A Time to Harvest: Evidence on Consumer Choice Frictions from a Payment Revision in Medicare Part D *

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Abstract

In many federally-subsidized insurance markets, insurers are paid on the basis of enrollee diagnoses; in principle, insurers are indifferent between individuals with different diagnoses due to this system of diagnosis-specific payments. Between 2010 and 2011, the diagnosis-specific payment system in Medicare Part D was revised, changing an insurer's incentive to enroll an individual with a particular diagnosis. This research uses the response of insurers to the payment update to develop evidence on consumer choice frictions. We first document that, consistent with prior theory, Part D insurers improved benefits for drugs that treat diagnoses with positive payment updates; conversely, insurers made coverage for diagnoses receiving negative payment updates less generous. We compute that an extra dollar in diagnosis-specific payments reduced out-of-pocket costs for the typical enrollee's demand by about $0.20, a measure of pass-through in this market. We then develop an analytically tractable model of dynamic insurer benefit design in the presence of consumer switching costs. In this setting, insurers receiving higher payments balance improving benefits to attract new enrollment and harvesting from locked-in enrollees; the latter effect is larger when the insurer has a large market share. Empirically, we find that Part D insurers with a large share of a diagnosis responded less strongly to the payment revision. Relative to insurers with a small share of a diagnosis, those with a large share reduced out-of-pocket costs about one-third less when receiving a positive payment update. This analysis provides indirect evidence of the presence of demand-side choice frictions using only supply-side behavior.

JEL codes: L13 (Oligopoly and Other Imperfect Markets); I11 (Analysis of Health Care Markets); I13 (Health Insurance, Public and Private); H51 (Government Expenditures and Health)

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1 Introduction

Public payments to private health insurers are a major market design element in the managed-competition model of public health insurance. These payments – "risk adjustment" – aim to make insurers indifferent between enrolling individuals of varying *ex ante* health status by compensating them for each individual's expected cost, thus encouraging insurers to provide the same level of benefits to all enrollees. In this paper, we explore a revision to the payment system in Medicare Part D that sharply changed payments for different diagnoses and, therefore, an insurer's expected profit from enrolling an individual with a given diagnosis. Confirming prior theoretical and empirical work, we find that insurers improve benefits for diagnoses receiving positive payment updates, while out-of-pocket costs rise for diagnoses receiving negative payment updates. Our novelty lies in recognizing that, if consumers are "locked into" their current insurer due to switching costs, the response of each insurer to the payment system revision should be mediated by current market share. Since insurers must offer the same benefits to both current and new enrollees, an insurer considering a reduction in out-of-pocket costs must consider both the potential profits from new enrollees and the higher outlays for current enrollees. For an insurer with a large share of the market, the former is smaller and the latter is larger, making the insurer more likely to "harvest" current enrollees by not improving benefits. This research develops theoretical and empirical evidence about the response of benefits to a change in diagnosis-specific payments in a large prescription drug insurance program, Medicare Part D.

Medicare Part D is a publicly-funded private prescription drug insurance benefit for twenty million elderly and disabled. The majority of Federal payments to insurers in Part D are diagnosis-specific, meaning they aim to pay insurers the marginal cost of treating each of an enrollee's diagnoses. For example, an average-premium plan in 2010 enrolling a 66 year old man whose medical claims reflect Multiple Sclerosis would receive a diagnosis-specific payment of $659. If a similar enrollee's medical claims instead reflect HIV/AIDS, the plan would receive $2217. In theory, plans are equally willing to enroll both men because the diagnosis-specific payments offset the higher expected cost of the HIV/AIDS patient. The levels of the diagnosis-specific payments were calibrated using data from the early 2000s and then left in place through 2010, despite new drug entry and the onset of generic competition raising or lowering the costs of treating certain diagnoses. In 2011, the payment system was updated to again set payments equal to associated treatment costs. For the two men discussed previously, their insurer in 2011 now receives $889 for the Multiple Sclerosis patient (a 35% increase) and $2081 for the HIV/AIDS patient (a 6% decrease). We demonstrate in Section 4 that the payments for many diagnoses were raised or lowered by considerable amounts as a result of the payment system revision.

An insurer's profit-maximizing enrollment mix will change as a result of the payment system revision: an

increase in a diagnosis's payments between 2010 and 2011 will make insurers want to attract individuals with that diagnosis, and conversely for diagnoses where payments are reduced. Prior theoretical and empirical work suggests that insurers in this setting, who must accept all enrollees at a uniform premium, will seek to attract preferred enrollees through improved benefit design (Frank et al. (2000) among others). In Section 5.1, we propose a panel data model to predict the out-of-pocket costs for each plan and drug between 2009 and 2012 as a function of payments for the diagnosis the drug treats. Fixed effects net out all time-invariant plan×drug factors affecting out-of-pocket costs, identifying the impact of payments purely from the changes that co-occur with the 2011 revision. In alternative models, we also control flexibly for drug prices or allow a drug-specific linear trend. We document that out-of-pocket costs fall for diagnoses that receive positive payment updates. This finding complements the analysis of Brown et al. (2014), who show that after the introduction of diagnosis-specific payments in Medicare Advantage, insurers successfully raised enrollment among individuals who were made more profitable by the change in payments. It extends their analysis by showing the response of the exact mechanism – benefit designs – that insurers use to effectuate selection. As noted by Geruso et al. (2016), because prescription drugs tend to treat a single diagnosis, their benefits are a particularly effective selection mechanism.

We can use the same model to estimate the rate at which payment updates pass-through to out-of-pocket costs. We compute an outcome measure equal to the out-of-pocket costs in each plan for a typical individual with each diagnosis. We find that insurers lower out-of-pocket costs about \$0.20 for each \$1 in increased payments. This estimate is similar to those found exploiting policy changes (Cabral et al., 2015) or policy thresholds (Duggan et al., 2016) in Medicare Advantage payment rates, even though by conventional measures Medicare Advantage is much less competitive than Medicare Part D. However, we note that our low rate of pass-through can be rationalized by market power among either insurers or prescription drug manufacturers (Weyl and Fabinger, 2013). We do not find conclusive evidence of pass-through to upstream drug prices; however, our observed drug prices are prior to an unobserved plan-drug rebate, which may affect our estimates.

We augment our basic findings with the insight that, in the presence of consumer switching costs, an insurer facing a change in payments will respond differently depending on the insurer's current enrollment. In Section 3, we develop a theoretical model where (myopic) individuals with switching costs have logit demand for insurance. We consider two supply-side scenarios: a insurer monopoly (solved analytically) and an insurer duopoly (solved numerically). Forward-looking insurers select profit-maximizing out-of-pocket costs, taking into account a government subsidy payment. The response to a higher payment depends on the insurer's market share: large insurers reduce out-of-pocket costs less than small insurers.

We test this theoretical prediction in the Part D market by assessing how an insurer's response to the

payment revision is mediated by whether they have an above-median or below-median share of the market for the diagnosis. Compared to plans with a below-median share, those with an above-median share react less strongly to payment updates, reducing out-of-pocket costs for a positive payment update about one-third less. This finding is consistent with the presence of switching costs in Part D, which has been documented by a number of empirical papers that study demand directly (Ericson (2014)[1], Ho et al. (2017), and Polyakova (2016), reviewed in Section 2).

If benefits for a given diagnosis become more generous as a result of the payment system revision, enrollees will respond by increasing utilization (days supplied). Therefore, we use the payment system update as an input cost shock in an instrumental variables demand estimation. By exploiting the revision of the payment system in a panel data setting, we recover an estimate of overall drug demand elasticity while flexibly controlling for all time-invariant individual-level preference heterogeneity. Our elasticity estimates are about 2%, somewhat lower than previous estimates (Einav et al., 2015; Jung et al., 2014). However, our elasticity applies to a relatively elderly and sick population, and due to program rules it is estimated from the richer half of Medicare Part D enrollees (those not receiving the low-income subsidy). In addition, our elasticity reflects how total annual demand responds to relatively small changes in out-of-pocket costs, rather than the demand response within the year when a beneficiary encounters the large salient increase in out-of-pocket costs at the onset of the coverage gap.

This paper makes two contributions. First, it describes a method of inferring the presence of demand-side switching costs based only on supply-side behavior. Secondly, payment systems such as Part D's also underlie Medicare Advantage and the Affordable Care Act health insurance exchanges. There are significant practical and theoretical challenges to designing payment systems that truly make insurers indifferent among enrollees. This research demonstrates how economists can exploit inaccuracies in these payment systems to estimate market parameters.

In what follows, we first describe demand, supply, and Federal regulation in Medicare Part D, focusing on the features that facilitate this analysis. Next we introduce a theoretical model to predict the behavior of insurers in a stylized setting similar to Part D. We then describe an econometric model to test those predictions. Next, we document the response of benefit designs to the change in incentives provided by the payment system revision. Finally, we obtain the elasticity of demand by examining the response to the change in out-of-pocket costs that results from the payment system revision.

[1]Ericson (2014) shows that firms in Part D may attempt to discriminate between new and continuing consumers by introducing new plans; consistent with this theory, he finds that old plans have higher premiums than new plans, even conditioning on plan characteristics. We return to this prediction in Section 5.5.

2 Medicare Part D

This section details the design of the Medicare Part D market, with special attention to insurer incentives and the diagnosis-specific payment system. We first describe how enrollees choose Part D plans and drugs. We then describe the insurers' plan benefit design problem and the regulations that constrain their actions. Finally, we review how Part D plans were paid in their first five years and the nature of the recalibration in 2011.

2.1 Enrollment and Drug Demand

In Medicare Part D, enrollees choose among competing insurance plans on the basis of premium and benefit design. In this section, we describe the demand side of Part D, and develop evidence that the demand side is characterized by private information on drug needs and switching costs in plan choice.

Medicare Part D implements the managed competition model of public health insurance that underlies Medicare Advantage, Medicaid managed care, and the Affordable Care Act marketplaces. In the managed competition model, individuals choose among competing insurers offering a regulated benefit. Approximately half of Medicare beneficiaries are in the market for stand-alone Medicare Part D (i.e., no prescription drug coverage through a retiree benefit and not enrolled in a combined medical-drug Medicare Advantage plan). In 2010, they chose among on average of 45 insurance plans operating in their PDP region (either a state or a group of states); plans must accept everyone who applies at a uniform premium. Plans differentiate themselves both vertically (overall level of benefit generosity) and horizontally (level of coverage for competing drugs within a therapeutic class), subject to the regulations described in Section 2.2.

Because Medicare beneficiaries have very persistent drug utilization, choice of insurance plan commonly incorporates enrollees' private information on predicted drug demand. There are several pieces of evidence for enrollees' private information. Firstly, prior to the onset of Medicare Part D in 2006, no free-standing prescription drug insurance existed for this population; Pauly and Zeng (2004) and Goldman et al. (2006) suggest the threat of adverse selection inhibited the development of such a market. Secondly, beneficiaries who remain uninsured despite eligibility for Part D appear to be positively selected (Yin et al., 2008; Levy and Weir, 2010); however, the presence of substantial government funding, covering 75% of Part D expenditure on average, means that most eligible beneficiaries enrolled. Thirdly, direct evidence on prescription drug utilization reflects substantial year-over-year persistence in drug needs (Hsu et al., 2009). An analysis by Heiss et al. (2013) finds that basing ones' choices entirely on last year's drug needs is the choice rule that minimizes *ex post* expenditures in a broad set of heuristics and rational expectations models they test. Finally, direct evidence gathered by Polyakova (2016) documents a substantial degree of asymmetric information, resulting

in adverse selection into the most generous Part D plans.

A number of papers have found evidence of plan switching costs in Part D. Ho et al. (2017) show that Part D enrollees rarely switch plans; only 8% of New Jersey enrollees change plans between 2008 and 2009. Their simulations suggest that plans "harvest" profits from these enrollees via higher prices; if firms faced enrollees who reoptimized each year, their counterfactual lower prices would save consumers more than $600 per year. Polyakova (2016) finds somewhat higher estimates of switching costs; her counterfactual without switching costs accounts for changes in adverse selection[2] that result from altering plan choices, but finds welfare improvements of the same magnitude of Ho et al. (2017). However, other research has demonstrated that Part D enrollees do improve their plan selections over time, and also are more likely to switch when the gain from doing so is higher; this research implicitly bounds switching costs from above (Ketcham et al., 2012, 2015).

The presence of private information and switching costs in plan choice affects insurers' incentives because it means that enrollment will respond, but respond incompletely, to insurers' benefit design decisions. In the next section, we explain insurers' strategic choices in Part D as well as applicable benefit design regulation.

2.2 Insurers & Drug Firms

Insurers recognize that Part D enrollees can forecast their drug needs. Since they must accept all applicants at a uniform preannounced premium, they cannot directly select enrollees. Instead, they must use their benefit designs –what drugs are covered and at what out-of-pocket costs– to attract *ex post* profitable enrollees and deter those who will spend more than the payments the insurer receives for them.

Federal regulation constrains both choice of coverage and choice of out-of-pocket costs in hopes of providing access to an equitable benefit for all enrollees. For coverage, insurers must cover two drugs in each United States Pharamacopeia therapeutic class and all drugs in six "protected" classes (drugs for serious chronic illness). This regulation still allows considerable variation in coverage across plans. The plans we study in this analysis vary from covering 47 to 97 percent of studied drugs.

Out-of-pocket costs are also subject to regulation. Out-of-pocket costs are defined in relation to the Part D "Basic Benefit", which is the coverage level funded by Federal payments. In the Basic Benefit, individuals' OOP costs depend on their expenditure so far in the year: individuals pay a deductible, then 25% of drug expenditures in an "initial coverage zone", then 100% of drug expenditures in the doughnut hole, and finally 5% of drug expenditures after a catastrophic threshold. Plans can satisfy OOP cost regulation by either

[2]Handel (2013) finds that choice frictions such as switching costs *mute* adverse selection by reducing consumers' exploitation of asymmetric information. Polyakova (2016), however, finds that in Part D over this time period, regulatory changes led to a compression in the distribution of plan generosities. In this setting, switching costs actually aggravate adverse selection because individuals who previously sorted to the most generous plans do not switch even as other plans become more appropriate for them.

offering the Basic Benefit OOP costs or raising certain OOP costs and lowering others such that OOP costs still attain the Basic Benefit percentages on average. Alternatively, they may offer "enhanced coverage", financed fully out of premiums, that reduces OOP costs below the Basic Benefit percentages in some zones of coverage.

Enrollees also pay a premium to their chosen plan. Premiums are computed from a *bid* that represents for each plan their expenditure on a "typical" enrollee. The premium is then set to $prem_i = (bid_i - \overline{bid}) + \gamma\overline{bid}$. In this equation, $\overline{bid}$ is the national average bid (weighted by last year's enrollment) and γ is a fixed percentage (36% in 2010). Plans that cover many drugs at low OOP costs spend more for a "typical" beneficiary and therefore have a higher bid; their premiums are higher by the full amount that their bid exceeds the national average bid.

Because plans set coverage and OOP costs for approximately 5000 drugs, they have a relatively fine-grained tool for attracting or deterring potential enrollees who prefer certain drugs (Geruso et al., 2016). In the next section, we explore the diagnosis-specific payments meant to make insurers indifferent between all enrollees.

2.3 Diagnosis-Specific Payments

Diagnosis-specific payments, as well as government payments in general, play a critical role in Part D market design. In the absence of any subsidization, many individuals who know their (persistent) drug needs are inexpensive would not wish to pool with those with high expected expenditures. The high degree of government subsidies to the Part D market induces the healthy to voluntarily enroll, facilitating a balanced risk pool and providing financial protection for unexpected drug needs. To see why payments are diagnosis-specific, suppose Medicare had simply paid each Part D plan the average expenditure for each individual: approximately $1200. Within the benefit design regulations above, insurers would have designed benefits to disproportionately attract healthy beneficiaries and deter the sick. Instead, Medicare conditions its payments on diagnoses: payments to plans are higher for enrollees with high-cost diagnoses and lower for those who are relatively healthy. Payments that vary with individuals' expected health status are known as "risk adjustment". A recent literature has pointed out the weaknesses of basing payments exclusively on diagnoses. Diagnoses may not directly predict demand for insurance (Layton, 2014); alternatively, diagnosis-based payment systems may incompletely adjust for predictors of economic choices such as service elasticity (Einav et al., 2016) or inertia (Bijlsma et al., 2014). Still, diagnosis-based payment systems can be easily computed by regulators and can significantly reduce the scope for selection (Newhouse et al., 2013).

A payment system such as Part D's contains three distinct elements: diagnostic definitions, weights representing the relative cost of each diagnosis, and a conversion from weights to payments. The first

diagnosis-specific payment system was calibrated prior to Part D's beginning in 2006 and is detailed in Robst et al. (2007). The diagnostic definitions, built up from ICD-9 codes, were borrowed from the payment system used in Medicare Advantage; in addition to diagnoses, individuals were grouped by demographics: age, sex, and originally entitled to Medicare due to disability. The payment system designers obtained a sample of prescription drug and medical claims from Federal retirees (incurred in 2000) and disabled Medicaid beneficiaries (incurred in 2002). They applied the Part D Basic Benefit to each individual's claims to simulate the expenditure of a Part D plan for these individuals.

To set relative cost weights for diagnoses and demographics, they ran the following regression:

$$\mathcal{E}_i/\overline{\mathcal{E}} = \sum_x \omega_x \delta_{ix} + \sum_g \omega_g \delta_{ig} + \varepsilon_i \tag{1}$$

In this expression, $\mathcal{E}_i/\overline{\mathcal{E}}$ is the simulated Part D expenditure for this Federal retiree or disabled Medicaid beneficiary, normalized by the sample mean expenditure. δ_{ix} and δ_{ig} are 0/1 flags for the 84 diagnoses[3] or demographic categories, and the coefficients on these flags are the relative weights for each. A fixed factor increases the weight for low-income or long-term institutionalized individuals, since such individuals generally have more severe forms of diagnoses. An individual with a weight of one is expected to spend the sample average $\overline{\mathcal{E}}$.

The payment a plan receives for an individual is the product of the plan's bid and the sum of the individual's demographic and diagnostic weights. Scaling weights by a plan's bid allows payments to increase with the overall generosity of a plan's benefit design.

To see how the original payment system works, suppose an insurance plan enrolls a 66-year-old man (never disabled, not low-income, not institutionalized). His medical claims from the previous year reflect an Infectious Disease. The total weight for this man is the ω_x for Infectious Disease, 0.073, and his demographic weight, 0.355. A plan that bids the national average for 2010 ($1060) would receive $454 for this man. A more generous plan bidding $1500 would receive $642.

As explored in Carey (2017), technological change in the form of the entry of new molecules and the onset of generic competition (among other forces) caused actual treatment costs in Part D to drift from the payment weights set in the initial calibration. Therefore, Part D revised the payment system for 2011 (detailed in Kautter et al. (2012)).

[3]Robst et al. (2007) refer to 87 diagnoses; we disregard two related to Cystic Fibrosis because of extreme rarity, and we treat as a single diagnosis two that were constrained in Equation 1 to have the same coefficient.

2.4 The Payment System Revision

The payment system revision altered the diagnostic definitions and recalibrated the weight associated with each diagnosis (the conversion of weights to payments remained the same). Firstly, diagnostic definitions were altered by reorganizing the ICD-9 codes. For example, the diagnoses *Quadriplegia* and *Motor Neuron Disease & Spinal Muscular Atrophy* in the old payment system are collapsed into one diagnosis – *Spinal Cord Disorders* – in the new system. *Chronic Renal Failure*, on the other hand, is expanded from one diagnosis to four subtypes. Various forms of cancer are completely reorganized.

In addition, each diagnosis now comes in five subtypes for disabled $\times$ low-income status and long-term institutionalized. This is because those factors can dramatically change the expenditure associated with a given diagnosis. In principle, creating a payment weight for each diagnosis-subtype can better align a diagnosis's payment and a plan's expenditures for that diagnosis ("fit" in the framework of Geruso and McGuire (2016)); this reduces the risk an insurer faces for that diagnosis.

Finally, Equation 1 was reestimated on free-standing Part D enrollees in 2008. The introduction described the change in payments for two diagnoses – *HIV/AIDS* and *Multiple Sclerosis* – which were defined by the same ICD-9 codes in both the new and old systems. The payment update for those two diagnoses suggests that many diagnoses received much larger or smaller payments in 2011 relative to 2010. Later, we develop evidence that this is indeed the case.

We have seen that, firstly, beneficiaries' plan choices are characterized by private information on their drug needs; secondly, insurers can attract individuals by generous benefit design for drugs that treat their diagnoses; and, finally, the diagnosis-specific payment system and its recalibration provide variation over time in the payment a plan receives for each diagnosis. However, in the presence of switching costs, the response to the payment system will be mediated by the insurer's current enrollment. In the next section, we explore this interaction in a simple theoretical model.

3 Theory

In this section, we describe a simplified model of dynamic insurance benefit design under circumstances of varying government subsidies. The model combines two strands of literature. Firstly, we follow the insight of models of insurer benefit design (reviewed in Ellis (2008)) when individuals differ in their preferences for medical services in a way known to them and predictable to insurers, and insurers must accept everyone who applies at a uniform premium. In this setting, if certain enrollees are more profitable for insurers, they will attempt to effect selection through designing more generous benefits for the services preferred by those individuals. The second strand is the active literature, building from Klemperer (1987), exploring markets

where an individual must pay switching costs upon changing products. In the classic models, switching costs give nominally-competitive firms a kind of "market power" that leads to higher equilibrium prices; in particular, a forward-looking firm would "invest" in loyalty via low prices, and then "harvest" profits via higher prices.

On the demand side, myopic individuals make a logit discrete choice for insurance, paying switching costs upon first enrollment or plan change. We analytically characterize the response of a forward-looking monopolistic insurer to a change in government subsidies, and show how that response varies in the insurer's market share. We then extend the model to two asymmetric insurers using numerical simulation. Our model borrows from Pearcy (2016) in solving a dynamic discrete choice model directly rather than deriving an insurer policy function.

3.1 Consumer Demand for Insurance

Myopic individuals choose whether to enroll in insurance according to a logit discrete choice model with switching costs. The insurance plan has a mean utility of y, which represents the value of obtaining treatment relative to not (or relative to paying full price for the treatment in the unenrolled state). The plan sets an out-of-pocket cost for drugs in year t of c_t. All plan enrollees will buy drugs at out-of-pocket cost c_t and obtain value y from enrollment; there is no adverse selection.

$$U_{it} = y - c_t + \varepsilon_{it} \text{ if not enrolled at } t-1$$

$$U_{it} = y - c_t - s' + \varepsilon_{it} \text{ if enrolled at } t-1$$

The only source of consumer heterogeneity is the error term ε_{it} is i.i.d. over individuals and time, and is distributed Type I Extreme Value. The utility of remaining unenrolled is normalized to zero, and let $s = 1 - e^{-s'}$, which implies that $s \in (0, 1)$. Then the choice probabilities can be written

$$P_{N_t} = \frac{exp(y - c_t)}{exp(y - c_t) + 1} \qquad P_{L_t} = \frac{exp(y - c_t)}{exp(y - c_t) + 1 - s}$$

where P_{N_t} denotes the probability of enrollment for currently unenrolled "new" individuals, and P_{L_t} denotes the probability of re-enrollment for currently enrolled "loyal" individuals. Note that $P_{L_t} > P_{N_t}$.

3.2 Firm's Dynamic Profit Maximization Problem

Because loyal individuals choose differently from new individuals, we define a state variable σ_t to represent the plan's market share at time $t-1$. The market share in year t can then be written

$$Q_t(c_t, \sigma_t) = (1-\sigma_t)P_{N_t} + \sigma_t P_{L_t}$$

where $\sigma_t = Q_{t-1}$. The insurance firm collects a subsidy r from the government and purchases treatment at an exogenous cost κ, offset by their chosen out-of-pocket cost c_t. Within a single period, therefore, firm profits can be written $(r - \kappa + c_t)Q_t(\mathbf{c_t}, \sigma_t)$. Firms solve the following problem by choosing a vector of out-of-pocket costs $\mathbf{c} = \{c_1, c_2....\}$

$$\max_{\mathbf{c}} \sum_{t=1}^{\infty} \delta^t (r - \kappa + c_t) Q_t(c_t, \sigma_t)$$

The Bellman equation that describes the firm's problem is

$$V(\sigma_t) = \max_{c_t}[(r - \kappa + c_t)Q_t(c_t, \sigma_t)] + \delta V(\sigma_{t+1})$$

The Euler equation representing the intertemporal first order condition is

$$\frac{\partial V(\sigma_t)}{\partial \sigma_t} = (r - \kappa + c_t)\frac{\partial Q_t}{\partial \sigma_t} + \delta \frac{\partial V(\sigma_{t+1})}{\partial \sigma_{t+1}} \frac{\partial Q_t}{\partial \sigma_t}$$

where the second term reflects that $\sigma_{t+1} = Q_t$. Finally, the in-period first order condition for profit maximization is

$$0 = Q_t + (r - \kappa + c_t)\frac{\partial Q_t}{\partial c_t} + \delta \frac{\partial V(\sigma_{t+1})}{\partial \sigma_{t+1}} \frac{\partial Q_t}{\partial c_t}$$

3.3 Steady State

We analyze the steady state of the model, when $V(\sigma_t) = V(\sigma_{t+1})$. In the notation, we drop the time subscripts to denote the steady state. Subbing in for $\frac{\partial Q}{\partial \sigma} = P_L - P_N$, the intertemporal first order constraint holds when

$$\frac{\partial V(\sigma)}{\partial \sigma} = \frac{(r - \kappa + c)(P_L - P_N)}{1 - \delta(P_L - P_N)}$$

The steady state market share is derived by setting $Q = \sigma$ and can be written $\sigma = P_N/(1 - (P_L - P_N))$. The in-period derivative of share with respect to out-of-pocket cost can be simplified, using the steady state

market share, to

$$\frac{\partial Q}{\partial c} = -(1-\sigma)P_N(1-P_N) - \sigma P_L(1-P_L) = -P_N(1-P_L)\left[\frac{1+P_L-P_N}{1-(P_L-P_N)}\right]$$

Finally, applying all this to the FOC for profit maximization, we characterize the (interior) steady state solution using a single equation.

$$\begin{aligned}
0 = &\quad Q + \tfrac{\partial Q}{\partial c}\left[(r-\kappa+c) + \delta\tfrac{(r-\kappa+c)(P_L-P_N)}{1-\delta(P_L-P_N)}\right] = Q_t + \tfrac{\partial Q}{\partial c}\left[\tfrac{(r-\kappa+c)}{1-\delta(P_L-P_N)}\right] \\
0 = &\quad \tfrac{P_N}{1-(P_L-P_N)} - P_N(1-P_L)\left[\tfrac{1+P_L-P_N}{1-(P_L-P_N)}\right]\left[\tfrac{(r-\kappa+c)}{1-\delta(P_L-P_N)}\right] \\
0 = &\quad 1 - \tfrac{(r-\kappa+c)(1-P_L)(1+P_L-P_N)}{1-\delta(P_L-P_N)}
\end{aligned}$$

3.4 Effect of Subsidies on Out-of-Pocket Costs

The c that satisfies the above FOC is the out-of-pocket cost that solves the monopoly insurer's dynamic optimization problem. In the empirical analysis of this paper, we will study how out-of-pocket costs respond to a payment system revision that changed subsidies for a given diagnosis between 2010 and 2011. We examine the theoretical analog to this revision by asking how the steady-state equilibrium out-of-pocket cost c varies with subsidy r.

Let $F(c, r, \kappa, \delta, s) = 0$ represent the FOC above. Implicit differentiation yields

$$\frac{dc}{dr} = -\frac{\partial F/\partial r}{\partial F/\partial c} = \frac{\frac{(1-P_L)(1+P_L-P_N)}{1-\delta(P_L-P_N)}}{\partial F/\partial c}$$

$\frac{dc}{dr}$ is negative: the numerator is positive as long as per-person maximized profits $r-\kappa+c$ are positive (implied by the steady state FOC above), and the denominator is negative by the second order condition for in-period profit maximization. In economic terms, this implies that an insurer who receives higher subsidies for a given diagnosis will partially pass-through the higher subsidy to lower out-of-pocket costs.

After simplification and substitution for steady-state $r-\kappa+c$

$$\frac{dc}{dr} = -\frac{(1-P_L)(1+P_L-P_N)^2}{(1+P_L-P_N)^2 - (1+\delta)(P_L-P_N)\left(1-P_N+P_L(P_L-P_N)\right)}$$

Note that both P_L and P_N still depend on equilibrium out-of-pocket costs, so we cannot, for example, easily obtain the comparative static with respect to δ.

3.5 Pass-through of Subsidies for Large and Small Insurers

In our empirical analysis, we consider how the pass-through of subsidies differs for insurers with a large or small market share. Our model allows us to find the analogous theoretical object, the cross-partial of out-of-pocket costs with respect to r and σ, for a monopolist insurer. In the Appendix, we report the full analytical solution. The cross-partial is positive, implying that an insurer with a large σ has a smaller (less negative) dc/dr. In economic terms, an insurer with a larger market share lowers out-of-pocket costs less for a given increase in subsidies.

In the following sections, we will develop two extensions to this baseline model. Both extensions move the model beyond analytical tractability, and we instead simulate them numerically. In Figure 1, we show the numerical performance of our baseline theoretical model. The top panel shows how steady state out-of-pocket costs and market share change for all possible values of switching costs s. The text in the box shows the values at which we fix the other parameters. Switching costs result in higher out-of-pocket costs[4] and higher equilibrium market share. The next two panels show the same values across a range of inputs for subsidy r and innate plan value y. As shown above, higher subsidies lead to lower out-of-pocket costs; the lower out-of-pocket costs result in higher market share. Higher innate plan values lead to higher out-of-pocket costs, but at less than one-for-one so that market share rises as well. In Figure 2, we show the path of out-of-pocket costs as subsidies increase ($\frac{dc}{dr}$) for two monopoly plans (i.e., in different markets). The plan represented by the solid line has a higher innate plan value ($y = 8$) and therefore a higher market share. Relative to the lower-value plan with the lower market share, the high-share plan responds less strongly to r, as described by the analysis above.

3.6 Extension to Insurer Duopoly

A key parameter in models of pass-through is the degree of competition, with monopoly pass-through often serving as the lower-bound scenario (Weyl and Fabinger, 2013). We therefore pursue numerical solutions to an insurer duopoly. Plans i and j are endowed with valuation y^i and y^j. Previously unenrolled individuals choose plan i with probability P^i_N. Those previously enrolled in plan i continue in it with probability P^i_L, or switch to the outside option with probability P^i_O. Switching costs apply when an enrolled individual changes plans or becomes unenrolled.

$$P^i_{N_t} = \frac{exp(y^i - c^i_t)}{exp(y^i - c^i_t) + exp(y^j - c^j_t) + 1} \quad P^i_{L_t} = \frac{exp(y^i - c^i_t)}{exp(y^i - c^i_t) + (1-s)exp(y^j - c^j_t) + 1 - s} \quad P^i_{O_t} = \frac{1-s}{exp(y^i - c^i_t) + (1-s)exp(y^j - c^j_t) + 1 - s}$$

$$P^j_{N_t} = \frac{exp(y^j - c^j_t)}{exp(y^i - c^i_t) + exp(y^j - c^j_t) + 1} \quad P^j_{L_t} = \frac{exp(y^j - c^j_t)}{(1-s)exp(y^i - c^i_t) + exp(y^j - c^j_t) + 1 - s} \quad P^j_{O_t} = \frac{1-s}{(1-s)exp(y^i - c^i_t) + exp(y^j - c^j_t) + 1 - s}$$

[4]Several recent papers have shown circumstances under which switching costs actually lower equilibrium prices (Pearcy, 2016; Somaini and Einav, 2013; Rhodes, 2014), but find that switching costs nearly always raise prices in monopolies.

σ_i represents the share of individuals previously enrolled in plan i. Firms face the following demand equations:

$$Q_t^i(c_t^i, c_t^j, \sigma_t^i, \sigma_t^j) = \sigma_t^i P_{L_t}^i + \sigma_t^j(1 - P_{L_t}^j - P_{O_t}^j) + (1 - \sigma_t^i - \sigma_t^j)P_{N_t}^i$$
$$Q_t^j(c_t^i, c_t^j, \sigma_t^i, \sigma_t^j) = \sigma_t^j P_{L_t}^j + \sigma_t^i(1 - P_{L_t}^i - P_{O_t}^i) + (1 - \sigma_t^i - \sigma_t^j)P_{N_t}^j$$

The Euler equations for intertemporal optimization reflect the fact that a change in i's share this period affects j's demand equation next period.

$$\begin{aligned}
\frac{\partial V(\sigma_t)}{\partial \sigma_t^i} &= (r - \kappa + c_t^i)\frac{\partial Q_t^i}{\partial \sigma_t^i} + \delta\left\{\frac{\partial V(\sigma_{t+1})}{\partial \sigma_{t+1}^i}\frac{\partial Q_t^i}{\partial \sigma_t^i} + \frac{\partial V(\sigma_{t+1})}{\partial \sigma_{t+1}^j}\frac{\partial Q_t^j}{\partial \sigma_t^i}\right\} \\
\frac{\partial V(\sigma_t)}{\partial \sigma_t^j} &= (r - \kappa + c_t^j)\frac{\partial Q_t^j}{\partial \sigma_t^j} + \delta\left\{\frac{\partial V(\sigma_{t+1})}{\partial \sigma_{t+1}^j}\frac{\partial Q_t^j}{\partial \sigma_t^j} + \frac{\partial V(\sigma_{t+1})}{\partial \sigma_{t+1}^i}\frac{\partial Q_t^i}{\partial \sigma_t^j}\right\}
\end{aligned}$$

First order conditions for profit maximization close the model:

$$0 = Q_t^i + (r - \kappa + c_t^i)\frac{\partial Q_t^i}{\partial c_t^i} + \delta\left\{\frac{\partial V(\sigma)}{\partial \sigma_{t+1}^i}\frac{\partial Q_t^i}{\partial c_t^i} + \frac{\partial V(\sigma)}{\partial \sigma_{t+1}^j}\frac{\partial Q_t^j}{\partial c_t^i}\right\}$$

$$0 = Q_t^j + (r - \kappa + c_t^j)\frac{\partial Q_t^j}{\partial c_t^j} + \delta\left\{\frac{\partial V(\sigma)}{\partial \sigma_{t+1}^j}\frac{\partial Q_t^j}{\partial c_t^j} + \frac{\partial V(\sigma)}{\partial \sigma_{t+1}^i}\frac{\partial Q_t^i}{\partial c_t^j}\right\}$$

We solve the model numerically, and report our findings in Figure 3. We have simulated two insurers with different innate values competing against one another; the insurer with the larger innate value obtains a larger market share. Similar to the monopoly setting, both insurers reduce out-of-pocket costs as subsidy r increases. For a given increase in subsidy r the larger insurer (solid line) reduces out-of-pocket costs less than the smaller insurer (dashed line).

4 Measuring Payment Updates

We now move to testing the predictions generated by our theoretical model. Our empirical analysis proceeds in two steps. In this section, we describe a substantial payment system revision in Medicare Part D. In the next section, we will test the impact of the revision on benefit designs, and show how the impacts differ by the insurer's market share at the time of the revision.

4.1 Data

This research combines Medicare claims data with the publicly-available Part D benefit designs. Our Medicare claims dataset provides medical and prescription drug claims for a 5% panel of Part D enrollees between 2007 and 2012. The medical claims enable us to assign diagnoses to individuals in the exact same way as Medicare: if an individual has a specified ICD-9 code in an Inpatient, Outpatient or Carrier (Physician)

claim in year $t-1$, the payment for that diagnosis is given to their Part D in plan year t. Diagnoses can only be observed for individuals enrolled in fee-for-service Medicare (not Medicare Advantage) because claims from Medicare Advantage enrollees are not released to researchers.

The benefit designs of all Part D plans are contained in the Prescription Drug Plan Formulary files. The Formulary files contain coverage and, if covered, out-of-pocket costs for all drugs and all plans in 2009 through 2012. For all covered drugs a negotiated price paid by the plan is also listed in the data, but the price is before an unobserved rebate.

4.2 Measurement of Payment System Change

The first step is measuring the sign and magnitude of payment system updates for each diagnosis in the payment system. As discussed in Section 2.3, this step is nontrivial because the recalibration also revised the mapping of ICD-9 codes to payment system diagnoses. We take advantage of our claims dataset to estimate the change in payments associated with each diagnosis. Our methodology is straightforward: we calculate the diagnosis-specific payments for Part D enrollees in 2011 under both the new and old payment systems. The payments are based on the same 2010 medical claims: we simply change the diagnostic definitions and diagnosis-specific weights. We then predict the difference between the payment under the two systems using flags for the 84 diagnoses under the old system's diagnostic definitions.

$$\Delta P_i = P_i^N - P_i^O = \sum_x U_x \delta_{ix} + \varepsilon_i \tag{2}$$

P_i^N is the diagnosis-specific payment for individual i under the new system, P_i^O is the diagnosis-specific payment for the same individual in the same year under the old system, and ΔP_i is their difference. δ_{ix} is an indicator for individual i having diagnosis x in 2010, and its coefficient U_x is what we refer to as the "payment update" for diagnosis x.

4.3 Results: Measurement of Payment System Change

We estimate Equation 2 using the medical and prescription drug claims of 764,621 Part D enrollees. The sample is a random 5% sample of individuals enrolled in Part D in 2011 (so that their prescription drug claims are observed) and in fee-for-service Medicare in 2010 (so that their diagnoses can be obtained from medical claims). In Table 1, we report the features of the distribution of our sample. The first two rows describe the distribution of diagnosis-specific payments under the old and new payment system, and third row is their difference, ΔP_i, which is the left hand side of Equation 2.[5] If the difference in payments is positive, payments

[5]Note that each row reports the distribution for the stated variable, but an individual at the 5^{th} percentile in one row may appear elsewhere in the distribution in another row.

for that individual are larger under the new system compared to the old system. Payments for more than 75% of individuals decrease under the new system. More importantly, we find that many individuals have very different payments under the new and old systems, suggesting that the payments for various diagnoses rose or fell significantly.

Figure 4 shows the enrollee-level variation we use to measure how the new and old payment systems differ. Figure 4 shows each individual's diagnosis-specific payments under the new and old systems; the overall decline in payments is visual in the presence of more mass under the 45° line.

Table 2 reports the diagnosis-specific coefficients U_x from Equation 2. For each diagnosis, we report the old payment, the payment update for the diagnosis, and its robust standard error. The diagnoses are sorted by the magnitude of the old payment. Note that standard errors are quite small relative to coefficients; we nearly always reject the hypothesis that a diagnosis's payment or variance is not affected by the transition to the new payment system.

Several figures illustrate the variation in payment updates between 2010 and 2011, which in the next section we use to identify the impact on benefit designs. Figure 5 shows the magnitude of payment updates across diagnoses, sorted by the magnitude of old payments. Updates are economically large; in addition, it is clear that payment updates are not strongly related to the magnitude of old payments. Figure 6 graphs payments before (x-axis) and after (y-axis) the payment update, with the 45 degree line, which would imply no update, provided for reference. The five most common diagnoses are labeled. Figure 7 depicts the change in the payment level over time. For each diagnosis in each figure, we have normalized its level in 2009 to be 1. Instead of the full set of 84 diagnoses, we are showing the ten most common, which range from tripling in payment to halving.

4.4 Associating Drugs and Diagnoses

While drugs are relatively closely linked to diagnoses, there is no reference work we can consult that tells us which drugs treat which diagnoses. Instead, we take advantage of our large claims datasets to estimate the empirical association of drugs and diagnoses using six years of prescription drug claims (2007-2012) and matched contemporaneous medical claims. In particular, we run a linear probability model to predict whether an individual takes a given ingredient combination (I abstract from differences in strength and route of administration) using flags for the 84 diagnoses.

$$\overbrace{T_{ict}}^{\substack{1 \text{ if ind } i \\ \text{takes ing combo } c \\ \text{in year } t}} = \sum_x \gamma_{cx} \overbrace{\delta_{ixt}}^{\substack{1 \text{ if ind } i \\ \text{has diag } x \\ \text{in year } t}} + \varepsilon_{ict} \tag{3}$$

Each coefficient γ_{cx} gives the marginal increase in the probability of taking the ingredient combination associated with having the given diagnosis. For each ingredient combination, I define it as "treating" the diagnosis with the largest γ_{cx}. We assign all drugs containing that ingredient combination to set $\mathcal{D}_x$, the set of drugs that treat diagnosis x.

We estimate these models on the prescription drug and medical claims of Part D enrollees in 2007-2012[6]: more than five million beneficiary $\times$ year observations in all. We restrict to 791 ingredient combinations taken by at least 200 beneficiaries in one of years.

We define an ingredient combination as "treating" the diagnosis that most strongly predicts taking it. On average, the largest coefficient (i.e., the one for the treating diagnosis) exceeds the second largest coefficient by a factor of three. Eight of 84 diagnoses are not found to "treat" any ingredient combination we study; these diagnoses tend to be catch-alls (*Other Neurological Conditions, Coagulation Defects and Other Specified Blood Diseases*) or diagnoses, such as *Pelvic Fracture*, where drugs are used for general symptoms such as pain or infection but not for the underlying diagnosis.

We check this linkage against the Johns Hopkins Adjusted Clinical Groups Case-Mix System. The ACG System gives a "prescription drug morbidity group" for any drug. Prescription drug morbidity groups do not correspond exactly to the diagnoses (and therefore cannot supply our linkage) but many are very similar. This comparison suggests that this step links drugs to diagnoses fairly accurately. Poor linkage of drugs and diagnoses will create measurement error in estimation that will bias our results towards zero.

5 Insurer Response to Payment System Change

In the last section, we measured how payments for a particular diagnosis vary over time and what drugs treat each diagnosis. We now propose a panel data model that tests the response of benefit designs to diagnosis-specific payments. Our first model analyzes benefit designs for the universe of drugs and plans, using fixed effects to isolate variation plausibly related to the changes in the payment system. Our second model tests the impact of payments on the annual out-of-pocket costs faced by a typical individual enrolled in each plan; the advantage of this analysis is that it generates a "pass-through" parameter showing how much benefits improve for a given dollar increase in payments. Our third model extends the first two by showing how the impact of payments varies with diagnosis market share. Finally, a panel of utilization at the individual level recovers demand elasticities using payments as an instrument.

[6]It is possible that the joint distribution of diagnostic codes and drug utilization adjusts endogenously to payment system incentives (e.g., if a diagnosis's payment rise, Part D plans increase efforts to ensure providers code it.) When we use only 2007-2010 to associate drugs with diagnoses, we find nearly the same correspondence and very similar results for Equations 4, 5, and 6. A downside of using only pre-period years is that drugs introduced in 2011 and 2012 cannot be included in analysis.

5.1 Testing Benefit Design Response

We are now ready to show how payments for a particular diagnosis affect the benefit design of the drugs they treat. Our simplest model is described below.

$$\overbrace{Y_{djt}}^{\substack{\text{OOP cost/}\\ \text{coverage}\\ \text{for drug } d\in\mathcal{D}_x\\ \text{in plan } j\\ \text{in year } t}} = \beta \overbrace{P_{xt}}^{\substack{\text{payment}\\ \text{for diag } x\\ \text{in year } t}} + \overbrace{\delta_{dj}}^{\substack{\text{plan}\times\text{drug}\\ \text{fixed}\\ \text{effect}}} + \overbrace{\delta_{jt}}^{\substack{\text{plan}\times\text{year}\\ \text{fixed}\\ \text{effect}}} + \varepsilon_{djt} \tag{4}$$

Our sample is an unbalanced panel of 1891 free-standing Part D plans and 4931 drugs[7] operating between 2009 and 2012. The panel is unbalanced both because both plans and drugs enter and exit over the sample period.

We consider three different outcome variables. The first is the monthly out-of-pocket cost for the drug in this plan in the initial coverage zone, which is only observed if the plan covers the drug. We use the out-of-pocket costs in the initial coverage zone because, while out-of-pocket costs in the pre-deductible and doughnut hole regions are frequently equal to drug prices, out-of-pocket costs in the initial coverage zone display meaningful cross-plan variation. Approximately 85% of plan outlays result from claims in the initial coverage zone, meaning that plan profits are much more sensitive to OOP costs in this zone relative to other zones. Out-of-pocket costs can be a flat copay or a percentage; if the latter, we use the percentage times the price to obtain the dollar cost to the individual. The second outcome is a binary indicator for whether the drug is covered by the plan. The third outcome is the out-of-pocket cost if the drug is covered and an imputed OOP cost equal to the average price if the drug is not covered. This measure is meant to approximate the true out-of-pocket cost under inelastic drug demand.

Our primary right-hand side variable is the payment for diagnosis x in year t. In 2009 and 2010, P_{xt} is equal to the diagnosis-specific risk adjustment weight described in Section 2.3 times the national average bid in that year. In 2011 and 2012, P_{xt} is incremented by the payment update estimated by Equation 2.

We include two sets of fixed effects: plan $\times$ drug and plan $\times$ year. The fixed effect δ_{dj} represents all time-invariant demand or supply factors that affect the benefit design for this plan $\times$ drug observation. This controls for unobserved drug efficacy and side effects, marginal cost of production, or (time-invariant) market power of the drug's maker. In addition, it controls for the plan's time-invariant preferences for this drug, such as a plan's (constant) desire to attract individuals who take this drug, or a strong negotiating position with the relevant drug firm. The plan $\times$ year fixed effect corrects for any plan-level changes that

[7] Our "drug" concept is defined by RxNorm's *rxcui*, meaning an ingredient combination $\times$ strength $\times$ form (tablet, ointment, etc.).

treat all diagnoses equally, such as a change in plan strategy that affects all out-of-pocket costs. Given these fixed effects, our identification comes within plan $\times$ drug observations across diagnoses as payments vary over time due to the revision. Our equation is analogous to a difference-in-differences model: we compare the change in benefit designs for drugs that treat diagnoses receiving positive payment updates relative to drugs that treat diagnoses receiving negative payment updates.

We weight each observation by the plan enrollment and the number of individuals taking the drug in Medicare Advantage. Essentially, we are capturing the overall importance of the observation. In the framework of Solon et al. (2015), these weights recover the average partial effect of payments in the presence of unmodeled heterogeneity across plans and drugs in the response of agents to the change in incentives. Such heterogeneity would result if plans reoptimize benefits for popular drugs but ignore the long tail of uncommon drugs, or if larger plans are more likely to reoptimize. We demonstrate robustness to weighting choices in Section 5.5. We use number of takers in Medicare Advantage plans because the majority of payments to these insurers are made under medical risk adjustment, rather than the prescription drug risk adjustment we study here, and therefore utilization is less endogenous.

Finally, we cluster our standard errors in two ways: at the plan $\times$ year and at the diagnosis$\times$market. The first clustering recognizes that plan benefit designs must comply with regulations requiring an actuarial value of 25%. While our plan $\times$ year fixed effect will absorb all positively correlated changes, these requirements may induce negative cross-sectional correlation in benefit design outcomes within a plan $\times$ year, since if some out-of-pocket costs exceed 25% or price others must be lower to compensate. The second clustering allows arbitrary correlation in how plans in the same market design benefits for the drugs that treat a given diagnosis. Errors may be serially correlated across time in a diagnosis$\times$market due to market-specific differences in diagnostic subtype or treatment preferences, or cross-sectionally correlated across plans due to competition.

Our preferred specification builds on Equation 4 by recognizing the economic content of payments and payment updates. The revision may raise or lower payments for a given diagnosis as a result of various factors: differences in the original calibration sample (Federal retirees and Medicaid beneficiaries) and the Part D sample used in recalibration; technological change – new drugs or the onset of generic competition – changing the costs of treating certain diagnoses; changes in the supply-side environment such as insurer or drug firm consolidation; or changes in demand parameters. Holding other factors fixed, suppose that drug prices for a particular diagnosis have been rising since 2000. Price rises through 2008 will be incorporated into a positive payment update, but benefit designs in 2009-2012 will reflect the continued increase in price between 2009 and 2012. This could induce a positive correlation between payments and the error term of Equation 4. In the below, we explicitly condition on the price we observe in the data for drug d in plan j in

year t. In particular, we control for a linear spline for price at ventiles of the price distribution.

In a more general sense, any persistent trends between 2000 and 2008 that affect benefit design can generate a spurious correlation between the payment update and benefit design outcomes that is *not* via the pass-through of diagnosis-specific payments.[8] We therefore consider models with a time trend in drug d. In the presence of the time trend, we are identifying β from any deviation from trend that occurs between 2010 and 2011. Equations adding these controls to Equation 4 are below.

$$\overbrace{Y_{djt}}^{\substack{\text{OOP cost/}\\ \text{coverage}\\ \text{for drug } d\\ \text{in plan } j\\ \text{in year } t}} = \beta \overbrace{P_{xt}}^{\substack{\text{payment}\\ \text{for diag } x\\ \text{in year } t}} + \overbrace{\text{price spline}_{djt}}^{\substack{\text{spline for price}\\ \text{of drug } d\\ \text{in plan } j\\ \text{in year } t}} + \overbrace{\delta_{dj}}^{\substack{\text{drug}\times\text{plan}\\ \text{fixed}\\ \text{effect}}} + \overbrace{\delta_{jt}}^{\substack{\text{plan}\times\text{year}\\ \text{fixed}\\ \text{effect}}} + \varepsilon_{djt}$$

$$\overbrace{Y_{djt}}^{\substack{\text{OOP cost/}\\ \text{coverage}\\ \text{for drug } d\\ \text{in plan } j\\ \text{in year } t}} = \beta \overbrace{P_{xt}}^{\substack{\text{payment}\\ \text{for diag } x\\ \text{in year } t}} + \overbrace{\gamma_d t}^{\substack{\text{time}\\ \text{trend}\\ \text{for drug } d}} + \overbrace{\delta_{dj}}^{\substack{\text{drug}\times\text{plan}\\ \text{fixed}\\ \text{effect}}} + \overbrace{\delta_{jt}}^{\substack{\text{plan}\times\text{year}\\ \text{fixed}\\ \text{effect}}} + \varepsilon_{djt} \tag{4a}$$

We also conduct a placebo test that predicts outcomes using the lead of payments: i.e., predicts outcomes in 2010 using the payments in 2011. Given our fixed effects, this specification looks for a response to payment updates between years 2009 and 2010, when payments were not updated.

Table 3 reports the results of estimation of Equations 4 and 4a. Each panel represents a different outcome variable, and each column is a separate regression. In the first panel, we predict the out-of-pocket cost for covered drugs. With no controls, we find no significant association. Using either the price spline or linear drug trends, we find that diagnoses experiencing positive payment update in 2011 have lower out-of-pocket costs. The magnitude is approximately a half-cent reduction in the monthly out-of-pocket costs for a $1 increase in (annual) payments. The next panel reports the impact of payments on whether a drug is covered (for scale, the outcome is 100 when a plan covers a drug in a year, 0 otherwise). We find that higher payments are associated with *less* coverage, which is contrary to our expectations that plans improve benefits for a diagnosis when its payment increases. However, the next section will reanalyze the coverage outcome when we have accounted for typical patterns of demand. Finally, in the third panel the outcome variable is the out-of-pocket cost when the drug is covered, or the price when it is not. We find the same patterns as the first panel. When we run the same models using the lead of payment, we generally find no association, or

[8] To see why, suppose each year since 2000 insurers have simply raised the OOP costs for drugs that treat diagnosis x a fixed amount η_x: $OOP_{xt} = OOP_{x00} + \eta_x t$. Medicare's payment recalibration process finds that the diagnosis-specific costs in 2008 are a linear function of OOP costs plus some error: $\omega_{x08} = \rho OOP_{x08} + \nu_{x08}$, where ν_{x08} captures all the other features of costs in 2008. Payment in 2011 is set to ω_{x08}. Insurers continue to raise out-of-pocket costs, so for example the change in out-of-pocket costs between 2010 and 2011 is simply η_x. In our analysis, we will calculate that the payment update is $U_x = \omega_{x08} - \omega_{x00} = \rho(8\eta_x) + \nu_{x08} - \nu_{x00}$. If we use this payment update to identify Equation 4 we will find that the change in payment and change in OOP costs are correlated through η_x. But there is no "pass-through" in this setting – it is simply that a time trend in OOP costs influences both the updated payment and the change in benefit designs that interests us.

an association in the opposite direction.

5.2 Measuring "Pass-Through": Out-of-Pocket Costs for Typical Demand

The disadvantage of the above analysis is that the magnitude of the coefficient on payment has no natural interpretation; not every drug that treats a diagnosis is taken by every beneficiary with the diagnosis, and the duration of treatment varies as well. We augment the above with a measure that captures the out-of-pocket costs and coverage that would result from a plan's benefit design for the typical individual with the diagnosis.

Our basic framework is to characterize the typical demand for drugs that treat diagnosis x using the prescription drug claims, and then calculate the out-of-pocket cost of taking those drugs in each plan operating in the same year. We first total the months' supply for each drug d in the set $\mathcal{D}_x$ treating diagnosis x in each zone of coverage z in year t of the claims, averaging across all those who have the diagnosis I_{xt}.

$$\text{months}_{dzt} = \frac{1}{I_{xt}} \sum_i \text{months}_{idzt}$$

A difficulty arises here about how to handle those who take drugs that treat the diagnosis but do not have the flag for the diagnosis; our approach is described in the Empirical Appendix.

Next, we compute the out-of-pocket costs in each plan for the typical demand. The out-of-pocket costs for diagnosis x in plan j are equal to the dot product of typical demand for each drug that treats x and j's out-of-pocket costs, summed across the zones of coverage (pre-deductible, etc.).

$$W_{jxt} = \sum_z \sum_{d \in \mathcal{D}x} \text{months}_{dzt} * \text{OOP cost}_{jdzt}$$

Here, we must confront the problem that different plans cover different drugs within a set, and that we may not want to penalize plans that cover e.g., one of a pair of close substitutes. We therefore compute two different versions of W_{jxt} that nest the two extremes. In one case, we assume that individuals in plan j do not consume any uncovered drugs. In the second case, we assume that individuals in plan j consume the typical amount of uncovered drugs at the average price observed in the formulary data. To consider coverage directly, we also calculate the share of months demanded under the typical demand that would be covered under the plan.[9]

Analogous to the above models, we use payments to predict typical OOP cost, coverage, or OOP cost

[9] In the formulary files, most drugs are reported as "uncovered" in the pre-deductible and donut hole zones. However, we treat drugs in these zones as "covered" at the full price. This is because our typical demand as calculated from the claims data reflects the general lack of coverage in these zones. Essentially, we think of coverage as capturing variation between plans, not variation that is created by the zones of coverage and is therefore mostly uniform across plans. In addition, we account for the reduction in out-of-pocket costs in the donut hole in 2011 and 2012 due to provisions of the Affordable Care Act.

with imputation for uncovered drugs.

$$\overbrace{W_{xjt}}^{\substack{\text{typical}\\ \text{OOP/coverage}\\ \text{for diag } x\\ \text{in plan } j\\ \text{in year } t}} = \beta \overbrace{P_{xt}}^{\substack{\text{payment}\\ \text{for diag } x\\ \text{in year } t}} + \overbrace{X_{xjt}}^{\substack{\text{price}\\ \text{spline}\\ \text{or diag}\\ \text{trend}}} + \overbrace{\delta_{xj}}^{\substack{\text{diag}\times\text{plan}\\ \text{fixed}\\ \text{effect}}} + \overbrace{\delta_{jt}}^{\substack{\text{plan}\times\text{year}\\ \text{fixed}\\ \text{effect}}} + \varepsilon_{xjt} \tag{5}$$

Again, we consider models alone (without X_{xjt}), with a spline for price (constructed as the plan's price for the typical demand), and with linear diagnosis trends.

Table 4 reports our estimates of how much an extra dollar in payment passes-through to benefits in the wake of the recalibration. With either set of controls, we find that higher payments are associated with better benefits. We find that an extra dollar in payment is associated with economically-meaningful pass-through to expected annual out-of-pocket costs. While the point estimate depends on specification, a pass-through rate of 20% is in each estimate's CI.

5.2.1 Interpretation of Pass-Through Estimate

As stated, we cannot interpret the complement of our pass-through rate as retained by the Part D insurer. Insurers must negotiate the price of prescription drugs from drug manufacturers who may have upstream market power. Because drugs tend to treat a single diagnosis, contracting between insurers and drug firms may be strongly affected by the payment for a given diagnosis. Theoretical research provides little guidance, however, on how negotiations would respond to the payment system incentives we study, although there is recent progress by de Fontenay and Gans (2014) and Douven et al. (2014). Our ability to empirically evaluate the "upstream" pass-through is limited by the fact that the prices in our data are prior to a drug $\times$ plan unobserved rebate. However, in Table 5 we estimate Equations 4 and 5 using price as a dependent variable. Similar to our treatment of OOP cost, we use two versions of the variable: price for covered drugs (no imputation), and price for all drugs (w/ imputation). We estimate a model with no controls and one with a drug-specific linear trend (diagnosis-specific linear trend for plan $\times$ diagnosis analyses). We find little evidence for a robust effect on prices; in particular, once we control for a time trend in prices, payment never has an impact on price that differs from zero at the five percent level.

The regression coefficients reported in Table 4 represents the pass-through of payments to typical out-of-pocket costs. The welfare-relevant pass-through rate should incorporate any adjustment that plans make to premiums as a result of the payment recalibration. To determine whether any such adjustment exists, we first calculate the average payment update a plan would receive based on its 2010 enrollment – i.e., the change in payments that would arise if the plan kept all its 2010 enrollees and received payments for them

under the new system. We call this quantity the average update:

$$\text{Avg. Update}_j = \frac{\sum_x U_x(\sum_{i \in j} \delta_{ix})}{\text{enrollment}_j}$$

In words, the numerator multiplies each diagnosis's payment update by the number of people with that diagnosis in plan j, and then sums that quantity across diagnoses. We normalize by the plan's enrollment to get the plan's payment update per enrollee. When weighted by enrollment, the average update is about \$5.56 for plans observed in both 2010 and 2011. We will compare this with each plan's change in its basic premium between 2010 and 2011, which averages \$22.18.

Figure 8 depicts the average payment (x-axis) and change in basic premium (y-axis) for 1072 plans observed in 2010 and 2011, with the size of the marker representing the plan's enrollment. If the payment update is passing-through to premiums, plans that get a higher average update should have reduced premiums. Instead, the lack of relationship is visually apparent. The weighted least-squares line is shown, and its insignificant slope coefficient is reported. We conclude that plans are not significant adjusting overall premiums in response to the payment recalibration.

5.3 Testing the Impact of Diagnosis Market Share

Our theoretical model predicted that a plan's response to a change in payments will vary depending on its share of the diagnosis – Part D plans with a large share of a diagnosis receiving a positive payment update will improve benefits less than a plan with a small share of the diagnosis. In order to test this theory, we consider each plan's share of the total market for a diagnosis, defined as the total number of Part D enrollees in the PDP region who have the diagnosis, in the last year before the update, 2010. We separate plans by whether they have an above- or below-median market share compared to other insurers in their PDP region. Our equation, below, interacts that measure with our payment measure.

$$\overbrace{Y_{djt}}^{\substack{\text{OOP cost/ coverage for drug } d \\ \text{in plan } j \\ \text{in year } t}} = \beta \overbrace{P_{xt}}^{\substack{\text{payment} \\ \text{for diag } x \\ \text{in year } t}} + \beta_2 \overbrace{(\text{High Share} \times P)_{xjt}}^{\substack{\text{dummy for high} \\ \text{share of diag } x \\ \text{in plan } j \\ \text{in 2010}}} + \overbrace{X_{djt}}^{\substack{\text{price} \\ \text{spline} \\ \text{or drug} \\ \text{trend}}} + \overbrace{\delta_{dj}}^{\substack{\text{drug} \times \text{plan} \\ \text{fixed} \\ \text{effect}}} + \overbrace{\delta_t}^{\substack{\text{year} \\ \text{fixed} \\ \text{effect}}} + \varepsilon_{djt} \tag{6}$$

The above describes a plan × drug analysis; an analogous model applies to plan × diagnosis data constructed using typical demand. β_2 is identified off of differences in how plans with a large share of a diagnosis in 2010 respond to the changes in payment as compared to plans with a small share of a diagnosis. Our theoretical model predicts $\beta < 0$ and $\beta_2 > 0$ when Y is out-of-pocket costs.

To examine our identifying variation more directly, Figure 9 depicts the histogram of plans characterized

by the number of diagnoses (of 76) where they have a high share of the diagnosis in 2010. For example, nearly 8% of 2010 plans are below the median share for every diagnosis. It is not surprising that there is a large mass with few diagnoses above market share because there are a number of very low enrollment plans (in 2010, the 100 smallest plans have an average enrollment of 49). If all plans simply enrolled a representative share of the population, diagnosis market share would be equal to overall market share and all plans would be located at the extremes of this histogram. If this were true, the "High Share" variable would be 1 for all diagnoses for large plans, and β_2 would simply reflect how large plans responded to the change in recalibration. Instead, β_2 is identified both from two sources of variation: how the same plan responds to payments for which it has a high vs. low diagnosis share, and how plans with a high vs. low diagnosis share respond differently to the payment for the same diagnosis. We think both sources of variation are useful but report in Section 5.5 a specification that includes a plan $\times$ year fixed effect. Including this fixed effect (present in Equations 4 and 5 but excluded from the above) focuses identification on variation within a plan between diagnoses where it has a high or low share.

Table 6 shows that, the response to the payment revision reflects plans' market shares of each diagnosis. Compared to plans with a below-median market share of each diagnosis, plans with an above-median market share reduced OOP costs approximately a third less. Analogously, these plans raised rates of coverage less than plans with a below-median market share. We conclude that, as predicted by theory, the response of plans to payments depends on their current enrollment. We note here that we cannot determine empirically whether the choice friction we detect is driven by switching costs or persistent preference heterogeneity.

One potential concern with the above analysis is that having a high share of a diagnosis in 2010 causes plans to react differently to the payment revision for a reason other than the high share *per se*. For example, perhaps plans with a high share of a diagnosis in 2010 have low out-of-pocket costs for that diagnosis, and reduce them less because they are already low. To test this alternative explanation, we first create a time-invariant indicator variable that is 1 if plan j's typical OOP cost for diagnosis x in 2010 W_{xj10} is in the bottom half of all plans' typical OOP cost for this diagnosis in this market in 2010. We describe this plan as "generous" for this diagnosis. We then estimate Equation 6 on two subsamples: generous plan $\times$ diagnosis combinations, and those that are not generous, and report the results in Table 7. For out-of-pocket costs (either imputed or not) the coefficients on payment $\times$ high share are never different from each other or from our estimate in Table 6. In the final two columns, we interact payment with the generosity indicator and add it as a control. Plans that are already generous for a particular diagnosis indeed improve benefits less than those that are not. However, the coefficient capturing the differential response of plans with a high share of a diagnosis is very similar to that in Table 6 when this control is added.

5.4 Recovering Demand Elasticities

Finally, we proceed to estimating demand as a function of OOP cost instrumented by payment. We propose a panel data model to predict an individual's demand – months supplied – for drug d in year t. Our panel data is balanced across t for id combinations – i.e., if an individual i takes a particular drug d in 2010, months_{idt} is imputed to zero for years 2009, 2011, and 2012. A balanced panel includes both the intensive and extensive margins of months supply, but results are similar when we use only the intensive margin (drop zeroes). We instrument for the out-of-pocket cost the individual paid using models similar to Equation 4a: using the payment for the diagnosis in year t and either a price spline or a linear drug trend.

$$\overbrace{\text{months}_{idt}}^{\substack{\text{demand for } i \\ \text{for drug } d \\ \text{in year } t}} = b\overbrace{\widehat{\text{OOP cost}_{idt}}}^{\substack{\text{predicted} \\ \text{OOP cost for } d \\ \text{in } t}} + \overbrace{X_{djt}}^{\substack{\text{price} \\ \text{spline} \\ \text{or drug} \\ \text{trend}}} + \text{Fixed Effects} + \varepsilon_{idt} \tag{7}$$

$$\text{OOP cost}_{idt} = \beta P_{xt} + X_{djt} + \text{Fixed Effects} + \varepsilon_{idt}$$

We consider two sets of fixed effects. The first uses an individual, a drug × plan, and a plan × year fixed effect. This specification is more similar to Equation 4a. In the second set, we use an individual × drug fixed effect and an individual × year fixed effect. This second set is better suited to capturing individual heterogeneity – both time-invariant taste for a particular drug and overall demand for drugs in a particular year. We two-way cluster ε_{idt} on individuals and drugs.

We estimate this equation on more than 35 million individual × drug × year observations between 2009 and 2012. We drop individuals who receive the low-income subsidy because their out-of-pocket costs are subsidized by the government. Our results are reported in Table 7. The top panel estimates the relationship between out-of-pocket cost and months supply using ordinary least squares, and the bottom panel reports the full instrumental variables model. As is common, the co-determination of out-of-pocket cost and demand biases our OLS coefficients towards zero. In the IV, the first stage recovers estimates somewhat larger in magnitude than those in Table 4. Our second stage, which is only significant (and based on an significant fist stage) when we control for a price spline, implies elasticity estimates of about -2%. Previous research has computed elasticities using the increased out-of-pocket costs at the coverage gap, and has found larger estimates: -30% to -50% in Einav et al. (2015) and -14% to -36% in Jung et al. (2014). Similar to those papers, we are estimating elasticity among those who do not receive the low-income subsidy, meaning those in the top half of the Medicare income and wealth distribution. The benefit design changes we study may induce less of a utilization response because they are less salient for beneficiaries than the large discrete changes in out-of-pocket costs at the coverage gap; in addition, beneficiaries entering the coverage gap may

be able to delay purchases for a few weeks or months until the following contract year, a strategy unavailable to beneficiaries in the setting we study.

5.5 Results: Robustness

Our first robustness check tests the importance of weighting. Our baseline analyses weight each observation by the product of the plan enrollment and the drug's takers in Medicare Advantage (plan $\times$ drug analyses) or the product of the plan's enrollment and the number of people who have the diagnosis (plan $\times$ diagnosis analyses). Appendix Tables A.1 and A.2 show that our basic findings are robust to weighting all observations equally, particularly for plan $\times$ diagnosis analyses. In general, our estimates here are somewhat larger in magnitude; however, returning to Figure 6, we can see that the most common diagnoses tended to have relatively small changes. By equally weighting diagnoses, we may be finding estimates more determined by outliers.

Appendix Table A.3 repeats the analysis of Table 6, but includes plan $\times$ year fixed effects. This means that the impact of a high share of diagnosis is identified by differences in how the same plan designs benefits for diagnoses for which it has a higher vs. lower share. When we pursue this identification, we find more null results in the plan $\times$ drug analyses (left columns). Our plan $\times$ diagnosis analyses are robust to this alternative identification strategy.

Finally, Ericson (2014) suggests that Part D insurers responded to switching costs by introducing new plans. Introducing new plans facilitates the price discrimination between new and old enrollees that is formally disallowed in Part D. Our fixed effects exclude plans introduced in 2011 or 2012 from identification of the effect of payments. However, there were relatively few plans introduced in 2011: only 3% of plans were new that year compared to 10% in either 2009 or 2012.[10] Applying Ericson's insight to our setting, our hypothesis would be that new plans would reflect the payment updates more fully. This means that, comparing new plans to continuing plans, new plans would have lower out-of-pocket costs for diagnoses that had received positive payment updates, and higher out-of-pocket costs for diagnoses with negative payment updates. In results available upon request, we find that, while plans that entered in 2011 or 2012 have generally lower out-of-pocket costs than continuing plans, those costs are actually higher for diagnoses that received positive payment updates. It is possible that newly-introduced plans disproportionately target 65 year old Medicare beneficiaries; Medicare beneficiaries do not receive diagnosis-specific risk adjustment until their second year of enrollment, which could explain why such plans appear less sensitive to the diagnosis-specific payment updates.

[10] In part, plans were responding to new regulations that required insurers to reduce the number of plans offered.

6 Conclusion

In this paper, we explore the effect of a revision to diagnosis-specific payments in Medicare Part D. We found that many diagnoses received large increases or reductions in payments as a result of the revision. We show that Part D benefit designs responded as predicted by prior theory to the change in incentives that resulted from the payment system revision: plans improved benefits for diagnoses with positive payment updates and vice versa for diagnoses with negative payment updates. In particular, if the revision raised payments for a diagnosis by $1, out-of-pocket costs for the typical beneficiary with that diagnosis fell by about $0.20. Furthermore, we explored how plans respond differently depending on whether they have a high or low share of the diagnosis. In a theoretical model, we show that a monopoly with a large insurer will improve benefits less for a positive payment update; the intuition is that the insurer balances the gains from attracting new enrollees and the losses from improving benefits for locked-in current enrollees. We show that, consistent with the model, insurers with an above-median share of a given diagnosis market raised out-of-pocket costs less for a positive payment update. This finding infers the presence of switching costs using only supply-side behavior.

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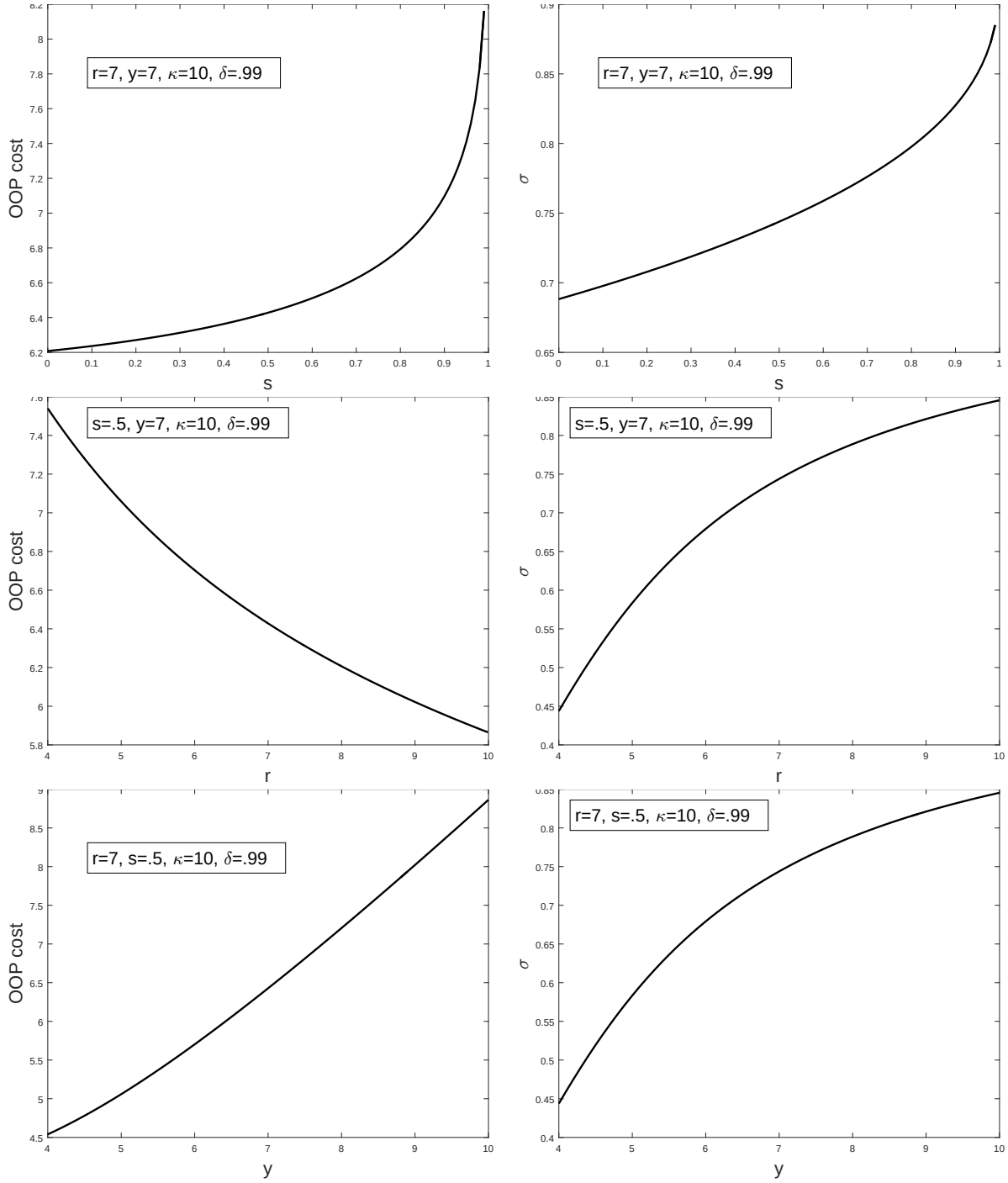
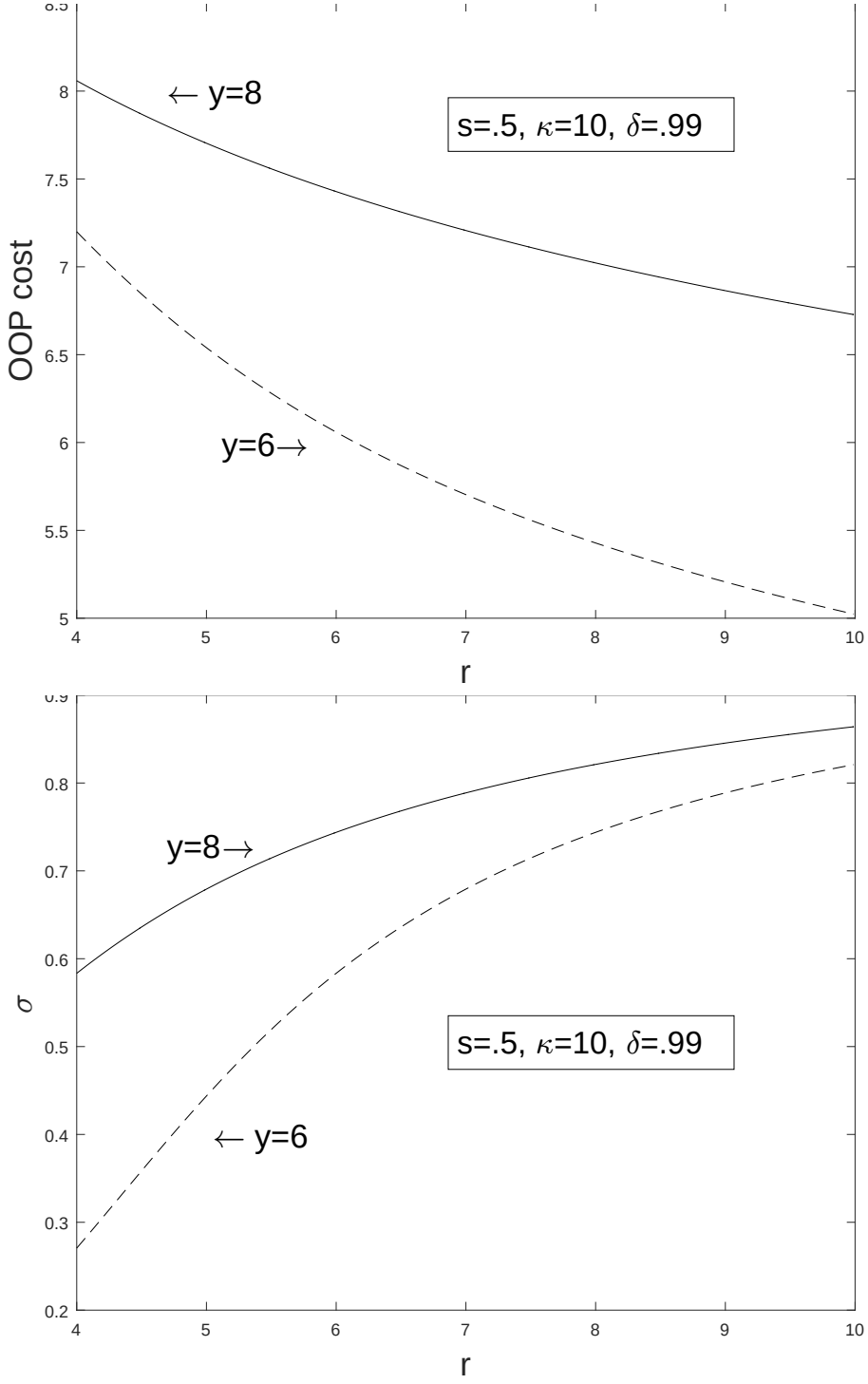
Figure 1: Theoretical Simulation: Exploration of Parameters in Insurer Monopoly



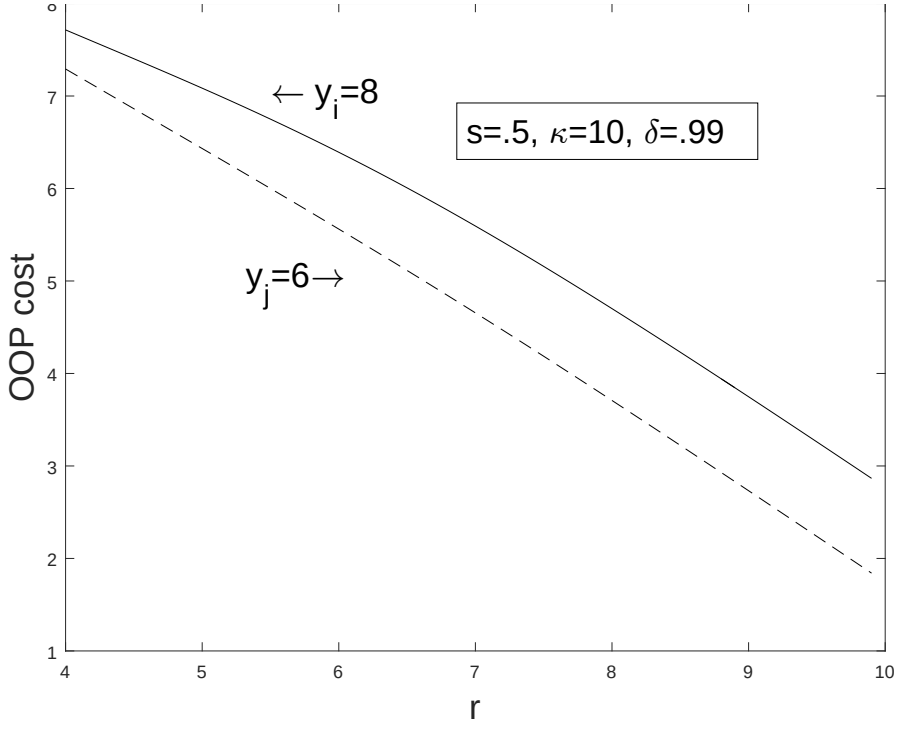
These figures simulate out-of-pocket costs (left column) and market shares (right column) for the forward-looking monopolist described in Section 3. The top row shows outcomes across possible values of switching costs. The middle row shows outcomes across possible values of subsidy r. The bottom row shows outcomes across possible innate plan values y. Other parameters are held at the value described in the graph.

Figure 2: Theoretical Simulation: Effect of Increasing Subsidy in Insurer Monopolies with Varying Market Shares



This figure shows the pass-through of subsidy r for two different monopoly plans. One has a higher innate value, obtains a larger market share, and reacts less strongly to increasing subsidy r.

Figure 3: Theoretical Simulation: Effect of Increasing Subsidy in an Insurer Duopoly



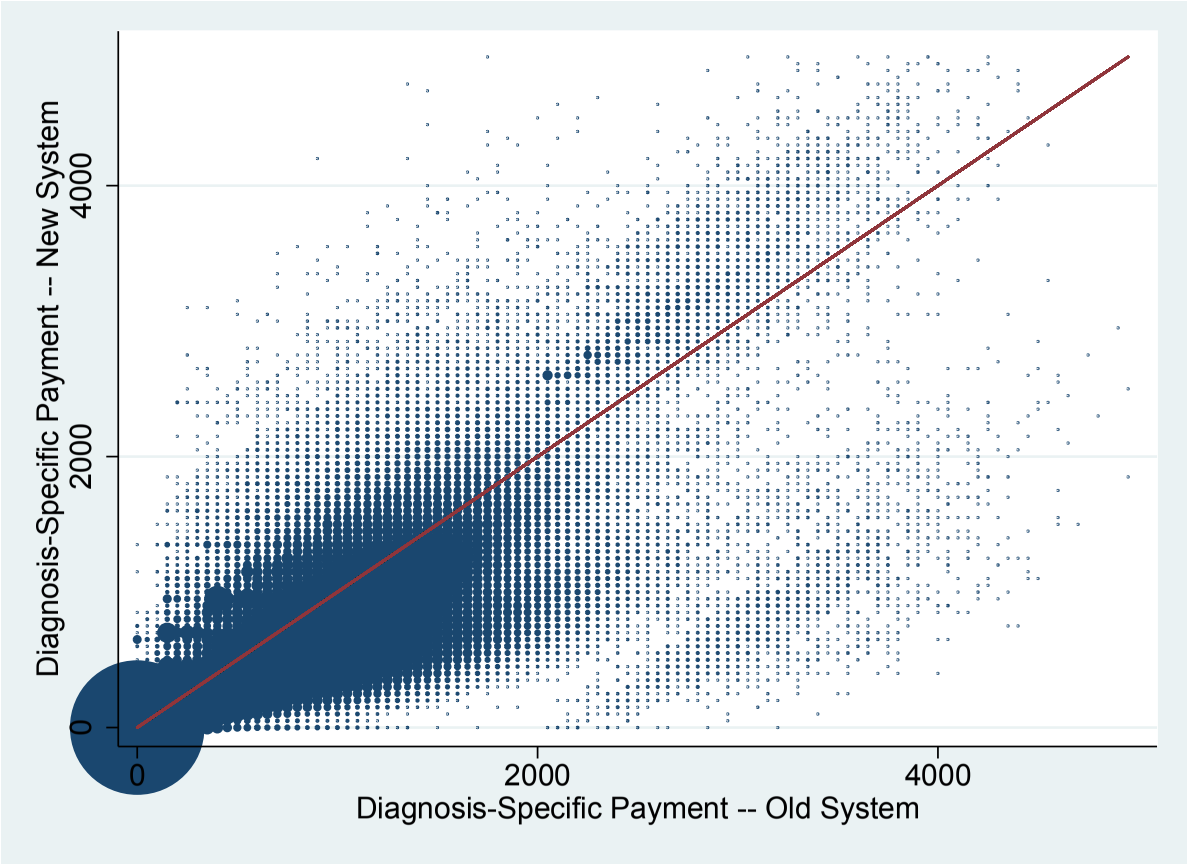
This figure shows the results of duopolistic competition between two plans with different innate values. Insurer i obtains a larger market share and reacts less strongly to increasing subsidy r.

Table 1: Summary Statistics on Part D Enrollees

Measuring Change in the Payment System: Estimation Sample					
N=764,621 enrollees	Percentile of Distribution				
	5^{th}	25^{th}	50^{th}	75^{th}	95^{th}
Payment: Old System	0	458	751	1069	1636
Payment: New System	0	294	536	824	1419
Difference in Payments	-687	-314	-171	-30	326

This table describes the sample of enrollees used to estimate Equations 2 . The sample is composed of individuals enrolled in free-standing Part D in 2011 and fee-for-service Medicare in 2010. The first row shows the distribution in payments in dollars for each individual under the old system (P_i^O in Equation 2). The second row shows the distribution in payments for each individual under the new system (P_i^N in Equation 2). The third row shows the distribution of the difference in an individual's payments between the new and old system (positive numbers mean payments increase). Rows are independent, such that the person at the 5^{th} percentile in the first row may be at a higher or lower percentile in the next row.

Figure 4: Enrollee Subsidies Under New and Old Subsidy Systems (Enrollee-Level)



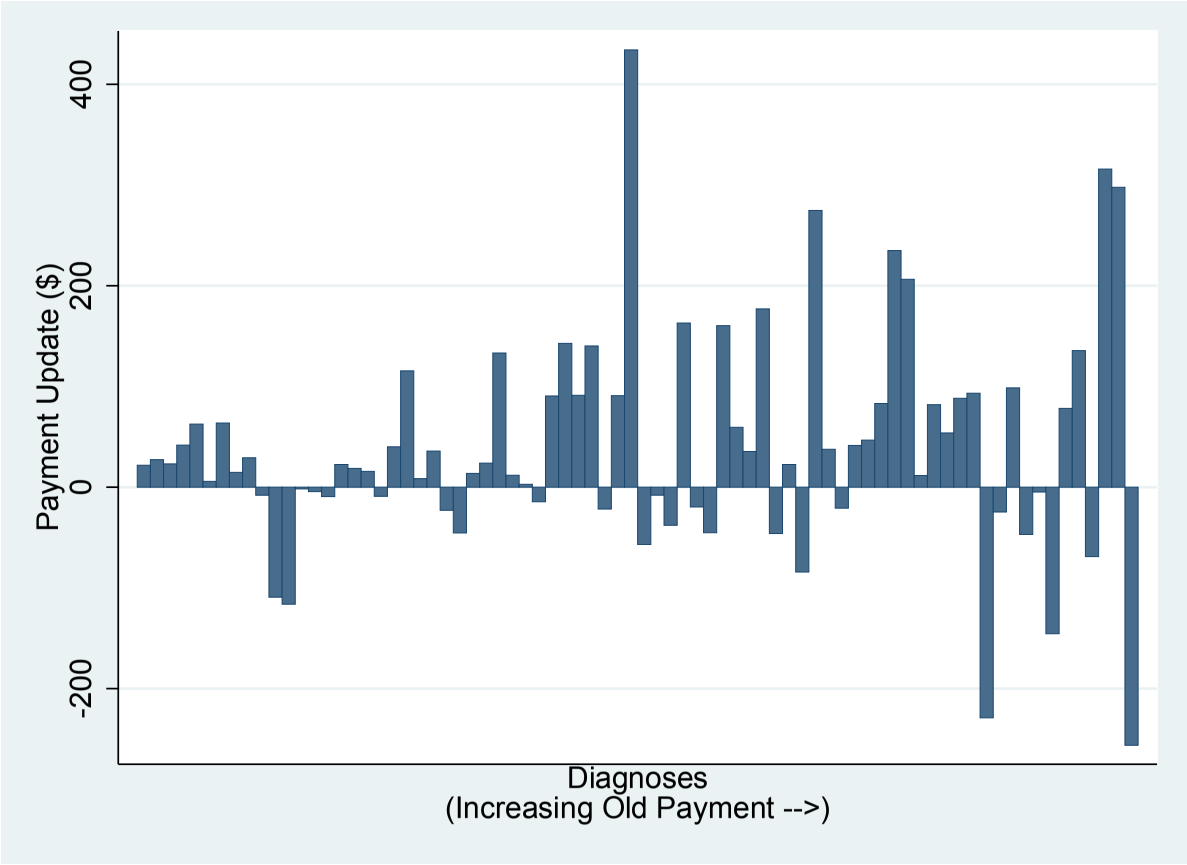
This figure depicts the diagnosis-specific payment for each individual enrolled in Part D in 2011 and fee-for-service Medicare in 2010, coded under both the 2010 and 2011 payment systems and binned in $50 intervals. The size of the dot indicates the number of individuals represented, of 764,621, with the large dot at zero representing approximately 49,000 individuals with no diagnoses in either year. Plans enrolling individuals above the 45° line receive more for them under the new system than the old system. Conversely, plans enrolling individuals below the 45° line received more under the old system than the new system. An individual's diagnosis-based weight is scaled into dollars by the 2010 national average bid. A small number of observations with new or old payments exceeding $5000 are excluded from the figure.

Table 2: Old Payments and Payment Update for Each Diagnosis

Diagnosis	Old Payment ($)	Payment Update ($)	SE
HIV/AIDS	1889	-256	14
Age<65 & Schizophrenia	347	298	3
Multiple Sclerosis	331	316	9
Parkinson's Ds	296	-69	4
Leukemia	271	136	41
Diabetes w/ Comps	239	78	1
Opportunistic Infections	238	-146	8
ADD	235	-5	6
Congestive Heart Failure	232	-47	1
Schizophrenia	231	99	5
Hypertension	205	-25	1
Dementia w/ Depression	204	-229	3
Kidney Transplant	199	93	7
Dsr of Immunity	191	88	8
Rheumatoid Arthritis	183	54	2
Inflamm. Bowel Ds	168	82	4
Esophageal Ds	163	12	1
Metastatic Acute Cancers	161	206	6
Age<65 & Other Major Psych. Dsrs	153	235	2
Asthma and COPD	151	83	1
Lipoid Metabolism	151	47	1
Open-angle Glaucoma	149	41	1
Other Major Psych. Dsr	146	-21	1
Motor Neuron Ds/Atrophy	141	38	15
Psoriatic Arthropathy	139	275	12
Dsr of Spine	130	-84	1
Myocardial Infarction/Unstable Angina	129	23	1
Seizure Dsr & Convulsions	117	177	2
Other Psych.	117	-46	3
Osteoporosis	106	35	1
Severe Hematological Dsr	105	59	5
Migraines	98	160	3
Incontinence	94	-45	2
Heart Arrhythmias	86	-20	1
Polycythemia Vera	85	-38	8
Hepatitis	85	163	6
Muscular Dystrophy	77	-57	16
Other Upper Respiratory Ds	77	-8	1
Major Organ Transplant	73	434	12
Other Endocrine	72	91	2
Polyneuropathy exc. Diabetic	71	91	2
Psoriasis	71	140	3
Other Musculoskeletal	71	-22	1
Inflamm. Spondylopathies	69	143	3
Chronic Renal Failure	68	91	1
Infectious Ds	68	-14	3
Mononeuropathy/Abnormal Movement	66	3	1
Female Stress Incontinence	62	12	3
Connective Tissue Dsr	61	133	3
Cerebral Hemorrhage/Stroke	58	24	1
Vascular Retinopathy exc. Diabetic	52	14	2
Huntington's Ds	51	-23	12
Vertebral Fracture w/o Spinal Injury	51	-45	3
Nephritis	47	36	7
Salivary Gland Ds	46	8	5
Lung Cancer	46	115	1
Other Spec. Endocrine	45	40	1
Bullous Dermatoses	44	-9	1
Cellulitis & Skin Ds	44	-2	1
Fecal Incontinence	44	19	6
Chronic Skin Ulcer exc. Decubitus	44	-9	2
Urinary Obstruction	44	-4	2
Quadriplegia	44	23	4
Pancreatic Ds	44	16	3
Bronchitis & Congenital Lung Dsr	40	29	1
Pneumonias	40	-116	5
Empyema, Abscess, & Lung Ds	40	-109	16
Polymyalgia Rheumatica	40	-8	3
Macular Degeneration & Retinal Dsr	37	15	1
Vascular Disease	32	64	1
Vaginal & Cervical Ds	31	63	2
Ulcer & Gastro Hemorrhage	31	6	2
Pulmonary Embolism & Thrombosis	25	42	2
Larynx/Vocal Ds	22	23	8
Impaired Renal Function	21	27	1
Bone Infections	21	22	4

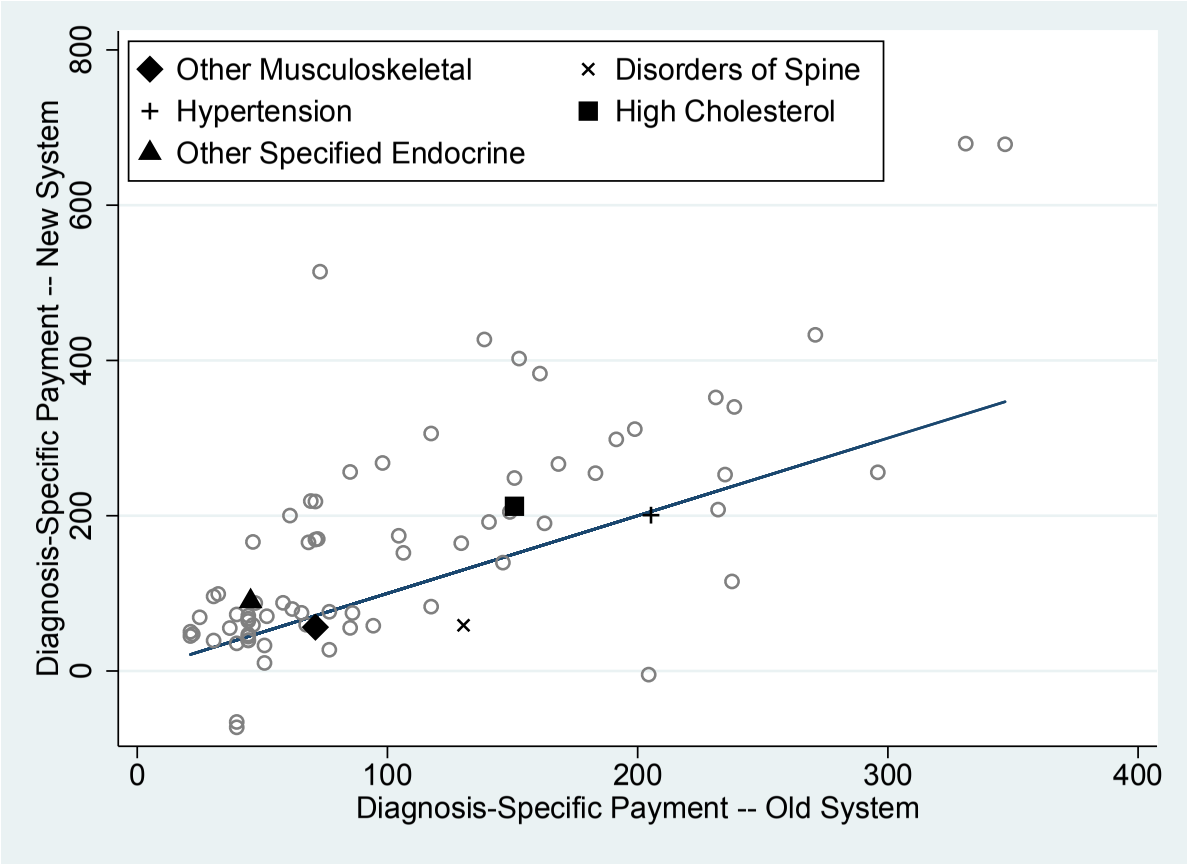
This table reports the results of the estimation of Equation 2 on 764,621 2011 Medicare Part D enrollees. The first column reports the diagnosis name. The second column reports the payment for the diagnosis in a plan bidding the national average bid under the 2010 system. The next columns report the payment update and its robust standard error. Only the 76 diagnoses used in later analyses are reported.

Figure 5: Magnitude of Payment Updates



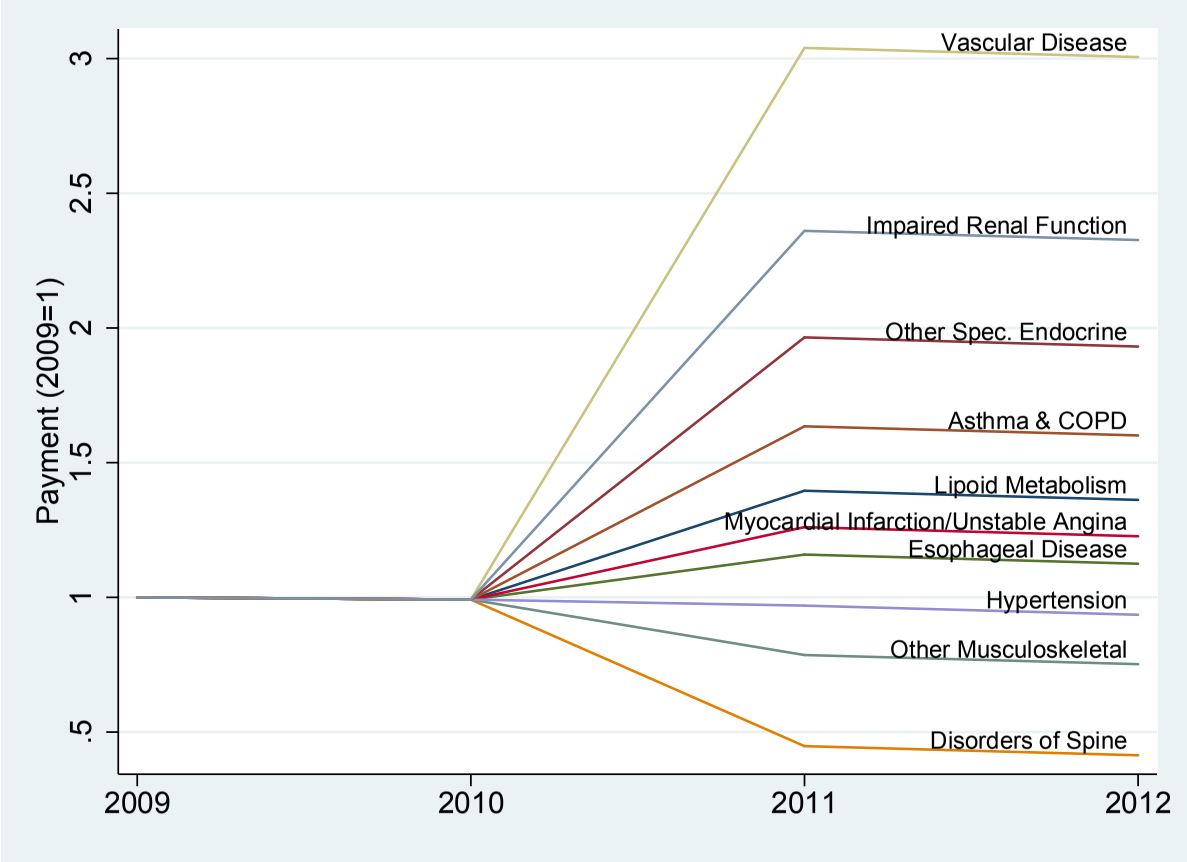
This figure displays the payment updates reported in Table 2. The 76 diagnoses used in later analyses are arrayed along the y axis by increasing 2010 payment level.

Figure 6: Diagnostic Payments Pre- and Post- Recalibration



Each marker in this figure represents one of 76 diagnoses, with its 2010 payment measured along the x-axis. The y-axis measures the diagnosis's 2011 payment, computed as its 2010 payment plus the update reported in Table 2. The five most common diagnoses are identified in the legend.

Figure 7: Changes in Payments, Relative to Initial Payments



This figure shows payments for the ten most common diagnoses between 2009 and 2012. Each diagnosis's payment in 2009 has been normalized to one; payments range from falling by half to rising by a factor of three.

Table 3: Impact of Payment on Benefit Designs: Plan × Drug Analyses

	OOP cost ($), no imputation					
payment	-0.00115		-0.00374**		-0.00672**	
	(0.000806)		(0.000701)		(0.000725)	
lead of payment		0.000608		-0.00219**		0.00343**
		(0.000785)		(0.000611)		(0.000626)
spline for price			X	X		
drug trends					X	X
plan X drug FEs	X	X	X	X	X	X
plan X year FEs	X	X	X	X	X	X
N	11,952,896					
	covered (p.p.)					
payment	-0.00176**		-0.00176**		-0.000279	
	(0.000364)		(0.000357)		(0.000716)	
lead of payment		-0.000330		-0.000492		-0.000574
		(0.000386)		(0.000374)		(0.000409)
spline for price			X	X		
drug trends					X	X
plan X drug FEs	X	X	X	X	X	X
plan X year FEs	X	X	X	X	X	X
N	17,894,785					
	OOP cost ($), w/ imputation					
payment	0.00123		-0.00258**		-0.00935**	
	(0.00111)		(0.000940)		(0.00120)	
lead of payment		0.00346**		-0.000442		0.00597**
		(0.00109)		(0.000825)		(0.000899)
spline for price			X	X		
drug trends					X	X
plan X year FEs	X	X	X	X	X	X
plan X drug FEs	X	X	X	X	X	X
N	17,416,781					

This table reports the results of estimation of Equation 4 on an unbalanced panel of 1891 plans × 4931 drugs between 2009 and 2012. In the first panel, the dependent variable is the out-of-pocket cost for the drug in the plan (only observed if the drug is covered). Columns alternate between using the contemporaneous payment and the future payment (a placebo test). The first two columns use payment with no other covariates, the second two control for price using a spline, and the third two estimate the impact of payment net of a drug time trend; plan × year and plan × drug fixed effects are always included. The next panel repeats this analysis for whether a drug is covered; for scale, the outcome is 100 when a plan covers a drug in a year and 0 otherwise. The third panel uses a different measure of out-of-pocket cost: the cost itself if the drug is covered by the plan, or the average drug price if the drug is not covered. All analyses are weighted by plan enrollment and the number of takers of the drug in Medicare Advantage. Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

Table 4: Impact of Payment on Benefit Designs:
Plan × Diagnosis Analyses Using Typical Demand

	OOP cost ($), no imputation		
payment	-0.167	-0.182**	-0.360**
	(0.125)	(0.0373)	(0.0855)
spline for price		X	
diagnosis trends			X
plan X year FEs	X	X	X
plan X diag FEs	X	X	X
N		397,100	

	covered (p.p.)		
payment	0.0114**	0.0114**	0.00480*
	(0.00163)	(0.00153)	(0.00224)
spline for price		X	
diagnosis trends			X
plan X year FEs	X	X	X
plan X diag FEs	X	X	X
N		397,100	

	OOP cost ($), w/ imputation		
payment	-0.161	-0.165**	-0.377**
	(0.122)	(0.0363)	(0.0855)
spline for price		X	
diagnosis trends			X
plan X year FEs	X	X	X
plan X diag FEs	X	X	X
N		397,100	

This table reports the results of estimation of Equation 5 on an unbalanced panel of 1891 plans × 76 diagnoses between 2009 and 2012. In the first panel, the outcome variable is the total amount of out-of-pocket costs for a plan enrollee who consumes the typical demand for the diagnosis would pay, under an assumption that the individual consumes no uncovered drugs. The first column uses payment with no other covariates, the second column controls for a spline of the price for the typical demand for this plan × diagnosis, and the third column estimates the impact of payment net of a diagnosis-specific time trend; plan × year and plan × diagnosis fixed effects are always included. In the next panel, the outcome variable is the share of consumption under the typical demand for the diagnosis would be covered by the plan, where 100 signifies that all the drugs for a diagnosis are covered by a plan and 0 signifies none are. In the final panel, the dependent variable is again the out-of-pocket costs for typical demand, now under an assumption that uncovered drugs are purchased at the mean price for the drug. All analyses are weighted by plan enrollment and the number of individuals who have the diagnosis. Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

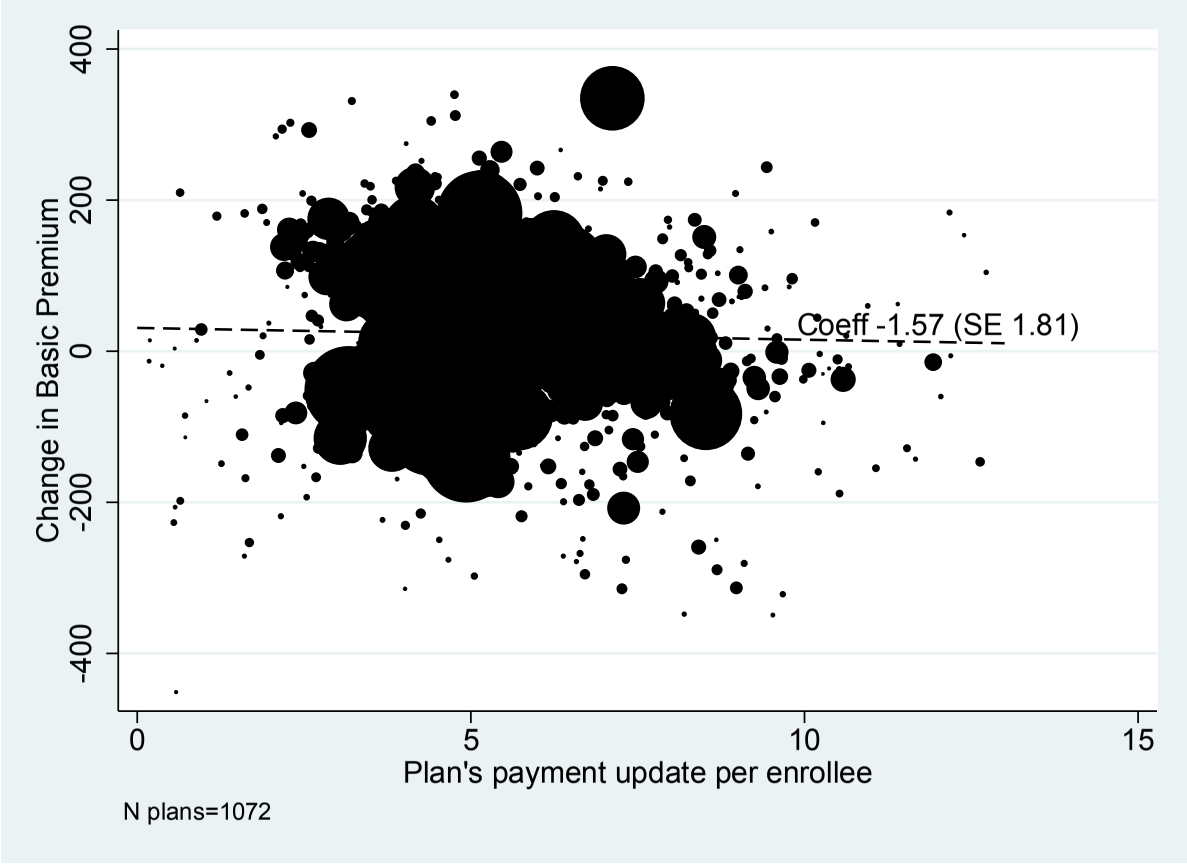
Table 5: Impact of Payment on Prices

	Pre-Rebate Price ($), no imputation			
	Plan X Drug		Plan X Diag	
Payment	0.0143**	0.00438+	0.00998	-0.0533
	(0.00244)	(0.00248)	(0.159)	(0.0947)
trends		Drug		Diag
FEs	Plan X Year		Plan X Year	
	Plan X Drug		Plan X Diag	
N	11,898,300		397,100	

	Pre-Rebate Price ($), w/ imputation			
	Plan X Drug		Plan X Diag	
Payment	0.0154**	0.00383	0.0160	-0.0706
	(0.00249)	(0.00253)	(0.157)	(0.0986)
trends		Drug		Diag
FEs	Plan X Year		Plan X Year	
	Plan X Drug		Plan X Diag	
N	17,359,939		397,100	

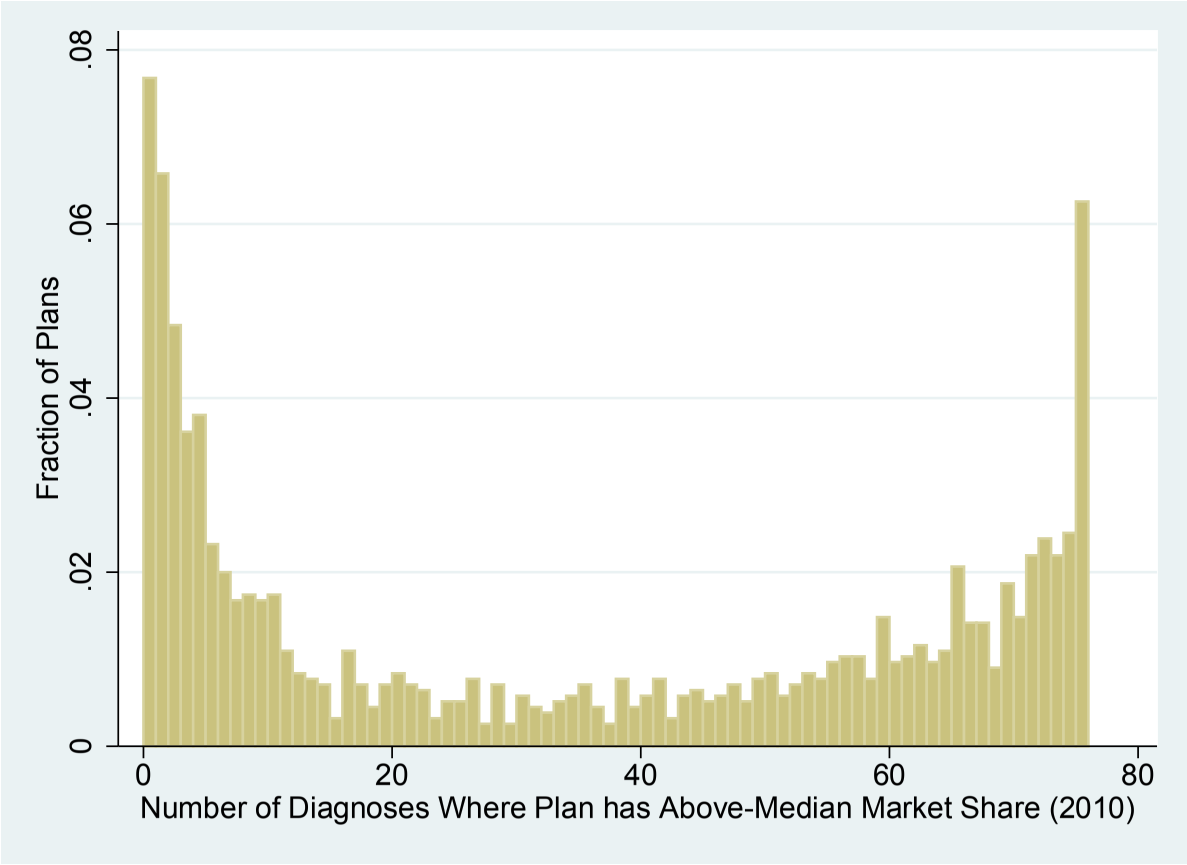
This table reports the estimation of Equations 4 (left columns) and 5 (right columns) with price as a dependent variable. In the top panel, the outcome is pre-rebate price for a covered drug in a plan (left columns) or the total drug price paid for a plan enrollee who consumes the typical demand, under an assumption that the individual consumes no uncovered drugs (right columns). In the bottom panel, the outcome is the pre-rebate price for a drug in a plan, imputing the annual mean price for the drug when the drug is not covered (left columns) or the total drug price paid for a plan enrollee who consumes the typical demand, under an assumption uncovered drugs are purchased at the annual mean price for the drug (right columns). The second and fourth columns control for a time trend for each drug or diagnosis. Analyses are weighted by plan enrollment and the number of individuals who take the drug in Medicare Advantage (left columns), or plan enrollment and the number of individuals who have the diagnosis (right columns). Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

Figure 8: Change in Basic Premium for a Plan's Expected Payment Update



For 1072 plans observed in both 2010 and 2011, this figure depicts the plan's change in annual basic premium (y-axis) versus the plan's payment update per enrollee (x-axis). The plan's payment update per enrollee is calculated as the change in payments the plan would expect based on its 2010 enrollment. The size of the marker is the plan's enrollment. The dashed line shows the weighted least-squares line of the corresponding regression and reports its slope and standard error.

Figure 9: Histogram of Plan Variation in High-Share of Diagnosis



In this figure, we have first characterized 2010 plans by the number of diagnoses in which they have an above-median share of the diagnosis market, and then reported the distribution of this variable. For example, about 6% of 2010 plans have an above-median share of every diagnosis.

Table 6: Impact of Payment on Benefit Design by Plan's Share of a Diagnosis's Market

	OOP cost ($), no imputation			
	Plan X Drug		Plan X Diag	
Payment	-0.00692**	-0.0108**	-0.283**	-0.525**
	(0.000833)	(0.000921)	(0.0475)	(0.0944)
Payment X High Share	0.00366**	0.00441**	0.108**	0.177**
	(0.000926)	(0.000952)	(0.0246)	(0.0275)
spline for price	X		X	
trends		Drug		Diag
FEs	Plan X Drug, Year		Plan X Diag, Year	
	covered (p.p.)			
	Plan X Drug		Plan X Diag	
Payment	-0.000029	0.000619	0.0167**	0.0105**
	(0.000668)	(0.000898)	(0.00174)	(0.00235)
Payment X High Share	-0.00183*	-0.000985	-0.00581**	-0.00619**
	(0.000767)	(0.000731)	(0.000974)	(0.000849)
spline for price	X		X	
trends		Drug		Diag
FEs	Plan X Drug, Year		Plan X Diag, Year	
	OOP cost ($), w/ imputation			
	Plan X Drug		Plan X Diag	
Payment	-0.00552**	-0.0132**	-0.289**	-0.575**
	(0.00109)	(0.00134)	(0.0472)	(0.0932)
Payment X High Share	0.00323**	0.00426**	0.133**	0.212**
	(0.00106)	(0.00109)	(0.0254)	(0.0263)
spline for price	X		X	
trends		Drug		Diag
FEs	Plan X Drug, Year		Plan X Diag, Year	

This table reports the results of estimation of Equation 6, showing how the impact of a diagnosis's payment varies with the plan's diagnosis market share. The left two columns repeat the analysis of Table 3, while the right two columns repeat the analysis of Table 4. Each regression adds as an independent variable the interaction of the diagnosis's payment and an indicator for a plan having an above-median diagnosis market share. Analyses are weighted by plan enrollment and the number of individuals who take the drug in Medicare Advantage (left columns), or plan enrollment and the number of individuals who have the diagnosis (right columns). Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

Table 7: Impact of Payment on Benefit Design by Plan's Share of a Diagnosis's Market, Sampling by or Controlling for Generosity

	OOP cost ($), no imputation					
sample	Generous		Not Generous		Full Sample	
Payment	-0.193**	-0.327**	-0.219**	-0.594**	-0.278**	-0.527**
	(0.0477)	(0.0977)	(0.0613)	(0.101)	(0.0514)	(0.0981)
Payment X High Share	0.0929**	0.147**	0.0502	0.209**	0.0533*	0.136**
	(0.0287)	(0.0355)	(0.0427)	(0.0368)	(0.0269)	(0.0293)
Payment X Generous					0.111**	0.138**
					(0.0192)	(0.0141)
spline for price	X		X		X	
diagnosis trends		X		X		X
plan X year FEs	X	X	X	X	X	X
plan X diag FEs	X	X	X	X	X	X
	covered (p.p.)					
sample	Generous		Not Generous		Full Sample	
Payment	0.0117**	0.00251	0.00646**	0.00272	0.0108**	0.00450*
	(0.00177)	(0.00255)	(0.00174)	(0.00229)	(0.00161)	(0.00229)
Payment X High Share	-0.00513**	-0.00388**	0.00940**	0.00757**	0.00280**	0.00255**
	(0.00146)	(0.000980)	(0.00121)	(0.00115)	(0.000895)	(0.000738)
Payment X Generous					-0.00455**	-0.00478**
					(0.00123)	(0.00104)
spline for price	X		X		X	
diagnosis trends		X		X		X
plan X year FEs	X	X	X	X	X	X
plan X diag FEs	X	X	X	X	X	X
	OOP cost ($), w/ imputation					
sample	Generous		Not Generous		Full Sample	
Payment	-0.200**	-0.366**	-0.200**	-0.603**	-0.243**	-0.506**
	(0.0503)	(0.102)	(0.0581)	(0.0964)	(0.0504)	(0.0954)
Payment X High Share	0.120**	0.154**	0.0416	0.214**	0.0571*	0.136**
	(0.0313)	(0.0346)	(0.0404)	(0.0356)	(0.0272)	(0.0277)
Payment X Generous					0.0593**	0.0582**
					(0.0192)	(0.0121)
spline for price	X		X		X	
diagnosis trends		X		X		X
plan X year FEs	X	X	X	X	X	X
plan X diag FEs	X	X	X	X	X	X

This table repeats the analysis of the right two columns of Table 6 on different subsamples (columns 1-4) or with an additional control (columns 5-6). In the first two columns, we use only plan × diagnosis combinations where the plan's 2010 out-of-pocket costs for an enrollee with that diagnosis with typical demand is in the bottom half of the plan's market. In the third and fourth columns, we use only the remaining observations. In the last two columns, we add as an independent variable this "generosity" indicator interacted with the payment for the diagnosis. Analyses are weighted by plan enrollment and the number of individuals who have the diagnosis. Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

Table 8: Demand Elasticity: Instrumental Variables for Out-of-Pocket Cost

OLS

	Months	Months	Months	Months
OOP Cost ($)	-0.00034+	-0.00060*	-0.00020*	-0.00039**
	(0.00019)	(0.00027)	(0.00010)	(0.00014)
spline for price	X		X	
drug trend		X		X
FEs	Individual		Individual X Drug	
	Plan X Year		Individual X Year	
	Plan X Drug			
Implied ε (%)	-0.64	-1.14	-0.38	-0.74

IV

First Stage				
	OOP Cost ($)	OOP Cost ($)	OOP Cost ($)	OOP Cost ($)
Payment ($)	-0.01553+	-0.00660	-0.01449+	-0.00463
	(0.00882)	(0.00572)	(0.00806)	(0.00444)
Second Stage				
	Months	Months	Months	Months
OOP Cost ($)	-0.00141*	0.08069	-0.00121*	0.07460
	(0.00064)	(0.09674)	(0.00048)	(0.10408)
spline for price	X		X	
drug trend		X		X
FEs	Individual		Individual X Drug	
	Plan X Year		Individual X Year	
	Plan X Drug			
Implied ε (%)	-2.67	153.01	-2.29	141.46
N	35,469,096			

This table reports the results of estimating Equation 7 on the months supplied to each individual between 2009 and 2012. The top panel estimates ordinary least squares with the stated controls (price spline or drug trend) and fixed effects. The bottom panel instruments for out-of-pocket cost using payment and reports both the first and second stage of estimation. Standard errors are two-way clustered at the individual and drug. +, * and ** represent significance at the 10, 5 and 1 percent levels.

A Time to Harvest:
Evidence on Consumer Choice Frictions from a Payment Revision in Medicare Part D
Online Appendix

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Appendix

A.1 Theoretical Appendix

A.1.1 Pass-through of subsidies for large and small insurers

In this section, we wish to show the analytical cross-partial for steady state equilibrium out-of-pocket cost c with respect to subsidy r and plan market share σ. In Section 3.4, we found the effect of subsidy on equilibrium out-of-pocket costs. We redefine this equation as G.

$$G(c, r, \kappa, \delta, s) = \frac{dc}{dr} = -\frac{(1-P_L)(1+P_L-P_N)^2}{(1+P_L-P_N)^2 - (1+\delta)(P_L-P_N)\left(1-P_N+P_L(P_L-P_N)\right)}$$

In particular, we vary model primitive y, which controls the plan's value relative to the outside option. We will show that a monopoly insurer with higher y obtains a higher market share (even after accounting for changes in equilibrium out-of-pocket costs).

$$\frac{d^2c}{drd\sigma} = \frac{dG}{d\sigma} = \frac{dG}{dy} \Big/ \frac{d\sigma}{dy} = \left(\frac{\partial G}{\partial y} + \frac{\partial G}{\partial c}\frac{\partial c}{\partial y}\right) / \left(\frac{\partial \sigma}{\partial y} + \frac{\partial \sigma}{\partial c}\frac{\partial c}{\partial y}\right)$$

In the above, the last equality recognizes that G and σ depend on y both directly and via any changes in out-of-pocket costs c that result. Because c and y always enter P_L and P_N as $y - c$, $\frac{\partial G}{\partial y} = -\frac{\partial G}{\partial c}$ and $\frac{\partial \sigma}{\partial y} = -\frac{\partial \sigma}{\partial c}$.

$$\frac{d^2c}{drd\sigma} = \left(\frac{\partial G}{\partial y} + \frac{\partial G}{\partial c}\frac{\partial c}{\partial y}\right) / \left(\frac{\partial \sigma}{\partial y} + \frac{\partial \sigma}{\partial c}\frac{\partial c}{\partial y}\right) = \frac{\partial G}{\partial y}\left(1 - \frac{\partial c}{\partial y}\right) / \left(\frac{\partial \sigma}{\partial y}(1 - \frac{\partial c}{\partial y})\right) = \frac{\partial G}{\partial y} \Big/ \left(\frac{\partial \sigma}{\partial y}\right)$$

A.1.1.1 $\frac{\partial G}{\partial y}$

We will use the following substitutions: $\mathbf{a = 1 - P_L, b = P_L - P_N}$.

$$G(c, r, \kappa, \delta, s) = \frac{dc}{dr} = -\frac{a(1+b)^2}{(1+b)^2 - (1+\delta)b(a+b(2-a))}$$

$$\frac{\partial G}{\partial y} = -\frac{[(1+b)^2 - (1+\delta)b(a+b(2-a))][\frac{da}{dy}(1+b)^2 + 2a(1+b)\frac{db}{dy}] - [a(1+b)^2][2(1+b)\frac{db}{dy} - (1+\delta)(\frac{db}{dy}(a+b(2-a)) + b(\frac{da}{dy} + \frac{db}{dy}(2-a) - b\frac{da}{dy}))]}{[(1+b)^2 - (1+\delta)b(a+b(2-a))]^2}$$

After some simplifications, we arrive at

$$\frac{\partial G}{\partial y} = -(1+b)\frac{\frac{da}{dy}(1+b)^3 - 2(1+\delta)b^2(1+b)\frac{da}{dy} + (1+\delta)a\frac{db}{dy}[a(1-b) + 2b(2-a))]}{[(1+b)^2 - (1+\delta)b(a+b(2-a))]^2}$$

We substitute in the differentials $\frac{da}{dy}$ and $\frac{db}{dy}$.

$$\frac{da}{dy} = -P_L(1-P_L) = -(1-a)a \quad \frac{db}{dy} = (P_L - P_N)(1-P_L-P_N) = -b(1-2a-b)$$

After further simplifications,

$$\frac{\partial G}{\partial y} = a(1+b)\frac{(1-a)(1+b)^3 + (1+\delta)b[b(1-a)(2-2a-b) - 4b(1-a)(a+b) + a(1-a) - (a+b)^2]}{[(1+b)^2 - (1+\delta)b(a+b(2-a))]^2}$$

$$\frac{\partial G}{\partial y} = (1-P_L)(1+P_L-P_N)\frac{P_L(1+P_L-P_N)^3 + (1+\delta)(P_L-P_N)[P_L(P_L+P_N)(P_L-P_N) - 4P_L(1-P_N)(P_L-P_N) + P_L(1-P_L) - (1-P_N)^2]}{[(1+P_L-P_N)^2 - (1+\delta)(P_{OL}-P_N)(1-P_L+(P_L-P_N)(1+P_L))]^2}$$

The term in brackets can be negative. When $\delta = 0$, $\frac{\partial G}{\partial y}$ is positive for all values of P_N in the $[0,1]$ interval and all values of P_L in the $[P_N, 1]$ interval. When $\delta = 1$, $\frac{\partial G}{\partial y}$ is positive except for very small values of P_N that do not arise from equilibrium out-of-pocket costs.

A.1.1.2 $\frac{\partial \sigma}{\partial y}$

In the steady state, $\sigma = P_N/(1-P_L+P_N)$.

$$\frac{\partial \sigma}{\partial y} = \frac{(1-P_L+P_N)P_N(1-P_N) - P_N[-P_L(1-P_L)+P_N(1-P_N)]}{(1-P_L+P_N)^2}$$

$$\frac{\partial \sigma}{\partial y} = \frac{P_N(1-P_L)(1+P_L-P_N)}{(1-P_L+P_N)^2} > 0$$

A.2 Empirical Appendix

A.2.1 Calculating Standard Demand

Let d index drugs, z index zones, i index individuals, j index plans, and x index diagnoses. $\mathcal{T}_{xt}$ are the set of individuals taking a drug that treats diagnosis x in year t, and $\mathcal{F}_{xt}$ are the set of individuals with a flag for diagnosis x in the same year. Recall that diagnostic flags are generated by medical encounters, and that individuals may fill prescriptions without regard to the presence of related diagnostic flags. The two sets can diverge for a number of reasons: individuals may be choosing no treatment for a given diagnosis; individuals may have a chronic diagnosis well-controlled by drug therapy for which they did not seek a medical encounter; medical providers, whose payment is independent of the diagnostic flags, may not record them accurately; and the algorithm that assigns drugs to diagnoses in Section 4.4 may mistakenly assign drugs to a diagnosis with which they are not well connected.

We choose to characterize demand as the total utilization of drugs that treat a given diagnosis, normalized by the number of people who have the diagnosis. The first item is denoted as months_raw_{dzt}:

$$\text{months\_raw}_{dzt} = \sum_{i \in \mathcal{T}_{xt}} \text{months}_{idzt} | d \in \mathcal{D}_x$$

$$\text{months}_{dzt} = \frac{\sum_{i \in \mathcal{T}_{xt}} \text{months}_{idzt} | d \in \mathcal{D}_x}{\sum_{i \in \mathcal{F}_{xt}} 1}$$

In words, months_{dzt} is the months supply of related drugs per person with the diagnosis. The advantage of this definition is that $\sum_z \sum_d \text{months\_raw}_{dz} = \text{total demand}$. This holds because every drug d is in $\mathcal{D}_x$ for some diagnosis x. If we instead summed utilization from only those with the diagnosis, a significant fraction of Part D utilization would be excluded from the measure.

A.2.2 Supplementary Figures and Tables

Table A.1: Robustness: Impact of Payment On Benefit Designs: All Observations Equally Weighted

	OOP cost ($), no imputation			
	Plan X Drug		Plan X Cond	
Payment	-0.0203**	-0.0666**	-0.301**	-1.405**
	(0.00120)	(0.00492)	(0.0699)	(0.199)
spline for price	X		X	
diag trends		X		X
FEs	Plan X Year		Plan X Year	
	Plan X Drug		Plan X Diag	

	covered (p.p.)			
	Plan X Drug		Plan X Cond	
Payment	0.000329	-0.00194**	0.00979**	0.00858**
	(0.000435)	(0.000485)	(0.000887)	(0.000945)
spline for price	X		X	
diag trends		X		X
FEs	Plan X Year		Plan X Year	
	Plan X Drug		Plan X Diag	

	OOP cost ($), w/ imputation			
	Plan X Drug		Plan X Cond	
Payment	0.0130**	-0.0341**	-0.297**	-1.386**
	(0.00285)	(0.00422)	(0.0696)	(0.191)
spline for price	X		X	
diag trends		X		X
FEs	Plan X Year		Plan X Year	
	Plan X Drug		Plan X Diag	

This table repeats the analysis of Tables 3 (left columns) and 4 (right columns), except that all observations are equally weighted. Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

Table A.2: Robustness: Impact of Payment on Benefit Design by Plan's Share of a Diagnosis's Market: All Observations Equally Weighted

	OOP cost ($), no imputation			
	Plan X Drug		Plan X Diag	
Payment	-0.0197**	-0.0688**	-0.519**	-1.570**
	(0.00136)	(0.00498)	(0.0771)	(0.203)
Payment X High Share	-0.000769	0.00584	0.508**	0.401**
	(0.00232)	(0.00377)	(0.0456)	(0.0513)
spline for price	X		X	
trends		Drug		Diag
FEs	Plan X Drug, Year		Plan X Diag, Year	
	covered (p.p.)			
	Plan X Drug		Plan X Diag	
Payment	0.00149*	-0.000855	0.00907**	0.00854**
	(0.000633)	(0.000623)	(0.000859)	(0.000947)
Payment X High Share	-0.00243*	-0.00243*	0.00166**	8.77e-05
	(0.00106)	(0.00104)	(0.000392)	(0.000229)
spline for price	X		X	
trends		Drug		Diag
FEs	Plan X Drug, Year		Plan X Diag, Year	
	OOP cost ($), w/ imputation			
	Plan X Drug		Plan X Diag	
Payment	0.0138**	-0.0372**	-0.516**	-1.575**
	(0.00341)	(0.00444)	(0.0773)	(0.197)
Payment X High Share	-0.00205	0.00711+	0.506**	0.462**
	(0.00372)	(0.00410)	(0.0458)	(0.0498)
spline for price	X		X	
trends		Drug		Diag
FEs	Plan X Drug, Year		Plan X Diag, Year	

This table repeats the analysis of Table 6, except with all observations equally weighted. Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.

Table A.3: Robustness: Impact of Payment on Benefit Design by Plan's Share of a Diagnosis's Market, Controlling for Plan × Year FEs

	OOP cost ($), no imputation			
	Plan X Drug		Plan X Diag	
Payment	-0.00214**	-0.00599**	-0.222**	-0.483**
	(0.000663)	(0.000827)	(0.0494)	(0.0958)
Payment X High Share	-0.00163*	-0.000817	0.0434	0.133**
	(0.000801)	(0.000776)	(0.0269)	(0.0289)
spline for price trends	X	Drug	X	Diag
FEs	Plan X Year	Plan X Drug	Plan X Year	Plan X Diag

	covered (p.p.)			
	Plan X Drug		Plan X Diag	
Payment	-0.00155**	-0.000833	0.00887**	0.00252
	(0.000338)	(0.000694)	(0.00173)	(0.00252)
Payment X High Share	-0.000231	0.000614	0.00278**	0.00244**
	(0.000495)	(0.000470)	(0.000883)	(0.000755)
spline for price trends	X	Drug	X	Diag
FEs	Plan X Year	Plan X Drug	Plan X Year	Plan X Diag

	OOP cost ($), w/ imputation			
	Plan X Drug		Plan X Diag	
Payment	-0.000366	-0.00824**	-0.214**	-0.509**
	(0.000927)	(0.00126)	(0.0489)	(0.0939)
Payment X High Share	-0.00245**	-0.00123	0.0528+	0.142**
	(0.000871)	(0.000868)	(0.0273)	(0.0279)
spline for price trends	X	Drug	X	Diag
FEs	Plan X Year	Plan X Drug	Plan X Year	Plan X Diag

This table repeats the analysis of Table 6, except with the inclusion of a plan × year fixed effect. Analyses are weighted by plan enrollment and the number of individuals who take the drug in Medicare Advantage (left columns), or plan enrollment and the number of individuals who have the diagnosis (right columns). Standard errors are two-way clustered on plan×year and diagnosis×market. +, * and ** represent significance at the 10, 5 and 1 percent levels.