Online Appendix for:
Screening in Contract Design:
Evidence from the ACA Health Insurance Exchanges

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A Model

In this section, we present a formal model of the contract design problem of a profit-maximizing insurer in the setting where the insurer offers only one contract, must charge the same premium to all enrollees (community rating), and cannot prohibit any consumer who desires to purchase the contract from enrolling (guaranteed issue). We show that in this setting, the equilibrium contract differs from the socially efficient contract and that the size of the distortion is related to the correlation between the use of the distorted health care service and a consumer's profitability. We note that this model is a more general version of the simple model described in Section 2.

We start by following much of the prior literature in assuming that insurers offer a single contract that consists of a price p and a coinsurance rate $1-x$, so that $x \in [0,1]$ is the portion of spending paid by the insurer. In our context, this can be thought of as an insurance contract providing partial coverage for spending on one drug.[77] Each individual faces a distribution of potential drug spending with mean μ and variance σ^2. We most closely follow Veiga and Weyl (2016) in specifying an individual's expected cost to the insurer as the product of two components: a fixed component μ, and a component $k(x)$ that varies with coverage and incorporates both the *direct* effect of coverage on insurer costs (a smaller x implies that the insurer pays a smaller portion of the cost of the drug) and the *indirect* moral hazard effect (a smaller x induces less consumption of the drug). Formally, $c^j = \mu k(x^j)$ is the expected cost to insurer j. We assume that the components are independent so that $k(x)$ does not vary with μ.

Define v as the product of the coefficient of absolute risk aversion and the variance of the spending distribution, σ^2, so that v is related to the expected utility cost of anticipated risk. Veiga and Weyl (2016) show that under the assumption of CARA utility, willingness-to-pay for coverage x is given by

$$u = \mu h(x) + v\psi(x), \tag{5}$$

where $\mu h(x)$ is the benefit the individual gets from insurer spending equal to $\mu k(x)$, and $v\psi(x)$ is the benefit the individual gets from the level of risk protection offered by the contract.

In this environment, with a distribution of consumer types defined by $f(\mu, v)$, social welfare can be described with the following expression:

$$W = \int_{\mu}\int_{v} f(\mu,v)[\mu h(x) + v\psi(x) - \mu k(x)]dv\, d\mu. \tag{6}$$

The additional term between Equations (5) and (6) is $\mu k(x)$, which captures the cost of coverage, including that due to moral hazard. It is straightforward to show that in order to maximize social welfare, the social planner would set coverage generosity x^* to solve the following equality:

$$\psi'(x^*) = \phi(k'(x^*) - h'(x^*)), \tag{7}$$

[77] Empirically, we consider contracts with many such cost sharing parameters for many drugs, but the one parameter framework is common in the literature and sufficient to highlight the core intuitions here.

where $\phi = \frac{E[\mu]}{E[v]}$. This is the classic trade-off between the benefits of risk protection, $\psi'(x^*)$, and the social cost of moral hazard, $k'(x^*) - h'(x^*)$, as first pointed out by Zeckhauser (1970) and Feldstein (1973).

We next consider insurer j's choice of x in a competitive health insurance market. We specify insurer j's profit function as

$$\pi^j = \int_\mu \int_v f(\mu, v) D(x^j; \mu, v)[r(x^j, \mu, v) - \mu k(x^j)] dv \, d\mu, \tag{8}$$

where $D(x^j; \mu, v)$ is demand—the probability of enrollment in a plan with coinsurance rate $1 - x^j$ for an individual of type (μ, v). The term $r(x^j, \mu, v)$ is the payment the plan gets for an individual of type (μ, v), including risk adjustment, reinsurance, or any other regulatory transfer or payment. As above, $\mu k(x^j)$ denotes the cost of providing insurance.

The insurer sets the portion of spending it covers, x^j, to maximize profits. To understand the insurer's problem, we differentiate π^j with respect to x^j holding the premium fixed:

$$\frac{\partial \pi^j}{\partial x^j} = \int_\mu \int_v f(\mu, v) \left[\frac{\partial D(x^j; \mu, v)}{\partial x^j} \left(r(x^j, \mu, v) - \mu k(x^j) \right) - \mu k'(x^j) D(x^j; \mu, v) \right] dv d\mu. \tag{9}$$

The derivative consists of two components inside the brackets. The first component captures changes in demand (i.e. enrollment) due to a change in the portion of spending covered by the plan, x^j. The second component captures the change in plan spending among the existing enrollee population.[78]

The demand effect (the first term in brackets in equation 9) can be further decomposed to reveal two distinct demand-related consequences of a change in x^j. If we define $\bar{r} = E[r(\widehat{x^j}, \mu, v)]$ and $\bar{c} = E[\mu k(\widehat{x^j})]$ as the average net revenue and the average cost (for a given $\widehat{x^j}$) across the entire population, then:

$$\frac{\partial D(x^j; \mu, v)}{\partial x^j} (r(x^j, \mu, v) - \mu k(x^j)) = \underbrace{\frac{\partial D(x^j; \mu, v)}{\partial x^j} [\bar{r} - \bar{c}]}_{\text{More enrollees}} + \underbrace{\frac{\partial D(x^j; \mu, v)}{\partial x^j} [(r(x^j, \mu, v) - \mu k(x^j)) - (\bar{r} - \bar{c})]}_{\text{Different enrollees}}. \tag{10}$$

The "more enrollees" term above represents the change in insurer profits due to a change in the number of individuals of average profitability enrolled in the plan. This arises because consumers' willingness-to-pay for the plan, as described by Equation (5), varies with the plan generosity. Importantly, this component is related to the social planner's problem because valuation in excess of cost will increase as x^j converges to the social optimum. The "different enrollees" component reveals that the insurer has an additional consideration in setting x, beyond trading off risk protection and moral hazard: The plan will attract marginal enrollees who may be differentially profitable to the insurer depending on their specific payments and costs.

Note that if the "different enrollees" term is zero, then the insurer solving the first order condition in Equation (10) under a symmetric competitive equilibrium will decrease the coinsurance rate ($1 - x^j$) until the additional profits from enrolling more individuals equals the additional costs due to providing better coverage. This parallels the social planner's problem of trading off the benefits of risk protection with the cost of moral hazard.[79] In fact, Einav, Finkelstein and Polyakova (2016)

[78] The change in spending among existing enrollees is due to both the direct effect of the increase in the portion of spending covered by the plan and the indirect effect of the increase in the individual's total spending caused by moral hazard.

[79] To see this, let the demand function be described as $D(x^j; \mu, v) = G(u^j = \mu h(x^j) + v\psi(x^j))$. This implies that $\frac{\partial D(x^j; \mu, v)}{\partial x^j} = G'[\mu h'(x^j) + v\psi'(x^j)]$. It is now straightforward to see that the same expression for the social benefit that

show via simulation that the social planner's problem and that of the profit-maximizing firm coincide when the "different enrollees" term is zero, with both trading off the social costs and benefits of more generous insurance.

The possibility of screening types by setting the coinsurance rate thus represents a margin that drives a wedge between the level at which a profit-maximizing insurer sets the coinsurance rate and the socially efficient level. Though we merely sketch the intuition here, this result is shown rigorously by Glazer and McGuire (2000), Frank, Glazer and McGuire (2000), and Veiga and Weyl (2016), who also show that the size of the wedge is proportional to the covariance among marginal consumers between willingness-to-pay for coverage and the consumer's cost to the insurer. Ellis and McGuire (2007) devise a practical empirical metric that reflects this covariance, which we follow when we empirically operationalize the insurer's selection incentive.

B Simulated payments

This section provides more detail on the simulated payments used to compute selection incentives and the HHS-HCC risk adjustment model.

We define costs as the sum of all health care spending (inpatient, outpatient, and prescription drug) for person i in a given year. We observe this in the Marketscan data. Revenues are not observed in the data and must be simulated. We simulate revenues according to Exchange plan payment formulas specified by the Department of Health and Human Services (HHS). Exchange plan revenues for plan j consist of three components: premiums, p_i^j, risk adjustment transfers, R_i^{RA}, and reinsurance payments R_i^{Re}.

For risk adjustment transfers, we start by specifying a risk score, r_i, for each individual using the risk adjustment formula used in the Exchanges (Kautter et al., 2014). This formula assigns risk scores according to diagnoses in claims data. We use an individual's diagnoses from 2012 to assign his/her risk score. We then specify risk adjustment transfers according to the Exchange risk adjustment transfer formula:[80]

$$R_i^{RA} = \left(\frac{r_i}{\bar{r}} - 1\right)\bar{p},$$

where $\bar{r} = \frac{1}{n}\sum_{i=1}^{n} r_i$ and $\bar{p} = \frac{1}{n}\sum_{i=1}^{n} p_i^j$ are the average risk score and average premium across all individuals in the market, respectively. Similarly, we define reinsurance payments as

$$R_i^{Re} = .8 \times \left(C_i - 60,000\right)$$

for claim costs above \$60,000.[81] We assume that reinsurance is funded by an actuarially fair per capita reinsurance premium, $\overline{re}$.[82] In words, the reinsurance payment is 80% of the individual

enters the social planner's problem ($\mu h'(x^j) + v\psi'(x^j)$) also enters the insurer's profit maximization problem. It is also straightforward to see in Equation (10) above that the same expression for the social cost that enters the social planner's problem ($\mu k'(x^j)$) also enters the insurer's profit maximization problem. While the expressions differ in other ways, there are clear similarities that lead the level of coverage chosen by a profit maximizing insurer to mimic the level chosen by the social planner.

[80] Note that risk adjustment transfers occur at the plan level, but in fact they are a sum of individual-level transfers. Here we specify the component of the plan's transfer attached to individual i.

[81] A policy with a cutoff of \$60,000 and a coinsurance rate of 0.8 was the originally announced reinsurance policy for the Exchanges. This was later adjusted *ex post* to a cutoff of \$45,000 and a coinsurance rate of 0.5. We use the originally announced policy, as insurers likely designed their formularies according to the announced policy rather than the one implemented *ex post*. In practice, there is little difference between the two policies for insurer incentives.

[82] In practice, the Exchange reinsurance program is also funded by a similar premium, but it is assessed across almost all

cost above the $60,000 attachment point minus the actuarially fair reinsurance premium equal to the average reinsurance payment. For premiums, we assume that competition forces all plans to charge a premium equal to the average cost in the market. We also assume a symmetric equilibrium so that all plans have the same premium and average cost:[83]

$$p_i^j = \bar{C} = \frac{1}{n}\sum_{i=1}^{n} C_i,$$

for all i and j. Given these three components, we can generate simulated revenues at the individual level as the sum of the three components which we then use to compute our selection incentive measures.

C Drug Level Analysis

Although our analysis operates at the level of the drug class, we investigated incentives related to individual drugs as well. To do so, we recalculated selection incentives following the same procedure as in our main analysis, but at the level of individual drug codes. An important consideration in this exercise is that sample sizes get small when focusing on individual drugs. Specifically, there is a danger of misinterpreting noise in our estimates of drug-specific costs and revenues as evidence of payment errors. Therefore, we try various restrictions on the analysis sample to assess sensitivity. We restrict to either the top 3 drugs within each class in terms of frequency of use, or the top 6 or top 10. In each case, we throw out drugs for which we do not observe at least 1,000 observations, which is about 0.01% of the enrollee sample.

Figure A7 shows the distribution of the implied profit incentives compared at the drug and class levels. Panel A repeats the histogram from Figure A3 for comparison, showing the distribution of incentives at the class level. Panel B presents the analogous histogram for the top 10 drugs in terms of frequency of use within each class. (Results for the top 3 or top 6 are not shown, but similar.) Panels C and D zoom into just the middle 75% and middle 50% of classes, by the class-level incentive. This shows how the drug-specific incentives within class vary conditional on the class-level incentive itself being close to neutral. For example, *antihyperlipidemics* (statins) are essentially neutral as a class, but Figure B2 tells us whether specific statins are differentially predictive of patient profitability.

In Figure A8, we plot several drug-level scatterplots for the top 10 drugs by use in each class, side-by-side with the class-level scatterplot (which repeats Figure 3 from the main text). This gives a visual sense of how the deviations at the class-level and at the drug-level compare. Our summary reading of the facts in Figures A7 and A8 is (a) that risk adjustment and reinsurance neutralize selection incentives at the drug level in most cases, as most points in Figure A8 remain tightly clustered around the 45 degree line, and (b) that drug-specific variation is comparable in size to the variation across classes.

In results not reported here, we estimate regressions that include both drug-level and class-level selection incentives and find that drug-level incentives are not correlated with formulary restrictiveness while the class-level coefficient estimates remain similar in size to our main results (though with considerable noise). We interpret these results as suggesting that insurers are more focused on patient types revealed by demand for a therapeutic class of a drug (e.g, women seeking infertility treatments)

covered lived in the US, not just across individuals in the Exchanges.

[83] Note that this assumption is not as strong as it may seem. If premiums are equal to a value different from average cost, this affects the profitability of all individuals equally, leaving relative profitability across individuals unchanged. The stronger assumption here is that individuals are all in plans that have the same premiums. However, our goal in this paper is not to assess differential incentives for different types of plans, as our data are insufficient for this type of analysis. Instead, we seek to assess the average incentive and the average insurer response to that incentive.

rather than on a particular drug product (e.g., Ovidrel). This is consistent with a case study by Jacobs and Sommers (2015) of HIV drug coverage in Exchange plans across a handful of states. They explain: "A formal complaint submitted to the Department of Health and Human Services (HHS) in May 2014 contended that Florida insurers offering plans through the new federal marketplace (exchange) had structured their drug formularies to discourage people with human immunodeficiency virus (HIV) infection from selecting their plans. These insurers categorized all HIV drugs, including generics, in the tier with the highest cost sharing." Similarly, we note that in November 2015, the National Multiple Sclerosis Society filed a comment with HHS's Office for Civil Rights explaining that, "common health insurance practices that can discriminate against people with MS are formularies that place all covered therapies in specialty tiers." Both of these anecdotes are consistent with the notion that insurers are targeting people (who can substitute across alternative drug therapies) rather than individual drug products.

D Demand Elasticities and the Selection Incentive

The drug class fixed effects in our regressions are intended to control for any class characteristics that are similar across ESI and Exchange settings, including own and cross-price elasticities. However, if ESI plans were differentially responsive to the same consumer price responsiveness, and if class-specific price elasticities happened to be correlated with class-specific payment errors generated by HHS's risk adjustment and reinsurance algorithms, then the tiering patterns we identify in Exchange plans could be a result of profit maximizing insurers responding to the incentive to efficiently limit moral hazard rather than due to selection-related incentives. In this appendix, we provide some direct evidence against this possibility by incorporating external measures of consumer price elasticities.

We incorporate the class-specific demand elasticities estimated by Einav, Finkelstein and Polyakova (2016), who identify price sensitivity of prescription drug utilization by exploiting Medicare Part D's "donut hole" at which drug cost-sharing changes abruptly.[84] To map the EFP estimates into our analysis, we begin by re-organizing our data to match their therapeutic class grouping, developed by the American Hospital Formulary Service (AHFS). Besides allowing us to import the EFP demand elasticities, this exercise demonstrates the robustness of our results to an alternative classification system.

In most of the analyses presented in this paper we rely on the REDBOOK therapeutic classification that is also used in the Marketscan data. There are 257 classes in the REDBOOK classification, of which we analyze the 220 classes for which we are able to construct our selection incentive measures (because they are associated with claims in the Marketscan data) and that also appear in our formulary data. For the analysis in this appendix, we use the American Hospital Formulary Service (AHFS) 8-digit classification. There are 332 classes in the AHFS of which we analyze the 294 classes for which we are able to construct our selection incentive measures (because they are associated with claims in the Marketscan data) and that also appear in our formulary data. We also conduct analyses restricted to the 99 classes that we are able to match to the 108 "common" classes for which Einav, Finkelstein and Polyakova (2016) provide price elasticity measures.

Figure A9 plots the analog of Figure 2, using the 294 AHFS drug classes in place of the 220 REDBOOK classes used in the main analysis. As above, marker sizes reflect the relative number of consumers using drugs in each class, and the dashed line separates the space into profitable and unprofitable types. In the figure, a subset of the classes are indicated with blue markers. These are

[84] Econometrically identified estimates exist for own-price elasticities only. Nonetheless, as Glazer, Huskamp and McGuire (2012) show, cross-price responsiveness may matter as well.

the 99 classes for which EFP generate demand elasticity estimates that we can match to our data.[85] For the whole sample of classes and for this demand elasticity subset in blue, there are significant outliers above the dashed line, mirroring Figure 2.

In Table A10, we replicate the main results using the AHFS classification. We generate our selection incentive measures exactly as above. In column (1) we include the full schedule of AHFS drug classes. In column (2) we restrict to only those classes for which we can directly control for a demand elasticity. In column (3) we add controls for the EFP estimate of class-specific elasticity interacted with the indicator for an Exchange plan. (The elasticity main effects are naturally absorbed by the class fixed effects.) We repeat this ordering of specifications for each of the three selection incentive measures and for both of the dependent variables from Table 3. The findings of Table A10 mirror those of Table 3 in that unprofitable classes are differentially assigned to restrictive tiers in Exchange plans. Most importantly, the addition of demand elasticity controls have essentially no effect on the coefficient estimates of interest. For completeness, Appendix Figure A10 plots the semi-parametric versions of the regressions.[86]

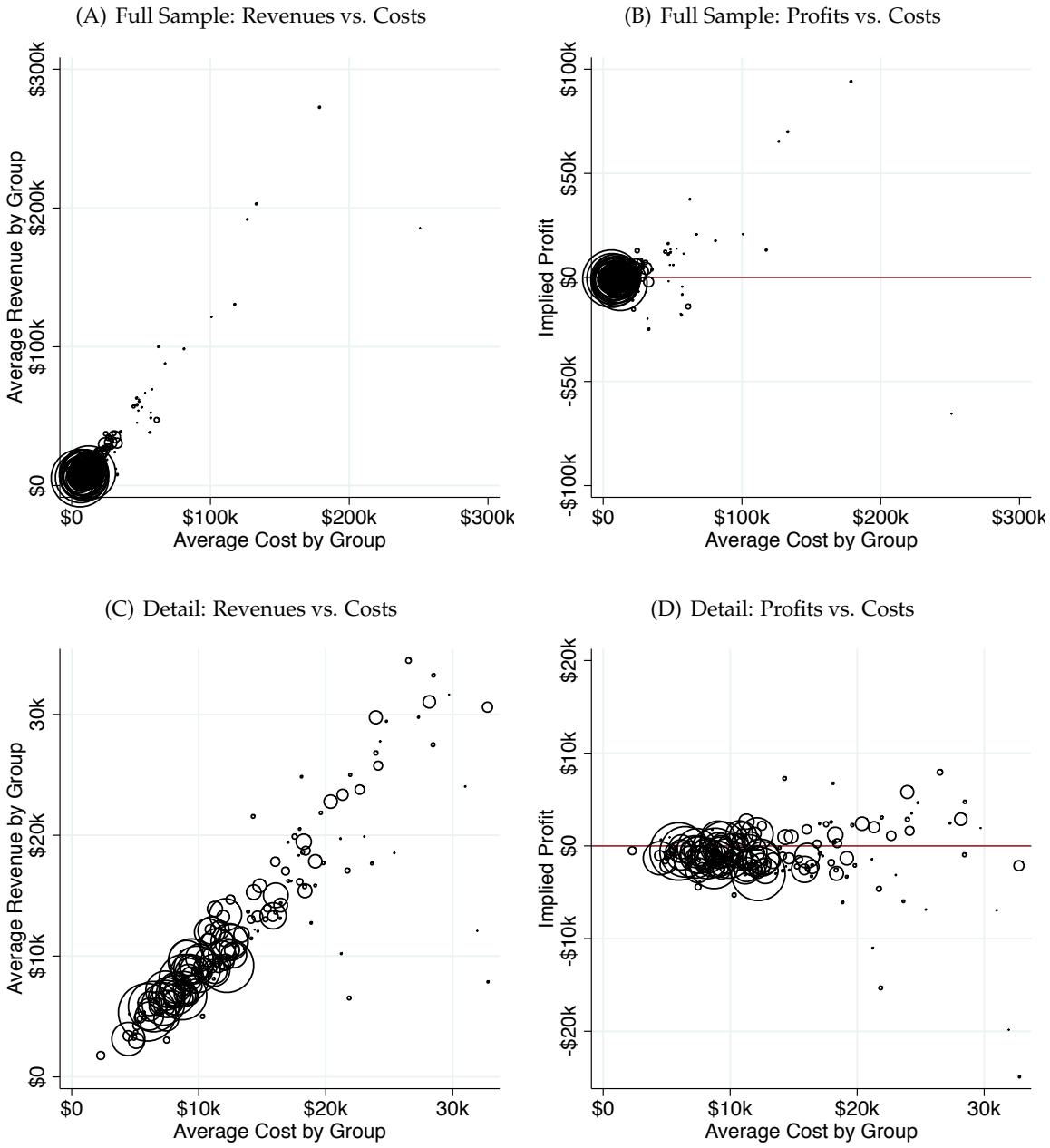
To better understand these results, we examine the correlation between the demand elasticity estimates and the selection incentive measures. Figure A6 graphs scatterplots of elasticity versus selection incentive by class. The three panels correspond to the three measures of S_{mc}. There is no significant correlation between the selection incentive generated by the payment system error and the demand elasticity. Taken together, Table A10 and Figures A6, A9, and A10 provide strong evidence that Exchange plans are not merely differentially responding to socially efficient profit-maximizing considerations regarding class-specific consumer moral hazard in a way that ESI plans are failing to do.

[85] Einav, Finkelstein and Polyakova (2016) generate demand elasticities for 108 AHFS classes. We can match these classes and generate our selection incentive and tiering variables for 99 of these.

[86] The specifications using the Ellis-McGuire measures do not produce significant effects under the linear specification shown. Like the main results, however, there are significant non-linear effects for the E-M measure, concentrated among the most unprofitable classes.

E Additional Figures and Tables

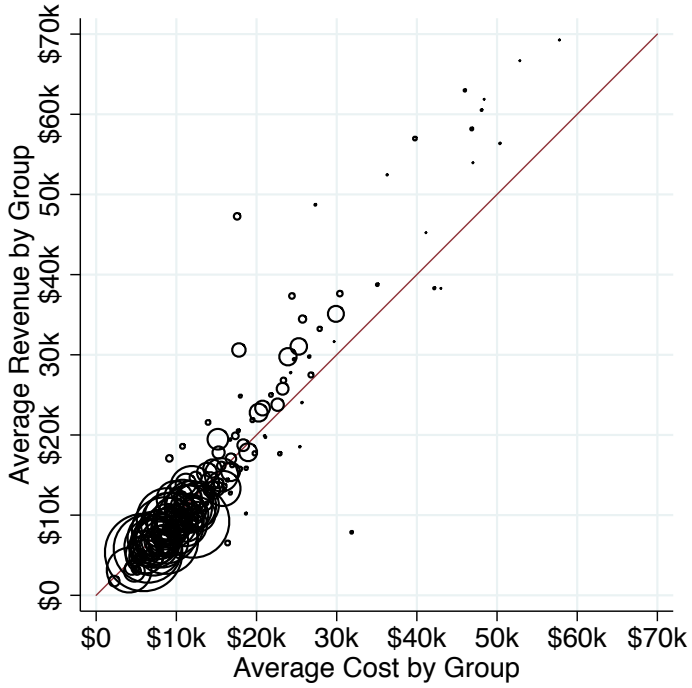
Figure A1: Selection Incentives



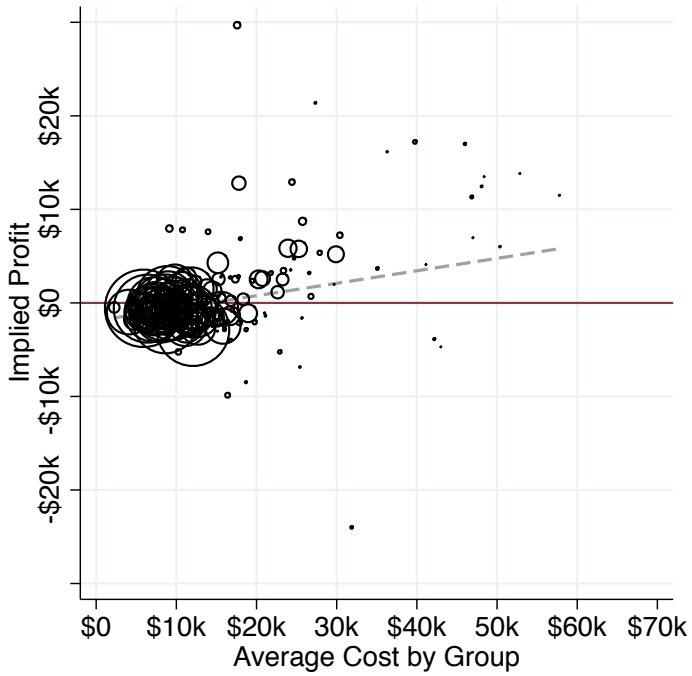
Note: Panels A and B of the Figure replicate Figure 2 without constraints on which classes are included, other than requiring 100 consumers observed in each class. Panels C and D zoom into the region of the graph with less than $35,000 in mean spending and revenue. Means are for total spending, revenue, or profit, calculated over the set of consumers who generate at least one drug claim in the class. Simulated revenue is calculated according to the HHS risk adjustment and reinsurance algorithms as described in the text. Each circle plots the spending and revenue means for a therapeutic class with marker sizes proportional to the number of consumers generating claims in the class. See Figure 2 for additional details.

Figure A2: Removing In-Class Drug Spending from Figure 2

(A) Costs vs. Revenues



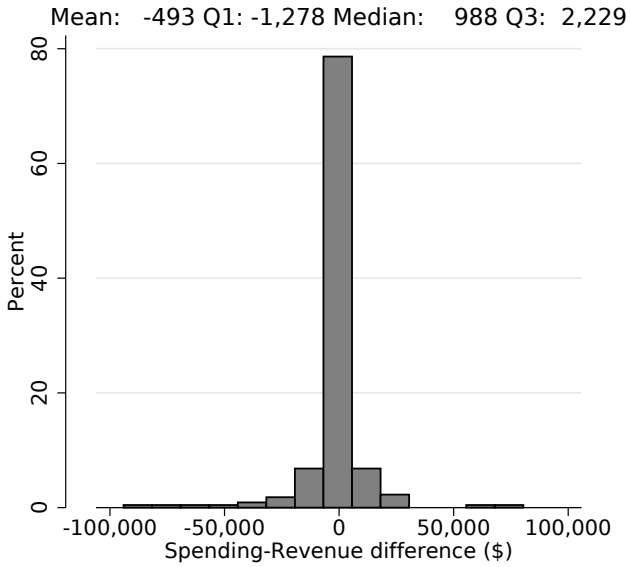
(B) Selection Incentive vs. Costs



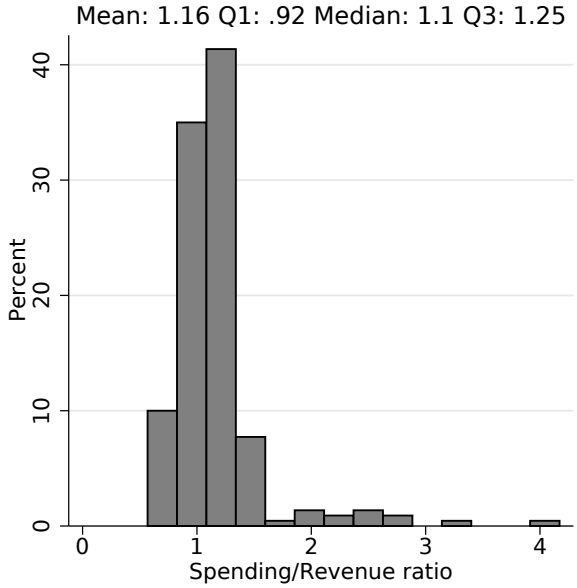
Note: Figure replicates Figure 2 but leaves out the contribution of in-class drug spending when calculating average costs and profits. See Figure 2 for additional details.

Figure A3: Distributions of Selection Incentives Across Drug Classes

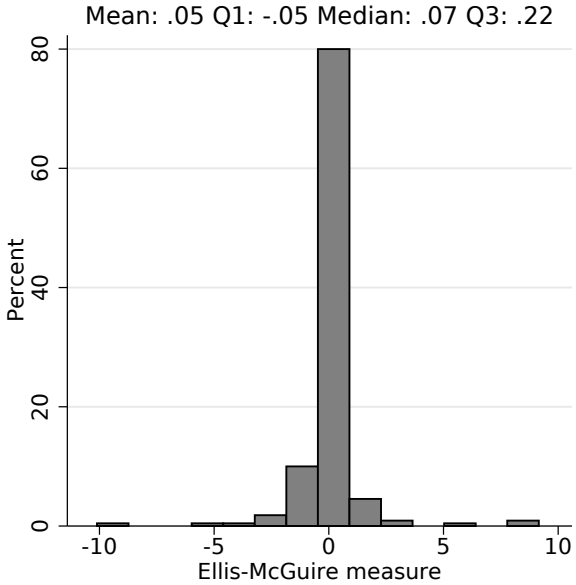
(A) Level Difference



(B) Spending/Revenue Ratio



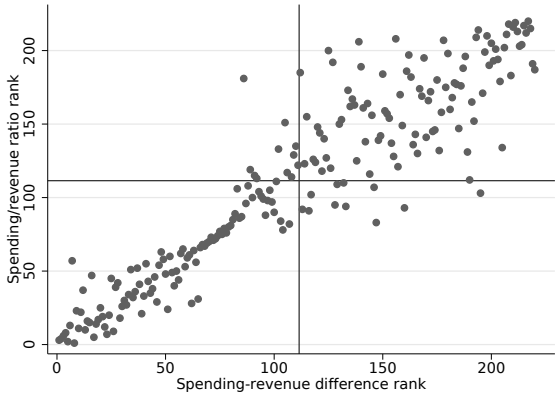
(C) Ellis-McGuire Measure



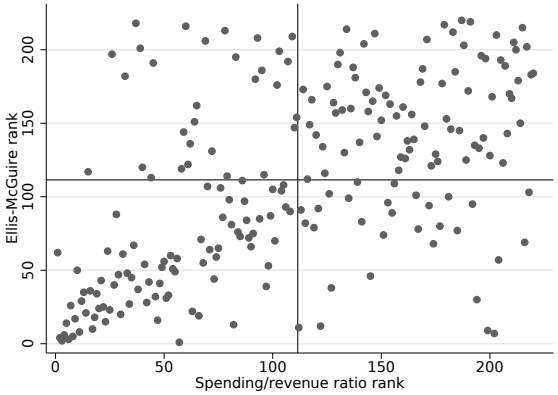
Note: Figure displays histograms of the selection incentives described by Equation (1). Panel (A) shows the distribution of the level difference measure. Panel (B) shows the distribution of the spending/revenue ratio, in which a value of 1 is neutral. Panel (C) shows the Ellis-McGuire selection incentive, in which a value of 0 is neutral. Although most classes have neutral or small associated incentives, important outliers exist.

Figure A4: Rank-Rank Correlations of the Three Selection Incentive Measures

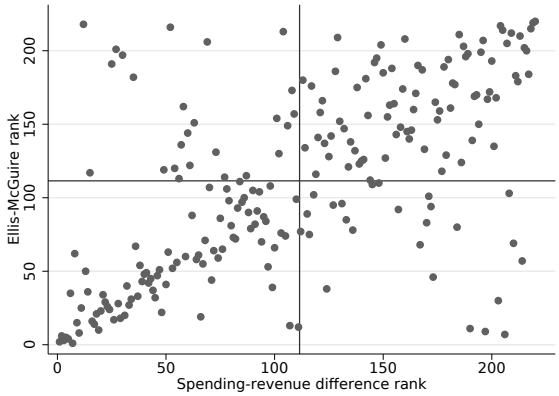
(A) Ratio and Difference



(B) Ellis-McGuire and Ratio



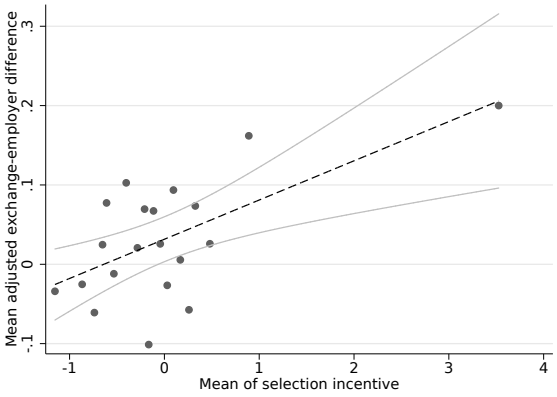
(C) Ellis-McGuire and Difference



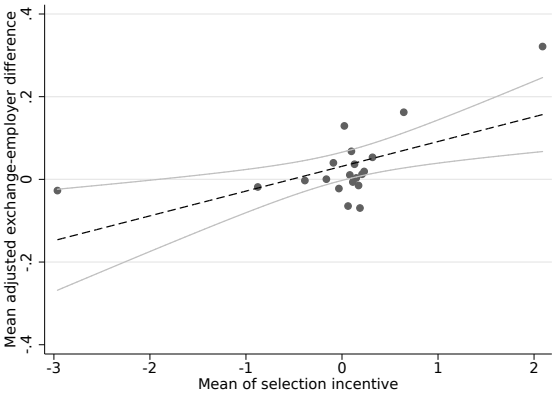
Note: Figure plots rank-rank scatters of the three selection incentive measures discussed in Section 5.1. The axes range from rank 1 to rank 220, with rank 1 implying the strongest incentive to avoid enrollees. For each of the 220 classes, the scatterplot shows how the ordering of profitable and unprofitable classes compares across the measures. Panel A shows the rank correlation between the level and ratio measures. Panel B shows the rank correlation between the Ellis-McGuire and ratio measures. Panel C shows the rank correlation between the Ellis-McGuire and level measures.

Figure A5: Screening Coefficients by Ventile

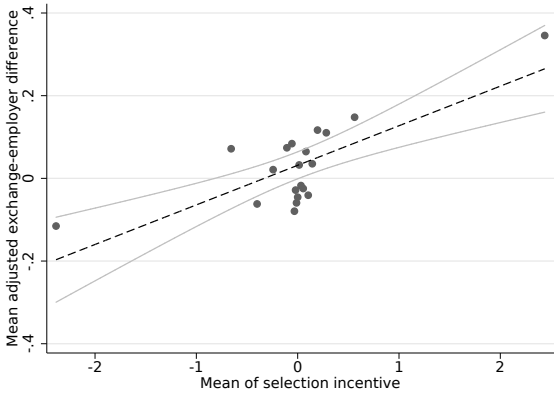
(A) Ratio



(B) Difference

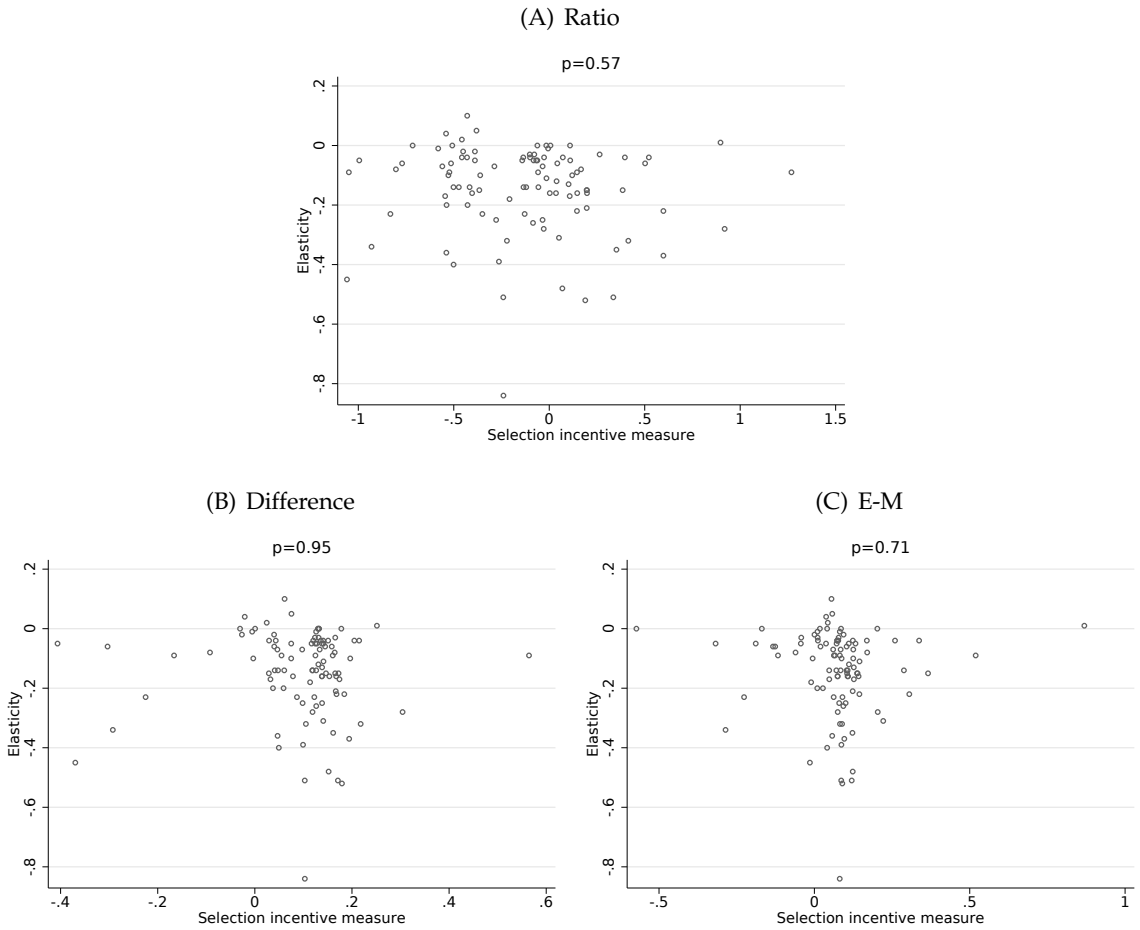


(C) Ellis-McGuire



Note: Figure plots binned means of the 220 regression coefficients β_c from the regression $Y_{mcj} = \sum_{c \in C} \beta_c \times [\text{HIX}_j \times I_c] + \gamma_c + \alpha_j + \epsilon_{mcj}$, where Y is the fraction of drugs assigned to a restrictive tier and I_c is an indicator for class c. Fixed effects for class (γ_c) and plan (α_j) are included. The F-statistic on the joint hypothesis test that the therapeutic class $\times$ HIX terms are 0 yields p<0.001. To construct the scatterplots, the classes are binned into ventiles of the strength of the selection incentive, S_c, and the means of β are plotted against the means of S_c for each ventile. A linear regression and 95% CI is also displayed. Panels A, B, and C correspond to the Ratio, Difference, and Ellis-McGuire measure of S_c. See the text for additional details.

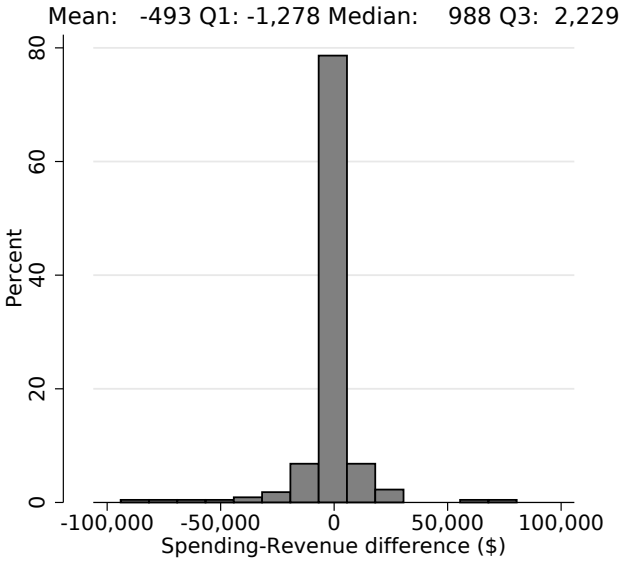
Figure A6: Class Selection Incentives Uncorrelated with Drug Class Demand Elasticities



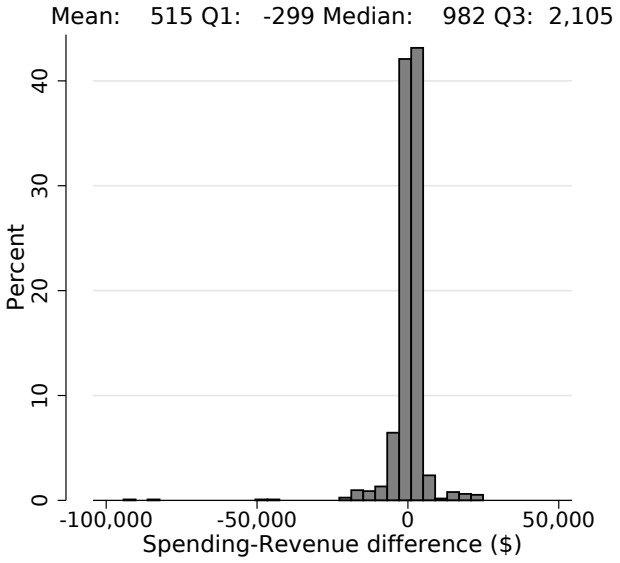
Note: Figure plots scatters of the three selection incentive measures and estimates of class-specific demand elasticities from Einav, Finkelstein and Polyakova (2016). p-values correspond to the coefficient in a linear regression of the elasticities on the selection incentive measures.

Figure A7: Distributions of Selection Incentives at the Drug Level

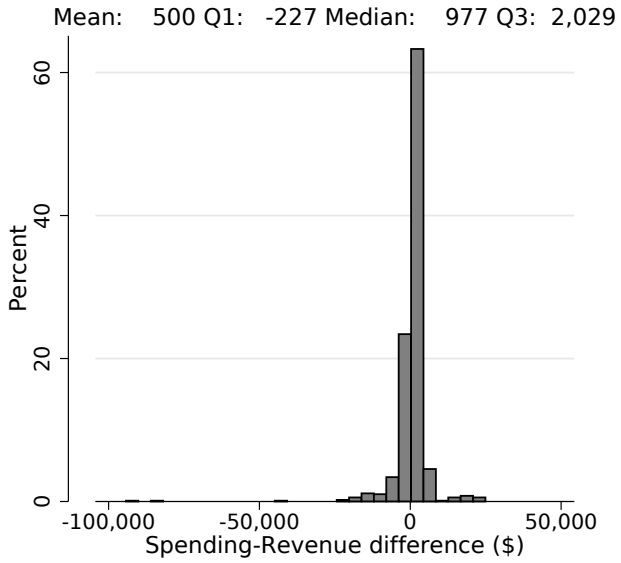
(A) Class Level (Figure A3)



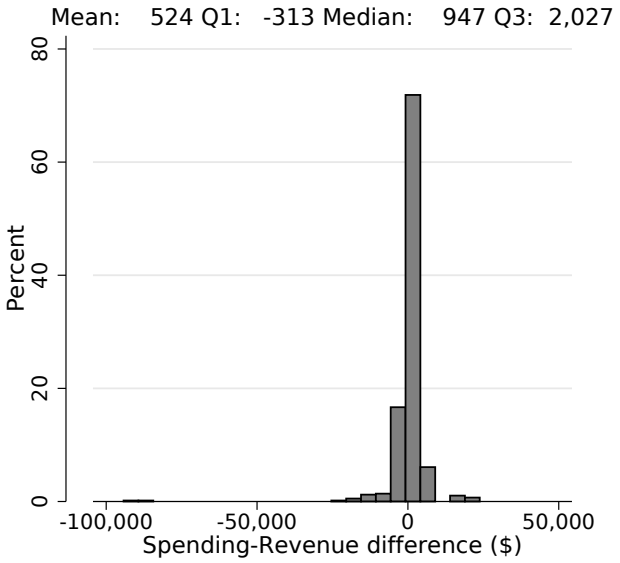
(B) Drug Level, All



(C) Drug Level, Middle 75%

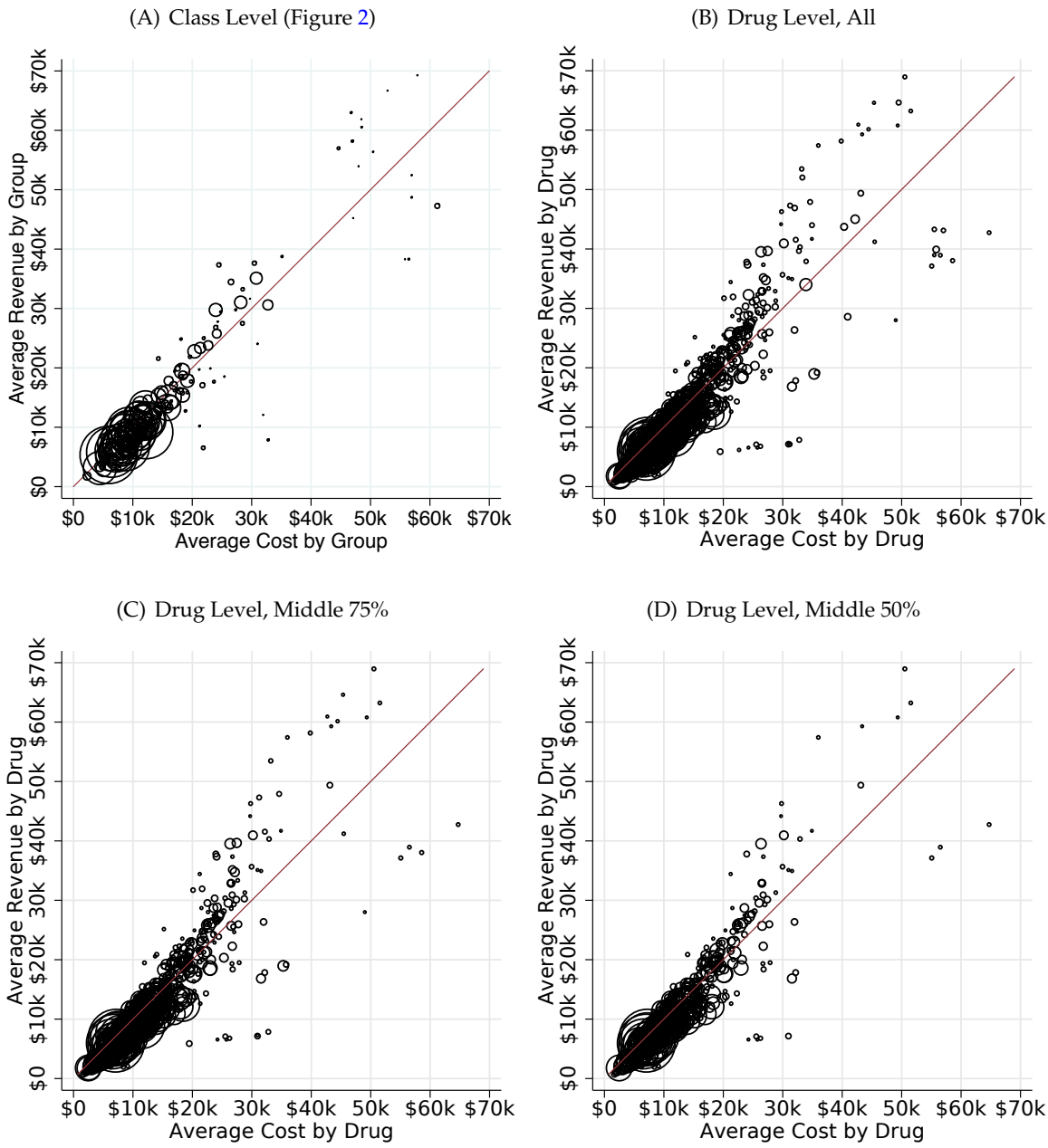


(D) Drug Level, Middle 50%



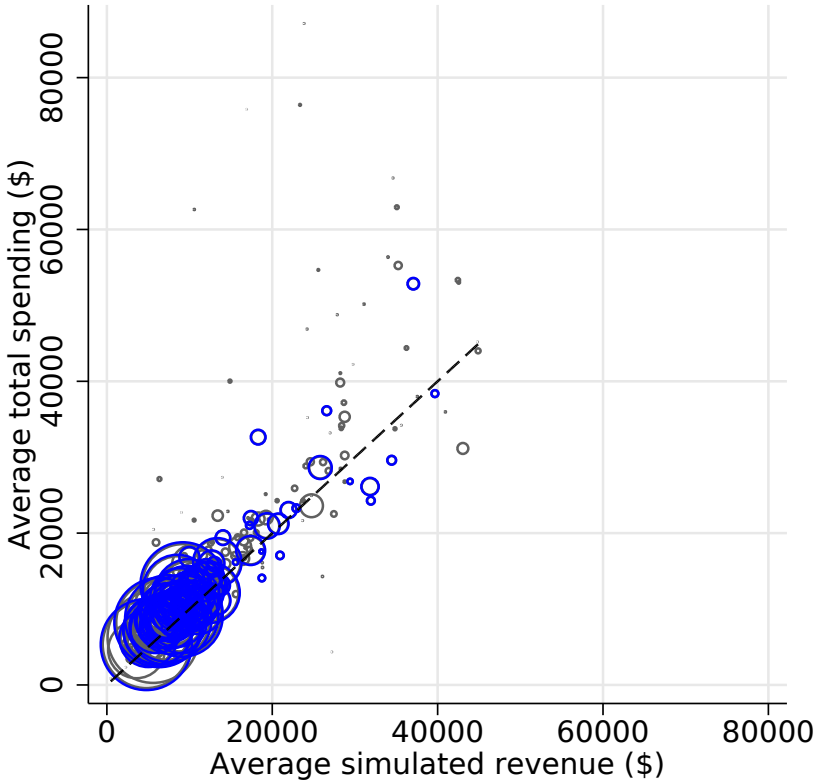
Note: Figure displays histograms of the selection incentives described by the difference measure (costs minus revenues). We restrict our analysis to the top 10 most used drugs within each class, and to drugs for which we observe at least 1,000 observations. Panel A repeats Panel A from Figure A3 (class level) for comparison. Panel B is at the drug level. Panels C and D also present results at the drug level but restrict to the middle 75% and middle 50% of *class*-level selection incentive. See Appendix Section C for additional details.

Figure A8: Selection Incentives at the Drug Level



Note: Panels replicate Figure 2 with statistics calculated at the drug, rather than class, level. Each scatterpoint corresponds to an individual drug product. We restrict our analysis to the top 10 most used drugs within each class, and to drugs for which we observe at least 1,000 observations. Panel A repeats Figure 2 (class level) for comparison. Panel B is at the drug level. Panels C and D also present results at the drug level but restrict to the middle 75% and middle 50% of *class*-level selection incentive. See Appendix Section C for additional details.

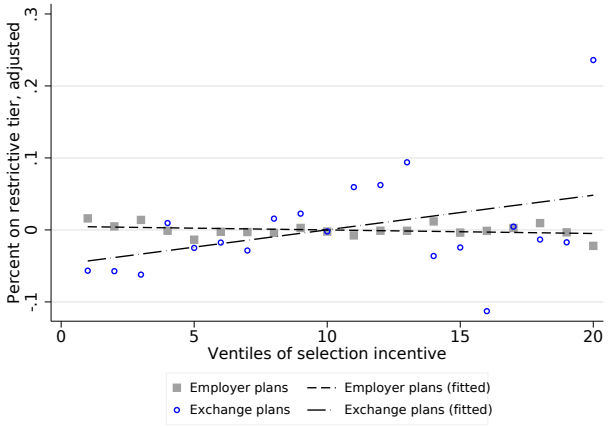
Figure A9: Selection Incentives, AHFS Classification



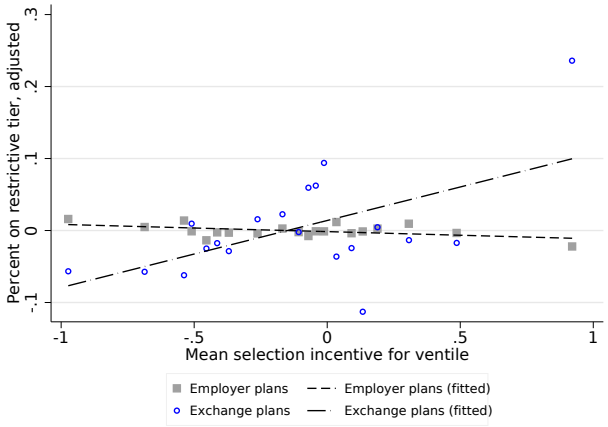
Note: Figure plots the relationship between healthcare spending and simulated revenue for each therapeutic class of drugs, as in Figure 2. Here, drugs are re-organized from REDBOOK classes into classes based on the AHFS classification. Blue circles indicate the classes for which Einav, Finkelstein and Polyakova (2016) estimate a demand elasticity that we can import to our analysis. See Figure 2 for additional notes.

Figure A10: Selection Incentive and Restrictive Tiering, AHFS Classification

(A) $S_c = \text{Ratio}_c$



(B) $S_c = \text{Ratio}_c$



Note: Figure plots semi-parametric versions of the difference-in-differences regression described in Equation (3). Figure repeats Figure 5, using the AHFS therapeutic classification of drugs in place of the RED BOOK classification. The horizontal axes in the top panels are scaled by the ventile number. The horizontal axes in the bottom panels are scaled by the mean selection incentive value within the ventile. In each panel, the OLS regression line is plotted separately for Marketplace and employer plans. See the Figure 5 notes for additional details.

Table A1: Main Results with Alternative Functional Forms

Dependent Variable:	Fraction of Class Tiered Specialty or Higher					Fraction of Class Tiered Prior Auth./Step Therapy/Not Covered				
Selection Incentive Variable:	Ratio (Cost/Revenue)					Ratio (Cost/Revenue)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Exchange X Selection incentive	0.046***	0.045**	0.025	0.025		0.018*	0.031**	0.027*	0.036**	
	(0.014)	(0.022)	(0.022)	(0.023)		(0.011)	(0.016)	(0.015)	(0.016)	
Exchange X Selection incentive ventile 20		0.006	0.087	0.088	0.180**		-0.074	-0.054	-0.092	0.042
		(0.105)	(0.107)	(0.111)	(0.070)		(0.092)	(0.092)	(0.094)	(0.062)
Exchange X Selection incentive ventile 19			0.126	0.127	0.154*			0.031	0.017	0.057
			(0.085)	(0.086)	(0.080)			(0.074)	(0.074)	(0.070)
Exchange X Selection incentive ventile 18				0.003	0.019				-0.071	-0.045
				(0.057)	(0.054)				(0.048)	(0.046)
Exchange X Selection incentive ventile 1					-0.039					-0.025
					(0.056)					(0.035)
Selection Incentive Variable:	Difference (Cost - Revenue)					Difference (Cost - Revenue)				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Exchange X Selection incentive	0.044**	0.012	0.005	0.004		0.020*	0.008	0.008	0.009	
	(0.017)	(0.014)	(0.013)	(0.013)		(0.011)	(0.011)	(0.011)	(0.011)	
Exchange X Selection incentive ventile 20		0.300***	0.325***	0.330***	0.337***		0.108	0.109	0.104	0.123
		(0.076)	(0.076)	(0.076)	(0.066)		(0.083)	(0.083)	(0.084)	(0.075)
Exchange X Selection incentive ventile 19			0.153*	0.157*	0.158**			0.006	0.003	0.009
			(0.080)	(0.080)	(0.079)			(0.062)	(0.062)	(0.061)
Exchange X Selection incentive ventile 18				0.044	0.045				-0.034	-0.031
				(0.035)	(0.035)				(0.043)	(0.043)
Exchange X Selection incentive ventile 1					-0.022					-0.030
					(0.055)					(0.041)
Selection Incentive Variable:	Ellis-McGuire Measure					Ellis-McGuire Measure				
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Exchange X Selection incentive	0.046***	0.010	0.002	-0.001		0.018*	-0.002	-0.004	-0.003	
	(0.018)	(0.015)	(0.014)	(0.013)		(0.010)	(0.014)	(0.015)	(0.015)	
Exchange X Selection incentive ventile 20		0.296***	0.324***	0.340***	0.330***		0.159**	0.166**	0.164**	0.151**
		(0.089)	(0.087)	(0.087)	(0.069)		(0.078)	(0.079)	(0.079)	(0.067)
Exchange X Selection incentive ventile 19			0.154***	0.162***	0.155***			0.041	0.040	0.033
			(0.054)	(0.054)	(0.053)			(0.050)	(0.050)	(0.048)
Exchange X Selection incentive ventile 18				0.106*	0.099*				-0.012	-0.018
				(0.056)	(0.055)				(0.052)	(0.051)
Exchange X Selection incentive ventile 1					-0.101*					-0.070*
					(0.055)					(0.036)
Therapeutic class FEs	X	X	X	X	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440	858,440	858,440	858,440	858,440

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the results in Table 3 under a variety of alternative functional forms. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Main Results with Flexible Severity Controls

Dependent Variable:	Fraction of Class Tiered Specialty or Higher				Fraction of Class Tiered Prior Auth./Step Therapy/Not Covered			
Selection Incentive Variable:	Ratio (Cost/Revenue)				Ratio (Cost/Revenue)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exchange X Selection incentive	0.048***	0.047***	0.053***	0.062***	0.019**	0.020**	0.022**	0.024*
	(0.012)	(0.011)	(0.015)	(0.017)	(0.009)	(0.009)	(0.011)	(0.012)
Exchange X [Indicators for cost bins]	Deciles of Rx costs	Ventiles of Rx costs	Deciles of total costs	Ventiles of total costs	Deciles of Rx costs	Ventiles of Rx costs	Deciles of total costs	Ventiles of total costs
Selection Incentive Variable:	Difference (Cost - Revenue)				Difference (Cost - Revenue)			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Exchange X Selection incentive	0.040**	0.036**	0.060***	0.064***	0.013	0.012	0.026*	0.025*
	(0.016)	(0.017)	(0.016)	(0.018)	(0.012)	(0.013)	(0.013)	(0.013)
Exchange X [Indicators for cost bins]	Deciles of Rx costs	Ventiles of Rx costs	Deciles of total costs	Ventiles of total costs	Deciles of Rx costs	Ventiles of Rx costs	Deciles of total costs	Ventiles of total costs
Selection Incentive Variable:	Ellis-McGuire Measure				Ellis-McGuire Measure			
	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Exchange X Selection incentive	0.033***	0.028**	0.049***	0.051***	0.006	0.005	0.019	0.019*
	(0.012)	(0.012)	(0.016)	(0.016)	(0.015)	(0.017)	(0.012)	(0.011)
Exchange X [Indicators for cost bins]	Deciles of Rx costs	Ventiles of Rx costs	Deciles of total costs	Ventiles of total costs	Deciles of Rx costs	Ventiles of Rx costs	Deciles of total costs	Ventiles of total costs
Therapeutic class FEs	X	X	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440	858,440	858,440

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the linear specifications in Table 3 but include as controls interactions between the Exchange indicator and indicators for bins of costs associated with the therapeutic classes. Specifications across columns vary according to whether deciles or ventiles are used and whether total spending or spending on drugs only (Rx) is used to define costs. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Additional Summary Statistics: Generic and Branded Tiering Separately

	Branded Drugs Only		Generic Drugs Only	
	Employer Plans	Exchange Plans	Employer Plans	Exchange Plans
	(1)	(2)	(3)	(4)
Non-Retrictive Tiers Total:	**0.56**	**0.30**	**0.60**	**0.61**
Generic preferred	0.00	0.00	0.60	0.48
Generic	0.00	0.00	0.00	0.13
Preferred brand	0.12	0.08	0.00	0.00
Covered/ Non-preferred brand	0.44	0.22	0.00	0.00
Restrictive Tiers Total:	**0.44**	**0.70**	**0.40**	**0.39**
Specialty	0.00	0.01	0.00	0.00
Not listed	0.33	0.28	0.34	0.24
Medical	0.00	0.01	0.00	0.00
Prior Authorization/Step (PA/ST)	0.01	0.15	0.00	0.03
Not covered	0.10	0.25	0.06	0.11
Therapeutic Classes	218	218	192	192

Note: Table lists formulary statistics separately for self-insured employer and Exchange plans. Tiers are listed from top to bottom in order of increasing restrictiveness, though the Prior Authorization/Step Therapy (PA/ST) tier is horizontally differentiated by imposing non-price hurdles to access. See notes to Table 1 for additional detail.

Table A4: Additional Summary Statistics: Cost Sharing and Tiering Across Metal Levels

	Bronze			Silver - No CSR		
	Mean Copay, if No Coins.	Fraction Subject to Coins.	Fraction Subject to Deductible	Mean Copay, if No Coins.	Fraction Subject to Coins.	Fraction Subject to Deductible
	(1)	(2)	(3)	(4)	(5)	(6)
Generic	$11	32%	77%	$10	11%	37%
Preferred brand	$30	39%	94%	$41	18%	50%
Covered/ Non-preferred brand	$45	45%	95%	$73	30%	59%
Specialty	$21	65%	95%	$117	66%	65%
	Silver - CSR to 87% AV			Silver - CSR to 94% AV		
	Mean Copay, if No Coins.	Fraction Subject to Coins.	Fraction Subject to Deductible	Mean Copay, if No Coins.	Fraction Subject to Coins.	Fraction Subject to Deductible
	(7)	(8)	(9)	(10)	(11)	(12)
Generic	$7	7%	37%	$5	7%	37%
Preferred brand	$29	13%	52%	$24	13%	52%
Covered/ Non-preferred brand	$54	30%	63%	$45	30%	63%
Specialty	$81	61%	70%	$61	61%	70%
	Gold			Platinum		
	Mean Copay, if No Coins.	Fraction Subject to Coins.	Fraction Subject to Deductible	Mean Copay, if No Coins.	Fraction Subject to Coins.	Fraction Subject to Deductible
	(13)	(14)	(15)	(16)	(17)	(18)
Generic	$8	5%	22%	$7	3%	11%
Preferred brand	$35	11%	37%	$29	5%	30%
Covered/ Non-preferred brand	$67	21%	41%	$56	16%	32%
Specialty	$125	65%	51%	$100	73%	50%

Note: Table lists summary statistics derived from CCIIO public use files that describe plan attributes for the universe of Exchange plans in 2015. The first column in each three-column panel lists the mean copay associated with the tier in a sample limited to plans that do not charge coinsurance at that tier. The second and third columns of each panel list the fraction of plans that subject to coinsurance and a deductible, respectively. Each three-column panel calculates statistics over plans of the metal level and CSR variant indicated at the panel header. See notes to Table 1 for additional detail.

Table A5: Main Results Restricted to Generic-Only and Branded-Only Within Class

	Panel A		
Within-Class Subsample:	Branded Drugs Only		
Selection Incentive Variable:	Ratio (Cost/ Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(1)	(2)	(3)
Exchange X Selection incentive	0.033*	0.041***	0.042***
	(0.018)	(0.013)	(0.014)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	218	218	218
Observations (plan X state X class)	850,636	850,636	850,636
	Panel B		
Within-Class Subsample:	Generic Drugs Only		
Selection Incentive Variable:	Ratio (Cost /Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(4)	(5)	(6)
Exchange X Selection incentive	0.040***	0.029*	0.024
	(0.013)	(0.015)	(0.019)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	192	192	192
Observations (plan X state X class)	749,184	749,184	749,184

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the results in Table 3, but alter the dependent variable. In Panel A, the dependent variable (fraction of drugs in class tiered specialty or higher) is calculated over branded products only. In Panel B, the dependent variable (fraction of drugs in class tiered specialty or higher) is calculated over generic products only. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Robustness: Stratifying by Fraction Generic in Class

	Panel A		
Subsample:	Classes with No Generics		
Selection Incentive Variable:	Ratio (Cost/ Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(1)	(2)	(3)
Exchange X Selection incentive	.087**	.045*	.037**
	(.036)	(.024)	(.016)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	28	28	28
Observations (plan X state X class)	109,256	109,256	109,256
	Panel B		
Subsample:	Classes with less than 10% Generics		
Selection Incentive Variable:	Ratio (Cost /Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(4)	(5)	(6)
Exchange X Selection incentive	.083***	.046*	.037**
	(.022)	(.024)	(.014)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	49	49	49
Observations (plan X state X class)	191,198	191,198	191,198
	Panel C		
Subsample:	Classes with less than 25% Generics		
Selection Incentive Variable:	Ratio (Cost /Revenue)	Difference (Cost - Revenue)	Ellis-McGuire Measure
	(4)	(5)	(6)
Exchange X Selection incentive	.065**	.047*	.048***
	(.026)	(.027)	(.016)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	84	84	84
Observations (plan X state X class)	327,768	327,768	327,768

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the results in Table 3, but alter the sample of drug classes included in the regression. Panel A is restricted to classes containing no generics. Panel B is restricted to classes containing less than 10% generics. Panel C is restricted to classes containing less than 25% generics. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Robustness: Controlling for Exchange × Fraction Generic in Class

Restrictive Tier Definition:	Specialty or Higher		
Selection Incentive Variable:	Ratio	Diff.	E-M
	(1)	(2)	(3)
Exchange X selection incentive	.041***	.035***	.034**
	(.012)	(.014)	(.016)
Exchange X class fraction generic	-.26***	-.25***	-.24***
	(.060)	(.064)	(.065)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the results in Table 3, controlling for the interaction of the Exchange indicator and the fraction of drugs in the class that are generic. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan × state × class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Robustness: Removing Fertility Treatment Classes from Analysis

Restrictive Tier Definition:	Specialty or Higher		
Selection Incentive Variable:	Ratio	Diff.	E-M
	(1)	(2)	(3)
Exchange X selection incentive	.046**	.041**	.046**
	(.020)	(.017)	(.018)
Therapeutic class FEs	X	X	X
Plan FEs	X	X	X
Therapeutic classes	217	217	217
Observations (plan X state X class)	846,734	846,734	846,734

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the results in Table 3, but remove the three therapeutic classes associated with fertility treatments. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Robustness: Patterns Persist within Pharmacy Benefit Managers

Dependent Variable:	Fraction of Class Tiered Specialty or Higher							
Selection Incentive Variable:	Ratio (Cost/Revenue)		Ellis-McGuire Measure		Ratio (Cost/Revenue)		Ellis-McGuire Measure	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exchange X Selection incentive	0.041***	0.041*	0.039**	0.001	0.046***	0.047**	0.042**	0.003
	(0.013)	(0.022)	(0.015)	(0.014)	(0.014)	(0.022)	(0.017)	(0.015)
Exchange X Selection incentive ventile 20		0.003		0.307***		-0.005		0.316***
		(0.106)		(0.091)		(0.110)		(0.093)
Therapeutic class FEs	X	X	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X	X	X
PBM FE X selection incentive	X	X	X	X				
PBM FE X state X selection incentive					X	X	X	X
Therapeutic classes	220	220	220	220	220	220	220	220
Observations (plan X state X class)	838,034	838,034	838,034	838,034	749,280	749,280	749,280	749,280

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. We repeat the results in Table 3, but add fixed effects for Pharmacy Benefit Managers (PBMs). All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Robustness: ESI-Exchange Differences Do Not Track Consumer Demand Elasticities

	Panel A								
Dependent Variable:	Fraction of Class Tiered Specialty or Higher								
Selection Incentive Variable:	Ratio (Cost/Revenue)			Difference Measure			E-M Measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Exchange X Selection incentive	0.037**	0.098**	0.097**	-0.004	0.349**	0.348**	-0.006	0.228	0.226
	(0.016)	(0.045)	(0.045)	(0.023)	(0.168)	(0.165)	(0.021)	(0.140)	(0.139)
Exchange X Elasticity			-0.053			-0.066			-0.059
			(0.089)			(0.095)			(0.090)
Therapeutic class FEs	X	X	X	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X	X	X	X
Therapeutic classes	294	99	99	294	99	99	294	99	99
Observations (plan X state X class)	1,147,188	386,298	386,298	1,147,188	386,298	386,298	1,147,188	386,298	386,298
	Panel B								
Dependent Variable:	Fraction of Class Tiered Prior Auth./Step Therapy/Not Covered								
Selection Incentive Variable:	Ratio (Cost/Revenue)			Difference Measure			E-M Measure		
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Exchange X Selection incentive	0.006	0.065**	0.065**	0.006	0.248***	0.248***	0.006	0.105	0.105
	(0.012)	(0.029)	(0.029)	(0.013)	(0.094)	(0.093)	(0.013)	(0.087)	(0.087)
Exchange X Elasticity			0.001			-0.008			-0.005
			(0.043)			(0.045)			(0.042)
Therapeutic class FEs	X	X	X	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X	X	X	X
Therapeutic classes	294	99	99	294	99	99	294	99	99
Observations (plan X state X class)	1,147,188	386,298	386,298	1,147,188	386,298	386,298	1,147,188	386,298	386,298

Note: Table reports results from a series of regressions of formulary restrictiveness on an interaction between an indicator for Exchange plans and the selection incentive. To create this table, we use an alternative mapping of drugs to therapeutic classes generated by the American Hospital Formulary Service. This allows us to match classes to those for which Einav, Finkelstein and Polyakova (2016) estimate demand elasticities. In the third column of each set of three specifications, we additionally control for an interaction between these imported demand elasticities and the Exchange plan indicator. See text for full detail. All regressions include fixed effects for each of the therapeutic classes of drugs and fixed effects for each plan in the data. Observations are at the plan $\times$ state $\times$ class level. Standard errors are clustered at the the level of the therapeutic class (220 clusters). See Table 3 for additional details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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