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Screening in Contract Design: Evidence from the ACA Health Insurance Exchanges
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ABSTRACT

By steering patients to cost-effective substitutes, the tiered design of prescription drug formularies can improve the efficiency of healthcare consumption in the presence of moral hazard. However, a long theoretical literature describes how contract design can also be used to screen consumers by profitability. In this paper, we study this type of screening in the ACA Health Insurance Exchanges. We first show that despite large regulatory transfers that neutralize selection incentives for most consumer types, some consumers are unprofitable in a way that is predictable by their prescription drug demand. Then, using a difference-in-differences strategy that compares Exchange formularies where these selection incentives exist to employer plan formularies where they do not, we show that Exchange insurers design formularies as screening devices that are differentially unattractive to unprofitable consumer types. This results in inefficiently low levels of coverage for the corresponding drugs in equilibrium. Although this type of contract distortion has been highlighted in the prior theoretical literature, until now empirical evidence has been rare. The impact on out-of-pocket costs for consumers affected by the distortion is substantial—potentially thousands of dollars per year—and the distortion creates an equilibrium in which contracts that efficiently trade off moral hazard and risk protection cannot exist.

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1 Introduction

The Patient Protection and Affordable Care Act (ACA) of 2010 significantly altered the structure of the individual and small group health insurance markets in the US. In establishing the new health insurance "Exchanges," the ACA created a system that largely resembles managed competition in US Medicare Parts C and D and in health insurance markets throughout the OECD. Two hallmark features of these markets are (1) no consumer can be denied coverage and (2) plans cannot price discriminate based on an individual's health status. This ban against discrimination on pre-existing conditions continues to garner wide bipartisan public support, reflected in consumer polling in the years since the ACA's passage.[1] Indeed, the non-discrimination provisions are so overwhelmingly popular that proponents of repealing the ACA often explicitly note an intention to keep in place protections for consumers with pre-existing conditions.[2]

Enforcing a policy of non-discrimination against the chronically ill can generate improvements in both equity and efficiency (Handel, Hendel and Whinston, 2015). But such reforms may also generate a relationship between non-contractible consumer characteristics and the underlying cost to the insurer of providing coverage. In such settings, two classes of distortions may arise. The first is a price distortion caused by adverse selection of consumers on price, as originally studied by Akerlof (1970) and more recently applied to the context of health insurance by Einav, Finkelstein and Cullen (2010), Handel, Hendel and Whinston (2015), and Hackmann, Kolstad and Kowalski (2015). In this case, welfare losses occur because feedback from costs into prices result in inefficiently low takeup of insurance. The second—the focus of this paper—is a distortion of insurance contract features like risk protection and multidimensional quality. This type of distortion was first studied by Rothschild and Stiglitz (1976) and more recently applied to the context of modern health insurance by Glazer and McGuire (2000), Frank, Glazer and McGuire (2000), Azevedo and Gottlieb (2016), and Veiga and Weyl (2016). Under this type of distortion, insurers recognize that non-price features of the contract can act as screening mechanisms, allowing them to design contracts that cause consumers to self-sort

[1] For example, a 2012 Reuters poll indicated that 82 percent of Americans favored banning insurance companies from denying coverage to people with pre-existing conditions. A 2014 Kaiser Family Foundation poll indicated that 70 percent of all respondents and 69 percent of Republicans favored the guaranteed issue provision for consumers with pre-existing conditions.

[2] For example the Patient CARE Act proposed by Republican Senators Burr and Hatch, and Republican Representative Upton in February 2015 would repeal the ACA's individual mandate but prohibit insurance companies from denying coverage or charging higher premiums to people with pre-existing conditions. Similarly, Republican Representatives Ryan, Kline, and Upton also put forth a proposal in March 2015 that would replace the ACA but prohibit insurance companies from unfairly canceling coverage or discriminating against individuals with pre-existing conditions.

by profitability. This screening behavior drives a wedge between the socially-optimal contract that efficiently trades off risk protection and moral hazard and the contract insurers offer in equilibrium.

Although the theoretical importance of both types distortions is well-established, empirical evidence has largely focused on price distortions.[3] Distortions in the multidimensional space of contract design are more difficult to identify for a number of reasons, including that many dimensions of an insurance contract are not practically observable and that in equilibrium certain relevant contracts may not exist. Even when the contract distortion can be cast in terms of observables, such as a coinsurance rate that is "too high," the dimensionality of the problem can be intractably large. A modern health insurance contract typically consists of many thousands of parameters, such as the copay for an in-network specialist visit or the formulary tier and corresponding coinsurance rate for a particular immunosuppressant drug. This complexity makes it difficult to identify whether any individual product characteristic that comprises an observed contract is consistent with the kind of socially efficient design that would result from a well-functioning market. For these reasons, the empirical study of contract distortions has been limited, and this limitation that has been widely noted in the literature—for example, by Einav, Finkelstein and Levin (2010), Einav and Finkelstein (2011), and Azevedo and Gottlieb (2016). Only a handful of empirical studies have provided econometric evidence that (non-price) contract features respond to selection incentives. This prior empirical work has focused on the Medicare Part D prescription drug insurance market (Carey, 2016; Lavetti and Simon, 2016) and on distortions of hospital networks in the pre-ACA Massachusetts Exchange (Shepard, 2016).[4]

In this paper, we add to the small body of empirical evidence on non-price contract distortions. We examine the design of prescription drug formularies in the context of the ACA Exchanges. Even setting aside the popular and policy interest in the functioning of these markets, the setting is ideal for investigating the general phenomenon of contract distortions. Pharmaceuticals for managing chronic illness are likely to be among the most price-transparent and predictable medical goods that healthcare consumers encounter. This implies that formulary benefit design—i.e., how plans arrange

[3] Einav, Finkelstein and Cullen (2010) provide a framework in which the welfare loss from price distortions can be quantified and show how variation in prices can be used to estimate the welfare loss empirically.

[4] A separate but related literature considers insurance coverage distortions due not to selection, but due to the potential for drug and medical spending to offset each other and the feature that some markets separate these kinds of coverage. In integrated medical-drug plans, like those offered in the ACA Exchanges, Chandra, Gruber and McKnight (2010), Lavetti and Simon (2016), and Starc and Town (2015) discuss how formulary design can also be used to efficiently promote drug consumption that lowers overall healthcare costs by offsetting substitutable medical spending.

prescription medication coverage into various cost-sharing tiers—may be particularly salient to consumers, and therefore particularly effective as a screening mechanism. Indeed, the idea that these benefits may be used as screening devices is implicit in a growing body of news reports and open letters from patient advocacy groups to state and federal regulators. These have noted that consumers with certain high-cost chronic conditions, such as multiple sclerosis, rheumatoid arthritis, and certain cancers, face difficulty finding Exchange plans that affordably cover their drugs. In addition, a recent case study of HIV drug coverage by Jacobs and Sommers (2015) shows that Exchange plans in several states appear to place an entire class of a commonly-prescribed HIV medication on a high-cost sharing tier, possibly in an attempt to avoid attracting such patients. Such phenomena could be rationalized as a profit-maximizing strategy by firms only if these patients were predictably unprofitable in spite of the risk adjustment system intended to neutralize such incentives.

To investigate, we begin by systematically examining whether prescription drug use constitutes a plausible screening mechanism for patient profitability. Using a large sample of employer health claims, we combine the HHS risk adjustment and reinsurance algorithms with Exchange premium policies (such as 3:1 age banding) to simulate enrollee-specific net revenue. As a first result, we show simple scatterplots of actual costs versus simulated Exchange revenues across 220 therapeutic classes of drugs that correspond to our consumer types. Although risk adjustment and reinsurance neutralize selection incentives for the majority of drug classes, some classes are associated with consumer types that exhibit significant unprofitability. For example, a consumer taking a drug in the Biological Response Modifiers class is among the most unprofitable in our data. Such a consumer on average will generate $61,000 in claims costs but only $47,000 in net revenue after accounting for the (large) risk adjustment and reinsurance transfer payments to the plan enrolling her. This suggests insurers could potentially screen out these unprofitable types from their plans by placing these drugs on a high cost-sharing specialty tier and by raising the shadow price of drug access in other ways, such as requiring prior authorization from the insurer.[5]

After generating measures of consumer profitability at the drug class level, we ask whether insurers' actual equilibrium contracts appear to reflect the incentives implied by these class-specific selection incentives. To do so, we turn to a unique dataset containing the universe of Exchange plan

[5]The most commonly filled prescription in this class in our claims data is Copaxone, which is used to treat and to prevent relapse of MS. Press reports and consumer group complaints about Exchange drug coverage have often specifically noted the case of MS patients.

formularies, covering every plan offered in the state and federal Exchanges in 2015, as well as a large sample of employer plans. For both, we observe how drugs are arranged across the formulary tiers. The unique, disjointed structure of US healthcare allows us to compare equilibrium Exchange plan formularies (in which incentives for coverage distortions exist) to equilibrium employer plan formularies (in which these incentives do not exist) operating side-by-side in the same geographic markets. The comparison allows us to difference-out other welfare-relevant considerations important in contract design—for example, variation in consumer demand elasticities across drug classes (Einav, Finkelstein and Polyakova, 2016)—and to isolate the distortionary screening behaviors that are the focus of our study. Many of the employer and Exchange plans even utilize the same pharmacy benefits managers (who design the formularies, contract with pharmacies, and negotiate prices), allowing us in some specifications to hold constant unobservable features like the contract designer's institutional knowledge.

Using this difference-in-differences strategy, we show that Exchange insurers design formularies to be differentially unattractive to unprofitable individuals. These results are not driven by the overall lower coverage generosity of Exchange plans. Instead, the pattern is that within a plan, drug classes used by less profitable consumers appear higher on the formulary tier structure (implying higher out-of-pocket costs) in Exchange plans only. The pattern is particularly stark for the tails of the distribution of selection incentives. We find that drug classes in the upper 5% of the selection incentive distribution are 30 percentage points (50 percent) more likely to be placed on a specialty tier, to face utilization management, or simply to not be covered—relative to the same drugs in employer plans. The associated out-of-pocket financial exposure can be significant. As we show, specialty tier coverage is likely to be governed by coinsurance rates rather than copays. This implies that for a prescription from a class like Biological Response Modifiers (which we find to be particularly unprofitable) out-of-pocket consumer costs can exceed $1,000 per month in a typical Exchange Silver plan.[6] On the other hand, we show that drug classes that are used by consumers who are *over*-compensated by the payment system, placing them in the bottom 5% of the selection incentive distribution, are actually covered relatively *generously* by Exchange plans.

After presenting our main results, we perform several extensions of our analysis to show that the contract design pattern we document among Exchange plans is not simply a phenomenon of passing

[6]Such costs could push consumers up to the out-of-pocket annual maximum, which in 2016 was $6,850 for an individual plan and $13,700 for a family plan.

on underlying drug costs to the consumer, or of nudging consumers toward lower-cost substitutes within a therapeutic class of alternatives. We show that while insurers do appear to place higher cost drugs on more restrictive tiers, they are sophisticated enough to react not only to overall cost heterogeneity across consumers but also to the *net* incentive generated by revenue heterogeneity embedded in the Exchange payment system. Even *cheap drugs* that are associated with *expensive patients* are placed on high cost sharing tiers. To our knowledge, ours is the first empirical investigation of insurer's sophistication in responding to selection incentives via contract design. We also present a variety of evidence showing that our results are not consistent with an alternative explanation that Exchange plans are merely better (or more motivated) than employers in responding to moral hazard. The tradeoff between moral hazard and risk protection is a fundamental tension in both optimal (Pauly, 1968, 1974; Zeckhauser, 1970) and profit-maximizing formulary design (Einav, Finkelstein and Polyakova, 2016). We import class-specific demand elasticities estimated by Einav, Finkelstein and Polyakova (2016) and show that these elasticities, which vary significantly, do not covary with the measures of the distortionary selection incentive we estimate and do not explain the difference in the designs of employer and Exchange plans we document.

We view our paper as filling an important gap in the literature on adverse selection in insurance markets. While several papers, including Frank, Glazer and McGuire (2000), Ellis and McGuire (2007), and Geruso and McGuire (2016), construct measures characterizing selection incentives that vary by service type or setting, only a small recent literature has been able to empirically document insurer *responses* to such incentives. Shepard (2016) investigates network benefit design in response to selection incentives. Carey (2016) and Lavetti and Simon (2016) examine the use of formulary design to induce favorable selection in the context of Medicare Part D. Our paper connects most closely to these. Our study is unique in providing evidence on the ACA Exchanges.

Our findings are also immediately relevant for the continued evolution of the ACA Marketplaces. The functioning of these markets has attracted significant policy and popular interest, though the debate has for the most part outpaced research progress. The novel results here indicate that while the current regulatory framework goes a long way toward weakening insurer incentives to avoid unhealthy enrollees, some selection incentives remain and lead to an equilibrium in which the offered contracts expose consumers to significant drug cost-sharing risk. This issue is important to American consumers: An October 2016 Kaiser Family Foundation poll asked consumers about the top health-

care priorities for the next President and Congress. 74% of respondents agreed that "making sure that high-cost drugs for chronic conditions, such as HIV, hepatitis, mental illness and cancer, are affordable to those who need them" was a top priority. It was the most agreed-to statement in a list that included items like network adequacy, price transparency, cost-sharing subsidies for people with moderate incomes, and repealing the tax penalty for remaining uninsured. Underlining the concern about drug costs and access, the second most agreed-to priority was "government action to lower prescription drug prices."

More generally, our findings connect to a broader literature investigating the role of private firms in delivering publicly funded or subsidized health benefits (e.g., Curto et al., 2014; Cabral, Geruso and Mahoney, 2014; Duggan, Gruber and Vabson, 2015; Einav, Finkelstein and Polyakova, 2016). The US Medicare and Medicaid programs, the US individual and small group markets, and the national health insurance programs of much of the OECD have all come to increasingly rely on private insurance carriers to design and manage publicly funded or subsidized health benefits. Private carriers in these settings are typically heavily regulated against discrimination in the form of differential price-setting or coverage denial. The findings here indicate that insurers may nonetheless be able to effectively discriminate and induce selection via benefit design, even in the presence of a generally well-functioning risk adjustment system, and mandated coverage rules such as the ACA's Essential Health Benefits. This carries both a distributional implication (the payment system error determines which patients face high cost sharing) and an overall efficiency cost (contracts that optimally balance moral hazard and financial risk protection across categories of services cannot exist in equilibrium). Understanding how this type of backdoor—which has featured prominently in the theory of adverse selection—functions in practice is critical to the continued reform of the managed competition health insurance markets.

2 Background

2.1 Conceptual Framework

The theory behind service-level selection in insurance contracts has been carefully developed elsewhere, including in Rothschild and Stiglitz (1976), Frank, Glazer and McGuire (2000), Glazer and McGuire (2000), Ellis and McGuire (2007), Veiga and Weyl (2016), and Azevedo and Gottlieb (2016).

Our goal in this section is not to generate new theoretical insights, but merely to adapt some results from the prior literature to guide our empirical analysis. This section provides intuition for how the socially efficient contract, which trades-off the benefits of risk protection against the costs of moral hazard, compares to equilibrium contracts that are likely to arise given the type of selection incentives we document as empirically relevant in the ACA Exchange setting.

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 $x \in [0, 1]$. In our context, this can be thought of as an insurance contract providing partial coverage for spending on one drug. 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. 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 medical spending as the product of two components, a fixed component μ and a moral hazard component $k(x)$ that incorporates additional spending due to the individual's demand response to a lower out-of-pocket price for the drug. 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 reflects 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

$$u = \mu h(x) + v\psi(x), \tag{1}$$

where $\mu h(x)$ is the benefit the individual gets from 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:

$$W = \int_{\mu} \int_{v} f(\mu, v)[\mu h(x) + v\psi(x) - \mu k(x)]dv\, d\mu. \tag{2}$$

The additional term between Equations (1) and (2) 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 x^* to solve the following equality:

$$\psi'(x^*) = \phi(k'(x^*) - h'(x^*)), \tag{3}$$

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 environment. We specify insurer j's profit function as

$$\pi^j = \int_\mu \int_v f(\mu, v) D(x^j; \mu, v)[r(\mu, v) - \mu k(x^j)] dv \, d\mu, \tag{4}$$

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

The insurer sets the coinsurance rate x^j to maximize profits. To understand the insurer's problem, we differentiate π^j with respect to x^j:

$$\frac{\partial \pi^j}{\partial x^j} = \int_\mu \int_v f(\mu, v) \left[\frac{\partial D(x^j; \mu, v)}{\partial x^j} (r(\mu, v) - \mu k(x^j)) \; - \; \mu k'(x^j) D(x^j; \mu, v) \right] dv \, d\mu. \tag{5}$$

The derivative consists of two components inside the brackets.The first component captures changes to demand due to a change in the coinsurance rate: If the coinsurance rate is increased, the plan will get fewer enrollees. The second component captures the change in plan spending due to moral hazard: An increase in the coinsurance rate decreases plan spending. If we define $\bar{r} = E[r(\mu, v)]$ and $\bar{c} = E[\mu k(x^j)]$ as the average net revenue and the average cost (given x^j) across the entire population, then the first component can be decomposed to reveal two distinct demand-related consequences of a change in x^j:

$$\frac{\partial D(x^j; \mu, v)}{\partial x^j} (r(\mu, v) - \mu k(x^j)) = \underbrace{\frac{\partial D(x^j; \mu, v)}{\partial x^j} [\bar{r} - \bar{c}]}_{\text{Fewer enrollees}} + \underbrace{\frac{\partial D(x^j; \mu, v)}{\partial x^j} [(r(\mu, v) - \mu k(x^j)) - (\bar{r} - \bar{c})]}_{\text{Different enrollees}} \tag{6}$$

The first term above represents the change in insurer profits due to a change in the number of individuals enrolled in the insurer's plan. This component is explicitly connected to the change in

a consumer's willingness-to-pay for the plan, as described by Equation (1), due to the change in the coinsurance rate. Importantly, this component is clearly related to the social planner's problem. If the other term ("different enrollees") is zero, then the insurer solving the first order condition in (6) will decrease the coinsurance rate until the additional profits from enrolling more individuals (due to increased risk protection) equals the additional cost caused by providing better coverage (due to moral hazard). This is analogous to the social planner's problem of trading off the benefits of risk protection with the cost of moral hazard. Einav, Finkelstein and Polyakova (2016) show that these two problems, that of the social planner and that of the profit-maximizing firm, in fact coincide, with both trading off the social costs and benefits of better insurances.

Now, return to the second term in Equation (6). This component reveals that the insurer has an additional motivation for setting the coinsurance rate, beyond trading off risk protection and moral hazard: Not only does the insurer attract *fewer* enrollees when it raises the coinsurance rate, but it also attracts *different* enrollees who may be differentially profitable to the insurer depending on their specific payments and costs. This represents an additional margin by which the insurer's decision about x^j affects profits, and this margin drives a wedge between the level at which a profit-maximizing insurer sets the coinsurance rate and the socially efficient level. While we merely sketch the intuition, 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, as suggested by the "different enrollees" component of the derivative above. This motivates our use of the Ellis and McGuire (2007) index below where we empirically operationalize the insurer's selection incentive.

Several takeaways here are important for our analysis below: First, the model indicates that insurers should respond to the residual incentive net of the payment system (including risk adjustment and reinsurance), not the gross cost of an individual.[7] Second, the overall profitability of an individual to the insurer matters for the distortionary incentive, not just the individual's spending on the particular service (in our case, drug) in a multi-service contract. This means that if an expensive group of consumers uses a cheap drug, an insurer will want to inefficiently distort coverage to be

[7]This is true in the setting where all individuals choose a plan and no individual chooses uninsurance, because in that setting all new enrollees a plan acquires when lowering its coinsurance rate come from other plans. If these enrollees come from the uninsurance pool, then it is in fact the gross cost rather than the net cost that matters, as risk adjustment transfers occur only across insurers not across the insurance/uninsurance state.

poor for that cheap drug. Third, the extent of the contract distortion should scale with the size of the selection incentive. Fourth, moral hazard, if correlated with the selection incentive, would confound reduced form estimates, because as revealed by Equation (6) and as shown by Einav, Finkelstein and Polyakova (2016) it plays a role in the insurer's decision over where to set x^j independent of the selection motive. These items motivate the details of how we implement an empirical test below. The moral hazard insight, in particular, motivates an in-depth examination below of whether our measures of the selection incentive correlate with class-specific price elasticities of demand.

Finally, the model makes clear that welfare loss here does not arise specifically because consumers with chronic diseases have to pay "too much" for their drugs. While that is an important (and as we show, potentially sizable) distributional consequence of poor coverage for certain service types, the welfare loss arises because in equilibrium consumers cannot be adequately insured against the negative shock of transitioning to the poorly-covered chronic disease state. This lack of risk protection affects the utility of *all* consumers with a non-zero probability of acquiring a disease requiring drug treatment, not just consumers who already have such a disease.

2.2 Regulatory Framework

The ACA contains several provisions aimed at curbing the use of benefit design as a means of selecting enrollees in the Exchanges. These fall into two broad categories. The first includes coverage mandates that directly constrain insurer benefit design.[8] Under the authority of the ACA, the Department of Health and Human Services (HHS) mandates a variety of essential health benefits (EHB). With respect to formularies, EHB regulations require that Exchange plans cover at least one drug in each therapeutic category and class of the United States Pharmacopeia (USP).[9] However, there is no requirement on how such drugs must be tiered within a formulary, which is the margin of benefit design we examine in this paper.[10]

The second category of adverse selection-related provisions includes payment adjustments that change the insurer's financial incentives with respect to selection. Whereas coverage mandates may compel insurers to act against their financial interests (e.g., benefit x must be covered, regardless

[8] These are in addition to the blanket prohibitions against coverage denial or the use of medical history in setting plan premiums.

[9] See 45 CFR 156.122.

[10] These minimum coverage rules are similar to those that govern the provision of Medicare Part D drug benefits by private insurers, and have been shown by Andersen (2016) to be binding in the Exchange setting.

of its effects on profits), the payment adjustments change the insurers' underlying profit function (e.g., covering x is no longer unprofitable). The two important payment adjustments in the ACA Exchanges are risk adjustment and reinsurance.[11]

Risk adjustment, which has become a ubiquitous feature in regulated health insurance markets in the US and much of the OECD, works by implementing a schedule of subsidies or transfers across insurers that are based on the diagnosed chronic health conditions of a particular insurer's enrollees. Diagnoses are first collected from medical claims. In the ACA Exchange setting, enrollees with diagnosed conditions that would predict expected costs higher than the market average generate positive transfers for insurers, while enrollees with conditions that would predict expected costs lower than the market average generate negative transfers. When functioning properly, risk adjustment makes all potential enrollees appear equally profitable to the plan, removing the incentive for insurers to attempt to cream skim via contract design (van de Ven and Ellis, 2000; Breyer, Bundorf and Pauly, 2011). Regardless of whether states created their own Exchanges or participated in the Federally Facilitated Marketplace, risk adjustment was implemented using the same HHS-HCC risk adjustment system.[12] This model was based on the CMS-HCC risk adjustment algorithm that has been used to adjust payments to private Medicare plans in Part C (Medicare Advantage) since 2004.

In addition to mandatory risk adjustment, plans were also required to participate in a mandatory reinsurance program that in 2015 paid out 50% of the individual claims that exceeded an attachment point of $45,000 and fell below a cap of $250,000.[13] The reinsurance operated separately from, and in addition to, the risk adjustment payment. While both sets of payments are based on individual-level characteristics, they were paid at the insurer level. The reinsurance subsidies were funded by health plan fees while the risk adjustment transfers were budget neutral in that transfers to plans with sicker than average enrollees were paid for by transfers from plans with healthier than average enrollees.

[11] Temporary risk corridors which insured insurers' overall plan profits were also in place from 2014 to 2016. These operated at the level of the plan, rather than at the level of the enrollee. Their purpose was to protect insurers from risk related to uncertainty around the average health status across the entire market rather than a particular insurer's draw of enrollees within the market.

[12] 49 states and Washington, DC used the HHS-HCC system, which consists of a set of 128 payment factors (18 age-by-sex cells, 91 indicators for chronic conditions, and 19 interaction terms capturing interactions between different sets of conditions) and associated payment weights reflecting the incremental cost associated with the factors. The risk adjustment payment weights (or risk adjustment coefficients) were determined by CMS. Massachusetts was the only exception. Massachusetts used a risk adjustment model based on the HHS-HCC system, but estimated its own set of risk adjustment coefficients using claims data from the Massachusetts All-Payer Claims Database and from a subset of MarketScan claims data that was limited to enrollees in New England States. These fairly minor differences are unlikely to affect the implications of the model for individual or group-level profitability.

[13] The attachment point was lowered from its original proposed level of $70,000.

Together, these two payment adjustments altered the underlying financial incentives associated with the composition of a plan's enrollees.[14]

2.3 Selection Incentives under the ACA

Risk adjustment and reinsurance systems are generally imperfect, leaving significant shares of enrollee spending "unexplained" by the the transfer payment. The key feature of a well-functioning risk adjustment system is that though it may only explain a small fraction of healthcare spending variance, it explains much of the *predictable* variation along which insurers would otherwise be able to induce selection. As we discuss above, and as originally pointed out by Frank, Glazer and McGuire (2000) and Ellis and McGuire (2007) in the healthcare setting, to the extent that risk adjustment and reinsurance leave payment errors that are correlated with the predictable use of particular services (in our setting, a particular therapeutic class of medication), insurers have an incentive to distort benefits to attract or deter enrollment by consumers seeking coverage for those services. Therefore, the relevant question is whether the Exchange risk adjustment and reinsurance systems result in predictable payment errors and whether these errors are significant enough to induce insurers to distort coverage.

There are several reasons to suspect that the Exchange regulatory framework left significant incentive and scope for insurers to use formulary design as a tool for avoiding unprofitable patients. First, as early as the first public comment period for the proposed HHS-HCC algorithm now used in the Exchanges, there was concern that the risk adjustment model was not well suited to compensate insurers for the drug costs of their enrollees. Critics noted that the CMS-HCC algorithm on which the HHS-HCC algorithm was based was originally developed to adjust payments only for the non-drug portion of Medicare Part C plans, suggesting a potential problem when applied to drug-inclusive total costs in the Exchanges. Second, since the inception of the Exchanges in 2014, patient advocacy organizations have claimed, and the popular press has reported, that patients with some chronic conditions have faced significant barriers to drug access in Exchange plan formularies.[15] Third, the Centers for Medicare and Medicaid Services (CMS) has suggested that by 2018, it may amend the

[14] See Centers for Medicare and Medicaid Services (2015) for additional detail on risk adjustment and reinsurance in the first years of the Exchanges.

[15] In 2014 a group of about 350 consumer advocacy groups expressed in an open letter to HHS that consumers with chronic conditions still faced important barriers, in particular in the area of prescription drugs. (http://www.theaidsinstitute.org/sites/default/files/attachments/IAmStillEssentialBurwellltr_0.pdf)

risk adjustment algorithm in the Marketplaces to better capture drug spending, suggesting that drug-related selection incentives are viewed as an important issue by the regulator.[16] Finally, in the context of formulary design in Medicare Part D, both Carey (2016) and Lavetti and Simon (2016) show that insurers adjust benefits packages in response to the residual selection incentives that exist net of risk adjustment. Taken together, there is reason to believe that Exchange insurers may be systematically designing formularies to induce selection. However, in the context of the ACA Exchanges, the prior literature has provided no econometric evidence on the issue.

3 Data

3.1 Formularies

We use a database from Managed Markets Insight & Technology (MMIT) that contains detailed formulary information for employer sponsored insurance (ESI) plans and plans offered in the ACA Exchanges. MMIT attempts to collect the universe of US plan formularies through agreements with insurance carriers, pharmacy benefit managers, pharmaceutical manufacturers and others. We observe 501 Exchange plans. Our definition of an Exchange "plan" in this context nests the various metal-level products offered by the same carrier in a market sharing a formulary. For example, a carrier's gold, silver, and bronze variants on the same benefits package that assign different levels of cost sharing to achieve different actuarial value targets would be counted in our analysis as a single plan, as long as these variants all utilized a common formulary.[17] The coverage of Exchange plan formularies in these data is remarkably complete: Plan-specific enrollment totaled across the 501 plans in our sample is 10.2 million covered lives. As a point of comparison, the Department of Health and Human Services reported that 11.7 million consumers selected plans for 2015, with 10.2 million effectuating that enrollment by paying premiums before March 31, 2015. The employer plan data represent a large sample, covering about 3,200 plans and 47 million enrollees in self-insured ESI plans in 2015. This amounts to about a third of the universe of ESI enrollees. Our focus on self-insured employers

[16] "[W]e intend to propose that, beginning for the 2018 benefit year, prescription drug utilization data be incorporated in risk adjustment, as a source of information about individuals' health status and the severity of their conditions." (June 8, 2016 CMS Press Release, https://www.cms.gov/Newsroom/MediaReleaseDatabase/Fact-sheets/2016-Fact-sheets-items/2016-06-08.html)

[17] What would differ across such options would be the particular cost sharing (copay and coinsurance) amounts associated with each formulary tier.

implies that this group does not include plans from the "small group" ACA Exchange markets.[18] For both settings, the data are a snapshot of plans operating in October 2015.

For each drug in each plan, the MMIT data indicate the formulary tier in which the drug appears. Drugs are coded at the level of a First Data Bank (FDB) drug identifier code, which is a minor aggregation from the 11-digit National Drug Code (NDC) directory.[19] In addition to a raw tier variable captured in the data, MMIT harmonizes tiering across plans.[20] Additional restrictions and exclusions, such as prior authorization and step therapy are also noted. These data do not provide the dollar cost-sharing amounts associated with each tier, only the tier itself. For our purposes, this coding of the data is sufficient, as it naturally aligns with our research design which examines the within-plan relative tiering across therapeutic classes of drugs. We also observe the pharmacy benefit manager (PBM) associated with each plan, the geographic coverage of the plan, and the number of beneficiaries covered. The PBM identifier is particularly useful because it allows us to compare formularies between employer and Exchange plans that use the same pharmacy benefits manager and to therefore hold many unobservables constant.

Table 1 presents summary statistics for the formulary data. Column (1) presents statistics for self-insured employer plans and column (2) presents statistics for exchange plans. We list tiers from top to bottom in decreasing order of formulary generosity. Drugs in the specialty tier have cost sharing higher than drugs in the covered/non-preferred tier, drugs in the covered/non-preferred tier have cost sharing higher than drugs in the preferred brand tier, and so on.[21] In order to illustrate the relationship between out-of-pocket consumer spending and tier, we import data made available by the Center for Consumer Information and Insurance Oversight (CCIIO) at CMS. The CCIIO public use files list the cost sharing details (copay amount and/or coinsurance rate) for each Exchange insur-

[18] We limit attention to employer plans that were successfully linked to a specific employer, as this allows us to clearly distinguish these from non-employer commercial plans. External sources, such as the Kaiser Family Foundation, estimate that approximately 150 million consumers were enrolled in ESI plans in 2015.

[19] Below, a "drug" means an FDB identifier. On average, an FDB drug identifier corresponds to five 11-digit NDC codes, which specify a labeler, product code, and package code. A "class" means one of the 257 therapeutic classes defined by the RED BOOK, unless otherwise stated.

[20] Plans set up their own formularies with a variety of different tiering structures. MMIT takes these tiering structures and synthesizes them into a unified structure that is common across plans. The unified tiers are generated by specialists who review the basic tiers as well as the specific drugs included in each. Among other benefits, the harmonization eliminates the possibility that "tier 1" indicates the lowest level of cost sharing in one formulary but the highest in another.

[21] Ordering of tiers such as "not listed," "medical," and "not covered" is less clear given that the coverage for these tiers is not transparent. Our conversations with the data provider, MMIT, indicated that the ordering in Table 1 is the most likely ordering of tiers by generosity. "Not listed" means that the plan likely covers the drug but they choose not to advertise it, "medical" means that the plan covers the drug but under the medical benefit rather than the drug benefit (likely implying higher cost sharing than the specialty tier), and "not covered" means the plan explicitly states that it will not pay for these drugs.

ance product in each state. Whereas the MMIT data describe the mapping from individual drugs to formulary tier, the CCIIO data describe the mapping between these tiers and dollars of out-of-pocket costs. The two databases are not linkable at the level of individual plans, but CCIIO summary statistics at the level of the tier are presented in columns (3) and (4) of Table 1. Column (3) lists the mean copay associated with each tier among Silver-level Exchange products, conditional on a cost-sharing structure that only includes copays. Column (4) indicates the unconditional probability that the tier faces a coinsurance regime.[22]

The copays increase moving down the table, consistent with our ordering. These levels are likely to understate the differences in cost sharing across tiers because the probability that the drug is covered by coinsurance, which could generate much higher out-of-pocket costs, is also increasing significantly moving down the table. For expensive drugs, such as those treating multiple sclerosis or rheumatoid arthritis, drug costs may be several thousand dollars per month (Lotvin et al., 2014), leading to coinsurance payments per enrollee exceeding $1,000 if such drugs are placed on the specialty tier.

About one third of drugs are not listed in a typical plan's formulary. This is an issue not of missing data but of the benefit schedule not specifying to the consumer how each drug in the pharmacological universe is covered. Also, although categories like generic preferred, preferred brand, and specialty have clear vertical rankings, the assignment of some drugs to prior authorization and step therapy represents a qualitatively different type of restrictiveness. These assignments impose non-monetary hurdles to drug access. Prior authorization (PA) requires consumers to obtain special dispensation from the insurer for use of the drug, and step therapy (ST) requires patients to first demonstrate that alternative drug therapies are ineffective before coverage for the drug will be considered. Simon, Tennyson and Hudman (2009) show that the prior authorization and step therapy designations significantly affect access and consumption. For that reason, we group all drugs with a PA/ST designation into a separate, mutually exclusive category.

While the tiers in the data are constructed to have somewhat consistent definitions across plans, consistency is not guaranteed. For example, some plans may not have a covered/non-preferred tier, while other plans may not have a generic preferred tier. To accommodate this, and to simplify

[22] A significant fraction of Exchange consumers receive a cost sharing subsidy. Such consumers enroll in plan variants that adjust down the overall cost sharing, which often includes reducing the cost sharing associated with the formulary tiers.

exposition and analysis, we group the tiers into two categories: restrictive and not restrictive. This definition, indicated in Table 1, breaks at the level of the specialty drug tier. The specialty tier is a natural breaking point suggested by plan design, as column (4) of the table shows that plans switch from relatively generous copay-based cost-sharing to relatively ungenerous coinsurance at this tier. The break also reflects consumer complaints and regulator concerns about the use of the specialty tier, in particular, to discriminate against certain chronically ill types. In our analysis, we examine robustness to the choice of which tier defines the cutoff for the restrictive classification.

It is clear from Table 1 that employer and Exchange formularies differ in how they distribute drugs across tiers, with Exchange plans relying more heavily on more restrictive tiers. We illustrate these differences in tier structure in more detail in Figure 1. In Panel A, we plot histograms of the fraction of each plan's formulary that is placed on the restrictive tier (specialty or higher). In Panel B, we repeat the histogram for the fraction of each plan's formulary that is placed in the PA/ST category or is specifically called out as "not covered" (distinct from not listed). In both panels, it is clear that Exchange plans make much more extensive use of the more restrictive tiers. Note that the relative tiering is related to, but different from, the implied cost sharing. For example, even if Exchange plans make more extensive use of the specialty tier than ESI plans overall, they could also place a lower price on the specialty tier than ESI plans, making the overall difference in generosity unclear. Fortunately, as we discuss below, our empirical strategy relies on differences between ESI and Exchange plans in *relative* generosity across drug classes within plans, not overall differences across plans.

The conceptual motivation above suggests that plans will attempt to select against patient types, rather than narrowly targeting one drug (among many) used to treat a patient type. Indeed, narrowly targeting some drugs within a class is perfectly consistent with steering patients to cost-effective options. In contrast, broadly restricting access to an entire therapeutic class of drugs cannot be rationalized by steering. For example, insurers wishing to avoid attracting MS patients might place all biological response modifiers used to treat MS on relatively high tiers, not merely the products within the class for which the insurer faces higher prices. We are therefore interested in categorizing the formulary list according to patient types.

To operationalize the idea that screening patient types is related to the benefit design over an entire class of potential substitutes, we organize prescription medications into therapeutic classes.

We follow the standard categorization of therapeutic classes in the RED BOOK, a comprehensive industry drug dictionary. RED BOOK partitions the universe of prescription drugs into 257 mutually exclusive therapeutic classes. These classes are the level at which we define the insurer's selection incentive. To measure how restrictive a formulary is with respect to a specific class, we calculate the percent of drugs in a class c that fall into the specialty tier or a more restrictive tier (i.e. not listed, medical, PA/ST, not covered). This is the main outcome variable (Y_c) below, though in some analyses, we limit attention to just the lowest-cost drugs within a class, or just the most popular drugs within a class. In a robustness exercise, we also re-run the analysis using an alternative classification system designed by the American Hospital Formulary Service.

3.2 Claims Costs Data

To quantify the selection incentives implied by the Exchange payment scheme, we use administrative claims data for *non*-Exchange plans from the Truven Health MarketScan Research Database for years 2012 and 2013.[23] The MarketScan data contain inpatient, outpatient, and prescription drug claims from commercial plans and are collected from a selection of large employers, health plans, government, and public organizations. We apply several sample restrictions to the MarketScan data. Because our method, described below in Section 4, requires calculating the intertemporal correlation of drug spending, we restrict to the most recent sample available for which we can create a panel of total costs and drug utilization: We include consumers who were enrolled for all 12 months in 2013 and for at least 9 months in 2012 and have prescription drug and mental health coverage. We drop patients who had any negative payments or any capitated payments in either the inpatient or the outpatient file. The resulting sample includes 11.7 million consumers generating 143 million drug claims.

For this sample of consumers, we directly observe all information needed to calculate the total of inpatient, outpatient, and prescription drug spending, C_i, at the individual level. Also at the individual level, we observe all the information needed to simulate Exchange plan revenues. We calculate the regulatory transfer that would result if each consumer in the non-Exchange claims data had generated their claims history while enrolled in an Exchange plan. Patient diagnoses revealed in the claims provide the information necessary to calculate the risk adjustment subsidy R_i^{RA}, and total uti-

[23] Access provided through the NBER.

lization can be used to determine the additional reinsurance payment R_i^{Re}, if any, implied by the Exchange regulations. These simulated payments are calculated precisely using the publicly-accessible algorithms that are supplied by the regulator for use by the participating plans. See Appendix A for full detail. We denote the total revenue (risk adjustment plus reinsurance plus premiums) as R_i.[24] Given R_i and C_i for each individual, we construct various measures of the relative profitability of patients, described in Section 4.1.

An important feature of using non-Exchange claims data is that it allows us to generate out-of-sample predictions for the costliness of patient types that are not susceptible to being contaminated by feedback from the Exchange formulary designs. In other words, we develop measures of costliness and drug utilization in a setting where the utilization is not impacted by the contract distortion we are interested in studying.[25]

4 Research Design

We begin in this section by constructing various metrics of the residual selection incentives left in place by the ACA payment system. We then discuss our research design for identifying the effects of these incentives on contract design.

4.1 Selection Incentive Measures

With patient-specific costs, C_i, and revenues, R_i, it is straightforward to characterize how patient profitability covaries with use of drugs in particular classes. We define S_{mc} as the measure of the selection incentive, which varies across therapeutic classes of drugs, c, and market setting, m. A market setting in this notation is employer sponsored insurance (ESI) or an ACA Health Insurance Exchange (HIX).

[24] Premiums are assumed to equal average claims costs, ignoring loading. As Geruso and Layton (2015) show, in a symmetric competitive equilibrium with properly functioning risk adjustment, premiums would equal the market-level average costs.

[25] In contrast, using data from the Exchange setting where insurers do face this incentive could create spurious correlation between our measure of the adverse tiering incentive and the equilibrium response to that incentive via formulary design. To see this point, consider the extreme case where providing *any* coverage from drug A results in a large increase in enrollment among a group of extremely unprofitable individuals. In such a setting, it is likely that no plan will provide coverage for drug A, resulting in zero spending on drug A in the data and no relationship between spending on drug A and profitability despite there actually being a strong relationship between demand for coverage for drug A and profitability. This is an extreme example, but it provides intuition for why it is beneficial to use data from a setting where benefit design is not affected by selection incentives.

To generate S_{mc} for plans competing in Exchange markets (denoted $S_{HIX,c}$), we begin by calculating the average class-specific costs and revenues associated with individuals taking drugs in each drug class, $\overline{C_c}$ and $\overline{R_c}$ for each class c. These are defined as cost and revenue means conditional on consumers having some drug consumption in the class. We can construct $\overline{C_c}$ and $\overline{R_c}$ only for the subset of therapeutic classes for which we observe drug claims in the MarketScan data. This removes classes like "toothpastes and floss" and "sunscreen agents" which are typically not covered by health plans. It also removes classes like "mumps," which are extremely rare and do not show up in our claims data. This leaves 220 of the 257 therapeutic classes. For this set, we generate three alternative measures of the drug-class-specific incentive for Exchange plans to distort coverage:

$$S_{HIX,c} = \begin{cases} \overline{C_c} - \overline{R_c} & \text{Cost-revenue difference,} \\ \dfrac{\overline{C_c}}{\overline{R_c}} & \text{Cost-to-revenue ratio,} \\ EM_c & \text{Ellis-McGuire predictable profitability.} \end{cases} \tag{7}$$

In all cases, higher positive values of $S_{HIX,c}$ are associated with stronger incentives to inefficiently restrict coverage for the class. The first two measures are self-explanatory. The third measure is based on Ellis and McGuire (2007), who, as discussed in more detail in Section 2, develop a theory of plan benefit design distortions in the presence of selection incentives. Ellis and McGuire (2007) show that a profit-maximizing insurer will have incentives to distort coverage defined by the following index:

$$EM_c = \underbrace{\frac{\sum_{i \in I_c} (\widehat{C_{ic}} - \overline{C_{ic}})^2}{\overline{C_c}}}_{predictability} \times \underbrace{\rho_c}_{predictiveness} \tag{8}$$

In the first term of (8), predicted spending $\widehat{C_{ic}}$ reflects consumers' ability to forecast drug needs in class c based on past use of drugs in any class. We regress 2013 spending in therapeutic class c on a vector that contains dummies for the quartiles of spending in each of the therapeutic classes in 2012. We then predict 2013 spending in therapeutic class c using the coefficients from this regression. Up to a normalization in the denominator, the predictability term is equivalent to the R-squared of that regression.[26] It captures the extent to which spending in a therapeutic class next period is predictable by a consumer looking backward to his or her past spending (across all drugs). The

[26] Changing the denominator in the predictability term would convert this term into an R-squared measure.

predictiveness term, ρ_c, is defined as the correlation of individual-level profitability ($R_i - C_i$) and spending in therapeutic class c in the same period ($\overline{C}_c$).

Like the other two measures, the Ellis-McGuire (E-M) measure considers the correlation between use of a service (a drug in our context) and profitability. Unlike the other two measures, it also considers the predictability of use of a drug. The intuition is that plans are most likely to distort benefits and services that are both predictive of higher insurer costs, and predictable in the sense that the consumer can anticipate his/her future demand for coverage for the drug when selecting a plan. Applied to our setting, drugs that treat chronic conditions are more predictable and thus more vulnerable to contract distortions by insurers aiming to avoid these patients. In contrast, there is little benefit in distorting coverage for a drug class for which consumers cannot anticipate need. For example, a local anesthetic may be an under-compensated drug, but because this would most likely be administered following a traumatic accident that is not predictable, the insurer faces little incentive to inefficiently distort coverage of this drug.

A second important difference between the E-M measure and the other measures, is that the E-M measure effectively weights individuals by their spending on drugs in class c, giving more weight to the profitability of individuals with higher utilization of the drugs in the class, as these higher-utilization individuals are likely to exhibit higher demand for plans that offer high levels of drug-class-specific coverage than lower-utilization individuals. The other measures effectively weight all individuals taking drugs in the class equally.

For all three measures of $S_{HIX,c}$ we are not attempting to isolate the impact of demand for drugs in class c on spending within class c or on revenue driven by only chronic conditions associated with class c. Instead, we are characterizing the association between utilization of drugs in the class and total spending, net of payment adjustments. Individuals who take drugs that treat chronic conditions typically have high non-drug spending to treat their conditions, further strengthening an insurer's incentive to restrict access to these drugs, making their plans appear less attractive to this unprofitable set of enrollees.[27] Our approach captures all drug spending and all medical spending that is predicted by patients' demand for class c. The implicit assumption is that insurers maximize over total profits, not the component of profits narrowly associated with consuming a particular drug class. Nonetheless, we investigate below the extent to which insurers appear to be unsophisticated in the

[27] As a more concrete example, a consumer with HIV or MS knows at the time of enrollment that she will demand these drugs in the coming plan year, and insurers may know that these patient types are expensive (even net of risk adjustment).

sense of responding to drug-class specific costs or revenues, rather than the bottom line impact on (our proxies for) profits.

All three S_{mc} measures are based on the unconditional effect on plan profits of increasing coverage for a drug in class c and not on partial effects that would condition on an consumers' utilization of drugs in other classes. This is consistent with the model of Frank, Glazer and McGuire (2000) and of Ellis and McGuire (2007) and with the implementation of Lavetti and Simon (2016). The unconditional relationship correctly characterizes the incentives of interest here because it aligns most closely with the thought experiment of using formulary design as a screening mechanism to avoid enrollment. The partial effects of drug use on spending would align with the thought experiment of keeping a consumer in a plan while reducing her costs associated with that particular drug holding other drug use fixed.[28]

Insurers may approximate profit-maximizing behavior in ways that could align with any of the three measures defined in (7). Therefore, in the results below, we report results with respect to each variant of S_{mc} separately. Although the measures are correlated, they do contain some independent information. To give a sense of the information overlap, in Appendix Figure A1, we graph rank-rank scatterplots of the measures against each other. The rank correlation of the level and ratio variables is high. Both of these differ non-negligibly from the Ellis-McGuire measure.[29] For parsimony, in some specifications below we report only the two measures with the least overlap: the ratio and Ellis-McGuire measures.

4.2 Regressions and Identification

Estimating the causal impact of S_{mc} on benefit generosity Y_{mjc} for plan j in market setting m for class c requires holding fixed any characteristics of drugs that could be correlated with S_{mc} and are

[28] For additional intuition, consider two drug classes for which consumer utilization is highly correlated and where one of the two classes has a stronger relationship with profitability. In such a setting, an insurer has an incentive to restrict access to *both* of these drugs because coverage for both drugs affects demand for its plans among these unprofitable groups. The unconditional effects capture these dual incentives, while the conditional effects may not. We thus proceed by using the unconditional effects as outlined above.

[29] The axes range from rank 1 to rank 220, with rank 1 implying the strongest incentive to avoid enrollees using drugs in the class. The plots include one point for each of the 220 classes and show how the ordering of profitable and unprofitable classes compares across the measures. Panel A shows a high rank correlation between the level and ratio measures. Panels B and C show that the information content of the Ellis-McGuire measure differs, especially at ranks outside of the top few. Unlike the other two metrics, E-M explicitly accounts for what types of spending are predictable by consumers, and therefore effective tools for selection.

relevant for contract design for other reasons.[30] For example, consumer price elasticity of demand for the drug class will impact benefit design because it plays an important role in the formulary design problem of both the profit-maximizing insurer and the social planner. If drugs that are more elastically demanded also happen to be under-compensated in the risk adjustment payment scheme, then a profit-maximizing (as well as an efficient) response to moral hazard could be mislabeled as an inefficient selection-driven distortion.

To isolate the impact of selection incentives from other determinants of formulary generosity that would influence the social planner's optimal contract—that is, the contract arising in a well-functioning competitive market—we compare formulary design in the Exchange to formulary design in Employer plans. Exchange plans and employer-sponsored plans plausibly face similar considerations with respect to balancing coverage with consumer moral hazard, steering consumers to cost-effective options, and other considerations that could lead to an efficient design. However, the selection incentives differ significantly. Exchange plans can influence their enrollee composition by altering their formularies, but in employer-sponsored plans, the insurer (the employer) cannot avoid the costly enrollees in its firm by offloading them to another insurer. Formally, we assume that S_{mc} equals zero for all drug classes in the ESI setting. In other words, we assume that the ACA-Exchange payment formula error does not generate any selection incentive in the self-insured ESI markets (in which the ACA payment formula does not apply).

We estimate difference-in-differences regressions of the following form:

$$Y_{jc} = \beta[S_{mc} \times HIX_j] + \gamma_c + \alpha_j + \epsilon_{cj}. \tag{9}$$

HIX_j is an indicator equal to one if plan j is an Exchange plan and zero otherwise.[31] γ_c are drug class fixed effects, and α_j are plan fixed effects. The parameter of interest in this equation is β, the correlation between the selection incentive and formulary generosity in Exchange plans after differencing out formulary generosity for the class among ESI plans. In most tables we present OLS estimates of (9), though we additionally present semi-parametric versions in several figures. To facilitate interpretation of β, in all regressions we standardize $S_{HIX,c}$ by subtracting the mean of the measure and

[30] In practice, generosity varies within class at the level of the drug. However, we are interested in the use of formularies to select classes of patients rather than steering across drugs within a class.

[31] Inclusion of the HIX_j is redundant because S_{mc} is zero for ESI plans. The notation is intended to emphasize that we allow the selection incentive to impact design in HIX plans only.

dividing by its standard deviation. This places results for the various operationalizations of $S_{HIX,c}$ on a comparable (z-score) scale. The estimation sample includes the universe of Exchange plans in 2015 and the large sample of employer plans described in Table 1. Observations are at the plan $\times$ state $\times$ class level. Data are weighted by covered lives within the plan, so that the estimates are representative of the Exchanges nationally for 2015. Standard errors are clustered at the level of the 220 drug classes.

Identification does not require that Exchange and employer plans are equally generous in practice or should be equally generous in their optimal design problem. Indeed, in Figure 1 we illustrate the raw generosity differences between employer and Exchange plans across drug classes. Plan fixed effects in Equation (9) address any differences in overall generosity between Exchange and employer plans, so that β is identified by the differential slope $\frac{\partial Y_{jc}}{\partial S_{mc}}$ within Exchange plans relative to ESI plans.

The identifying assumption is that employer plans respond to non-selection considerations and consumer demand constraints contained in γ_c similarly to Exchange plans, but do not face the same selection incentives. This seems plausible. First, there is essentially no scope for selection by employer-insurers because the employer is the residual claimant on health care spending for all of the plans in an employee's choice set.[32] Second, there is no reason *a priori* to believe the characteristics like drug-specific demand elasticities vary between Exchange consumers and ESI enrollees in a way that is correlated with the selection incentives generated by the ACA risk adjustment and reinsurance scheme. Although Exchange consumers may be more price-sensitive overall due to lower incomes and this would have implications for the overall level of optimal cost sharing, only differences across ESI and Exchange enrollees in demand elasticities that happened to be correlated with the over-/under-payment of risk adjustment and reinsurance would violate our identifying assumption. A related potential confounder is that even if demand elasticities do not differ importantly between the ESI and HIX market settings, HIX plans may for some reason be more responsive to those elasticities. We investigate this possibility directly, by examining the relationship between independent estimates of drug class-specific price elasticities of demand from Einav, Finkelstein and Polyakova (2016) and our S_{mc} metrics.

[32] It is possible in principle that employers attempt induce exit from insurance coverage by employees with expensive conditions, or to offload these employees to a spouse's employer plan. We know of no study documenting such behavior, however.

5 Results

5.1 Evidence of Payment Error

We begin by showing that Exchange risk adjustment and reinsurance systematically overpay for some patient types and underpay for others. It is important to note that risk adjustment doesn't strive to explain all of the idiosyncratic variance in healthcare spending. Payment "errors" in the sense of payments that deviate from costs are problematic in this context only if these deviations are correlated with a consumer's expected use of a service that the insurer can potentially restrict access to or limit coverage for.[33] If this correlation exists, it generates a lever for selection via formulary design, and thus drives a wedge between the socially optimal insurance contract and the contract offered inequilibrium by a profit maximizing insurer.

We illustrate this idea in Figure 2, where we plot the the mean of total spending among consumers utilizing drugs in a class ($\overline{C_c}$) versus the mean of total simulated revenue among those consumers ($\overline{R_c}$). A dashed line at 45 degrees separates the space into over- and underpayments. Each scatterpoint corresponds to one of the 220 drug classes. Marker sizes reflect the relative number of consumers using drugs in the class. Patients consuming drugs in classes above the dashed line are profitable to avoid, because for these patients costs exceed Exchange reinsurance and risk adjustment revenue.

In Figure 2 the majority of classes are clustered tightly around the 45-degree line, indicating that the payment system succeeds in neutralizing formulary selection incentives for the majority of potential enrollees. However, there is a small number of significant outliers, far off the diagonal. A few are labelled for illustration: The Gonadotropin-Releasing Hormone Antagonist class contains fertility treatment drugs for women. Biologic Response Modifiers treat several chronic conditions, including multiple sclerosis and rheumatoid arthritis. The existence of such outliers establishes that risk adjustment payment "errors" are correlated with drug use, a key necessary condition for insurers to use formularies as screening devices. If insurers are aware of these correlations and if coverage for these drugs is salient to consumers at the time of health plan purchase, distorting coverage of these

[33] Payment errors that are correlated with consumer "type" (geography, demographics, etc.) are aslo potentially problematic, but for subtly different reasons. The correlation between type and profitability generates incentives to avoid the type, but unless the type differentially uses a particular set of services, the tool of service-level selection or selection via benefit design is not feasible. Instead, these groups may be vulnerable to other forms of selection, such as via selective advertising, where the welfare consequences of selection are less clear. Investigation of these types of selection actions is beyond the scope of this paper.

drugs represents an opportunity to induce profitable selection.[34]

Figure 3 provides an alternative view of the selection incentives. Here we plot histograms of the level, ratio, and Ellis-McGuire measures of $S_m c$ (without the z-score transformations) for the 220 classes. This class-level variation interacted with an Exchange indicator constitutes our identifying variation. All three panels again show that risk adjustment appears to be working reasonably well in the Exchanges, with the majority of drug classes being essentially neutral with respect to selection incentives. In Panel A, the level difference measure is concentrated at zero, in Panel B the spending/revenue ratio around one, and in Panel C the Ellis-McGuire measure around zero (neutral). However, all three panels also confirm that important outliers exist. In our analysis below of the response to these incentives, we give particular attention to outlying classes.

Table 2 presents additional details on costs and revenues for the drug classes associated with the ten most profitable and ten least profitable groups. We restrict the list to classes that comprise at least 0.01% of drug claims. This drops classes for which we cannot generate precisely-estimated measures of costs and simulated revenues. Column (3) lists the most popular drug in the indicated class, by count of users in our claims data. Column (4) displays the average of total healthcare spending associated with the class, $\overline{C_c}$. Column (5) displays the average simulated revenue, $\overline{R_c}$. A single consumer whose claims span several drug classes will contribute to multiple rows of the table (and multiple points in Figure 2).

The particular outliers apparent in Figure 2 and Table 2 appear to corroborate external accounts of problems with Exchange formularies. Our data support these anecdotes: For example, Biologic Response Modifiers make our "top 10" list of unprofitability. The most commonly filled prescription in this class in our claims data is Copaxone, which is used to treat and to prevent relapse of MS. 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." In this sense, even without leaning on our difference-in-differences regression framework, and despite relying on predictions

[34] In contrast, it would not be problematic to observe all drug classes tightly clustered around the 45-degree line, as such variation might not be selectable. We also note it is the mean absolute deviation from the 45-degree line that represents a critical measure of the aggregate distortionary incentive here. The deviation from a regression line, as would be measured by the sum of squared errors, is not informative here. Consider the case where all drug classes lie in a straight line along the 10-degree line so that all classes lie above the 45-degree line. In this case, the sum of squared errors would be zero, but the insurer would face fairly strong incentives to distort coverage for *all* drug classes. In this case, theory would predict that the insurer would offer lower than efficient levels of coverage for all classes.

made completely out of the Exchange sample (these data come from ESI enrollees), the summary statistics here can rationalize the accounts in popular reporting and anecdotes from patient advocacy groups. Opiate Antagonists used to treat opiate addiction also surface as an unprofitable class. It is also worth noting that two of the five least profitable classes treat infertility in women, a condition for which the risk adjustment algorithm does not provide compensation. As far as we know, the strong selection incentives related to these drugs have not been previously noted. On the other hand, several of the *most profitable* classes in Table 2 treat cardiac conditions. Cardiac conditions were given close attention in Medicare's CMS-HCC risk adjustment algorithm on which the Exchange algorithm was based.[35]

5.2 Main Results

We start by illustrating our results semi-parametrically. Figure 4 shows average generosity in Exchange and ESI plans for each ventile of the distribution of the selection incentive measures. The left panels use the ratio measure of the selection incentive, and the right panels use the Ellis-McGuire measure. To create the figure, we regress formulary restrictiveness on drug class fixed effects and plan fixed effects and then take averages of the residuals within each ventile of the selection incentive measure. This yields a semi-parametric analog of Equation (9). In the top panels, the horizontal axes are scaled to the count of the ventile (1 to 20). In the bottom panels, the horizontal axes reflect the mean value of the selection incentive within the ventile. Each bin contains about 11 drug classes, and each class contains many individual drugs. The dashed lines in each panel correspond to OLS regressions over the scatters, separately for Exchange and ESI plans.

Figure 4 shows that across much of the middle of the distribution of selection incentives, employer and Exchange formulary restrictiveness is relatively similar, though with Exchange plans exhibiting substantially more noise given the size of the universe of Exchange plans ($n = 501$). Formulary restrictiveness diverges significantly between employers and Exchanges at the highest ventiles, with the Exchange plans providing much less generous coverage for the least profitable drugs. To put

[35]Interestingly, the antiviral therapeutic class that includes HIV medications like nucleoside reverse-transcriptase inhibitors is not associated with strong selection incentives by our measures, despite a focus on this class of drugs by (Jacobs and Sommers, 2015) and the news media when discussing "adverse tiering" behavior. The class is associated with costs in excess of revenues, but the difference is small. A potentially important characteristic of the antiviral class as it is constructed in our data is that its constituency is large: The incidence of use of antivirals in the claims data is about an order of magnitude larger than for biologic response modifiers and about two orders of magnitude larger than the interferon or gonadotropin classes. Thus our 220 drug classes are too aggregated to detect effects on subsets of HIV-specific drugs *within* the class like nucleoside reverse-transcriptase inhibitors.

the scatterplot in context, the 20th ventile, which is a clear outlier along both the horizontal and vertical axes, would include the top ten least profitable classes. Figure 4 also suggests that for the drug classes where risk adjustment is predicted to systematically *overpay* relative to costs (in the leftmost bins), Exchange formularies on average provide relatively *better* coverage. However, it is clear that the largest distortionary incentives and the largest responses to those incentives occur in the direction of unprofitable patient types, which is the focus of most of our attention below.

Table 3 presents regression results corresponding to Equation (9). We report the difference-in-differences coefficient estimates for the interaction between the Exchange dummy, HIX_j and the selection measure, S_{mc}. All regressions include plan and drug class fixed effects. The selection incentive variable, S_{mc}, varies across columns, as indicated in the column headers. In Panel A the dependent variable is the fraction of drugs within the class placed on the specialty tier or higher. This corresponds to the restrictive tier cutoff indicated in Table 1, and the measure used in Figure 4. In Panel B the dependent variable is the fraction of drugs within the class that require prior authorization or step therapy (PA/ST) or are explicitly called out on the formulary as "not covered." These specifications explore the non-price hurdles that may be differentially used by Exchange plans. Given the possibility of non-linear effects suggested in Figure 4, we present both linear specifications and specifications that allow the relationship to be non-linear at the top ventile.[36]

Table 3 shows that the interaction between the Exchange indicator and the selection incentive measure(s) always yields a positive and statistically significant coefficient. The signs on the coefficients indicate that Exchange plans tend to provide less generous coverage (placement on a more restrictive tier) for drug classes where Exchange plans face stronger selection incentives generated by the payment system. Coefficients across the linear specifications in Panel A are similar, regardless of which of the three measures is used. The interpretation of the coefficient (0.045) is that a one standard deviation increase in the strength of the selection incentive increases the class-specific drugs assigned to a restrictive tier by about 4.5 percentage points in Exchange plans relative to employer plans. This is a substantial increase relative to a baseline restrictive tier use of 40% in employer plans and 60% in Exchange plans. With respect to non-price hurdles, Panel B of Table 3 shows a large effect of selection incentives on the probability that a drug faces a non-price hurdle. A one standard deviation increase in the strength of the selection incentive increases the percent of drugs that are PA/ST or not covered

[36]These additionally include the regressor $HIX_j \times V^{20}$, where V^{20} is the ventile 20 indicator.

by 1.8 percentage points on a base of 30%.

For the difference and Ellis-McGuire measures, the non-linear specifications appear to generate a better fit. Under this specification, the results in column 6 indicate that even controlling for a linear relationship between S_{mc} and restrictiveness, drugs in the top ventile of the selection incentive measures face an additional 50 percent ($= \frac{.296}{.59}$) probability of being placed on a restrictive tier. Column 12 indicates that these same eleven drug classes face an additional 53 percent ($= \frac{.159}{.30}$) probability of either being dropped from coverage entirely or of requiring the insurer's prior authorization or a step therapy approach. For completeness, in Appendix Table A1, we report on a wider variety of non-linear specifications, which include a larger set of ventile indicators, coming closer to the semi-parametric results of Figure 4.[37]

Another way to put these patterns in context is to note that an Exchange consumer choosing a drug in the top 10 percent of unprofitable drugs (by the ratio measure) would face a restrictive tier 76% of the time, while an ESI consumer would face a restrictive tier 45% of the time. For a drug in the bottom 10 percent, an Exchange consumer would face a restrictive tier 53% of the time, while an ESI consumer would face a restrictive tier 43% of the time.[38] These differences are sizable. With drugs in unprofitable classes like immunosuppressants and biologic response modifiers potentially costing in excess of $4,000 per month (Lotvin et al., 2014), the out-of-pocket costs associated with even a 20% coinsurance rate would routinely push such patients to their annual out of pocket maximum in every year.[39]

Across all of the various parameterizations, we find health plans are designing their drug formularies to offer differentially worse coverage for classes used by the most unprofitable individuals, consistent with the hypothesis that Exchange plan formularies are designed to deter enrollment of unprofitable individuals. Below in Section 6, we show that these results are robust to a variety of alternative specifications, and we rule out competing explanations related to within-class substitution to less expensive alternatives and related to differential demand elasticity across classes and markets.

[37] These results show that for the Ellis-McGuire measure, the relationship is driven by the classes with the strongest incentives in both directions: the top 15% of drugs that are least profitable, along with opposite signed coefficients among the 5% of drugs that are *most* profitable.

[38] These statistics are based on simple means within the sample, they are not derived from regression coefficients.

[39] In 2016 the out-of-pocket annual maximum could not exceed $6,850 for an individual Exchange plan and $13,700 for a family plan, though plans were free to set lower limits.

5.3 How Sophisticated Do Insurers Appear?

Thus far, we have suggested that our results indicate that Exchange insurers have responded to the residual incentives that remain under the Exchange payment system—i.e. that insurers have considered the profitability *net of risk adjustment and reinsurance* of people who take drugs in a particular class when designing their formularies. It could be the case, however, that insurers are naively responding to the *gross* profitability of these individuals, not actually taking into account the fairly complex risk adjustment payments, and that gross profitability is correlated with net profitability. Similarly, it is also possible that insurers use an even cruder guide to profitability, the drug's cost. In such cases, our findings above would still be consistent with the hypothesis that insurers design their formularies to deter unprofitable individuals, but the interpretation regarding insurer sophistication would be very different and would lead to different policy implications for efficient regulation.

The possibility that insurers intending to screen consumers via formulary design may have done so imperfectly is made more likely by the fact that in 2015 insurers still had little experience with both the population of Exchange enrollees and the risk adjustment system.[40] This might have made it somewhat difficult to predict net profitability by group *ex ante*. In other words, formulary design to deter enrollment by unprofitable individuals is an equilibrium result, and the market we observe may not yet be in equilibrium.

We explore the possibility that the Exchange insurers are naively responding to gross profitability or other potentially salient cost and revenue metrics in Table 4. Columns (1) and (2) repeat results from Table 3 for reference. Columns (3) and (4) control for a naive selection incentive, where risk adjustment and reinsurance are not taken into account, so that $\overline{R_c}$ in Equation (7) is replaced with $\overline{R}$. This naive selection measure assumes that insurers perceive the drug-specific association with costs, but not the drug-specific association with revenues. Under these simulated naive selection incentives, all of the variation is due to variation in costs across the groups of individuals who take the drugs in the class.[41] Another related possibility is that Exchange insurers are responding not to net or gross profitability but simply to the costs of drugs within the specific class, ignoring the broader signal of

[40] It has also been the case that the particular terms of the reinsurance program were subject to amendment by CMS *ex-post*. For example, for 2015, the reinsurance attachment point was lowered to $45,000 from its its original proposed level of $70,000.

[41] All of our results are based on variation in these measures across drug classes, not on the actual level of the measures. Because of this, the key assumption here is that revenues are constant across individuals. The level to which we set $\overline{R}$ is unimportant and would yield mathematically identical results if we substituted any arbitrary constant. Nonetheless, it might be helpful intuition to think of $\overline{R}$ as equivalent to the revenue generated by premiums.

overall costs implied by use of a class.[42] Columns (5) and (6) include controls for the cost of the drugs underlying the class. Each of the additional controls in Table 4 are interacted with the HIX indicator to examine whether Exchange plans differentially respond to these measures relative to employer plans.

Table 4 suggests that insurers do in fact respond to various imperfect proxies of the selection incentive, as many of the coefficients on these proxies reveal significance (in the expected directions). However, the coefficient of interest on $HIX_j \times S_{mc}$ is remarkably robust to the inclusion of these controls. This implies that insurers respond to the net revenue in addition to and independently from the gross proxies for cost. In column (7) of the table, we simultaneously include the Ratio and E-M measures interacted with S_{mc}. Both coefficients attenuate relative to specifications that include these regressors separately, but both remain highly significant. This implies that to the extent that the two measures capture different information sets regarding the insurer's selection incentives (see Figure A1), insurers respond to both information sets. In sum, it appears that relative to employer plans, Exchange plans limit coverage of drugs in response to both naive and sophisticated selection incentives.

Another way in which insurers may reveal sophistication is to specifically target drugs that will be most salient in dissuading unprofitable consumers from joining at the time of plan enrollment, while retaining within-class substitutes to encourage proper (and potentially cost-saving) disease management among the population of patients who nonetheless enroll. In Panel A of Table 5 we investigate the possibility that popular drugs within each class are more likely to be differentially relegated to restrictive tiers in Exchange plans when under-compensated by the payment system. In that table, we recalculate the dependent variable—the mean of the restrictive tier indicator within the class—over just the most popular drugs in each class. To do so, we rank each drug within each class according to the frequency of its consumption in the Marketscan data. We then calculate the restrictive tiering variable for only those drugs lying above a cutoff percentile, where the percentiles are weighted by consumption.[43] Columns (1) through (4) of Table 5 present results for the 75th and

[42] To assess the importance of this channel, we also analyzed the relationship between the Ellis-McGuire measure of selection incentives and mean spending on drugs in the class, conditional on any spending on drugs in the class. It appears that for most of the distribution of the selection measure, there is no relationship between the cost of drugs in a class and the selection measure. However, at the very top of the distribution where we find that Exchange plans are much more restrictive than employer plans, we find drug classes that are both very expensive and likely to be useful for selection purposes.

[43] For example, to compute the 75th percentile of popularity for a class in which one drug comprises 30% of the consumption share and seven other drugs each comprise 10% shares, the dependent variable would be computed only for the

90th percentiles of popularity. At both thresholds, coefficients are larger when focusing on the most popular drugs, compared to coefficients applying to the entire class, as in Table 3. When narrowly focusing on the 90th percentile of popular drugs within each class, the coefficient sizes approach twice the size of the main results. Thus, Exchange plans seem to limit coverage for more popular drugs that are associated with unprofitable enrollees more than they do for less popular drugs, though it is unclear whether this reflects insurers that are responding to salience biases of enrollees, or insurers that are themselves displaying those same biases in formulary design.

6 Efficient Discrimination?

In this section, we provide further evidence that the tiering patterns we document in the Exchanges do not reflect a differential socially efficient response by Exchange insurers to the characteristics of drugs or to consumer behavior relative to employers. Specifically, we show that our results cannot be rationalized by Exchange plans' *differential* responses to: the availability of cost effective substitutes within therapeutic classes, differential attention to consumer price sensitivity across classes in employer and Exchange markets, or different pharmacy benefits managers across employer and Exchange markets. We emphasize that if Exchange plans and employers respond similarly to these motivations, our main analyses addressed these confounders via the inclusion of drug class fixed effects. It is only differential responses that could possibly violate our identifying assumption.

6.1 Substitution to Cheaper Drugs and Generics

A welfare-relevant consideration in formulary design is to steer consumers to cheaper substitutes among alternatives with similar efficacy. Therefore, one potential explanation for our findings is that Exchange plans simply have a stronger interest than ESI plans in operating at the efficient frontier and therefore do a better job of steering patients to lower-cost alternatives within a class, such as generics. There are two reasons that this is unlikely to explain our results. First, there is no *a priori* reason why, even if steering incentives were stronger in the Exchanges overall, the insurer's interest in steering would be *differentially* strong across classes in a way that is correlated with the error in the HHS risk adjustment and reinsurance scheme. Second, such an explanation would be difficult to motivate under a model in which employers providing ESI are profit maximizing. Such firms would

single drug with the 30% share.

have strong incentives to design an efficient health plan, allowing them to compensate workers with higher wages (Bhattacharya and Bundorf, 2009).[44] Nonetheless, we can provide some direct evidence that efforts by Exchange insurers to incentivize efficient substitution are not driving our results.

To begin, we note that many of the drugs in classes with the strongest selection incentives have no generic equivalents. For example, the entire class of Biologic Response Modifiers contains not a single generic. In Appendix Table A4, we show that our results hold if we limit attention to classes without generics (28 classes), with less than 10% generics (49 classes), or with less than 25% generics (84 classes). Therefore, our results cannot be driven by HIX plans using stronger nudges towards generics, as the results hold in the absence of a generic alternative. We also show in Appendix Table A3 that our qualitative patterns hold if we look just within the generic drugs of a class or just within the branded drugs of a class. Using the same specification as in the main results (Table 3) but including only generic drugs in the measure of formulary restrictiveness, we show in Panel B of Table A3 that the selection incentive significantly predicts *restricted access to generics*. The way tiers are harmonized across the diverse formularies of our data does not mechanically allow for generics to be allocated to the specialty tier, so this result comes from HIX plans using non-price hurdles to restrict access to generics. This is consistent with supplemental summary statistics we present in Table A2, which show that HIX plans are ten times more likely than an employer plan to require prior authorization or step therapy for a generic, and are about twice as likely to not cover a generic on their formulary. For completeness, we also show that additionally controlling for the fraction of generic drugs within each class in our main specification does not alter results (Table A5).

Encouraging substitution toward lower cost alternatives may still be relevant even in the absence of a generic option. To investigate this possibility, in columns (5) through (8) of Table 5, we repeat the main analysis but restrict attention to just the cheapest (generic and branded) drugs within each class, as observed in the Marketscan data. The specification focuses on only the low-cost potential substitutes in each class. Table 5 shows that the results hold up to examining the tiering of only the least expensive 25% or 10% of drugs in each class. Coefficients are similar to the main results, indicating that even cheap drugs that are associated with expensive patients are placed on high cost sharing tiers. Taken together, Tables 5, A2, A3, A4, and A5 support our claim that the contract designs we document do not merely reflect HIX plans pushing consumers to low cost and/or generic

[44]The alternative would be to offer an inefficient plan that generated the same utility at a higher cost, leading to lower wages, or to offer a plan at the same cost that generated lower utility.

alternatives.

6.2 Tiering and Demand Elasticity

As we highlight in Section 2, moral hazard, reflected in demand elasticities, is a key consideration in the design of a socially-efficient contract. Einav, Finkelstein and Polyakova (2016) show that it is also a key consideration in a profit-maximizing insurer's formulary design. The class fixed effects in our regressions are intended to control for any class characteristics that are similar across ESI and Exchange settings, including these elasticities. However, if ESI plans were differentially responsive to consumer moral hazard, and if the class-specific elasticities were correlated with our selection measure, then the differences we identify in our main analysis between Exchange and employer plans could be socially efficient. This is because in the absence of distortions like selection incentives, the profit-maximizing formulary design in a well-functioning competitive market matches the socially efficient contract design. Note that for this interpretation of our results to be correct, it would have to be the case that the difference-in-differences of price sensitivity by class and market happened to covary with the payment error generated by HHS's risk adjustment and reinsurance algorithm. Although we think this is unlikely, we can provide some direct evidence here 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. 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).[45] Besides allowing us to import the EFP demand elasticities, this exercise demonstrates the robustness of our results to an alternative classification system.

Figure 5 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 the 99 classes for which EFP generate demand elasticity estimates that we can match to our data.[46] For the

[45] For more information on differences across the classifications see Appendix B.

[46] Einav, Finkelstein and Polyakova (2016) generate demand elasticities for 108 AHFS classes. We can match these classes

whole sample of classes and for this demand elasticity subset in blue, there are significant outliers above the dashed line, indicating unprofitable enrollee types who can be screened and selected via class-specific drug coverage.

In Table 6, 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 6 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 A2 plots the semi-parametric versions of the regressions.[47]

To better understand these results, we examine the the correlation between the demand elasticity estimates and the selection incentive measures. Figure 6 graphs scatterplots of elasticity versus selection incentive by class. The three panels correspond to the three measures of S_{mc}. There is no correlation between the selection incentive generated by the payment system error and the demand elasticity. Taken together, Table 6 and Figures 5, 6, and A2 provide strong evidence that Exchange plans are not merely differentially responding to socially efficient or profit-maximizing considerations regarding class-specific consumer moral hazard in a way that ESI plans are failing to do.

Finally, we explore sensitivity to excluding fertility-related classes. Table 2 showed that two of the ten classes associated with the least profitable patients were associated with infertility, a class for which one might expect especially high price sensitivity.[48] To demonstrate that these particular classes are not driving the results, we re-estimate our main regressions excluding all fertility treatment classes. Results are reported in Appendix Table A6, and are almost numerically identical to our

and generate our selection incentive and tiering variables for 99 of these.

[47] 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.

[48] It is important to understand that differential price sensitivity for fertility treatments, in itself, would cause no problem for our research design, as long as consumers in employer plans are also differentially price sensitive to fertility treatments. Bias could result only if employers were responding to the elasticity differently than Exchange plans and only if that differential response happened to be correlated with the ACA payment formula error associated with the class.

main results.

6.3 Contracting and Institutional Knowledge

Another possibility is that the prices paid by insurers to drug manufacturers differ between Exchange plans and employer plans due to differences in insurer bargaining power. If upstream prices differ, then both profit-maximizing and (second-best) optimal consumer prices reflected in tiers, may also differ. To address this possibility to the extent possible in our data, we exploit the fact that many insurers outsource price negotiations with drug manufacturers to a fairly small set of pharmacy benefit managers (PBMs). PBMs design the formularies, contract with pharmacies, and negotiate prices. In our data, we observe the PBM used by each plan, allowing us to construct a full set of PBM fixed effects. Let $\mathbf{1}(PBM_p)$ be an indicator equal to 1 if plan j uses PBM p and zero otherwise. We estimate a set of specifications where we interact the selection incentive with the PBM fixed effects ($\mathbf{1}(PBM_p) \times S_{mc}$) when estimating our coefficient of interest (S_{mc}):[49]

$$Y_{jc} = \beta[S_{mc} \times HIX_j] + \sum_p \nu_p[\mathbf{1}(PBM_p) \times S_{mc}] + \gamma_c + \alpha_j + \epsilon_{cmj} \tag{10}$$

Under this specification, β is identified off of differences between Exchange plans and employer plans that use the same pharmacy benefits manager, alleviating concerns about differential drug prices for employer and Exchange plans.

Table A7 displays these results, again separately for each selection measure. We present two versions. In columns (1) through (4), we estimate Equation (10) such that the PBM_p variable is defined nationally. This implicitly compares, say, Aetna's Exchange plans in New Jersey to Aetna's employer plans in New Jersey and elsewhere. In columns (5) through (8), we define PBM_p at the state level, so that the control is defined as $[\mathbf{1}(PBM_p) \times \text{state}_s \times S_{mc}]$. Intuitively, in these specifications we are comparing reactions to the selection incentive in, say, employer plans in Texas that contract with the PBM OptumRx to Exchange plans in Texas that contract with OptumRx. In all cases the results in Table A7 are robust to these controls, lending further support to our identifying assumption. These regressions address not only the bargaining power confounder, but provide additional evidence that the effect is not driven by responses to (or biased subjective beliefs about) consumer moral hazard that differ across insurance carriers.

[49] PBM main effects are automatically included via the plan fixed effects.

7 Discussion

The prior literature, including Frank, Glazer and McGuire (2000), Ellis and McGuire (2007), and Geruso and McGuire (2016), has carefully examined and characterized the type of selection incentives that we examine here. However, only a small literature has been able to empirically document plan *responses* to such incentives. This paper documents this type of response in the setting of the ACA Exchanges. It is the first to do so in this context.

Our results are consistent with the hypothesis that Exchange insurers design their drug formularies to deter enrollment of unprofitable individuals. The "first stage" relationship between revenues and costs associated with drug classes align with anecdotal accounts of the types of patients facing formulary-based discrimination in the Exchanges. We isolate the plan responses to these selection incentives by exploiting the fact that while employer plans have similar interests in efficiently steering consumers between drugs, they face no selection incentives. Our findings show that insurers respond strongly both to the net incentives implied by the Exchange payment scheme, and in a less sophisticated way to gross costs associated with various drug classes. Additional analyses indicate that these results cannot be explained by differential incentives to steer consumers toward cheaper drugs in exchange plans, differential price sensitivity across employer and Exchange plan enrollees, or differential negotiated drug prices for employer and Exchange plans.

The findings here indicate that even in the face of coverage mandates such as Essential Health Benefits rules and payment system features such as risk adjustment, insurers may be able to effectively discriminate and induce selection. Formularies may be particularly important with respect to working around discrimination rules because the size of the contract design space is large and coverage for drugs for managing chronic illness is likely to be a relatively salient component of the insurance contract from the standpoint of consumers with chronic diseases who consistently use these drugs year after year, making formularies potentially effective as means of screening consumers. Our findings highlight the importance of designing a payment system that changes insurers' financial incentives with respect to discrimination, rather than attempting to constrain discriminatory activity directly.

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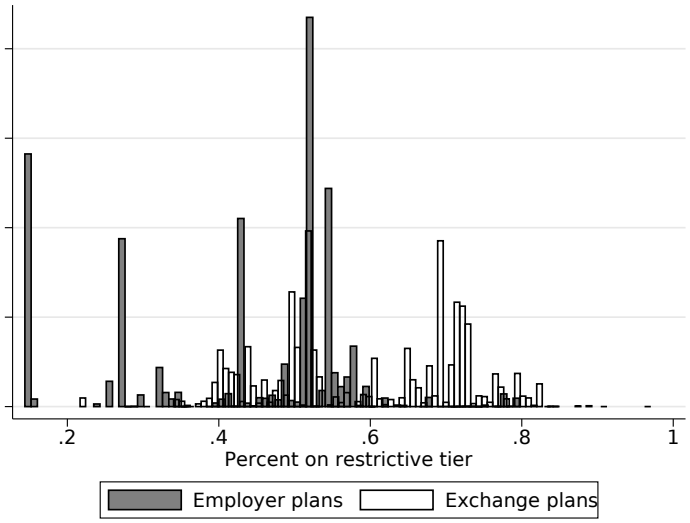
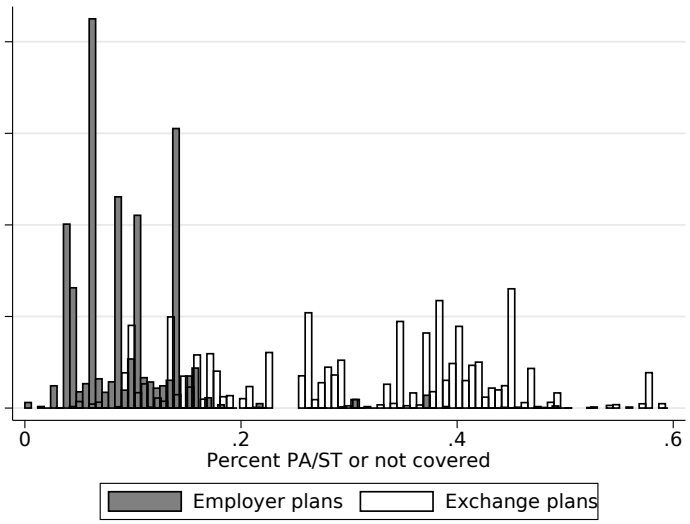
Figure 1: Formulary Data: Tiering in Employer and Exchange Plans

(A) Assignment to Restrictive Tier; Specialty or Higher

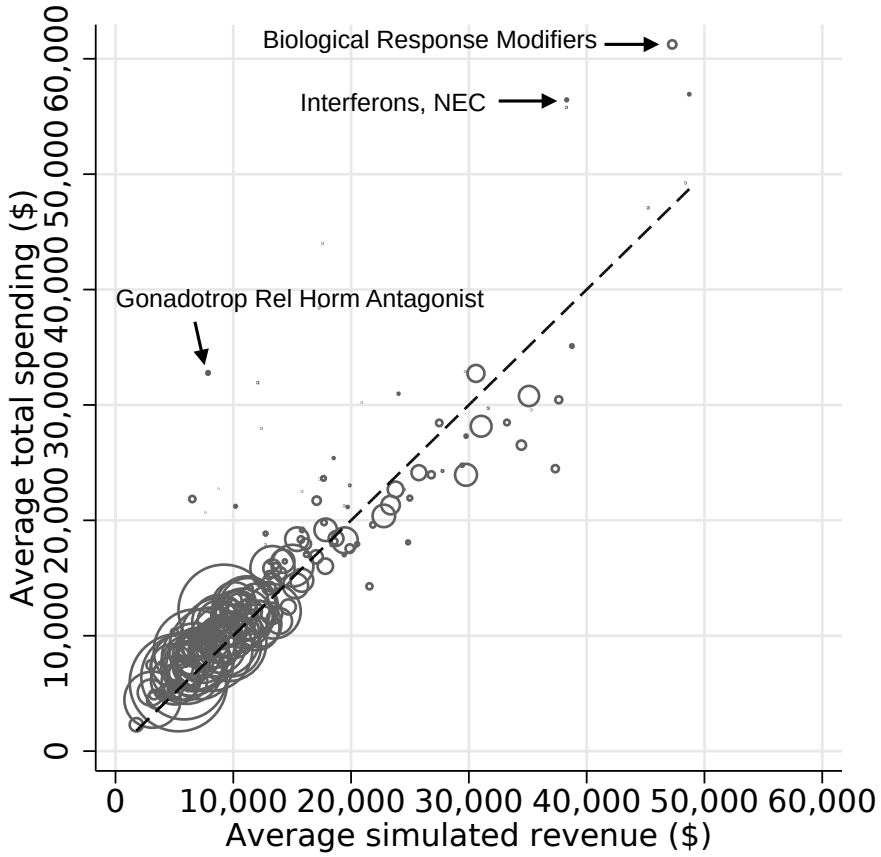


(B) Non-price Hurdles to Access



Note: Histograms indicate the fraction of drugs contained in restrictive tiers in employer and Exchange plans. Observations are plans. In Panel A, restrictive tiers are defined as the specialty tier or higher. See Table 1 for a complete ranked listing of the tiers. Panel B repeats the histogram for the fraction of drugs requiring prior authorization or step therapy (PA/ST) or explicitly listed in the formulary as not covered.

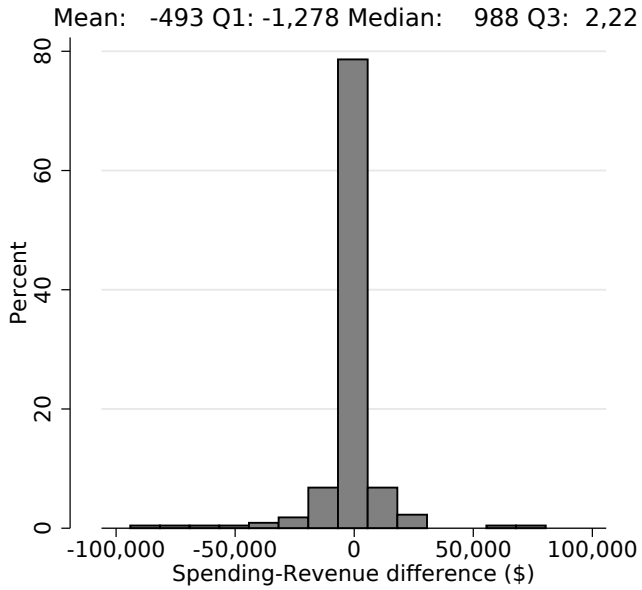
Figure 2: Actionable Selection Incentives Remain Net of Risk Adjustment



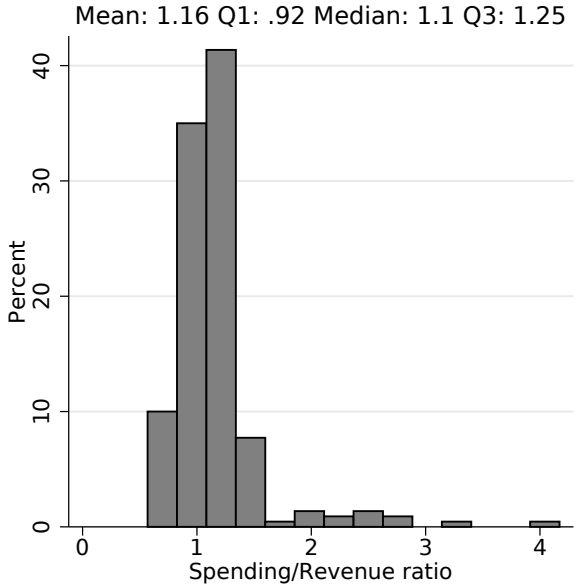
Note: Figure plots the relationship between healthcare spending and simulated revenue for each therapeutic class of drugs. Means are for total spending or revenue, calculated over the set of consumers who generate at least one drug claim in the class. Simulated revenue is calculated according to the 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. The dashed line at 45 degrees indicates the break even point.

Figure 3: Distributions of Selection Incentives Across Drug Classes

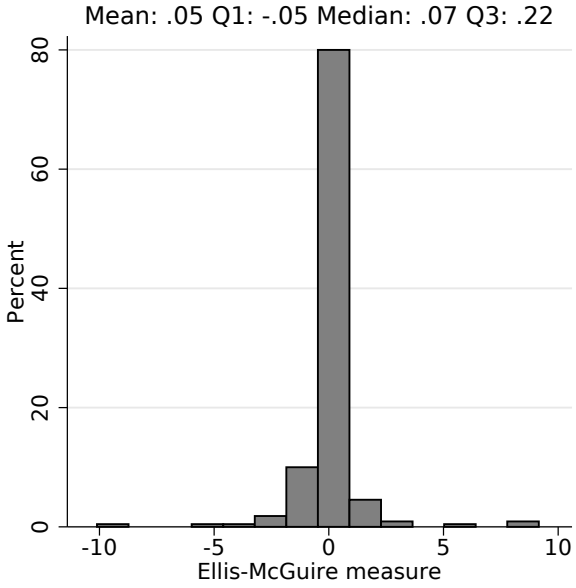
(A) Level Difference



(B) Spending/Revenue Ratio

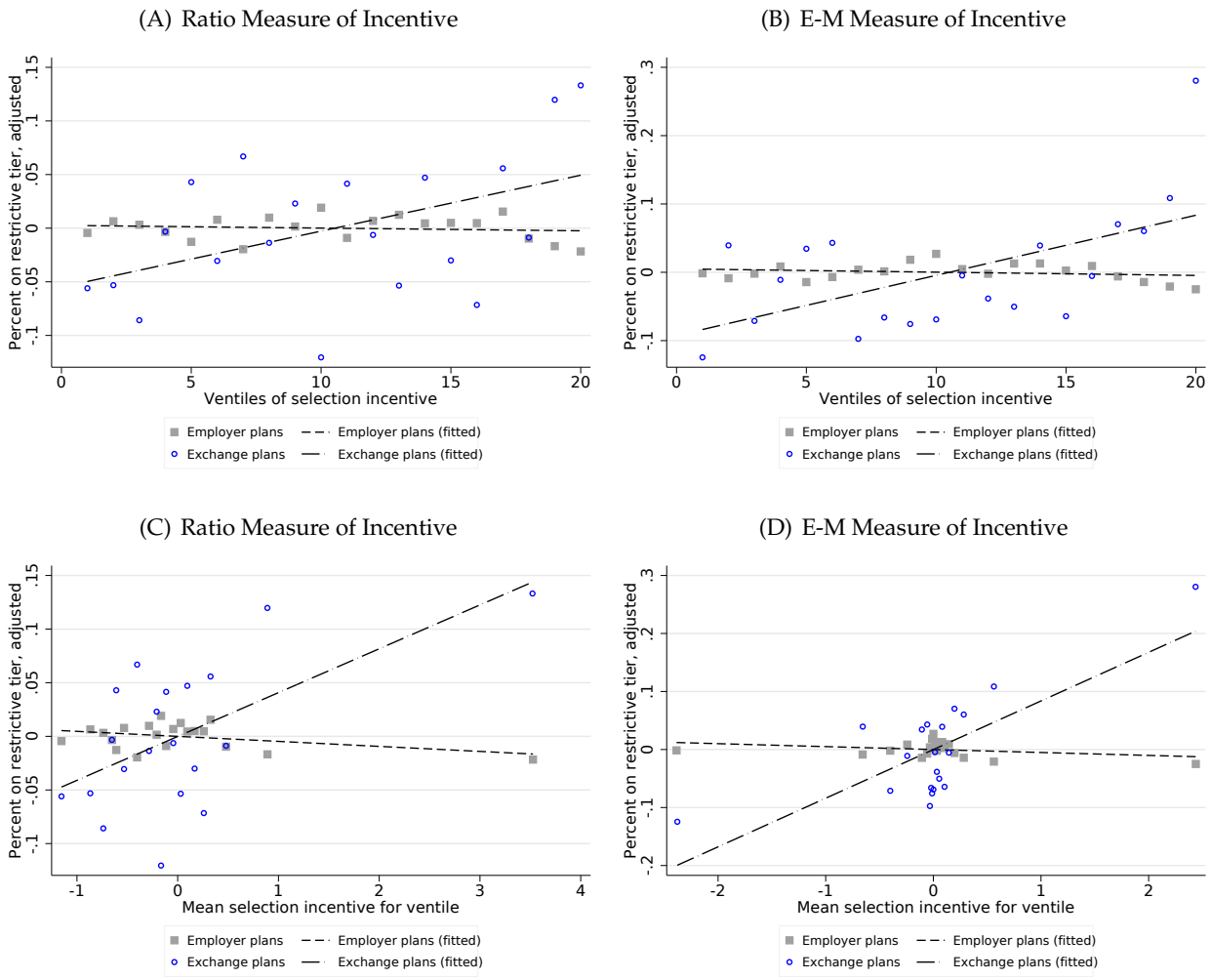


(C) Ellis-McGuire Measure



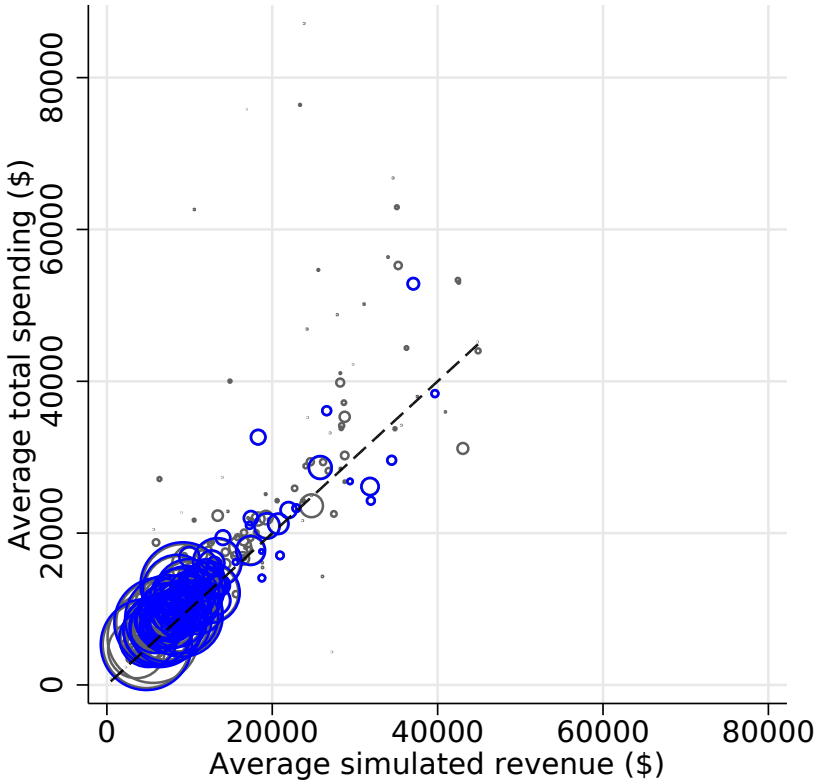
Note: Figure displays histograms of the selection incentives described by Equation (7). Panel (A) shows the distribution of the level difference measure. Panel (B) shows the distribution of the spending/revenue ratio, in which a value of 1 is neutral. Panel (C) shows the Ellis-McGuire selection incentive, in which a value of 0 is neutral. Although most classes have neutral or small associated incentives, important outliers exist.

Figure 4: Main Result: Selection Incentive and Restrictive Tiering in Two Markets



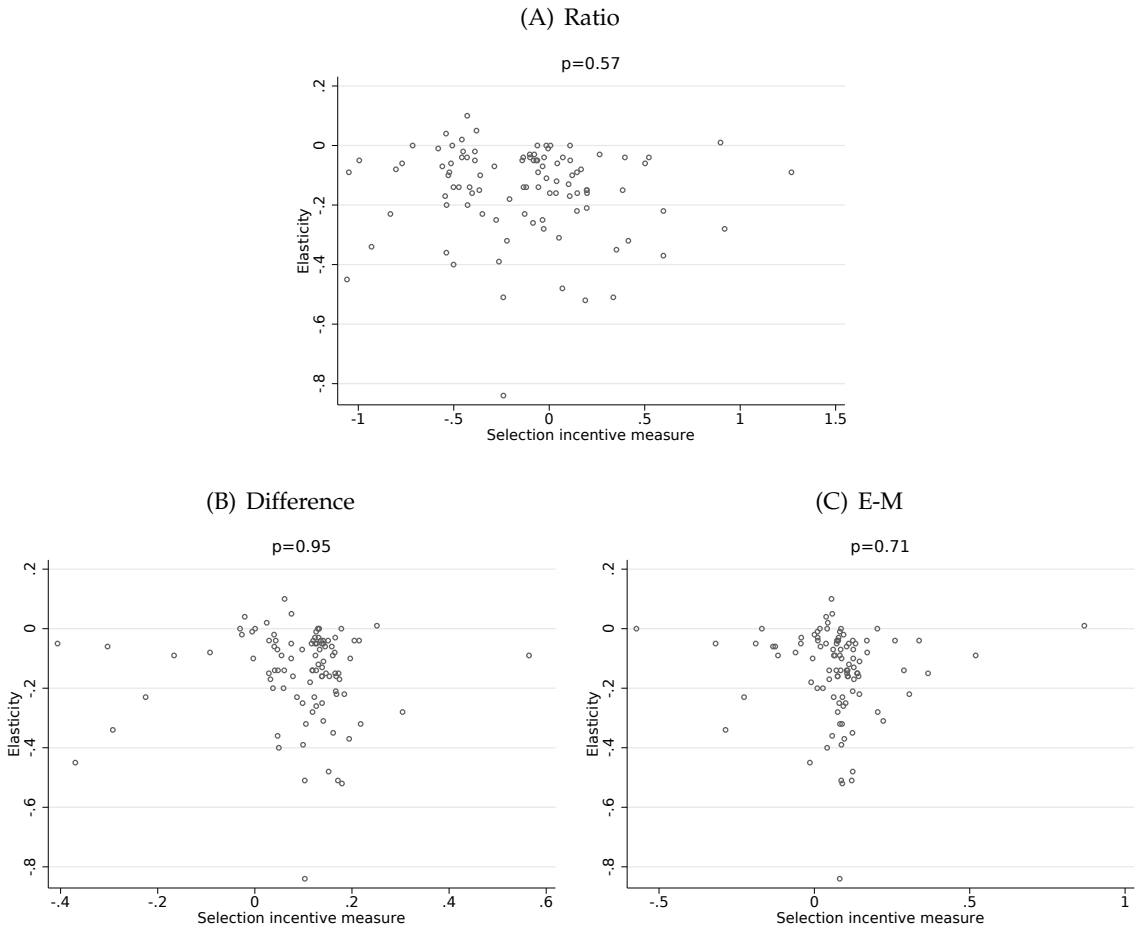
Note: Figure plots semi-parametric versions of the difference-in-differences regression described in Equation (9). Each point corresponds to a group of drugs within a ventile of the indicated selection incentive measure. To generate the position along the vertical axis, we find the residual from a regression of class-by-plan generosity on drug class fixed effects and plan fixed effects as in Equation (9). The left panels use the spending/revenue ratio selection incentive measure. The right panels use the Ellis-McGuire measure. 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 Exchange and employer plans.

Figure 5: 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 6: 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.

Table 1: Summary Statistics: Formulary Tiering in Employer and Exchange Plans

	Formulary Data		CCIIO Cost-Sharing Data	
	Employer Plans	Exchange Plans	Mean Silver Copay, if no Coinsurance	Fraction Subject to Coinsurance
	(1)	(2)	(3)	(4)
Number of plans	3194	501		
Covered lives per plan	14,723	20,343		
Non-Retrictive Tiers Total:	**0.57**	**0.41**		
Generic preferred	0.21	0.17	$10	11%
Generic	0.00	0.05		
Preferred brand	0.09	0.05	$41	18%
Covered/ Non-preferred brand	0.28	0.14	$73	30%
Restrictive Tiers Total:	**0.43**	**0.59**		
Specialty	0.00	0.01	$117	66%
Not listed	0.33	0.27		
Medical	0.00	0.01		
Prior Authorization/Step (PA/ST)	0.01	0.10		
Not covered	0.08	0.20		
Therapeutic Classes	220	220		

Note: Table lists formulary statistics separately for self-insured employer and Exchange plans in columns 1 and 2, respectively. The Exchange plans in column 2 cover the universe of Exchange formularies in 2015. The employer plans cover about one third of all consumers enrolled in an employer plan in 2015. 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. Tiers are harmonized across plans by the database creator, MMIT. Columns 3 and 4 are derived from a separate data source: the CCIIO public use files that describe Exchange plan attributes. In column 3, we calculate the mean copay associated with each tier in a sample limited to silver plans that charge only a copay (no coinsurance) in the relevant tier. Column 4 reports the fraction of plans that charge coinsurance at each tier.

Table 2: Actionable Selection Incentive: Drug Classes with the Largest Spending - Revenue Gaps

Selection Rank	Class	Most Used Drug in Class	Per Capita Enrollee Spending	Per Capita Enrollee Revenue	Net Loss: Cost - Revenue	Ratio: Cost/ Revenue	Ellis-McGuire Measure
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Largest Incentives to Avoid							
1	Gonadotropins, NEC	Ovidrel	$21,848	$6,522	$15,326	3.3	0.3
2	Biological Response Modifiers	Copaxone	$61,245	$47,268	$13,977	1.3	1.3
3	Opiate Antagonists, NEC	naltrexone	$23,639	$17,662	$5,977	1.3	0.3
4	Ovulation Stimulants, NEC	clomiphene citrate	$10,306	$5,003	$5,304	2.1	0.2
5	Pituitary Hormones, NEC	desmopressin	$21,711	$17,078	$4,633	1.3	1.0
6	Vitamin A and Derivatives, NEC	Claravis	$7,472	$3,044	$4,428	2.5	0.2
7	Bioflavonoids and Comb, NEC	Metanx (algal oil)	$19,170	$15,840	$3,329	1.2	0.2
8	Oxytocics, NEC	methylergonovine	$11,183	$8,112	$3,071	1.4	0.5
9	Analg/Antipyr, Opiate Agonists	hydrocodone-acetaminophen	$12,214	$9,212	$3,001	1.3	0.8
10	CNS Agents, Misc.	Lyrica	$18,369	$15,405	$2,965	1.2	1.3
Largest Incentives to Attract							
211	Antineoplastic Agents, NEC	methotrexate sodium	$28,157	$31,042	-$2,885	0.9	-0.4
212	Multivit Prep, Multivit Plain	Folbic	$21,928	$24,986	-$3,058	0.9	0.0
213	Coag/Anticoag, Anticoagulants	warfarin	$30,775	$35,103	-$4,328	0.9	-0.5
214	Cholelitholytic Agents, NEC	ursodiol	$28,481	$33,232	-$4,751	0.9	-0.7
215	Diuretics, Loop Diuretics	furosemide	$23,946	$29,759	-$5,813	0.8	-0.7
216	Ammonia Detoxicants, NEC	lactulose	$30,452	$37,633	-$7,181	0.8	-0.6
217	Anticonv, Hydantoin Derivative	phenytoin sodium extended	$14,284	$21,559	-$7,275	0.7	-0.5
218	Cardiac, Antiarrhythmic Agents	amiodarone	$26,519	$34,461	-$7,942	0.8	-0.5
219	Digestants and Comb, NEC	Creon	$44,621	$56,971	-$12,350	0.8	-0.7
220	Cardiac, Cardiac Glycosides	Digox	$24,480	$37,338	-$12,857	0.7	-1.0

Note: Table lists costs and revenues associated with the drug classes that map to the most and least profitable consumers. Column 2 lists the drug class name. Column 3 lists the most popular drug in the indicated class, by count of users in our MarketScan claims data. Column 4 displays the average total healthcare spending associated with consumers who utilize any drug in the class, $\overline{C_c}$. Column 5 displays the average simulated revenue associated with consumers who utilize any drug in class, $\overline{R_c}$. A single consumer whose claims span several drug classes will contribute to multiple rows of the table. Columns 6 through 8 display for the listed classes the three selection incentive measures used in the analysis.

Table 3: Main Result: Selection Incentive Predicts Restrictive Design in Exchanges Relative to ESI

	Panel A					
Dependent Variable:	Fraction of Class Tiered Specialty or Higher					
Selection Incentive Variable:	Ratio (Cost/Revenue)		Difference (Cost - Revenue)		Ellis-McGuire Measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Exchange X Selection incentive	0.046***	0.045**	0.044**	0.012	0.046***	0.010
	(0.014)	(0.022)	(0.017)	(0.014)	(0.018)	(0.015)
Exchange X Selection incentive ventile 20		0.006		0.300***		0.296***
		(0.105)		(0.076)		(0.089)
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	858,440	858,440	858,440	858,440	858,440	858,440

	Panel B					
Dependent Variable:	Fraction of Class Tiered Prior Auth./Step Therapy/Not Covered					
Selection Incentive Variable:	Ratio (Cost/Revenue)		Difference (Cost - Revenue)		Ellis-McGuire Measure	
	(7)	(8)	(9)	(10)	(11)	(12)
Exchange X Selection incentive	0.018*	0.031**	0.020*	0.008	0.018*	-0.002
	(0.011)	(0.016)	(0.011)	(0.011)	(0.010)	(0.014)
Exchange X Selection incentive ventile 20		-0.074		0.108		0.159**
		(0.092)		(0.083)		(0.078)
Therapeutic class FEs	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X
Therapeutic classes	220	220	220	220	220	220
Observations (plan X state X class)	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 the class-specific selection incentive. The coefficient of interest is on the interaction between an indicator for Exchange plans and the selection incentive variable, with the latter computed in the three ways described in Equation (7). The selection incentive used in each regression is indicated at the column header. In columns 1 through 6, the dependent variable is the fraction of drugs within the class placed on the specialty tier or higher. In columns 7 through 12, the dependent variable is the fraction of drugs within the class that require prior authorization or step therapy (PA/ST) or are explicitly listed in the formulary as "not covered." See Table 1 for a complete ranked listing of the tiers. 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). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: How Sophisticated is the Insurer Response to Selection Incentives?

Dependent Variable:	Fraction of Class Tiered Specialty or Higher						
Selection Incentive Variable:	Ratio	Ellis-McGuire	Ratio	Ellis-McGuire	Ratio	Ellis-McGuire	Ratio and E-M Simultaenoulsy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exchange X Selection incentive	0.046***	0.046***	0.051***	0.041***	0.043***	0.025	
	(0.014)	(0.018)	(0.015)	(0.013)	(0.013)	(0.019)	
Exchange X Average spending associated with class			0.042***	0.041***			
			(0.011)	(0.009)			
Exchange X Average in-class, drug-only spending					0.047***	0.036**	
					(0.013)	(0.018)	
Exchange X Ratio measure							0.038***
							(0.014)
Exchange X Ellis McGuire measure							0.039***
							(0.017)
Therapeutic class FEs	X	X	X	X	X	X	X
Plan FEs	X	X	X	X	X	X	X
Therapeutic classes	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

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. 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 5: Salience and Substitution: Popular Drugs and Cheap Drugs

	Panel A			
Within-Class Subsample:	Most Popular Drugs in Class			
	75th Percentile of Popularity or Higher		90th Percentile of Popularity or Higher	
Selection Incentive Variable:	Ratio (Cost/ Revenue)	Ellis-McGuire Measure	Ratio (Cost/ Revenue)	Ellis-McGuire Measure
	(1)	(2)	(3)	(4)
Exchange X Selection incentive	.061***	.081***	.074***	.098***
	(.022)	(.022)	(.025)	(.022)
Therapeutic class FEs	X	X	X	X
Plan FEs	X	X	X	X
Therapeutic classes	188	188	156	156
Observations (plan X state X class)	733,576	733,576	608,712	608,712
	Panel B			
Within-Class Subsample:	Least Expensive Drugs in Class			
	25th Percentile of Cost or Lower		10th Percentile of Cost or Lower	
Selection Incentive Variable:	Ratio (Cost /Revenue)	Ellis-McGuire Measure	Ratio (Cost /Revenue)	Ellis-McGuire Measure
	(5)	(6)	(7)	(8)
Exchange X Selection incentive	0.058***	0.051**	0.061***	0.048**
	(0.015)	(0.020)	(0.015)	(0.020)
Therapeutic class FEs	X	X	X	X
Plan FEs	X	X	X	X
Therapeutic classes	220	220	220	220
Observations (plan X state X class)	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. The dependent variable is the fraction of drugs in the plan $\times$ state $\times$ class tiered specialty or higher, as in Panel A of Table 3. In Panel A here, we limit the sample to the most popular drugs in each class when calculating the dependent variable. In columns 1 and 2, we limit the sample to the 75th percentile of popularity or higher *within each class* (and limit to classes with at least 4 drugs). In columns 3 and 4, we limit the sample to the 90th percentile of popularity or higher within each class (and limit to classes with at least 10 drugs). In Panel B we limit the sample to the least expensive drugs in each class when calculating the dependent variable. In columns 5 and 6, we limit the sample to the 25th percentile of drug prices and below in each class, and in columns 7 and 8, we limit the sample to the 10th percentile of drug prices and below in each class. When finding the least expensive drugs, we rank all drug claims in a class by cost, and make the sample cut at the appropriate point (25th percentile or 10th percentile) of the distribution of claim costs, including all drugs with any claims below the cutoff. 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 6: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

APPENDIX

A 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:[50]

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

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.[51] We assume that reinsurance is funded by an actuarially fair per capita reinsurance premium, $\bar{re}$.[52] In words, the reinsurance payment is 80% of the individual 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:[53]

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

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

[50] 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.

[51] 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.

[52] In practice, the Exchange reinsurance program is also funded by a similar premium, but it is assessed across almost all covered lived in the US, not just across individuals in the Exchanges.

[53] 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.

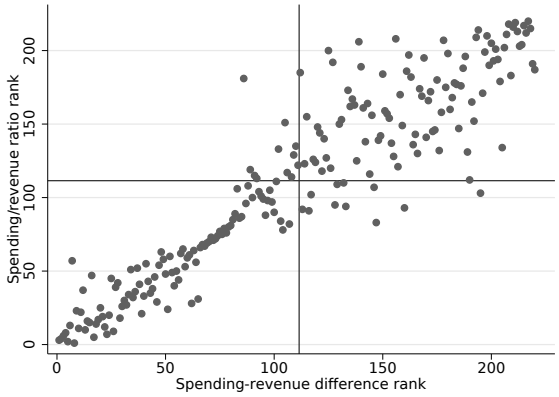
measures.

B Therapeutic classifications

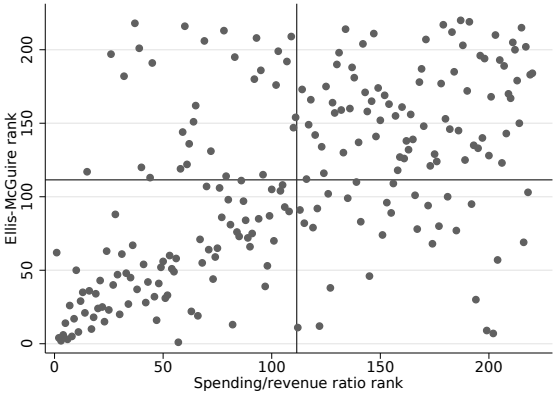
In most of the analyses presented in this paper we rely on the REDBOOK therapeutic classification that is also used in the Marketscan data. There are 257 classes in the REDBOOK classification, of which we analyze the 220 classes for which we are able to construct our selection incentive measures (because they are associated with claims in the Marketscan data) and that also appear in our formulary data. We also use another therapeutic classification system, 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 A1: Rank-Rank Correlations of the Three Selection Incentive Measures

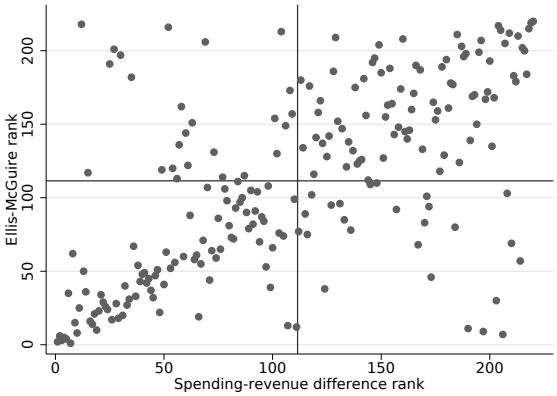
(A) Ratio and Levels



(B) E-M and Ratio



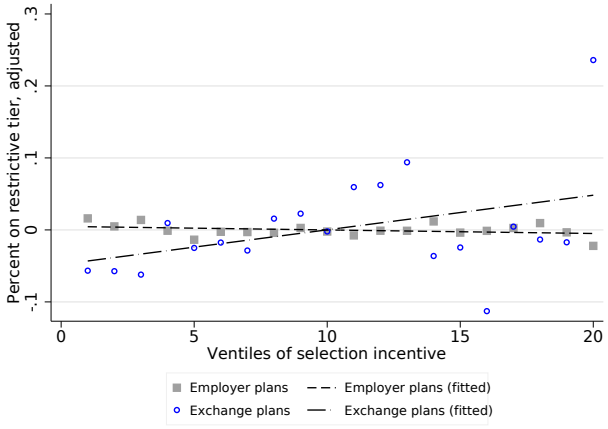
(C) E-M and Levels



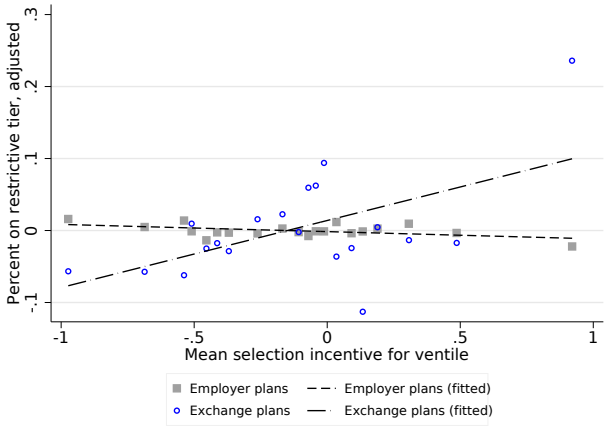
Note: Figure plots rank-rank scatters of the three selection incentive measures discussed in Section 4.1. The axes range from rank 1 to rank 220, with rank 1 implying the strongest incentive to avoid enrollees. For each of the 220 classes, the scatterplot shows how the ordering of profitable and unprofitable 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 A2: 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 (9). Figure repeats Figure 4, 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 4 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: 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. Tiers are harmonized across plans by the database creator, MMIT. See notes to Table 1 for additional detail.

Table A3: 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 A4: 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 A5: 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 A6: 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 A7: Patterns Persist within Pharmacy Benefits 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 Benefits 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.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$