystic Fibrosis & Age<65, because fewer than 200 (less than 0.02%) of the beneficiaries have these diagnoses.

The results of estimating Equation 3 are clear: the payment system overpaid for certain diagnoses and underpaid for others. Table 3 reports the results of Equation 3 for the 69 diagnoses that I use in later analyses. The second and third columns report the estimated treatment costs for each diagnosis: the coefficients (ω_x) of Equation 3 and their standard errors scaled into dollars by the 2009 national average bid. Payments

associated with each diagnosis (i.e., W_x scaled similarly into dollars) are reported in the next column, and then I subtract the treatment costs from the payment to compute the profitability of each diagnosis. For example, I find that beneficiaries with Multiple Sclerosis cost Part D plans $1241 on average, but insurers only received about one-third of that amount in diagnosis-specific payments. Therefore, Multiple Sclerosis is an unprofitable diagnosis. The average profitability across the 69 diagnoses is -$62 (SD $184), although an insurer who enrolled a representative sample of beneficiaries (i.e., weighting each diagnosis by its prevalence) would earn $1.00 on each.

The findings of Table 3 are illustrated in Figures 2.a and 2.b. Figure 2.a represents the payments W_x (solid circles) and estimated treatment costs ω_x (open circles), both scaled into dollars by the national average bid, of diagnoses reported in Table 3.[11] Figure 2.b depicts the profitability of each diagnosis (last column of Table 3). In each figure, diagnoses are sorted by payment level; there is no statistical relationship between payment level and profitability.

Figure 3 sorts the 69 diagnoses by the difference between payments and treatment costs, and shows the diagnoses at the 10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th} percentiles of profitability. The CI of treatment costs (the small dots above and below the open circles) exclude the payments except near the median. High Cholesterol, discussed in Section 2.3, appears at the 70^{th} percentile of profitability.

6.3 Results: Linking Drugs and Diagnoses

I estimate a series of probits predicting utilization of a given drug ingredient (or ingredient combination) by diagnoses in the payment system. The sample is described in the bottom panel of Table 1 and includes beneficiaries from 2007, 2008, and 2009, about nearly three million in all. I restrict to drug ingredients and diagnoses appearing in the claims of at least 200 beneficiaries per year, leaving 732 ingredients or combinations to match to diagnoses.

Drug ingredients "treat" the diagnosis with the largest coefficient in the probit. On average, the largest coefficient (i.e., the one for the treated diagnosis) exceeds the second largest coefficient by a factor of six, suggesting that in general the connection between drug ingredients and diagnoses is relatively strong. The 732 ingredients or combinations evaluated treat 69 of the diagnoses in the payment system. The diagnoses that, according to my analysis, are not treated by any ingredients are often catch-all categories, such as Other Neurological Conditions/Injuries or Other Blood Diseases; for other diagnoses such as Pelvic Fracture, drugs are used for pain and infection but do not address the underlying diagnosis.

For each ingredient combination, I compare the diagnosis with the largest coefficient in the probit to the "morbidity group" specified by the ACG Case-Mix System. In general, the probit-based strategy accurately

[11] To preserve scale, the diagnosis HIV/AIDS is excluded from this figure; both payments and treatment costs for HIV/AIDS much higher than for any other diagnoses.

links ingredients to diagnoses they treat. When problems arise, it is because the diagnoses in the Part D payment system are narrowly defined. For example, while pain is a common complaint for many diagnoses, pain drugs tend to be linked to only a few (mostly Disorders of the Spine and Migraine Headaches). Meanwhile, contraceptive hormones tend to be linked to Vaginal and Cervical Diseases. I include pain and hormonal drugs in my drug sample despite spurious matching; results are strengthened when they are excluded.

6.4 Results: Addressing Profitability's Endogeneity

Figure 4 depicts the Hausman instrument described in Section 5.4. Each marker represents profitability for a particular ingredient (or combination) of 732. Ingredients treating the same diagnosis are arranged together. Diamonds denote profitability as reported in the preceding paragraphs. Squares, in the same hue as corresponding diamonds but with lower saturation, represent the Hausman instrument for each ingredient, meaning profitability for the diagnosis that ingredient treats excluding that ingredient from the Part D claims. Hausman instruments are above profitabilities because removing an ingredient's claims lowers estimated treatment costs, sometimes greatly. As is visually evident in this figure, the Hausman instrument strongly and significantly predicts true profitabilities in the first stage of IV estimation.

Figure 5 depicts the results of the first-stage regression predicting profitability from technological change. Each marker represents profitability for a given diagnosis. In the figure, diamonds represent the profitability reported in the preceding paragraphs and triangles represent the predicted profitability for each diagnosis based on the number of new molecules and new generics among its treating drugs. Across the 69 diagnoses matched to ingredients, 41 have zero new molecules, while the remainder range from one new molecule to seven. 26 diagnoses have no new generics, while the remaining 43 range from one new generic to fourteen. New molecules always significantly reduce profitability; while exact amounts vary by specification, each new molecule is associated with about $35 lower profitability. New generics always significantly raise profitability, with average coefficients across specification approximately $25. It is clear from this illustration that a great deal of profitability is *not* explained by the number of new molecules and new generics. Alternatively, the uniform coefficient across each new molecule/new generic may mask significant heterogeneity in the effects of different new molecules/new generics. The best-fit line for the profitabilities predicted from technological change (the dashed line) slopes slightly upward with profitability. Technological change is a weak, but very valid, instrument for profitability.

6.5 Results: Assessing the Impact of Profitability

The relationship between profitability and benefit design is reported for the full drug sample and three subsamples, described in Table 4. The first sample is 522 branded drugs not in one of the six "protected"

therapeutic classes covered in Section 2.2. These drugs represent about half of Part D spending in 2009. In the second panel I describe benefit design for 2699 generic drugs. The final panel describes 371 drugs in the protected classes, where benefit design is constrained by regulation. Generic drugs and protected drugs account for about 30% and 20% of Part D spending, respectively. Plans could apply for permission to exclude a protected drug and according to the data a small number received it. However, across 1550 plans and 371 protected drugs, the rate of coverage is 97%, compared with 65% for unprotected drugs.

Table 5 reports the results of estimating Equations 4. The four panels reflect estimation on the full drug sample and the three subsamples. The first three columns report estimation by OLS. OLS estimation demonstrates a positive association between profitability and coverage, although the effect is only significant at the 5% level in the full sample. The magnitude of the association is quite small – an extra hundred dollars in payment for a given diagnosis would raise the drug's rate of coverage by a tenth of a percentage point. The OLS results for copay are more significant both statistically and economically. An extra dollar in a diagnosis-specific payment is associated with copays lower by 76 cents. We also find evidence that copay as a percent of list price falls. Recall we only observe copay for covered drugs, lowering the number of observations relative to the equation predicting coverage (list price is missing for a small number of drugs).

The second set of columns report estimation by Two Stage Least Squares (2SLS) when instrumenting with the Hausman measure described in Section 5.4. As expected from the relationship depicted in Figure 4, the Hausman instrument strongly predicts profitability. The results using this instrument are similar to the results using OLS. Standard errors inflate slightly and effect sizes for coverage and copay as a percent of list price are modestly larger.

The third set of columns report estimation by 2SLS instrumenting by the total number of new molecules and new generics treating each diagnosis entering after 2002 but before 2009. Standard errors inflate in this specification relative to OLS. Most coefficients are statistically null, although signs largely point in the same direction as reports using OLS and the Hausman instrument. This specification finds the strongest evidence for a causal relationship between profitability and copay.

Due to weak-instrument concerns, I also estimate a just-identified 2SLS model which instruments for profitability using only the number of generics. These results offer stronger evidence for a relationship between profitability and coverage: insurers covered more drugs for diagnoses with larger numbers of new generics. For the subsample of protected drugs when the outcome is copay or copay as a percent of list price, new generics do not significantly predict profitability in the first-stage regression, producing invalid second-stage results.

The relationship between profitability and copay varies across branded, generic, and protected drugs. The largest relationship is found for protected drugs and the smallest for generic drugs; the relationship

for branded drugs lies between the two in magnitude but is not robust to technological change instruments. As these nearly 3000 generic drugs account for only 30% of Part D expenditure, optimizing benefit design perfectly across each drug is probably not worth insurer's efforts. It is not surprising, then, that profitability affects benefit designs only weakly for generic drugs. Given the regulation requiring coverage for protected drugs, it is not surprising that insurers take advantage of the only benefit design tool remaining by strongly raising copays as profitability falls. However, coefficients above unity in magnitude are hard to explain without recourse to forces not studied in this paper. In particular, Duggan and Scott-Morton (2010) find evidence suggesting that insurers paid relatively higher prices to pharmaceutical firms for drugs in the protected classes.

Taken together, the results in Table 5 suggest (1) a relatively strong causal relationship between profitability and copay and (2) a weaker and economically minor relationship between profitability and coverage. In addition, the positive relationship between profitability and coverage relies on the inclusion of therapeutic class dummies. This suggests that plans are reacting to profitability within the bounds of what Part D regulation allows. Recall that coverage regulations require plans to cover two drugs per therapeutic class, while the copay regulations simply require that total copays amount to 25% of total expenditures. An insurer wishing to set unfavorable benefits for drugs that treat unprofitable diagnoses still must meet the two-drug coverage requirement for each therapeutic class (diagnoses and therapeutic classes are related but do not correspond perfectly). But the insurer is free to set high copays for these drugs as long as copays for other drugs (e.g., those that treat profitable diagnoses) are lowered. Given the success of the therapeutic class coverage regulation at limiting insurers' ability to act on benefit design incentives, policymakers should consider revising copay regulations to require the 25% standard to be met within therapeutic classes. When the payment system is diagnosis-specific, regulation should acknowledge insurers' diagnosis-specific benefit design incentives.

To place the effect sizes in context, I recompute copays in the Part D claims data as though payments had been accurate, but enrollment and utilization were held constant. That is to say, suppose I find that treatment costs for diagnosis x are \$50 lower than its payment, such that diagnosis x is profitable. If instead the payment for diagnosis x had been \$50 lower, such that payment equaled treatment costs, copays for drugs that treat diagnosis x would be higher.[12] In particular, copays for a branded drug that treat diagnosis x should rise by \$28.30 (50 $\times$ the coefficient on copay in the second row and second column in Table 5);

[12]Coverage for drugs that treat x would be lower, but I disregard changes in coverage due to the strong assumptions required to calculate the impact. Firstly, altering the rate of coverage of the drugs that treat a given diagnosis requires me to randomly select some drug-insurer combinations and reassign them to covering or uncovering. Secondly, when accurate payments imply the rate of coverage should rise, I must impute a copay to drug-insurer combinations reassigned to covering. Finally, the assumption of fixed enrollment and utilization is stronger when coverage is changing than when copays are changing. Excluding the effect of coverage leads to an underestimate of the total impact of inaccurate payments.

copays should rise $1.85 for each generic drug treating x. Summing recomputed copays across each Part D enrollee's claims, about three-fifths of Part D enrollees would pay more in copays if the payment system had been accurate, while the remainder would pay less. The size of the transfer from enrollees who happen to have profitable diagnoses to enrollees who happen to have unprofitable diagnoses is approximately $1.5 billion, which amounts of 9% of total enrollee outlays (copays + premiums) in Part D.

7 Conclusion

Payment systems that condition payments on enrollee type are essential when insurer discrimination is prohibited. In this paper, I first described why the payment system in Part D might have failed to neutralize insurer benefit design incentives in Medicare Part D. Next, a model of coverage and copay showed how these key strategic variables might be affected by diagnosis-specific payments that diverge from average treatment costs. I measured the profitability of diagnoses in Part D by comparing diagnosis-specific payments to treatment costs, and found that many diagnoses were clearly profitable or unprofitable. I introduced two instruments to counter the endogeneity of my profitability measure. Finally, I showed that insurers covered drugs that treat profitable diagnoses at higher rates and lower copay.

In practical terms, there are strategies that would make the diagnosis-specific payment system more accurate, but in the classic tradeoff identified by Newhouse (1996), they can result in inefficiencies. Since changes in the medical industry (in this case, the entry of new drugs and the expiry of patent-protected exclusivity) alter the costs of treating a diagnosis over time, more frequent updating of payment levels can improve accuracy. In the extreme, payments can be a function of past-year utilization, so that payments automatically rise when treatment becomes more expensive (Hsu et al., 2009; Kautter, Ingber, Pope, and Freeman, 2012). But as payment systems become more accurate, they come to resemble a standard reimbursement system. Insurers lose their incentive to select the profitable and deter the unprofitable, but they also lose their incentive to deter unnecessary utilization: an insurer who incurs high liabilities for a given diagnosis this year can count on higher payments for that diagnosis the next year (McAdams and Schwarz, 2007).

Future research should acknowledge the role of an upstream medical provider such as a drug firm. Current models (including my own) do not consider how profitability affects the price an insurer pays for a service. Suppose insurers cover services for the unprofitable rarely and at high copays, while covering services for the profitable generously. Might those who supply the service for the unprofitable react by lowering their price? Might those who supply the service for the profitable, seeing that insurers find them profitable, demand a higher service price? Carey (2013) establishes how risk-adjusted payments theoretically pass-through to an upstream provider in a bilateral monopoly, but further theoretical research and empirical verification await.

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Appendix

A.1 Second-Order Condition for Insurer Profit Maximization

The second-order condition for profit maximization holds under certain restrictions derived in this section on the shape of $n_x(c_{ix}, c_{-ix})$ and $q_x(c_{ix})n_x(c_{ix}, c_{-ix})$.

$$\text{SOC} \quad S(c_{ix}, n_x(c_{ix}), r_x, p_x) = n''_{ix}\pi_{ix} + 2n'_{ix}\pi'_{ix} + n_{ix}\pi''_{ix}$$

$$= n''_{ix}(r_x - (p_x - c_{ix})q_{ix}) + 2n'_{ix}(q_{ix} - (p_x - c_{ix})q'_{ix}) + n_{ix}(2q'_{ix} - (p_x - c_{ix})q''_{ix}) < 0$$

Substitute for c_{ix} from the first-order condition,

$$n''_{ix}n_{ix}\frac{r_xq'_{ix} - q^2_{ix}}{q'_{ix}n_{ix} + q_{ix}n'_{ix}} + 2{n'_{ix}}^2\frac{q^2_{ix} - r_xq'_{ix}}{q'_{ix}n_{ix} + q_{ix}n'_{ix}} + n_{ix}\frac{n'_{ix}(2q_{ix}q'_{ix} - r_xq''_{ix}) + n_{ix}(2{q'_{ix}}^2 - q_{ix}q''_{ix})}{q'_{ix}n_{ix} + q_{ix}n'_{ix}} < 0$$

multiplying through by the (negative) common denominator $q'_{ix}n_{ix}+q_{ix}n'_{ix}$, and collect all the terms containing r_x. Log-concavity of the enrollment function n_x and the product q_xn_x emerges as a sufficient condition for the negativity of the second-order condition. Log-concavity of a function f means that $\ln f$ is concave, or that $f''f - (f')^2 < 0$. If $f''f - (f')^2 < 0$, then $f''f - 2(f')^2 < 0$ or $2(f')^2 - f''f > 0$ as I apply the condition.

$$\underbrace{-r_x[\overbrace{(2n'^2_{ix} - n''_{ix}n_{ix})}^{+\text{ if } n_x \text{ is log-concave}}\overbrace{(q'_{ix})}^{-} + \overbrace{q''_{ix}n_{ix}n'_{ix}}^{-}]}_{+\text{ if } n_x \text{ is log-concave}} + \underbrace{2(q'_{ix}n_{ix} + q_{ix}n'_{ix})^2 - q_{ix}n_{ix}(q''_{ix}n_{ix} + 2q'_{ix}n'_{ix} + q_{ix}n''_{ix})}_{+\text{ if } q_xn_x \text{ is log-concave}} > 0$$

A.2 Partial Derivative of Entry Condition With Respect to Copay

The partial derivative of the entry condition G with respect to equilibrium copay can be shown to be positive as long as the second-order condition (shown above) is negative.

$$G(c^*_x, N^*_x, r_x, \kappa, p_x) = r_xq'^*_x - q^{*2}_x - \kappa N^*_x(N^*_xq^*_xn'_x(c^*_x, N^*_x) + q'^*_x) = 0$$

$$\frac{\partial G}{\partial c^*_x} = r_xq''^*_x - 2q^*_xq'^*_x - \kappa N^{*2}_x(q^*_xn''_x(c^*_x, N^*_x) - 2q^*_x[n'_x(c^*_x, N^*_x)]^2N^*_x + q''^*_x/N^*_x) > 0$$

First, I substitute in for κ by taking advantage of the fact that at equilibrium $G(c^*_x, N^*_x, r_x, \kappa, p_x) = 0$. I define $n'^*_x \equiv n'_x(c^*_x, N^*_x)$ and similarly for n''^*_x. Finally, I state N^*_x as $1/n^*_x$.

$$\frac{\partial G}{\partial c^*_x} = r_xq''^*_x - 2q^*_xq'^*_x - \frac{r_xq'^*_x - q^{*2}_x}{q^*_xn'^*_x + q'^*_xn^*_x}(q^*_xn''^*_x - 2q^*_x[n'^*_x]^2/n^*_x + q''^*_xn^*_x) > 0$$

I multiply by (negative) $q^*_xn'^*_x + q'^*_xn^*_x$, collect the terms containing r_x, and divide by $-q^*_x/n^*_x$.

$$r_x[q''^*_x(q^*_xn'^*_x+q'^*_xn^*_x)-q'^*_x(q^*_xn''^*_x-2q^*_x(n'^*_x)^2/n^*_x+q''^*_xn^*_x)]-2q^*_xq'^*_x(q^*_xn'^*_x+q'^*_xn^*_x)+q^{*2}_x(q^*_xn''^*_x-2q^*_x[n'^*_x]^2/n^*_x+q''^*_xn^*_x) < 0$$

$$r_x q_x^*/n_x^*[q_x''^* n_x^* n_x'^* - q_x'^* n_x^* n_x''^* + 2q_x'^*(n_x'^{*2})] - q_x^*/n_x^*[2(q_x^* n_x'^* + q_x'^* n_x^*)^2 - q_x^* n_x^*(q_x^* n_x''^* + 2q_x'^* n_x'^* + q_x''^* n_x^*)] < 0$$

$$\underbrace{-r_x[\overbrace{(2n_x'^{*2} - n_x''^* n_x^*)}^{+ \text{ if } n_x \text{ is log-concave}} \overbrace{(q_x'^*)}^{-} + \overbrace{q_x''^* n_x^* n_x'^*}^{-}]}_{+ \text{ if } n_x \text{ is log-concave}} + \underbrace{2(q_x'^* n_x^* + q_x^* n_x'^*)^2 - q_x^* n_x^*(q_x''^* n_x^* + 2q_x'^* n_x'^* + q_x^* n_x''^*)}_{+ \text{ if } q_x n_x \text{ is log-concave}} > 0$$

We therefore find that the condition for the sign of this partial derivative is identical to the condition for the negativity of the second-order condition. Then, as long as c_x^* is a local maximum, $\partial G/\partial c_x^* > 0$.

A.3 Denominator of Derivatives

The denominator of each derivative of interest is potentially ambiguous; I show that it is negative whenever the second-order condition for profit-maximization holds.

$$\underbrace{\frac{\partial F}{\partial c_x^*}\frac{\partial G}{\partial N_x^*}}_{-} - \underbrace{\frac{\partial F}{\partial N_x^*}\frac{\partial G}{\partial c_x^*}}_{-}$$

Recall that $\dfrac{\partial F}{\partial c_x^*}$ is the second-order condition (SOC) and that in the prior section we found $\dfrac{\partial G}{\partial c_x^*} = -\dfrac{q_x^*}{n_x^*}\text{SOC}$. Again, substitute for κ from the fact that $G(c_x^*, N_x^*, r_x, \kappa, p_x) = 0$, let $n_x'^* \equiv n_x'(c_x^*, N_x^*)$ and similarly for $n_x''^*$, and state N_x^* as $1/n_x^*$.

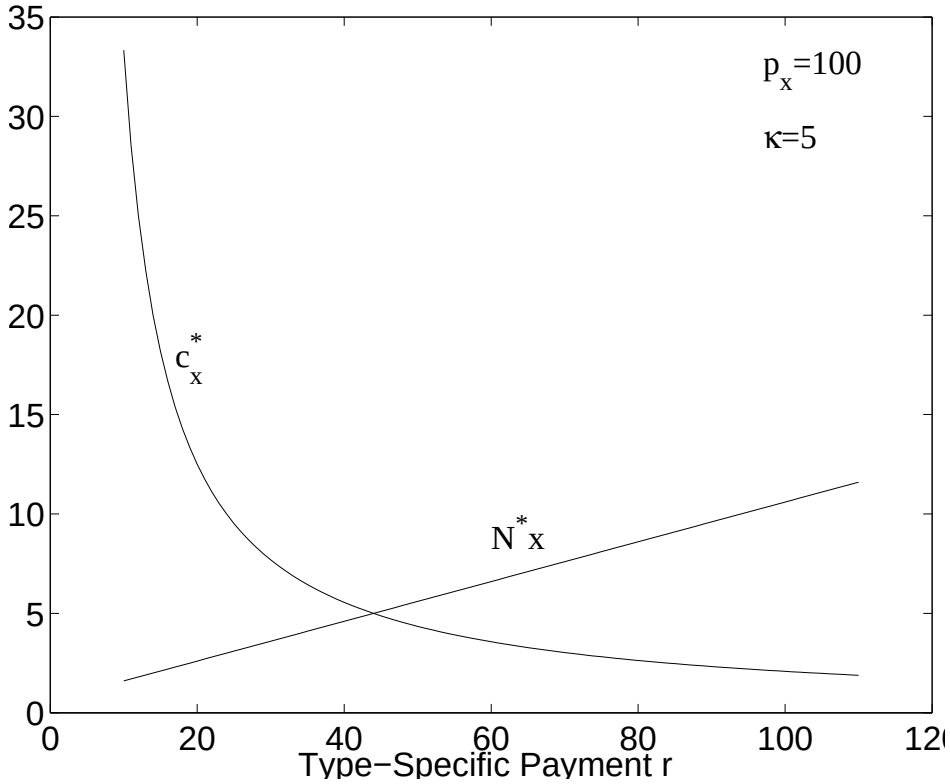
$$\text{SOC}\left(\frac{(r_x q_x'^* - q_x^{*2})(-2q_x^* n_x^* n_x'^* - q_x'^* n_x^2 - q_x^* \dfrac{\partial n_x^2}{\partial c_x^* \partial N_x})}{q_x^* n_x'^* + q_x'^* n_x^*}\right) + \left(\frac{n_x^*(r_x q_x'^* - q_x^{*2})(\dfrac{\partial n_x^2}{\partial c_x^* \partial N_x} + n_x^* n_x'^*)}{q_x^* n_x'^* + q_x'^* n_x^*}\right)\frac{q_x^*}{n_x^*}\text{SOC} < 0$$

$$\text{SOC}\left(\frac{(r_x q_x'^* - q_x^{*2})}{q_x^* n_x'^* + q_x'^* n_x^*}\right)(-2q_x^* n_x^* n_x'^* - q_x'^* n_x^2 - q_x^* \frac{\partial n_x^2}{\partial c_x^* \partial N_x} + q_x^* \frac{\partial n_x^2}{\partial c_x^* \partial N_x} + q_x^* n_x^* n_x'^*) < 0$$

$$\text{SOC}\underbrace{(r_x q_x'^* - q_x^{*2})}_{-}\underbrace{(-n_x^*)}_{-} < 0$$

Then the denominator of the derivatives is negative whenever the SOC holds.

Figure 1: Equilibrium c_x^* and N_x^* Under Log Utility and TIEV Distribution for μ_{ix}



Simulated equilibrium copays (c_x^*) and number of entrants (N_x^*) as generated by the model described in Section 4 under log utility for drugs and idiosyncratic preferences from the Type I Extreme Value Distribution. Drug price is 100 and the fixed cost of entry is 5, while type-specific payments r_x vary between 10 and 110.

Figure 2.a: Diagnosis-Specific Payments and Treatment Costs

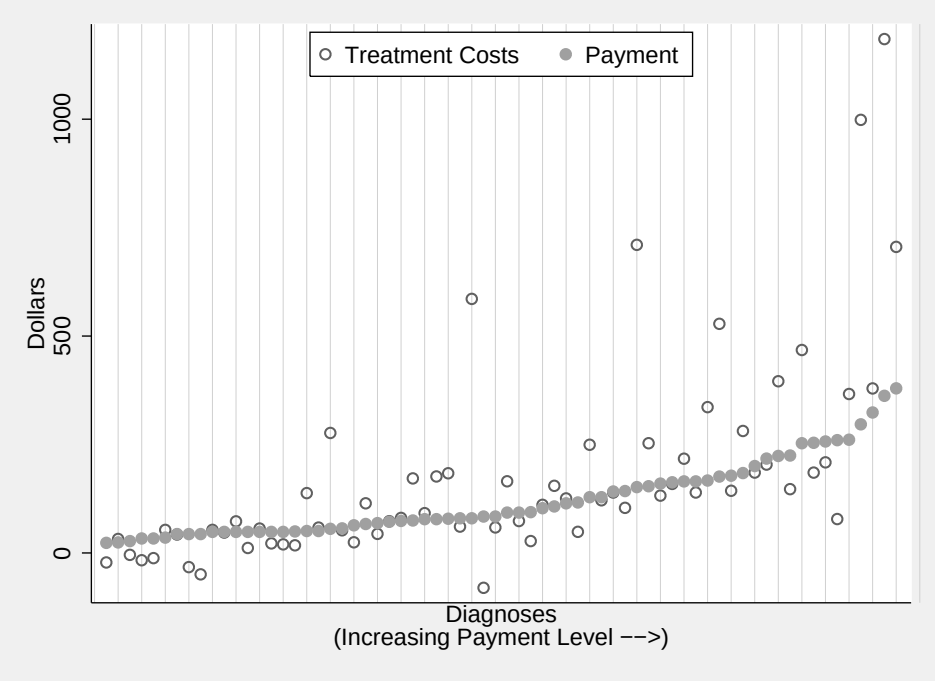
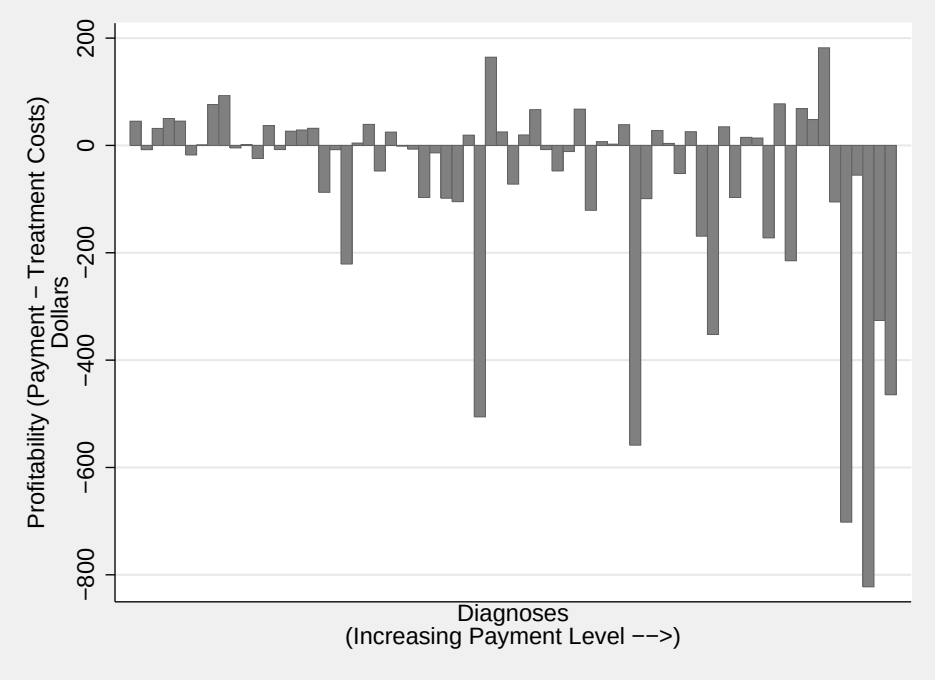
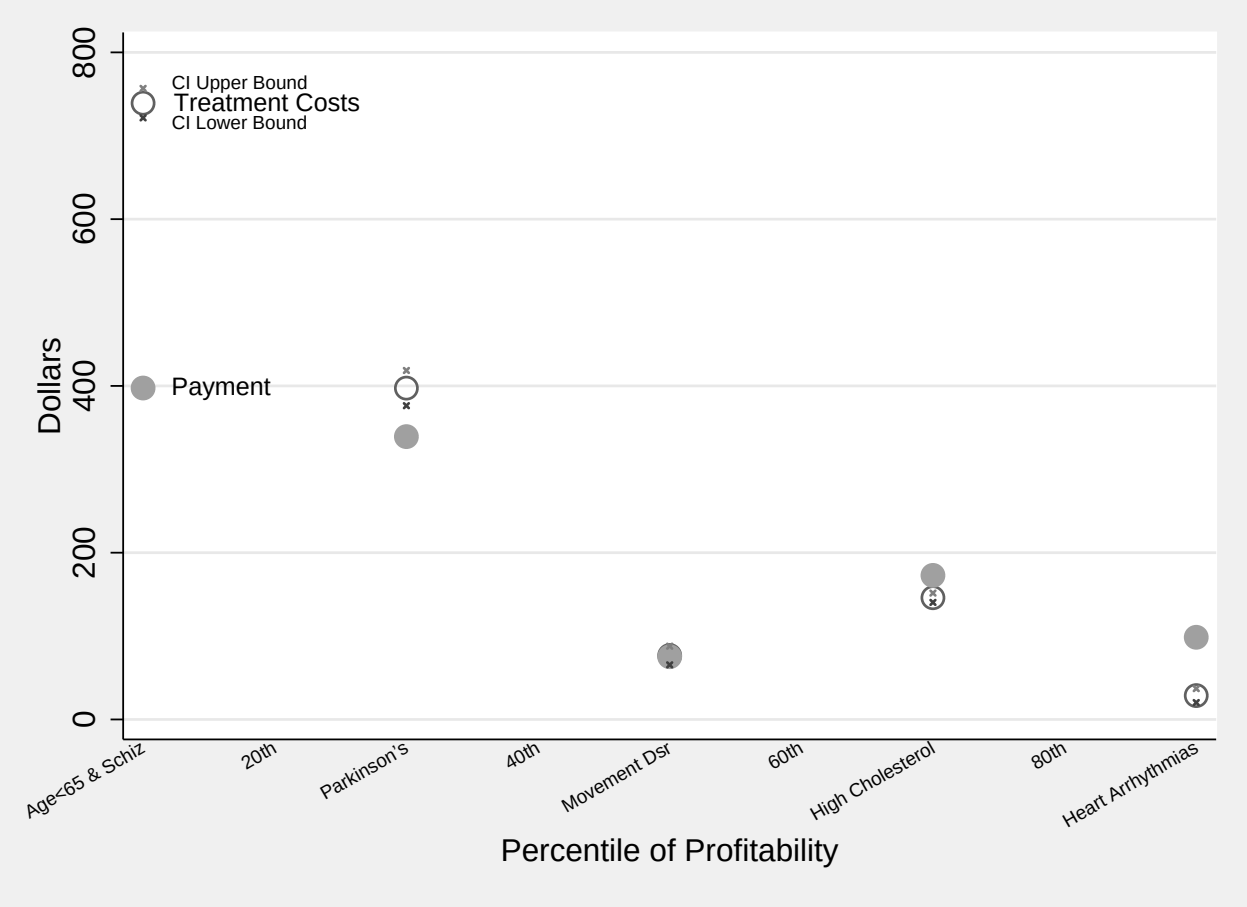


Figure 2.b: Diagnosis-Specific Profitability: Payments Minus Treatment Costs



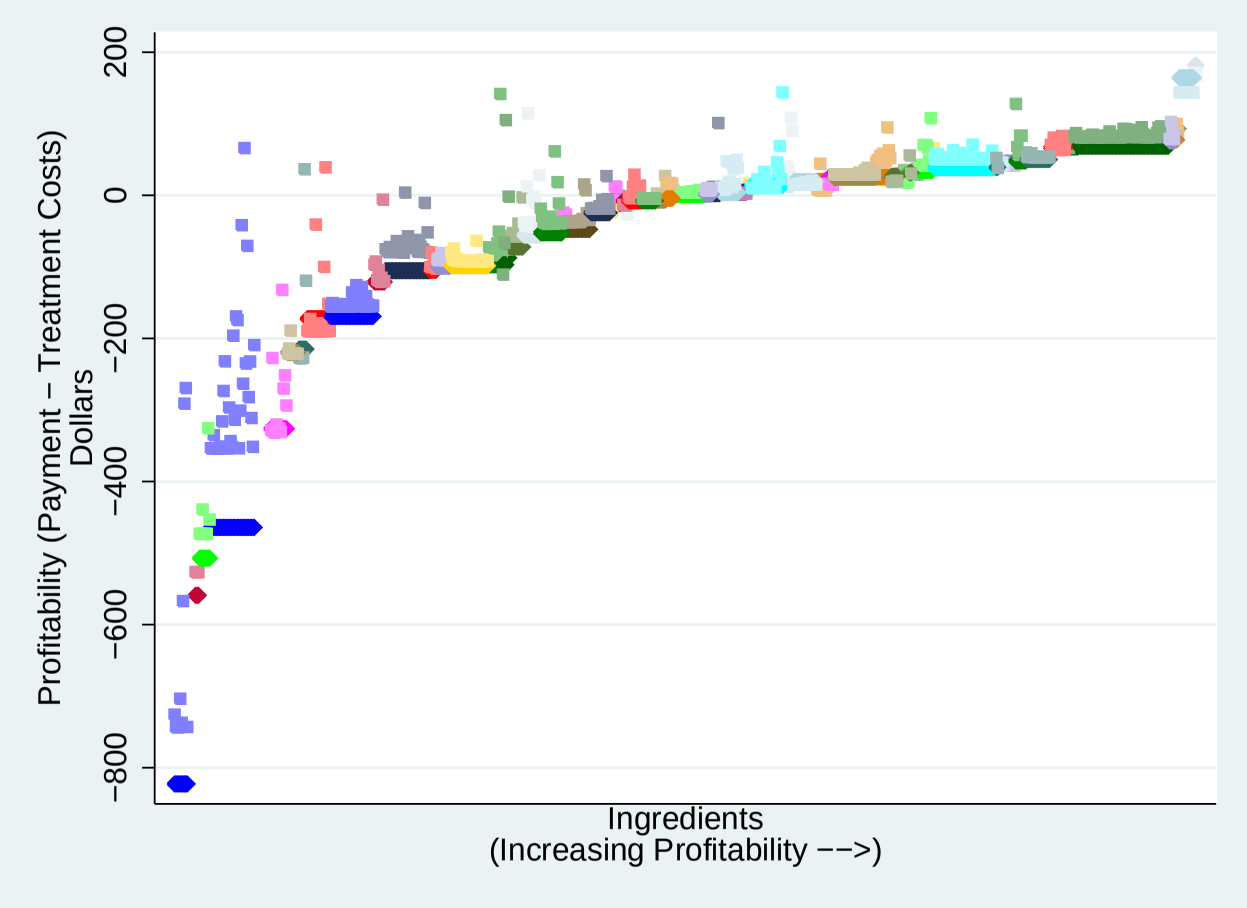
These figures illustrate the results reported in Table 3. In the top panel, the solid dots represent the diagnosis-specific payment in dollars for each diagnosis (69, excluding HIV/AIDS to preserve scale) treated by a sample drug (see text). The open dots represent the estimated treatment costs in 2009 for each diagnosis. In the bottom panel, bars represent the difference between diagnosis-specific payments and treatment costs in dollars. Positive values indicate that payments exceed treatment costs. Diagnoses are sorted by level of payment.

Figure 3: Diagnosis-Specific Payments and the Confidence Intervals of Treatment Costs



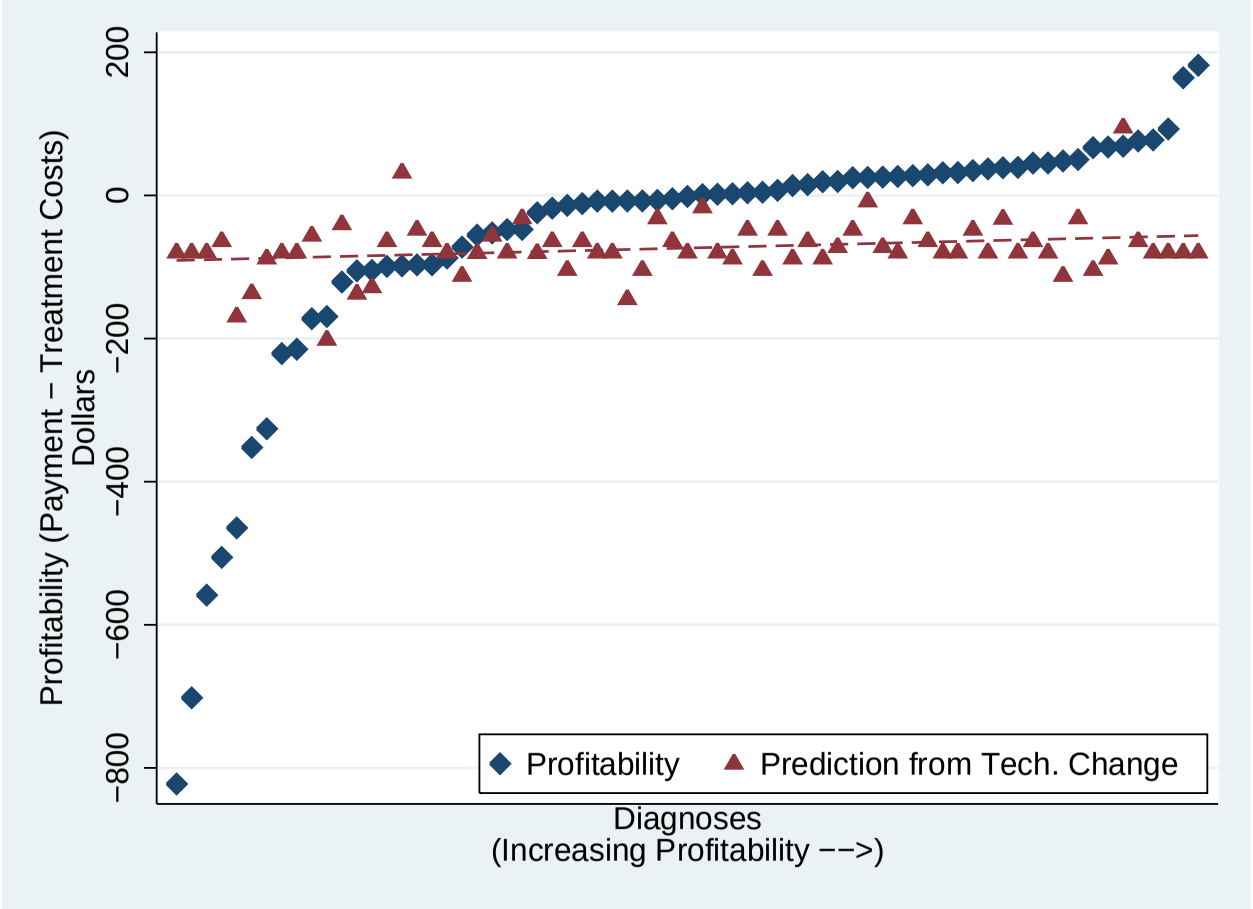
This figures illustrate the results reported in Table 3. The solid circles represent the diagnosis-specific payments (scaled into dollars by the national average bid) for diagnoses at the 10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th} percentiles of the distribution of profitability (where profitability is defined as the difference between diagnosis-specific payments and treatment costs) for the 69 diagnoses treated by a sample drug. The open circles represent the estimated treatment costs in 2009 for each diagnosis, and the dots above and below represent the 95% CI of estimation.

Figure 4: "Hausman" Instrument: Calculating Profitability Exclusive of Each Ingredient



This figure depicts the "Hausman" instrument described in Section 5.4. This instrument recomputes profitability according to Equation 3 but sequentially excludes from the plan liabilities all claims associated with each of 732 ingredients. In the figure, ingredients are arrayed along the x-axis. Diamonds represent the profitabilities for the diagnosis each ingredient treats. Squares (in the same hue but lighter saturation) represent the Hausman instrument calculated by excluding that ingredient from the claims data. Color printing recommended.

Figure 5: Predicting Profitability Using New Molecules and New Generics (First Stage Results)



This figure demonstrates the results of the first stage regression predicting profitability from technological change. The diamonds represent profitabilities for 69 diagnoses treated by a sample drug. The triangles represent the predicted profitabilities for each diagnosis based on the number of new molecules and new generics treating that diagnosis that entered after 2002 (the calibration data) but before 2009 (the claims data used to measure profitability). Diagnosis-specific profitability is measured as the difference between diagnosis-specific payments and average treatment costs. The diagnoses are sorted by level of profitability.

Table 1: Summary Statistics on Medicare Beneficiaries

Measuring Profitability Through Diagnosis-Specific Payments: Estimation Sample for Equation 3

N=848,780 beneficiaries	Percentile of Distribution				
	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
# of Diagnoses	0	3	5	8	12
Payments Received by Beneficiary's Insurer ($)					
Total Payments	440.75	848.09	1,163.24	1,555.94	4,631.89
Diagnosis-Specific	0.00	412.24	701.73	1,013.40	1,563.72
Other Payments	314.26	383.76	444.51	523.90	3,488.85
Liabilities of Beneficiary's Insurer ($)					
Adjusted Liability	-492.45	-188.73	619.05	1,280.40	2,080.90
Diag. Payment – Adj. Liability	-1,301.08	-406.41	204.21	647.02	1,199.08

Linking Drugs and Diagnoses: Estimation Sample for Section 5.2

N=2,908,936 beneficiaries × years	Percentile of Distribution				
	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
# of Diagnoses	0	3	5	8	13
# of Ingredient Combos Taken	0	2	7	11	20

The top panel reports on the distribution of diagnoses, payments to plans, and plan liabilities for 848,780 beneficiaries enrolled in traditional Medicare (not Medicare Advantage) in 2008 and Part D in 2009. The first row shows the number of diagnoses (of 84 possible) appearing on beneficiaries' medical claims. The next rows show the total payments received by beneficiaries' Part D plans, with diagnosis-specific and other payments broken out. The next rows show the adjusted liabilities incurred by beneficiaries' Part D plans – i.e., total plan liabilities less other payments (see text) and the difference between diagnosis-specific payments and adjusted liabilities. Positive values in this row indicate that diagnosis-specific payments exceeded adjusted liabilities. The bottom panel reports on the distribution of diagnoses and the number of drug ingredients taken for the beneficiary×years used to link drugs and diagnoses. Beneficiaries in this sample were enrolled in traditional Medicare (not Medicare Advantage) and Part D in 2007, 2008, or 2009.

Table 2: Part D Benefit Design and Expenditures

N=3921 drugs	Percentile of Distribution				
	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Lowest Quintile of List Price					
% of Plans Covering	19.29	88.06	99.81	100.00	100.00
Copay ($)	4.87	5.29	5.75	7.58	39.73
Copay as % of Price	16.80	28.95	44.73	78.62	216.00
MA Expenditure ($1000)	0	3	21	101	662
Second Quintile of List Price					
% of Plans Covering	10.26	56.77	95.10	100.00	100.00
Copay ($)	5.41	6.54	11.48	43.08	78.33
Copay as % of Price	12.01	19.70	32.58	70.53	151.50
MA Expenditure ($1000)	0	4	24	134	886
Middle Quintile of List Price					
% of Plans Covering	7.68	15.03	62.19	95.35	100.00
Copay ($)	5.75	19.26	50.17	74.88	82.32
Copay as % of Price	10.08	24.15	39.51	62.21	172.26
MA Expenditure ($1000)	0	2	18	109	780
Fourth Quintile of List Price					
% of Plans Covering	7.74	12.84	51.16	92.32	100.00
Copay ($)	6.39	36.71	63.49	79.00	86.27
Copay as % of Price	10.78	21.65	33.74	60.52	123.12
MA Expenditure ($1000)	0	3	21	159	1,951
Highest Quintile of List Price					
% of Plans Covering	7.55	14.84	62.03	95.65	100.00
Copay ($)	7.58	55.53	81.00	103.08	606.82
Copay as % of Price	11.01	19.05	26.79	42.70	105.93
MA Expenditure ($1000)	1	8	53	322	3,136

This table summarizes the distribution of benefit design and expenditure share for 3921 drugs, averaged across 1550 Part D plans operating in 2010. Drugs are grouped into quintiles by "list price" (Wholesaler Acquisition Cost). The first row in each group reports the distribution of the percent of plans covering a given drug. The second and third rows first average copay and copay as a percentage of plan-specific price across plans, and then report the distribution across drugs in the list price quintile. The next row reports the dollar value (in thousands) of total expenditures on the drug in Medicare Advantage.

Table 3: Diagnosis-Specific Payments and Treatment Costs

Diagnosis	Treatment Costs Coeff.($)	(SE)	Payment ($)	Profitability ($)
Multiple Sclerosis	1241.16	(16.8)	379.47	-861.70
Leukemia	1048.70	(60.1)	310.57	-738.13
Psoriatic Arthropathy	744.54	(32.2)	158.99	-585.55
Major Organ Transplant	614.89	(29.3)	83.74	-531.16
HIV/AIDS	2650.59	(17.6)	2164.44	-486.15
Metastatic Acute Cancers	552.64	(10.8)	184.43	-368.20
Age<65 & Schizophrenia	739.12	(8.8)	397.49	-341.64
Huntington's Ds	288.42	(41.8)	58.30	-230.12
Schizophrenia	490.07	(15.8)	264.99	-225.08
Dementia w/ Depression	414.67	(10.9)	234.25	-180.42
Age<65 & Other Major Psych. Dsrs	352.08	(5.1)	174.89	-177.19
Seizure Dsr & Convulsions	261.34	(6.5)	134.61	-126.73
Diabetes w/ Comps	383.82	(4.5)	273.47	-110.35
Other Endocrine	192.43	(6.1)	82.68	-109.76
Motor Neuron Ds/Atrophy	264.95	(48.5)	161.11	-103.84
Psoriasis	184.58	(12.8)	81.62	-102.97
Inflamm. Bowel Ds	294.65	(13.2)	192.91	-101.74
Chronic Renal Failure	180.03	(11.7)	78.44	-101.59
Lung Cancer	144.54	(5.2)	53.00	-91.54
Hepatitis	173.12	(15.3)	97.52	-75.60
Parkinson's Ds	397.40	(10.6)	339.19	-58.22
Asthma and COPD	227.58	(3.4)	172.77	-54.81
Connective Tissue Dsr	119.89	(10.8)	69.96	-49.93
Migraines	162.14	(9.3)	112.36	-49.78
Urinary Obstruction	76.34	(5.9)	50.88	-25.46
Vascular Disease	55.67	(3.8)	37.10	-18.57
Polyneuropathy exc. Diabetic	96.10	(6.2)	81.62	-14.48
Severe Hematological Dsr	131.70	(22.6)	119.78	-11.92
Salivary Gland Ds	61.38	(18.4)	53.00	-8.38
Larynx/Vocal Ds	33.80	(27.6)	25.44	-8.36
Incontinence	116.23	(6.3)	108.12	-8.11
Cellulitis & Skin Ds	58.95	(4.4)	50.88	-8.07
Infectious Ds	84.34	(10.7)	77.38	-6.96
Fecal Incontinence	55.19	(22.4)	50.88	-4.31
Mononeuropathy/Abnormal Movement	76.69	(5.6)	75.26	-1.44
Bronchitis & Congenital Lung Dsr	44.42	(5.0)	45.58	1.16
Bullous Dermatoses	49.20	(4.0)	50.88	1.68
Myocardial Infarction/Unstable Angina	145.87	(3.4)	148.39	2.53
Open-angle Glaucoma	166.67	(5.1)	170.65	3.98
Vascular Retinopathy exc. Diabetic	54.64	(7.1)	59.36	4.71
Other Psych.	127.21	(14.4)	134.61	7.41
Kidney Transplant	213.15	(22.4)	227.89	14.74
Rheumatoid Arthritis	194.08	(7.1)	209.87	15.80
Other Organ Transplant	63.69	(22.1)	83.74	20.05
Polycythemia Vera	77.08	(27.8)	97.52	20.44
Glaucoma and Keratoconus	46.04	(13.2)	72.08	26.04
Other Upper Respiratory Ds	61.62	(3.8)	87.98	26.36
Lipoid Metabolism	145.97	(2.8)	172.77	26.81
Chronic Skin Ulcer exc. Decubitus	23.18	(7.5)	50.88	27.70
Other Major Psych. Dsr	138.48	(4.0)	167.47	29.00
Quadriplegia	20.74	(11.0)	50.88	30.14
Pulmonary Embolism & Thrombosis	-4.52	(7.7)	28.62	33.14
Other Spec. Endocrine	18.43	(2.9)	51.94	33.50
Esophageal Ds	150.19	(3.3)	186.55	36.37
Pancreatic Ds	11.81	(11.2)	50.88	39.07
Dsr of Spine	108.93	(3.5)	149.45	40.52
Cerebral Hemorrhage/Stroke	25.70	(3.9)	66.78	41.07
Bone Infections	-22.90	(12.3)	24.38	47.28
Ulcer & Gastro Hemorrhage	-12.48	(5.6)	34.98	47.46
ADD	218.84	(21.0)	269.23	50.39
Vaginal & Cervical Ds	-17.56	(7.4)	34.98	52.54
Heart Arrhythmias	28.63	(4.2)	98.58	69.94
Osteoporosis	51.05	(3.8)	121.90	70.85
Congestive Heart Failure	194.07	(4.9)	266.05	71.98
Empyema, Abscess, & Lung Ds	-34.12	(37.1)	45.58	79.69
Hypertension	154.05	(3.0)	235.31	81.26
Polymyalgia Rheumatica	-51.92	(14.8)	45.58	97.50
Muscular Dystrophy	-84.24	(48.8)	87.98	172.22
Opportunistic Infections	82.12	(20.7)	272.41	190.29

This table reports the results of the estimation of Equation 3 on 848,780 Medicare Part D enrollees in 2009. The dependent variable is insurer liability adjusted for other Part D payments, and the independent variables are dummies that are one if the beneficiary had the diagnosis in 2008. Regression results and payments are expressed as dollars (instead of weights) by multiplying by the national average bid in 2009 (see Section 5.1). Profitability is the difference between payments and treatment costs. Only the 69 diagnoses used in later analyses are reported.

Table 4: Summary Statistics on Drug Samples

	Percentile of Distribution				
	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
522 Branded Drugs (Not Protected)					
% of Plans Covering	15.03	51.61	80.10	93.23	100.00
Copay ($)	13.08	39.55	54.52	72.58	326.93
Copay as % of Price	16.22	25.52	32.10	51.02	93.97
MA Expenditure ($1000)	1	13	104	601	4,294
2699 Generic Drugs (Not Protected)					
% of Plans Covering	7.61	19.29	82.13	99.87	100.00
Copay ($)	5.09	6.33	26.59	73.44	86.08
Copay as % of Price	11.36	21.54	36.66	68.07	164.23
MA Expenditure ($1000)	0	2	17	90	677
371 Protected Drugs					
% of Plans Covering	72.58	100.00	100.00	100.00	100.00
Copay ($)	5.11	6.22	13.19	69.85	341.96
Copay as % of Price	9.18	18.26	25.38	36.71	75.72
MA Expenditure ($1000)	2	15	80	374	2,734

This table summarizes the distribution of benefit design and expenditure, averaged across 1550 Part D plans operating in 2010, for various drug samples used in the estimation of Equation 4. The first group represents the same sample as Table 2. The first row in each group reports the distribution of the percent of plans covering a given drug. The second and third rows first average copay and copay as a percentage of plan-specific price across plans, and then report the distribution across drugs in the list price quintile. The next row reports the dollar value (in thousands) of total expenditures on the drug in Medicare Advantage.

Table 5: Effect of Profitability on Benefit Design in Medicare Part D

	OLS			IV: Hausman			IV: New Molecules & New Generics			IV: New Generics		
	coverage	copay	copay/list	coverage	copay	copay/list	coverage	copay	copay/list	coverage	copay	copay/list
Subsample: All												
Profitability	0.001*	-0.758***	-0.009**	0.015*	-0.738***	-0.017**	0.012	-0.466	-0.001	0.063**	-0.568	0.011
	(0.003)	(0.148)	(0.003)	(0.006)	(0.197)	(0.006)	(0.010)	(0.274)	(0.009)	(0.022)	(0.324)	(0.013)
N	5,567,600	3,800,118	3,798,884	5,567,600	3,800,118	3,798,884	5,567,600	3,800,118	3,798,884	5,567,600	3,800,118	3,798,884
Controls	TC			TC			TC			TC		
1st Stage F				127.4	209.5	209.5	63.3	134.6	134.6	89.3	51.8	51.8
Subsample: Brands												
Profitability	0.003	-0.566***	-0.014**	0.031	-0.465*	-0.023*	-0.006	0.394	-0.011	0.216	0.198	0.003
	(0.006)	(0.158)	(0.005)	(0.024)	(0.198)	(0.009)	(0.013)	(0.777)	(0.014)	(0.127)	(0.837)	(0.016)
N	809,100	573,667	573,665	809,100	573,667	573,665	809,100	573,667	573,665	809,100	573,667	573,665
Controls	TC			TC			TC			TC		
1st Stage F				43.7	50.6	50.6	16.9	45.7	45.7	34.3	10.2	10.2
Subsample: Generics												
Profitability	0.001	-0.037**	-0.012*	0.008	-0.008	-0.033*	0.000	-0.073**	0.017	0.048**	-0.202***	0.032
	(0.004)	(0.014)	(0.005)	(0.005)	(0.014)	(0.015)	(0.008)	(0.025)	(0.026)	(0.015)	(0.055)	(0.044)
N	4,183,450	2,666,371	2,665,139	4,183,450	2,666,371	2,665,139	4,183,450	2,666,371	2,665,139	4,183,450	2,666,371	2,665,139
Controls	TC			TC			TC			TC		
1st Stage F				219.1	311	311	43.7	56.3	56.3	56.5	40.4	40.4
Subsample: Protected												
Profitability	0.001	-1.295***	-0.004	0.004	-2.002*	0.002	0.003	-2.491**	-0.018	-0.007	-7.556	-0.076
	(0.001)	(0.327)	(0.006)	(0.004)	(0.811)	(0.010)	(0.009)	(0.882)	(0.017)	(0.006)	(6.340)	(0.085)
N	575,050	560,080	560,080	575,050	560,080	560,080	575,050	560,080	560,080	575,050	560,080	560,080
Controls	TC			TC			TC			TC		
1st Stage F				7.8	45.2	45.2	26.1	12.9	12.9	17.2	1	1

This table reports the results of estimation of Equations 4 across four samples of drugs described in Table 4. In each panel, the dependent variables are a binary coverage measure or, if covered, the copay or copay as a percentage of list price for each drug in 1550 Part D plans in 2010. The first results are OLS and the remaining are 2SLS with the indicated instrument. When the outcome is coverage, controls for therapeutic class are included. Standard errors (in parentheses) are clustered on drugs. Asterisks represent significance at 5, 1, and 0.1 percent.