Sorting on Plan Design:
Theory and Evidence from the ACA

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Abstract

Health insurance plans often have multi-dimensional cost-sharing features, including deductibles, coinsurance rates etc. In this paper, I show that under asymmetric information, the desire of the low risk types to avoid pooling with higher risk types create proliferation of plan designs: high risk types who are more likely to experience large losses prefer plans with a straight-deductible, while low risk types who are more likely to have no or small losses prefer plans with coinsurance for smaller losses and large maximum out-of-pocket. As a result, allowing for multidimensional contracts reduce the welfare loss from asymmetric information. Consistent with the theory, I show that in the ACA federal exchange, where multi-dimensional design is allowed, there is large variation in plan designs, and that straight-deductible plans attract individuals with significant higher ex-post medical spending and ex-ante risk scores. I simulate the potential welfare effects of removing the plan design variation. *JEL Codes*: D82, G22, I13.

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There is a growing literature studying the optimal contract design in selection markets like health insurance markets. Many of these works simplify plan options as vertical choices along a single dimension of financial attributes, typically represented by the coverage level, the deductible or the maximum out-of-pocket (MOOP) (Ericson and Sydnor, 2017; Marone and Sabety, 2022). In theory, however, any level of coverage can be achieved by many different combinations of deductibles, coinsurance rates and MOOPs. In fact, health insurance plans exist in real markets often have multi-dimensional financial attributes.

This extra variation in cost-sharing designs raises policy debates on plan standardization. Given that consumers are often confused about health insurance plans, limiting such variation is a choice by some health insurance markets (Abaluck and Gruber 2011, 2019; Bhargava, Lowenstein and Sydnor 2017). For example, several health insurance marketplaces require that plans can only vary along a single cost-sharing dimension, as a way to simplify the choices consumers face.[1] Whether these regulations improve efficiency depends crucially on how consumers evaluate and sort along these different designs. If multi-dimensional financial attributes provide financial values to certain individuals, then removing them may reduce social surplus.

In this paper, I develop a conceptual framework to show under asymmetric information, different risk types prefer different levels of coverage, but also different combinations of the cost-sharing attributes to achieve that coverage level. My model predicts that asymmetric information distorts not only the levels of coverage consumers seek but also the plan designs they will choose. The model setup is similar to Rothschild-Stiglitz (1978), where insurers use different cost-sharing rules to screen individuals with unknown risk types. The key difference from the classic model is that I allow individuals to have multiple loss states, thus different risk types differ in terms of their likelihood of experiencing smaller or larger losses. In response, insurers offer plans with multiple cost-sharing attributes, and plans differ in their average coverage rates (i.e. coverage level) and also the

[1] In the Netherland health insurance markets, plans have a single deductible and no other financial attributes. In some state-based Affordable Care Act (ACA) exchanges (e.g. California), a single design is allowed per coverage tier (the coverage tier is defined as the fraction of losses covered for the average population.)

coverage fraction for a specific loss state (i.e. cost-sharing design). I also assume plans have fixed, positive loading.

My model predicts that different risk types sort into different cost-sharing designs under asymmetric information. In a Rothschild-Stiglitz style separating equilibrium, the high-risk type sorts into their first best plan. Given positive loading, the first-best plan for the high-risk type is less than full insurance. Classic results from Arrow (1963) indicates that such plan has a straight-deductible, in which individuals pay full losses below the deductible and are fully insured once they reach the deductible level. The low-risk type distorts their coverage to avoid pooling with the other type. Asymmetric information creates a force that pushes lower-risk consumers to choose plan designs with more coverage for smaller losses (in the form of coinsurance and lower deductible) while forgoing coverage on larger losses (in the form of higher MOOP).[2] In summary, the equilibrium plan desired by the high-risk type has a straight-deductible design, while the plan desired by the low-risk type has lower deductible and some coinsurance and a higher MOOP. I demonstrate that this theoretical prediction holds both in an unregulated competitive separating equilibrium and in regulated markets with perfect risk adjustment.

My model predicts that restricting plan designs to be single dimension can create large welfare losses. In unregulated competitive markets, plan design variation—specifically, the existence of plans with low deductibles and high MOOP—helps sustain a more efficient separating equilibrium. When consumers can sort along only one dimension of cost-sharing (i.e., deductibles), low-risk individuals end up sacrificing substantially more coverage to avoid pooling with higher-risk individuals. When there is perfect risk adjustment, restricting plans to be only straight-deductible plans also reduces the surplus of the low-risk type. However, because under risk adjustment the marginal costs of insurance to the individual might be different from the social costs, the impacts on the overall social surplus is ambiguous.

[2] The sorting result relies on the insight that low-risk individuals signaling themselves by accepting less coverage in the states they are less likely to experience. This insight is also documented by theoretical works studying other selection markets, including the English annuity markets (Rothschild 2007, Finkelstein, Poterba, and Rothschild, 2009) and bundled coverage for property and casualty insurance (Crocker and Snow, 2011).

In the second part of the paper, I examine the empirical relevance of sorting by plans launched in the Affordable Care Act (ACA) Federal Exchange (healthcare.gov), a market with risk-adjustment regulations. I combine publicly available data on the cost-sharing attributes, premiums, enrollment, and claims costs for plans launched between 2014 and 2017 in this market. The ACA Federal Exchange organizes plans into four "metal tiers" based on the level of coverage they provide for a benchmark average population: Bronze (60%), Silver (70%), Gold (80%), and Platinum (90%). Within these tiers, insurers have significant latitude in designing the cost-sharing attributes of their plans in different combinations.

I use this empirical setting to examine two predictions from the model: first, in a market with heterogeneity in risk distributions and limited regulation in plan designs, there will be a proliferation of plans with different cost-sharing designs. Indeed, I find in the ACA Exchange there exists large variation in plan designs. For example, the within-county variation in the 2017 Silver deductible is more than $3,000 for half of the counties. Though previous models can also explain the variation in coverage levels, my model helps rationalize the fact that there are often multiple cost-sharing designs within and across coverage levels.

Second, variation in plan design creates room for sorting by risk type in the ACA market. My theoretical model predicts that plans with straight-deductible designs will be attractive to those with average to above-average risk but will be unattractive for lower-risk consumers. Using plan-level claims costs and insurer-level risk transfers information, I find that within a metal tier, individuals enrolled in the straight-deductible plans have significantly higher ex-post medical expenditure, and insurers offer straight-deductible plans receive significantly larger risk transfers. Other confounding factors, including moral hazard, plan type, national network, health savings account (HSA) eligibility, and rural versus urban availability, cannot fully explain these differences.

In the last part of the paper, I calibrate the likely impacts of removing plan design variation in the ACA Federal Exchange. Specifically, I compare the market outcome under two sets of menus: The actual 2017 plans offered in the ACA Exchange and a hypothetical choice set replacing all options with a straight-deductible plan of the same premium. I assume consumers have different risk distributions, but also allow a fraction of "behavioral types", who randomly pick plans available in the choice set, as opposed to choosing the plan maximizing their expected utility. The numeric exercise highlights the following trade-off: Restricting plans to be straight-deductibles reduces the chance that the behavioral high-risk types choose the wrong plan; however, that also removes valuable options for the low-risk types and might hurt them. The aggregate impact depends on the fraction of these different types.

To evaluate the implication of such regulations, I construct realistic distributions of health risks derived from Truven MarketScan data and use levels of risk aversion estimated in the literature. I then simulate the plans chosen by each type. Finally, I calculate the difference in market efficiency between these two environments.

I estimate that when there are no behavioral types, the overall efficiency for the ACA would be only slightly higher ($10 per person per year) with regulated plan designs. The increase in the higher-risk types surplus because of the availability of the straight-deductible plans are largely offset by the decrease in the lower-risk types surplus. When there are more behavioral types, however, the benefits to the higher-risk types dominate. This is because plans with high out-of-pocket limits create the possibility of a costly mistake for higher-risk consumers, who are disproportionately adversely affected by such plans. I show that the efficiency benefits of regulating plan design in the ACA Exchange are significantly higher if a moderate share of consumers makes plan-choice mistakes.

The paper contributes to the literature studying endogenous contract design under asymmetric information. Existing literature documents, both theoretically and empirically, that adverse selection forces can create differences in the coverage generosity for different medical services and providers, the so-called service-level selection (Frank, Glazer, and McGuire 2000; Ellis and McGuire 2007; Geruso and McGuire 2016; Layton et al. 2017). Empirical works illustrate that sorting can happen along the dimension of provider network (Shepard 2016), drug formulary (Lavetti and Simon 2014; Carey 2016; Geruso, Layton, and Prinz 2019), and overall plan generosity along a single dimension (Decarolis and Guglielmo, 2017). My paper highlights that a similar adverse selection force applies to the design of multi-dimensional cost-sharing attributes. The theoretical model formalizes the selection incentives and how these incentives shape the cost-sharing designs. I find selection happens along multi-dimensional cost-sharing attributes in the ACA markets. The model also provides explanations to empirical patterns found in previous literature in other markets.[3]

The paper also contributes to the discussion of optimal plan and menu design in health insurance markets (Ho and Lee, 2020; Tilipman 2022), including the optimal design of financial attributes when there exists consumer confusion and moral hazard (Ericson and Sydnor, 2017; Marone and Sabety, 2022). Prior literature studying the issue often simplify plans into vertical choices with a single-dimensional cost-sharing feature, i.e. deductible level or coverage level. My paper highlights that the multiple cost-sharing attributes represent important channels for risk sorting, and thus complicates the welfare implication of standardizing the cost-sharing attributes. The general insights that allowing multi-dimensional screening enhances efficiency has been discussed in prior theoretical works under different contexts.[4] I highlight the point explicitly in the design and regulation of cost-sharing attributes of health insurance plans, and calibrate its welfare implications in the ACA market when there also exists consumer confusion.

The rest of the paper is organized as follows: In Section 2, I lay out the conceptual framework and derive the conditions leading to design distortion. In Section 3, I examine the issue empirically using the ACA Federal Exchange data. In Section 4, I discuss the implications for regulating plan designs. The final section concludes.

2 Conceptual Framework of Optimal Plan Design

Modern health insurance plans often have complicated cost-sharing rules: different plans may have different deductible, coinsurance rates, maximum out-of-pockets etc. In this section, I present a conceptual framework to illustrate that different cost-sharing designs can be motivated by classic asymmetric information forces. A key difference of my model from previous works (for example, Rothschild and Stiglitz, 1976) is that I assume the losses are not binary and can take on multiple values. I show that under

[3] For example, Decarolis and Guglielmo (2017) documented that 5-star Medicare Part C plans increase OOP limits and decrease deductible levels in the face of the pressure of worsening risk pools. My conceptual framework predicts that this movement towards non-straight-deductible plans can be driven by the incentives to attract low-risk types.

[4] For example, Crocker and Snow (2011) shows that insurers exploit bundled coverage of different losses and perils in property and casualty insurance markets to screen consumers and enhance the efficiency. Cooper and Hayes (1987) and Dionne and Doherty (1994) illustrate the efficiency gain using experience rating and repeated contracts.

asymmetric information (community rating), individuals with different loss distributions sort into different cost-sharing designs. I then illustrate the welfare implications of policies removing such cost-sharing complexities and restrict to a single design.

2.1 Model Setup

The market is consisted of two risk types, L and H. Each type i face some uncertainty in their medical expenditure x_s in state s. The realization of $s \in S$ is uncertain, with state s obtaining with probability f_s^i for individual i.

I consider a general state-dependent insurance plan that captures the wide range of potentially complex plan designs consumers could desire. Specifically, an insurance plan is defined as a function $\boldsymbol{l}: s \to R^+$, where $l_s \equiv l(s)$ is the value of the function evaluated at s, and l_s represents the insurer payment in state s. l_s satisfies the condition $0 \leq \ l_s \leq \ x_s$.

DEFINITION 1 (Straight-Deductible Plan): *A straight-deductible plan with a deductible of d is defined as:*

$$l(x_s) = \begin{cases} 0, if\ x_s \leq d, \\ x_s - d, if\ x_s > d. \end{cases}$$

Under such plans, individuals pay full losses out-of-pocket below the deductible level and get full insurance once the losses reach the deductible level. Full insurance is a straight-deductible plan with zero deductible. All other plans are non-straight-deductible plan.

The financial outcome (consumption) after insurance in each loss state is $w_i - x_s + l_s - p(\boldsymbol{l})$, where w_i is the non-stochastic initial wealth level and $p(\boldsymbol{l})$ represents the premium of plan $\boldsymbol{l}$. I assume individual i has a concave utility function u_i over the financial outcome of each loss state: $u_i' > 0, u_i'' < 0$. Individuals are offered a menu of contracts C and choose the plan maximizing their expected utility:

$$\max_{\boldsymbol{l} \in C} \sum_s u_i(w_i - x_s + l_s - p(\boldsymbol{l}))f_s^i. \tag{1}$$

2.2 Model Predictions

We now turn to predictions from the model. I consider three cases: symmetric information, asymmetric information with no risk adjustment, and asymmetric information with perfect risk adjustment. All proofs are in Appendix A.

Case 1 - Symmetric Information/Risk-Based Pricing

For this single-risk-type case, I drop subscript i for simplicity of exposition. Assume perfectly competitive insurers set premiums as a linear function of the expected covered expenditure:

$$p(\boldsymbol{l}) = \theta \sum_{s} f_s l_s + c.$$

where $\theta \geq 1$ is a proportional loading factor, and $c \geq 0$ is a fixed loading factor. Suppose further that all possible insurance contracts are available and priced this way.

PROPOSITION 1**.** *For any fixed loading factors, the contract maximizing expected utility is a straight deductible plan.*

The result is a direct application of Arrow (1963) and Gollier and Schlesinger (1996). When there is no loading, the optimal contract will be full insurance. When there is positive loading, expected-utility-maximizing contract has some cost-sharing. Proposition 1 states that such a contract has a straight-deductible design.

Case 2 - Asymmetric Information/Community Rating

Now consider the case where there are two risk types (L and H) in the market, and insurers cannot distinguish L from H ex-ante, or they could not charge different premiums for the same plan because of community rating regulations. The premiums of the plan are a mechanical function of the expected covered losses given who sorts into that plan, plus loading.[5]

A key component of the model is how L and H are defined. It is not the purpose of the model to fully characterize that equilibrium. Instead, I consider a potential separating equilibrium similar to Rothschild and Stiglitz (1976), where one risk type (H) gets the first-best contract under symmetric information, and the other type (L) distorts their coverage to prevent the higher-risk type from pooling with them. H and L types are defined such that the incentive compatibility constraint is constrained for H and slack for L. In equilibrium, H sorts into the first-best plan, which, according to proposition 1, is a straight-deductible plan. L maximizes the expected utility by choosing from incentive compatible plans.

[5] The assumption rules out equilibrium concepts with cross-subsidization among plans (as in Spence 1978).

I further assume that both types face multiple loss states, and there exist at least two non-zero, positive coverage loss states, s and t, where $x_s \neq x_t$ and $\frac{f_s^L}{f_s^H} \neq \frac{f_t^L}{f_t^H}$.

PROPOSITION 2. *Among all incentive compatible plan for H, the one that maximizes the expected utility of L has a non-straight-deductible design.*

The intuition can be illustrated starting from the first-best plan for L, which has a straight-deductible design. Such a plan will not be incentive compatible, however, because it is priced based on the loss distribution of L, and makes H deviate. Therefore, L needs to change their coverage to prevent pooling with H. They could achieve this by either reducing coverage for larger loss states or reducing coverage for small loss states. Doing the former would make the plan less attractive to H since larger losses are more likely to happen for H. Sacrificing coverage for large losses and transferring to coverage for small losses is less problematic for L, though, since most of their losses are likely to be small.

Case 3 - Asymmetric Information/Community Rating with Perfect Risk Adjustment

In many markets, regulators impose risk adjustment regulations to flatten premium differences among plans and to remove screening incentives for insurers. I consider a market with perfect risk adjustment where the premium reflects the market average risk and is a linear function of the expected costs that would be obtained if both risk types enroll in the plan.[6] This setting approximates the regulatory environment in many US health insurance markets, including Medicare Advantage, Medicare Part D, and the ACA Exchange.

Under perfect risk adjustment, the premium is:

$$p(\boldsymbol{l}) = \frac{\theta}{2}\left(\sum_s f_s^L l_s + \sum_s f_s^H l_s\right) + c. \tag{3}$$

To obtain the sorting result, I assume that H and L have loss distributions with monotone likelihood ratio property in losses: for any two loss states s and t where $x_t > x_s$, it is also true that $\frac{f_s^L}{f_s^H} > \frac{f_t^L}{f_t^H}$. Further assume that there exist at least two non-zero loss

[6] This definition is a special case of Einav, Finkelstein and Tebaldi (2018), which defines risk adjustment as a transfer r_i to the insurer if individual i enrolls in the plan. Insurers' profits are then defined as $p_j - (\theta \sum_s f_s^i l_s - r_i)$. My setting is equivalent as setting r_i as the difference between the cost of insuring that type, $\theta \sum_s f_s^i l_s$, and the market average cost. Geruso et al. (2019) also uses the same formula to define perfect risk adjustment.

states for both types. I also assume that the feasible plans imply non-decreasing out-of-pocket spending when the loss increases: $x_s - l_s \leq x_t - l_t, \forall x_s < x_t$. This is a common feature for health insurance plans because the losses are cumulative within a year.

PROPOSITION 3. Under perfect risk adjustment, H sorts into a straight-deductible plan; L sorts into a non-straight-deductible plan.

Under perfect risk adjustment, the premiums are effectively "shared" between the two types. The marginal cost of reducing out-of-pocket spending depends on the spending of the both types. Ideally, both types want to have the premium covering more of their own spending than the spending of the other type. The utility-maximizing plans for each type thus direct more coverage into states where that type is relatively more likely to experience. Since H is more likely to experience larger losses, they sort into straight-deductible plans, which offer full coverage for large losses. The opposite is true for L.

The proposition can be extended to a scenario where both risk types are choosing from plans with the same premium:

COROLLARY 1. Under perfect risk adjustment and among all plans have the same premium, H sorts into a straight-deductible plan; L sorts into a non-straight-deductible plan.

The proposition can be further extended into a more general result comparing different risk types preference for plans with more or less coverage for smaller losses. Let $EU_i^{\boldsymbol{l}}$ denote the individual i's expected utility for plan $\boldsymbol{l}$.

PROPOSITION 4. Consider any two loss states such that $x_s < x_t$. Suppose there are two plans $\boldsymbol{a}$ and $\boldsymbol{b}$, which 1) have the same perfectly risk-adjusted premiums and 2) offer the same coverage except for loss states s and t: $l_s^{\boldsymbol{a}} - l_s^{\boldsymbol{b}} > 0 > l_t^{\boldsymbol{a}} - l_t^{\boldsymbol{b}}$. For two risk types L and H with the same utility function and whose loss distribution is such that $f_s^L > f_s^H$ and $f_t^L < f_t^H$, $EU_L^{\boldsymbol{a}} - EU_L^{\boldsymbol{b}} > EU_H^{\boldsymbol{a}} - EU_H^{\boldsymbol{b}}$.

In summary, the complexity of plan designs can be motivated by multiple loss states and asymmetric information (community rating). Under perfect information, all types desire straight-deductible plans. Under asymmetric information, L has incentive to deviate to non-straight-deductible designs. With perfect risk adjustment, the results hold when risk types satisfy monotone likelihood properties.

2.3 Implications for Plan Standardization Regulation

The sorting result presented in 2.2 may have welfare implications for evaluating welfare impacts of plan standardization policy. To illustrate, I first define the welfare notion as follows. The consumer surplus of individual i choosing plan $\boldsymbol{l}$, cs_{il}, is defined as the certainty equivalent of choosing plan $\boldsymbol{l}$ relative to no loss:

$$\sum_s u_i(w_i - x_s + l_s - p(\boldsymbol{l}))f_s^i = u_i(w_i + cs_{il}).$$

The social surplus of individual i choosing plan $\boldsymbol{l}$, ss_{il} is defined as:

$$\sum_s u_i\big(w_i - x_s + l_s - \tau_i(\boldsymbol{l})\big)f_s^i = u_i(w_i + ss_{il}),$$

where $\tau_i(\boldsymbol{l}) = \theta \sum_s f_s l_s + c$, is the social cost of offering plan $\boldsymbol{l}$ to individual i. Note that when there is no risk adjustment, $\tau_i(\boldsymbol{l}) = p(\boldsymbol{l})$, and cs_{il} is the same as ss_{il}. Under risk adjustment, this relation is in general not true. The overall social surplus is defined as the sum of ss_{il} for all individuals in the market.

First, consider a plan standardization regulation which restricts all plans to be straight-deductible. Under asymmetric information, *H* sorts into straight-deductible plan, so they are not affected. However, any straight-deductible plan *L* chooses under the design regulation makes them strictly worse off. When there is no risk adjustment, social surplus coincides with consumer surplus, so this implies a decrease in social surplus. Under perfect risk adjustment, however, exactly how the social surplus will change is ambiguous: perfect risk adjustment imposes externality in the pricing because the marginal costs of the extra cost-sharing are shared by the other risk type. Restricting to straight-deductible plan may or may not reduce such externality, so the social surplus may or may not improve. We summarize the result in proposition 5:

> *PROPOSITION 5. Removing non-straight-deductible plan makes L strictly worse off, H indifferent. It strictly reduces the social surplus under no risk-adjustment, and have ambiguous impacts on social surplus when there is perfect risk adjustment.*

The social and consumer losses from such a regulation can be sizable. Consider the following numeric example. Two risk types are constructed using the 2013 Truven MarketScan data, where *L* has a mean spending of \$1,843 (SD=\$7,414), and *H* has a mean spending of \$7,537 (SD = \$22,444). I assume both types have CARA utility function and a risk aversion level of 0.0004. I then calculate their desired plans among the three-arm design and constant coinsurance plans under 1) risk-based pricing and 2) community rating with no risk adjustment. The details of the calculation are in Appendix B.

Table 1 shows the numeric example. Under community rating, *L* sorts into a coinsurance plan with 23% self-paid coinsurance rate, which causes $561 welfare loss relative to the first-best plan. It happens to have the same fraction of losses covered as the first-best plan, so the welfare losses of community rating purely come from the design distortion. If *L* is forced to choose a straight-deductible plan, they sort into one with a $13,154 deductible, which offers much less coverage and the surplus reduction is more than doubled.

Table 1. Numeric Example: Community Rating and Design Regulation

		Risk Type	Plan	% losses covered	Surplus
Risk-Based Pricing		*H*	Straight-deductible, deductible = $1,820	82%	/
		L	Straight-deductible, deductible = $933	77%	0
Community Rating and No Risk Adjustment	No Regulation	*L*	Constant coinsurance, coinsurance rate = 23%	77%	-$561
	Straight-Deductible Only	*L*	Straight-deductible, deductible = $13,154	23%	-$1,256

Note: Risk types constructed from Truven MarketScan data with details in Appendix C. Risk-based pricing refers to the scenario where each plan is priced based on the risk type choosing it and the premium for the same plan can vary for different risk types. Community rating refers to the scenario that insurers cannot vary premiums for the same plan for different risk types, and the premium is a linear function of the expected spending of the risk type choosing the plan. Straight-deductible only refers to the scenario that only straight-deductible plans are available. Surplus refers to either consumer surplus or social surplus, as they are the same under this case. I rescale them so the value is the difference from the first-best plan.

Second, consider annother type of plan standardization regulation, which allows a single design for a specific coverage level. Here, coverage level is defined as the fraction of losses covered for the average population, as in the case of the ACA Exchange. Plans with the same coverage level thus have the same premiums under perfect risk adjustment. Given two risk types, the regulation is optimal only when the specified design coincides with the socially optimal design for each type. In general, it is not obvious whether such a policy will improve or reduce welfare.

There is one specific scenario under which such a regulation will reduce consumer surplus. Suppose L is more risk averse than H, such that under perfect risk adjustment, the plan desired by both types have the same premium. According to Proposition 3, however, the two types desire different plan designs. Table 2 shows a numeric example where, under perfect risk adjustment and no plan regulation, both types prefer plans with around \$6,200 premium under perfect risk adjustment, while only H chooses a straight-deductible design. When this is the case, restricting to a single design per coverage level will at least make one of the risk types worse off than if all designs are allowed.

Table 2. Numeric Example: Community Rating and Perfect Risk Adjustment

	Risk Type	Risk Aversion Level	Plan	Premium
Community Rating and Perfect Adjustment	H	0.00005	Straight-deductible, deductible = \$1,272	\$6,193
	L	0.002	Deductible=\$700, 10% coinsurance after deductible, Out-of-pocket Max=\$3,100.	\$6,152

Note: Risk types constructed from Truven MarketScan data with details in Appendix C. In calculating the plans chosen, I consider the three-arm design with a deductible, an out-of-pocket maximum, and coinsurance rate, and the constant coinsurance plans.

In summary, restricting to a single design often reduce the surplus of certain risk types. Besides, it may also reduce the overall social surplus. These regulations are often motivated by consumer confusion, and the rationale being that restricting to a single design makes consumers easier to choose. My conceptual framework suggests that a complete evaluation of such policies depends on the tradeoff of consumer confusion and welfare loss from a single design. An open question then is to what extent does the sorting force matters in reality, which I now discuss in Section 3.

3 Empirical Analysis in the ACA Market

There are two key predictions from the conceptual framework. First, in insurance markets with community rating, different risk types prefer different plan designs. Second, high risk types prefer straight-deductible plans, while the low risk types prefer non-straight-deductible designs. In this section, I show the empirical relevance of the theory by illustrating that these predictions are consistent with the plan offering and sorting pattern observed in the ACA Federal Exchange. The ACA Federal Exchange is particularly suitable to study the design variation because the market allows large freedom for insurers to offer different plan designs.

3.1 Institutional Background

The Affordable Care Act Exchange (the Exchange henceforth) was launched in 2014. Private insurers can offer comprehensive health insurance plans, and the federal government provides subsidy for certain low-income consumers who purchased plans. The Exchange regulates the actuarial value (AV) of plans, defined as the fraction of losses covered for the average population, but leaves insurers with latitude to offer a range of different plan designs. The Exchange has regulation on the market-average AV: Plans can only have a population-average AV of around 60%, 70%, 80%, and 90%, and are labeled as Bronze, Silver, Gold and Platinum plans respectively. The Exchange also requires plans to have an upper limit on the out of pocket spending ($7,150 in 2017). Some state Exchanges further regulate the plan designs.[7] Insurers are otherwise free to offer any cost-sharing attributes. Each state can either join the Federal Exchange or establish its state exchange. I focus on the federally administered Individual Exchange and state-Exchange operated via healthcare.gov, where insurers are allowed to offer any design satisfying the AV regulation and the out of pocket maximum limit.[8] The list of states are in Appendix Table 1.

There are also ACA regulations limiting insurers' ability and incentive to do risk screening. The regulators calculate risk scores for enrollees and transfer money from insurers with a lower-cost risk pool to insurers with a higher-cost risk pool, to equalize plan costs across insurers. Further, there is a single risk pool pricing regulation: the premiums of plans offered by the same insurer will be set based on the overall risk pool of that insurer,

[7] Regarding cost-sharing flexibility, insurers in Connecticut, District of Columbia, Massachusetts, New York, Oregon, and Vermont must offer standardized options and can offer a limited number of non-standardized options within a metal tier. California requires all insurers to offer only standardized plans.

[8] Plans launched in states using healthcare.gov are still subject to each state's insurance regulation, for example, the essential health benefits that must be covered by a plan may differ across states.

not the risk of individuals enrolled in each plan. Third, community rating limits insurers' ability to set premiums based on individual characteristics. Premiums can only vary by family composition, tobacco use status, and (partially) by age group.

3.2 Data and Sample

I use the Health Insurance Exchange Public Use Files from 2014 to 2017. This dataset is a publicly available dataset of the universe of plans launched through healthcare.gov. I define a unique plan based on the plan ID administered by CMS, which is a unique combination of state, insurer, network, and cost-sharing attributes, and also is the level of choice in the menu faced by consumers. For each plan, I observe its financial attributes (deductibles, coinsurance rates, copays, OOP-limits, etc.), premium (which varies at plan-rating area level), and enrollment numbers in that plan (at plan-state level). I focus on the 2017 year for the main analysis, but the results are similar for other years.

I use the Uniform Rate Review Data from 2016 to 2019 to study risk sorting.[9] The data include average premium and claim cost information at the plan level for 50% of plans, and insurer-level claim costs and risk transfer information for 75% of the insurers.[10] For the rest of the insurers, I match almost all of them in the Medical Loss Ratio filings, another insurer-level dataset reporting premium and claim costs, but not risk transfers. I use the 75% insurers as the baseline because all variables of interests are available, and use the Medical Loss Ratio filings as robustness checks. Appendix Table C1 summarizes the data sources used in the empirical analysis.

I focus on Bronze, Silver, Gold and Platinum plans. Catastrophic plans are dropped from the analysis because they have no officially reported AV and are only available to individuals below 30. Each Silver plan has three cost-sharing reduction variations available to the low-income population. These plans have the same premium as the standard Silver plan and a higher AV. In the analysis of plan design, I use the cost-sharing characteristics of the standard Silver plan. In studying the sorting pattern, because the claim costs are reported for all variations, I label straight-deductible design based on the standard Silver plan. It does not matter if I use the cost-sharing variation instead, because in almost all

[9] The reports have a two-year lag, so the 2016 -2019 reports match the 2014-2017 plan information.
[10] The plan level information is rare because only plans with more than 10% premium increase are required to report, while the insurer level information is required for all insurers unless they exit the market.

cases, the straight-deductible design is consistent across the standard plans and the cost-sharing variations.

I study the cost-sharing features of a plan's first-tier in-network coverage for essential health benefits. The utilization rate of the first-tier in-network coverage is 94.59% on average for the sample plans, and 99.47% of the total premium is contributed to cover the essential health benefits on average. I exclude preventive care because all plans are required to cover it with no cost-sharing. The resulting benefits is in Appendix Table 2 are consistent with the list of the AV calculator, a tool created by CMS to compute the AV of each plan.[11]

A straight-deductible plan is identified as one under which 1) all benefits are subject to the general deductible, 2) there is no coverage before hitting the deductible, and 3) there is no cost-sharing after the deductible. Screenshots of an example straight-deductible plan and a non-straight-deductible plan on the ACA Exchange are in Appendix Figure 1.

3.3 Analysis of Plan Design Variations in the ACA Market

The market is populated with both straight-deductible and non-straight deductible plans. Table 3 shows the market share of straight-deductible plans over time. Take the year 2016 as an example. There are around 4,000 unique plans offered in this market. Among them, 13% are straight-deductible plans. In total 9.7 million consumers purchased a plan in this market, and about 7.6% of them selected a straight-deductible plan.

Table 3. Market Share of Straight-Deductible Plans

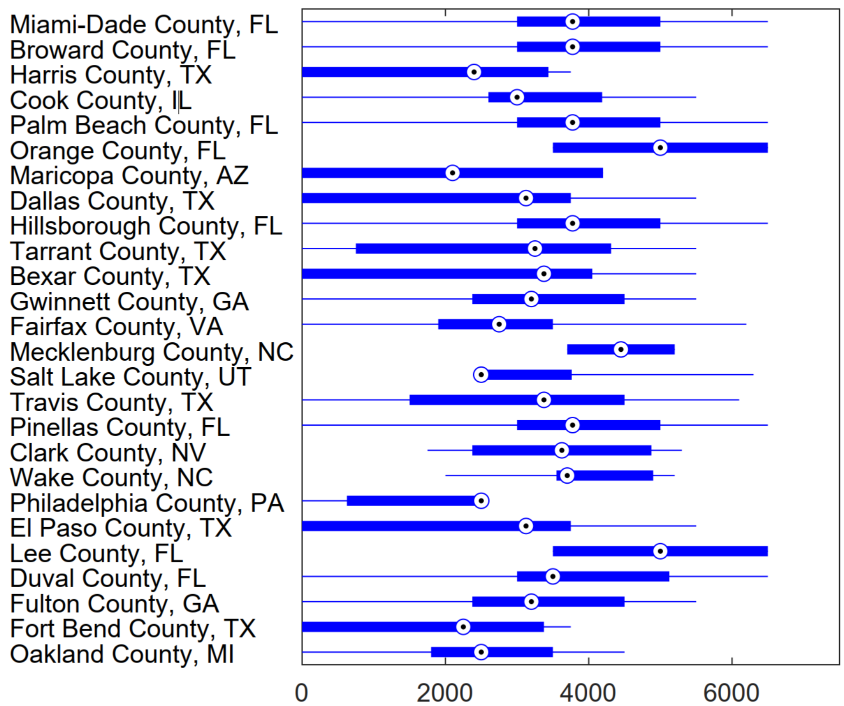
year	% plans that are straight-deductible	Total number of plans	Enrollment share in straight-deductible plans	Total number of consumers (mm)
2014	10.48%	2,871	5.40%	5.57
2015	9.58%	4,573	6.97%	9.22
2016	12.99%	3,966	7.63%	9.71
2017	11.14%	3,106	4.52%	9.00

Note: The sample includes the universe of plans launched via healthcare.gov. The enrollment data of Silver plans represent four cost-sharing variations: The standard Silver plans and three cost-sharing reduction plans (which are only available to lower-income households). I classify straight-deductible for these plans based on the standard plan.

[11] Accessed from https://www.cms.gov/CCIIO/Resources/Regulations-and-Guidance/

Consumers also face substantial variation in plan designs within a metal tier. Figure 1 shows the 2017 Standard Silver plan's deductible distribution for counties with the top 25 enrollment size via Healthcare.gov. In all these counties, consumers face over $2,500 differences in the Silver deductibles. The large variation in plan design faced by a particular consumer is prevalent for many other counties and different metal tiers. For example, on average, the range in the MOOP of Gold plans faced by a particular consumer is $2,000. Appendix Figure 2 shows the distribution of deductible and MOOP across all counties.

Figure 1. Distribution of the 2017 Silver Deductible for the Largest 25 County



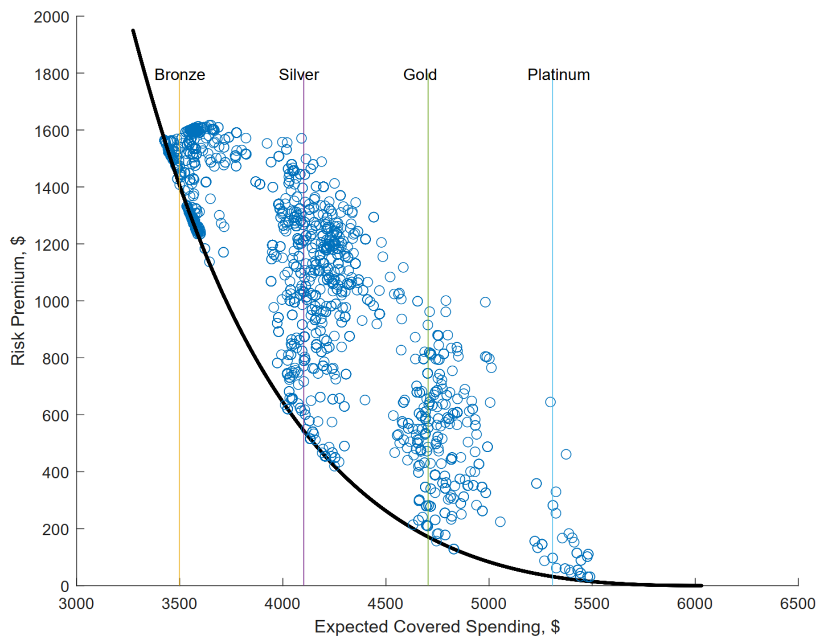
Note: Data from the 2017 CMS Health Insurance Exchange Public Use Files. Counties are ranked by the enrollments via Healthcare.gov, and included counties have enrollment number larger than 50,000. Silver plans are standard Silver plans. The deductible refers to tier-one, in-network coverage for an individual, cumulative over a year. The circle in the center of the bar indicates the median, the lower and upper bounds of the bar indicate the 25th and 75th percentile, and the lower and upper of the whiskers indicate the minimum and the max.

To quantify whether the variation in plan designs within a metal tier is economically important, I evaluate each plan available in the Exchange for the individual facing the market-average risk obtained from the CMS AV calculator. I first apply the cost-sharing rules to this distribution and calculate the stochastic out-of-pocket spending, a, for each plan. I then calculate the risk premium R, using the following formula:

$$E[u(w-a)] = u\,(w - E(a) - R),$$

where w represents the wealth level, a represents the stochastic out-of-pocket spending and $E(a)$ represents its expected value, and $u(\cdot)$ is the utility function. The risk premium represents the sure amount the individual need to receive to be indifferent between enrolling in that plan and a full-insurance plan, when both are priced at their fair AV. The risk premium is zero for a risk-neutral enrollee and increases when the risk aversion level increases and when the level of uninsured risk increases. In the calculation, I assume a CARA utility function with risk-averse coefficient at 0.0004 (Handel, 2013). Straight-deductible plans have the lowest R, holding fixed $E(a)$ (Gollier and Schlesinger 1996).

Figure 2. Risk Premium and Expected Covered Spending for 2017 Plans



Note: Data from 2017 CMS Health Insurance Exchange Public Use Files. The sample includes all Exchange qualified health plans offered to individuals via healthcare.gov. Each dot represents one plan, which is a unique combination of cost-sharing feature, insurer, plan type, drug formulary and state. Plans launched in multiple rating areas or counties are only counted once. For Silver tier, the sample excludes the cost-sharing reduction plans. Risk premium and expected covered spending is calculated using the 2017 CMS AV Calculator Distribution. The black solid line shows the lowest possible risk premium conditional on expected spending level (achieved by straight-deductible plans) and does not represent actual plans. A dot might represent multiple plans if they have the same cost-sharing feature. The vertical lines show the targeted AV for each metal tier. Not all plans line up with the vertical lines perfectly, partially because the regulator allows for a two percent error margin, and partially because of measurement error in my calculation.

The variation in risk premiums provided by different plan options within a metal tier is sizable for individuals facing the market average risk. Figure 2 shows the risk premium and the expected covered spending for all plans in the four metal tiers for 2017. The four clusters represent the four metal tiers. A substantial difference in risk premium exists for a range of AV levels. For example, among plans in the Silver tier, which have an AV around 70%, the smallest risk premium relative to full insurance is around $500 and is achieved by the straight-deductible plan (black line in Figure 2). In contrast, the largest risk premium for Silver plans is nearly $1,000 larger, originating from plans that have lower deductibles and MOOP closer to the maximum allowed by the regulation.

3.4 Evidence of Sorting by Health into Different Plan Designs

The existence of the plan design variation may create room for selection. The theoretical analyses in Section 2 suggest that straight-deductible plans are more attractive to the higher-risk types. An ideal test for the sorting pattern requires observing the full distribution of individuals enrolled in different plans. Unfortunately, I don't have that information for all plans available in the ACA Exchange. Instead, I focus on testing the first moment of the loss distribution. Specifically, I compare the plan-level average total claim costs per member month between straight-deductible and other designs. The values include the total ex-post medical expenditure, including consumer cost-sharing and insurer liability.

A comparison in unconditional means of the total medical expenditure illustrates that there is a strong correlation between average medical spending and plan designs, consistent with the theoretical predictions on sorting. Figure 3 shows the average monthly total medical expenditure for straight-deductible plans and the other designs across the metal tiers. The straight-deductible plans have significantly higher medical expenditure than the other plans. The difference is more than $400 per month for Silver and Gold plans.[12]

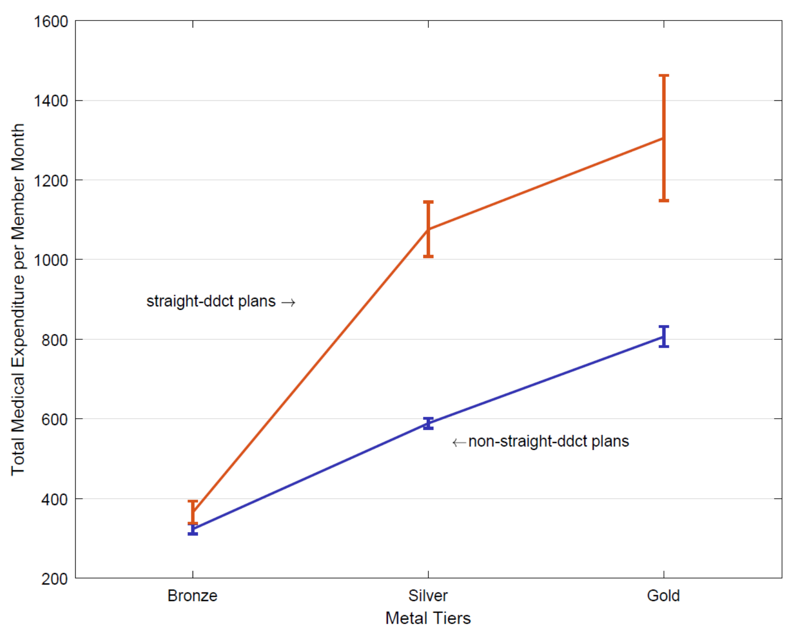
The correlation between plan design and expenditure might be driven by other confounding factors, which I address using the regression model. First, given that only plans with excessive premium increase is subject to report the claim information, the mean difference of reported plan may not be representative. To address the concern, I leverage the fact that insurers are subject to the single risk pool requirement and will spread out unexpected medical expenditure of a particular plan among all plans offered, making all plans subject to reporting. In the plan-level regression, I include insurer-year fixed effects

[12] The difference in the Bronze tier is smaller because the OOP-limit regulation limited the room for design difference. There are few Platinum plans in the market, so they are not shown in the graph.

so that the differences in claims costs between different plan designs are identified off of within-insurer variation.

Second, the correlation might be driven by other plan characteristics. I first examine whether other plan attributes are correlated with whether the plan has a straight-deductible design. Appendix Table C2 suggests that straight-deductible plans are not correlated with other plan attributes consumers might consider in choosing a plan, including plan types, whether having a national network, new or existing plan, offered to rural counties etc. The only significant difference is that straight-deductible plans are more likely to have a health savings account (HSA), which is due to the fact that these accounts require a high-deductible, and straight-deductible plans have high deductibles in a metal tier. Given that individuals with greater health needs may prefer HSA, the correlation between HSA-eligibility and straight-deductible may bias the difference away from zero. I add HSA-eligibility, along with dummies for plan type, and the service area fixed effects as control variables to address the concern.

Figure 3. Average Total Expenditure per Member Month by Plan Design



Notes: The graph shows the mean and 95% confidence interval of the total medical expenditure of plans launched through healthcare.gov in 2014-2017. Only plans with premium changes of more than 10% are reported in the Uniform Rate Review data. Such plans account for about 50% of the universe of plans launched.

Finally, and most importantly, the differences in the ex-post expenditure may reflect ex-post moral hazard instead of selection. Given that moral hazard is likely to be a primary concern for the differences in the ex-post expenditure *across* metal tiers, I control for metal tier fixed effects and actuarial values.[13] Note that it is unclear whether straight-deductible designs will imply more moral hazard than other designs *within* a metal tier: straight-deductible plans have no coverage for small losses and may deter large expenditure because of that.

I further address the moral hazard issue using risk transfer payments as the dependent variable. Risk transfers are calculated based on the average risk scores of enrollees, and reflect the ex-ante medical expenditure risk rather than moral hazard responses. This identification strategy is similar to Polyakova (2016). The risk transfers information is only available at the insurer level, so I construct the independent variable as whether the insurer offers any straight-deductible plan.[14] Consistent with the plan-level comparison, Appendix Table C3 shows that insurers offering any straight-deductible plans are similar to the rest in terms of enrollment size, network types, whether operate in rural areas etc. The only difference is that they are more likely to offer HSA-eligible plans. I add enrollment share in HSA-eligible plan, state and year fixed effects for the insurer-level analysis to control for the potential impacts of HSA-eligibility.

Table 4 shows the comparison at the plan level. On average, individuals enrolled in straight-deductible plans have significantly higher medical expenditure ($157 higher per month, and $1,884 annually), relative to the mean spending of $555 per month ($6,660 annually). I examine the robustness of the results by adding different plan characteristics one at a time. Appendix Figure C1 shows that the estimates are stable when different controls are added, suggesting that other plan characteristics could not explain the cost differences.

Table 4 also shows that premiums are similar for different plan designs in the same metal tier, evaluated either at the plan level or at the plan by rating area level. The little

[13] The sorting into designs within a metal tier could either be driven by the fact that there is negative correlation between risk aversion and risk levels, as illustrated in the numeric example in Table 2, or the sorting pattern conditional on coverage level, as stated in Corollary 1.

[14] Plan-level risk transfers are also estimated by insurers for a subset of plans. However, many insurers use plan premiums to allocate insurer-level risk transfers to plans. According to the single risk pool regulation, different designs are required to have similar premiums within a metal tier, making the allocated plan-level risk transfers inappropriate to capture selection within a metal tier.

difference in premiums suggests that the single risk pool requirement is well enforced and blunt the pass-through of these selection differences to consumers.

Table 5 shows the comparison at the insurer level. Similarly, insurers offering straight-deductible plans experience significantly higher total medical expenditure per member month (column 1) than other insurers. Moreover, they also receive higher risk transfer payments ($40 per member month.) The estimated risk transfer differences take account for more than 75% of the estimated differences in insurers liability.

Table 4. Average Monthly Total Medical Expenditure and Premium: Plan-Level

	(1)	(2)	(3)
	monthly total expenditure	monthly premium	
		collected	charged
straight-deductible	118.52	2.11	0.72
	(21.70)	(3.66)	(1.59)
N	7,842	7,842	72,829
R^2	0.55	0.85	0.73
y-mean	554.74	397.04	265.6
y-sd	382.28	120.56	93.05
Controls	metal tier, network type, HSA-eligibility, insurer FE, year FE		
Fixed Effects	service area FE		rating area FE

Note: Straight-deductible is a dummy variable indicating whether the plan has a straight-deductible design. The AV of a plan is the fraction of losses covered for the average population, which varies no more than four percentage point within a metal tier. Column (1) and (2) include plans between 2014 and 2017 with a premium increase for more than 10%. I dropped those reporting non-positive total expenditure or premium and plans with the top and bottom one percent of either value to avoid impact from extreme values. Each observation is a plan-state-year. The dependent variable in (1) is the average total medical expenditure per member month. The dependent variable in (2) is the average premium per member month. Column (3) includes all plans between 2014 and 2017. The dependent variable is the per-month premium of the single coverage for a 21-old non-tobacco user. Since premium varies by rating area, each observation is a plan-rating area-year. Standard errors are clustered at the insurer level and shown in parenthesis.

The results are robust when controlling for different sets of plan characteristics, imputing missing observations from the Medical Loss Ratio files, and using continuous plan design measures like risk premiums and deductible to MOOP ratios. I present the robustness checks in Appendix Table C4.

As a final note, the sorting pattern may be driven by certain (rational) choice heuristics. For example, the straight-deductible plans have the lowest MOOP within a metal tier. If high-risk individuals care only about the worst-case risk and choose based on MOOP, then they sort into straight-deductible plans. My conceptual framework provides one rationale for such heuristics.

Table 5. Average Monthly Total Medical Expenditure and Premium: Insurer-Level

	(1) Total Expenditure	(2) Insurer Liability	(3) Risk Transfers	(4) Average Premium
Offer Straight-Deductible Plan	71.92	53.84	40.58	14.34
	(27.55)	(22.23)	(13.51)	(13.84)
N	617	617	617	617
R^2	0.262	0.239	0.144	0.604
Dep. Var. Mean	474.7	357.1	-6.201	381.1
Dep. Var. SD	124.1	102.5	66.03	97.42

Note: Each observation is an insurer-year. "Offer Straight-Deductible Plan" is a dummy variable indicating whether an insurer offer any straight-deductible plan. In all columns, the dependent variables are measured using the per member per month value. The dependent variable in (1) is the average total medical expenditure of enrollees in a plan, including consumer cost-sharing and insurer payments. The dependent variable in (2) is the average medical expenditure paid by insurers. The dependent variable in (3) is the average risk transfers an insurer received. The dependent variable of (4) is the average premium. All models include year fixed effects and state fixed effects and the fraction of enrollees in health savings account. The regressions are weighted by the enrollment at each insurer-year. Standard errors are clustered at the insurer level.

4 Estimating Impacts of Plan Design Regulations for the ACA Federal Exchange

The plan offering and sorting pattern in the ACA Exchange suggests that limiting plan design variations might have economically meaningful impacts on consumer welfare. In this section, I calibrate the likely impacts of limiting plan designs in the ACA Federal Exchange. Specifically, I compare the market outcome under two sets of menus: The actual 2017 plans offered in the ACA Exchange and a hypothetical choice set replacing all options with a straight-deductible plan of the same premium. This new choice set has the same number of options and the same premiums as the existing one. The only difference is that all plans have a straight-deductible design.

The exercise highlights the tradeoff between two factors. First, consumers are often confused about the plan design and fail to sort into the suitable plans for them (Abaluck and Gruber 2011, 2019; Bhargava et al. 2017). The consequence of choosing the wrong plan is especially large for the higher-risk types. Given that their desired plans have a straight-deductible design, limiting only to these plans may help mitigate the consequence of sorting into the wrong plan for them. Second, as discussed in Section 2.3, limiting to straight-deductible plans will reduce the consumer welfare of the lower-risk types. The overall surplus then depends on which force dominates.

4.1 Simulation Setup

Demand side. Consumers are modeled as expected utility maximizers choosing plans based on the perceived utility:

$$v_{ij} = \overbrace{\underbrace{\int u\big(-OOP_j(x) - p_j\big)dF_i(x)}_{welfare-relevant\ utility} + \beta\epsilon_{ij}}^{decision\ utility}.$$

The deterministic part, $\int u\big(-OOP_j - p_j\big)dF_i$, is a function of the out-of-pocket spending, OOP_j, and net premium after subsidy, p_j. It determines the welfare-relevant value of each plan j for individual i. The second component of the choice utility is an error component, ϵ_{ij}, that is assumed to be i.i.d following the extreme value type one distribution. It affects the choice of each consumer but is not relevant for welfare. The error term allows me to incorporate the potential for consumer confusion into the simulations. Consumers in the ACA Exchange often face a large choice set, typically around 20 options in each county, making confusion a likely concern. The larger the scaling parameter β, the more randomness there will be in plan choice. $\beta = 0$ represents the case where all consumers choose optimally.

Supply side. On the supply side, I assume there is perfect risk adjustment in the market, which implies that plan premium is a mechanic function of the expected covered spending if all types choose the plan, and insurers are passive in which plan to offer. Even though other literature finds that the risk adjustment is not perfect along dimensions like drug formulary (Layton), the findings in section 3.3 suggests that single risk pool requirement and risk adjustment regulations is successful in flattening the premium level of different plan designs. The perfect risk adjustment assumption seems to be a good characterization of the sorting pattern of this model. Besides, the assumption mitigates the computation burden of finding the equilibrium plans in an environment with many risk types and endogenous plan designs. Finally, I assume all insurers occur the same loading factor of 1.2.

Model calibration. I calibrate the key components of the model to the observed data in the ACA market. I calculate out-of-pocket spending of each plan using the observed cost-sharing attributes. The raw premium is then calculated using the formula under perfect risk adjustment plus loading. In each county, a fraction of individuals receives premium subsidies or are eligible for cost-sharing reduction plans. I collect information on the fraction of subsidized population and the amount of premium subsidy from the 2017 Open Enrollment Period County-Level Public Use File (OEP data). I assume that all risk types are equally likely to receive a premium subsidy.

The risk distributions are constructed from Truven MarketScan data. I create 100 risk types using clustering method, and mean-shifted these distributions such that the average medical expenditure level is benchmarked to the average of the 2017 ACA Federal Exchange. Since I do not have information about the risk distributions at each county, I assume that all counties have the same risk distributions. I also assume that consumers have a constant absolute risk aversion utility function with a risk aversion coefficient of 0.0004.

4.2 Simulation Result

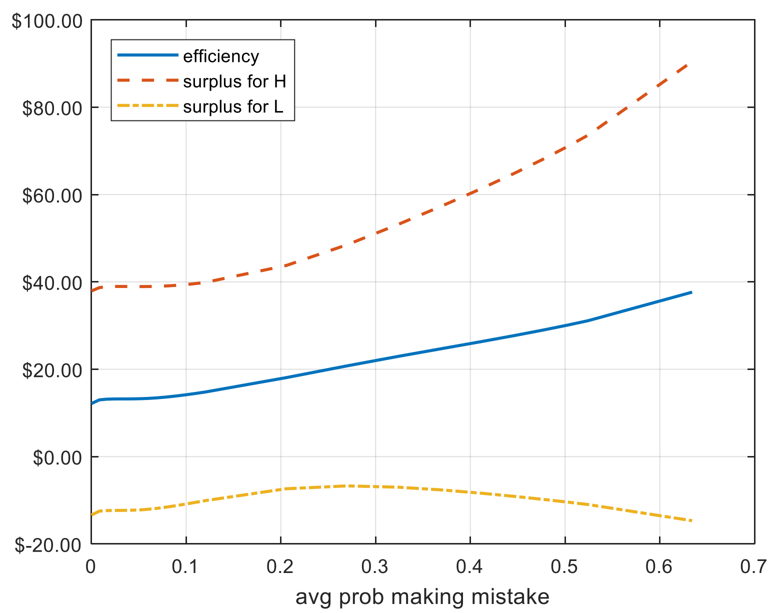
I calculate the impacts of limiting plans to straight-deductible plans on overall efficiency, defined as the expected value to consumers from the chosen plan minus the expected cost to insurer to offer the plan coverage. To illustrate the distributional effects, I also split consumers into those with above and below median expected medical expenditure, and calculate the aggregate consumer surplus for each group.

Figure 4 shows the welfare difference under the straight-deductible choice set and the current choice set. A positive number means consumers are better off under the straight-deductible-only environment than facing the current ACA menu. The x-axis is the fraction of consumers choosing the non-optimal plan, an increasing function of β. When there is no confusion, limiting plans to straight-deductible design increases welfare by about $10 per person per year.

When consumers in the market are more likely to make a mistake in choosing plans, both the overall efficiency and the surplus for higher-risk types increase. For example, when 50% of consumers sort into a wrong plan, the average efficiency is $30 higher with regulation per year, and the surplus for the higher-risk types is \$70 higher per year with regulation. However, such change is not a Pareto improvement: The lower-risk types are worse off under such regulation. At the 50% confusion level, they are worse off by about \$10 per year under the design regulation.

The simulation illustrates that the level of confusion matters for the welfare implications of plan design. DeLeire et al. (2017) show that a low percentage of enrollees who are eligible for cost-sharing reduction plans select dominated options. Their findings suggest that consumers can effectively sort into the optimal metal tiers in the ACA Exchange. However, there is also a broader literature documenting confusion in health insurance choices in other settings. At present, is not well understood how consumers can best choose between plan designs with different cost-sharing designs in the ACA Exchange. This provides an avenue for future research.

Figure 4. Efficiency Effects of Regulating Plan Designs in ACA



Note: The y-axis represents the difference between the value under the design regulation and without the regulation. The regulation replaces all current ACA plans with a straight-deductible plan of the same premium.

5 Conclusion

In this paper, I identify an understudied dimension of sorting in insurance markets: Sorting by plan design. I prove that in a market with asymmetric information, lower-risk consumers will sort into designs with less coverage for larger losses in exchange for more coverage for smaller losses, while higher-risk consumers sort into straight-deductible plans. The sorting pattern exists in both a separating equilibrium without price regulation and a market with perfect risk adjustment.

This sorting pattern is empirically relevant in the US health insurance markets. I document that in the ACA Federal Exchange, there is large variation in the cost-sharing features of plans launched and chosen within a similar coverage level. Such variation in cost-sharing features translates to an economically significant difference in risk protection for consumers facing the market-average risk. I further show that within a coverage level, the straight-deductible plans have a similar premium as the other designs, but have significantly larger claims costs.

The theory and empirical analysis presented here highlight how asymmetric information in risk types can explain the variation in plan designs. However, moral hazard is another rationale for the existence of non-straight-deductible plans. Theoretical research has shown that moral hazard can affect the optimal plan design, changing either the deductible level or the form of coverage (Zeckhauser 1970). Although models with moral hazard can help explain why plan designs are complex, they offer no ready explanation for the simultaneous existence of different plan designs. Empirically, my results using risk scores illustrate that the expenditure differences within an ACA coverage tier are mainly driven by selection and cannot be explained by moral hazard alone. Interesting dynamics might be at play when people have asymmetric information about their moral hazard responses. Those considerations are outside the scope of this paper but could be a valuable direction for future research.

In sum, this paper argues for the importance of studying variation in plan design. My framework illustrates that coverage design variation is an important dimension of sorting under asymmetric information. This work also highlights an underappreciated perspective in evaluating design regulations. Prior literature recognizes that simplifying insurance contract characteristics can make it easier for consumers to compare across plans and can promote competition and efficiency. I illustrate that in a market with asymmetric information, plan design variation can also serve as a tool to separate different risk types and support an equilibrium where lower-risk consumers distort less in their coverage. As a result, removing plan design variation may make the market more likely to unravel and harm efficiency. The overall benefits of standardizing plan design thus depend on the relative importance of these concerns. This paper illustrates the trade-off in a market with risk adjustment and perfect competition. More research is needed to understand the implications of design variation when there is market power.

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Appendix A. Proofs in Section 2

Proposition 1. Proof:

The optimization problem for the consumer is:

$$v = \max_{\boldsymbol{l}} \sum_s u(w - x_s + l_s - p(\boldsymbol{l}))f_s, \qquad \forall \boldsymbol{l}$$

subject to:

$0 \leq \; l_s \leq \; x_s,$

$$p(\boldsymbol{l}) \;= \theta \sum_s f_s l_s + c.$$

$\boldsymbol{l} = (l_1, l_2, \ldots, l_s, \ldots, l_S)$ is the vector of the insurance payments in each state.

The first-order condition is:

$$\frac{\partial v}{\partial l_s} = u_s'(1 - \theta f_s)f_s - \theta f_s \sum_{\tau \neq s} u_\tau' f_\tau \leq 0, \forall s,$$

with equality if $l_s > 0$.

First, note that if $l_s = x_s$ is binding for state s, then it's binding for all other states. This corresponds to the case when $\theta = 1$ and the optimal insurance is full insurance. For $\theta > 1$, full insurance is no longer optimal because of loading. For all states, $l_s < x_s$.

Second, note that the FOC can be rewritten as $u_s' \leq \theta \sum_\tau u_\tau' f_\tau$. The right-hand side is the same for all states, which implies that once binding, $x_s - l_s$ is a constant. Since $u'' < 0$, FOC is binding when x_s is larger than a certain level. Suppose $x_d = d$ is the level where $u_s'(w - x_d) = \theta \sum_\tau u_\tau' f_\tau$. Then the optimal insurance plan has the following form:

$$l_s^* = \begin{cases} 0, & if \; x_s < d \\ x_s - d, & if \; x_s \geq d' \end{cases}$$

which is the straight-deductible design. ■

Proposition 2. Proof:

The optimization problem for L is:

$$\max_{\boldsymbol{l}} \sum_s u_L(w - x_s + l_s - p(\boldsymbol{l}))f_s^L$$

subject to:

$$p(\boldsymbol{l}) \;= \theta \sum_s f_s^L l_s + c,$$

$$0 \leq \; l_s \leq \; x_s,$$

$$\sum_s u_H(w - x_s + l_s - p)f_s^H = A.$$

$\boldsymbol{l} = (l_1, l_2, \ldots, l_s, \ldots, l_S)$ is the vector of the insurance payments in each state. A represents the utility H gets from choosing their optimal contract under full information. The last condition thus represents the binding incentive compatibility constraint for H.

The Lagrange of the above optimization problem is:

$$\mathcal{L}(\boldsymbol{l}) = \sum_s u_L(w - x_s + l_s - p(\boldsymbol{l}))f_s^L - \lambda(\sum_s u_H(w - x_s + l_s - p(\boldsymbol{l}))f_s^H - A).$$

Let u'_{Ls} denote the derivative of lower-risk type utility function with regard to consumption in loss state s. The first-order condition is:

$$u'_{Ls} - \lambda \frac{f_s^H}{f_s^L} u'_{Hs} \leq \theta \left(\sum_{\tau} u'_{L\tau} f_\tau^L - \lambda \sum_{\tau} u'_{H\tau} f_\tau^H \right) \forall s, \tag{4}$$

with equality if $l_s > 0$. Note that since the right-hand side is a constant, $u'_{Ls} - \lambda \frac{f_s^H}{f_s^L} u'_{Hs}$ is the same across loss states with $l_s > 0$.

Now take two loss states s and t such that $x_s \neq x_t, l_s > 0$ and $l_t > 0$. $\frac{f_s^H}{f_s^L} \neq \frac{f_t^H}{f_t^L}$ by assumption. Suppose that a straight deductible is optimal, then $l_s - x_s = l_t - x_t$ (equal consumption when losses are larger than the deductible level). This then implies that $u'_{Ls} = u'_{Lt}$ and $u'_{Hs} = u'_{Ht}$. But since $\frac{f_s^H}{f_s^L} \neq \frac{f_t^H}{f_t^L}$, $u'_{Ls} - \lambda \frac{f_s^H}{f_s^L} u'_{Hs} \neq u'_{Lt} - \lambda \frac{f_t^H}{f_t^L} u'_{Ht}$, contradictory to (4). As a result, the optimal plan for the lower-risk type cannot be a straight-deductible plan. ■

Proposition 3 Proof:

Take any loss state s, and assume that the $\frac{f_s^L}{f_s^H} = \alpha$. The first-order conditions of the coverage in state s for H are:

$$u'_{sH} \leq \frac{\theta}{2}(1 + \alpha) \sum_{\tau} u'_{\tau H} f_\tau^H, \forall l_s,$$

with equality if $l_s > 0$. Similarly, the first-order conditions for L are:

$$u'_{sL} \leq \frac{\theta}{2}(1 + \frac{1}{\alpha}) \sum_{\tau} u'_{\tau L} f_\tau^L, \forall l_s,$$

with equality if $l_s > 0$.

For any two loss states $x_t > x_z$, we know that $\frac{f_t^L}{f_t^H} < \frac{f_z^L}{f_z^H}$. This means whenever $l_t > 0$ and $l_z > 0, u'_{tH} < u'_{zH}$ and $u'_{tL} > u'_{zL}$. Since $u''_H < 0$ and $u''_L < 0$, $l^*_{Ht} - x_t \geq l^*_{Hz} - x_z$ and $l^*_{Lt} - x_t \leq l^*_{Lz} - x_z$. That is, the consumption in state t is always no smaller than the consumption in z for the higher-risk type, and the consumption in state z is always no smaller than the consumption in t for the lower-risk type.

Note that among the plans with non-increasing consumption, the implied consumption in t cannot be larger than the implied consumption in z. This means the higher-risk type will either have zero indemnity at small loss states or a constant consumption c^* once the indemnity is positive. Higher-risk type would want to have larger consumption in state t than in z, but are not able to because of the non-increasing consumption constraint.[15] This means the higher-risk type will desire a straight-deductible plan. The lower-risk type is not constrained and will desire a plan with larger consumption for smaller losses (x_s) than in larger losses (x_t), a non-straight-deductible design. ■

[15] The non-increasing consumption constraint implies that for any loss states z and t where $x_t > x_z$, the allowed plan must imply $c_t \leq c_z$, where c_s denote consumption in state s. Empirically, since most health insurance plans accumulate spending over a year, almost all comprehensive health insurance plans satisfy this condition.

Corollary 1 Proof:

The optimization problem for i is:

$$\max_{\boldsymbol{l}} \sum_s u_i(w - x_s + l_s - \theta \sum_s f_s^L l_s - c) f_s^i$$

subject to:

$$\theta \sum_s f_s^L l_s + c = A,$$

$$0 \leq l_s \leq x_s.$$

$\boldsymbol{l} = (l_1, l_2, \dots, l_s, \dots, l_S)$ is the vector of the insurance payments in each state. A is the fixed premium level individuals are required to choose from.

The Lagrange of the above optimization problem is:

$$\mathcal{L}(\boldsymbol{l}) = \sum_s u_L(w - x_s + l_s - p(\boldsymbol{l})) f_s^L - \lambda(\theta \sum_s f_s^L l_s + c - A).$$

Take any loss state s, and assume that the $\frac{f_s^L}{f_s^H} = \alpha$. The first-order condition of the coverage in state s for H is:

$$u'_{sH} \leq \frac{\theta}{2}(1+\alpha)(\sum_\tau u'_{\tau H} f_\tau^H + \lambda), \forall l_s,$$

with equality if $l_s > 0$. Similarly, the first-order conditions for the lower-risk type are:

$$u'_{sL} \leq \frac{\theta}{2}(1+\frac{1}{\alpha})(\sum_\tau u'_{\tau L} f_\tau^L + \lambda), \forall l_s,$$

with equality if $l_s > 0$. The FOCs are the same as the FOCs in proposition 3 except for adding a constant in the last term of the right-hand side. All the other arguments follow as the proof of proposition 3. ■

Proposition 4 Proof:

Let u denote the utility function for both types, and let $p(a) = p(b) = p$ denote the premium of the two plans. Then i's expected utility under plan j, EU_i^j, is:

$$EU_i^j = \sum_\tau f_\tau^i u(w - x_\tau + l_\tau^j - p).$$

Then the expected utility difference between plan a and b is:

$$\begin{aligned} EU_i^{\boldsymbol{a}} - EU_i^{\boldsymbol{b}} &= \sum_\tau f_\tau^i \left[u(w - x_\tau + l_\tau^{\boldsymbol{a}} - p) - u\left(w - x_\tau + l_\tau^{\boldsymbol{b}} - p\right)\right] \\ &= \sum_{\tau=s,t} f_\tau^i \left[u(w - x_\tau + l_\tau^{\boldsymbol{a}} - p) - u\left(w - x_\tau + l_\tau^{\boldsymbol{b}} - p\right)\right] \\ &= \sum_{\tau=s,t} f_\tau^i \, u'_{\tau'}\left(l_\tau^{\boldsymbol{a}} - l_\tau^{\boldsymbol{b}}\right). \end{aligned}$$

The second equation uses the fact that the coverage is the same for the two plans except for loss states s and t. The last equation uses the first-order Taylor expansion, where τ' is a number between $w - x_\tau + l_\tau^{\boldsymbol{a}} - p$ and $w - x_\tau + l_\tau^{\boldsymbol{b}} - p$.

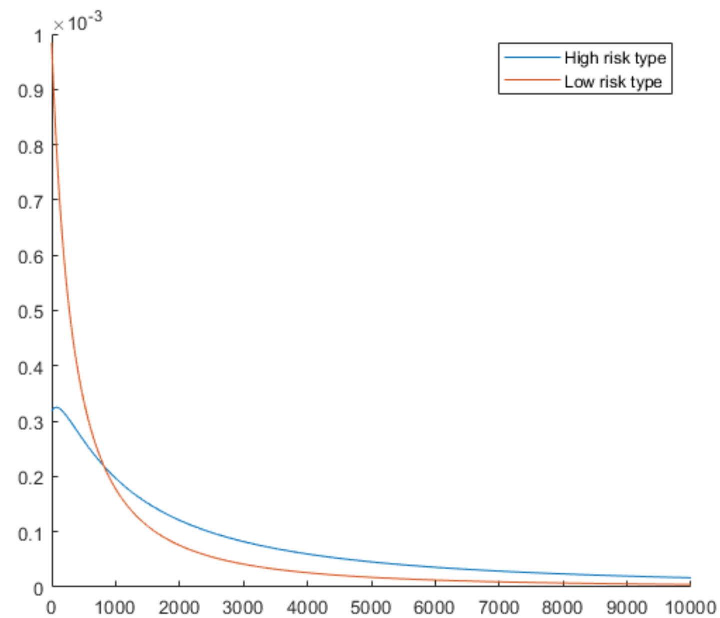
$$\left(EU_L^{\boldsymbol{a}} - EU_L^{\boldsymbol{b}}\right) - \left(EU_H^{\boldsymbol{a}} - EU_H^{\boldsymbol{b}}\right) = \sum_{\tau=s,t} f_\tau^L\, u'_{\tau'}\left(l_\tau^{\boldsymbol{a}} - l_\tau^{\boldsymbol{b}}\right) - \sum_{\tau=s,t} f_\tau^H\, u'_{\tau'}\left(l_\tau^{\boldsymbol{a}} - l_\tau^{\boldsymbol{b}}\right)$$
$$= (f_s^L - f_s^H)u'_{s'}\left(l_s^{\boldsymbol{a}} - l_s^{\boldsymbol{b}}\right) + (f_t^L - f_t^H)u'_{t'}\left(l_t^{\boldsymbol{a}} - l_t^{\boldsymbol{b}}\right).$$

Because $u'_{s'}$ and $u'_{t'}$ are both larger than 0, $f_s^L - f_s^H > 0$, $l_s^{\boldsymbol{a}} - l_s^{\boldsymbol{b}} > 0$, $f_t^L - f_t^H < 0$ and $l_t^{\boldsymbol{a}} - l_t^{\boldsymbol{b}} < 0$, so $\left(EU_L^{\boldsymbol{a}} - EU_L^{\boldsymbol{b}}\right) - \left(EU_H^{\boldsymbol{a}} - EU_H^{\boldsymbol{b}}\right) > 0$. ■

Appendix B. Constructing Risk Distributions from Claims Data

To calculate plans chosen by different risk types, I need information about the ex-ante medical expenditure distributions. I derive such information using the Truven MarketScan database, a large claims database for the US employer-sponsored plans. The Truven data have been used to benchmark health spending in many studies (for example, Geruso, Layton and Prinz 2019) and was also used to calculate the AV for plans in the first two years of the ACA markets. I select a sample of individuals enrolled in a non-capitated plan in both 2012 and 2013. In total, there are 190,283 unique individuals in the sample.

Appendix Figure B1. PDF of the Two Benchmark Risk Distributions



Note: Author estimation from Truven MarketScan data. Mass at zero omitted for easy of exposition.

The goal is to construct a few ex-ante risk types representing the heterogeneity in medical expenditure in the US health insurance markets. I use the k-means clustering method to get these groupings. K-means clustering is a non-supervised learning algorithm that groups individuals with similar characteristics together and puts individuals with dissimilar characteristics in different groups (Agterberg et al. 2019).[16] I use age, gender, employment status, pre-existing conditions (constructed based on diagnosis codes and procedures performed), and medical expenditure in 2012 as inputs to the model. For illustrative purposes, I initially create two clusters and use these to separate the population into two risk types. I consider more risk types in Section 2.3.1. After obtaining the clusters, I fit a three-parameter log-normal distribution with a mass at zero to the 2013 medical

[16] This method is different from the supervised learning approach (such as regressions) to predict medical expenditure and construct risk scores (Kautter et al. 2014).

expenditure for each group to get the risk distribution (Einav et al. 2013) and inflate the expenditure to 2017 dollars.

The resulting lower-risk type has an expected risk of $1,843 and a standard deviation of $7,414, representing 26% population in the sample. The higher risk has an expected risk of $7,537 and a standard deviation of $22,444. Appendix Figure 1 plots the probability density function of the two distributions. From the graph, it is clear that the two probability density functions have different shapes: The low-risk type has greater probability density on smaller losses while the high-risk type has greater probability density on larger losses.

Appendix C. Supplementary Materials for the Empirical Analysis

C1. Samples and Data Sources

The empirical analysis combines data from several different sources. Appendix Table C1 Panel A lists, for each data source, the download link, the unit of observation, key variables, and the analysis in the paper that uses the data.

Appendix Table C1. Data Source of Empirical Analysis

Panel A.

Data Source	Link	Unit of Observation	Key Variables	Analysis Using the Data
Health Insurance Exchange Public Use Files: 2014-2017	https://www.cms.gov/CCIIO/Resources/Data-Resources/marketplace-puf; https://www.cms.gov/CCIIO/Resources/Data-Resources/issuer-level-enrollment-data	Plan ID by year	Deductible, MOOP, coinsurance rates, AV, enrollment, HSA-eligibility	Figure 1-2, Table 3, Appendix Figure C1
		Plan ID by rating area by year	Premiums	Table 4 Column (3)
Uniform Rate Review Data: 2016 - 2019	https://www.cms.gov/CCIIO/Resources/Data-Resources/ratereview	Plan ID by year	Total expenditure and collected premiums per member per month (PMPM)	Figure 3, Table 4 Column (1) and (2), Appendix Figure C2
		Insurer by year	Total expenditure, insurer liability, risk transfers, and average premium PMPM	Table 5, Appendix Table C3-C4
Medical Loss Ratio	https://www.cms.gov/CCIIO/Resources/Data-Resources/mlr	Insurer by year	Risk transfers PMPM	Appendix Table C4

filings: 2014-2017		

Panel B. Matching across Different Datasets

Datasets	# of insurer-year: 2014-2017	% matched
Insurer-year with plan information	821	100%
Uniform Rate Review Data	619*	75.4%
Medical Loss Ratio filings	796	97.0%
Combined – risk transfers	746	90.9%

Note: Each plan ID represents a unique combination of cost-sharing structure, plan type, drug formulary, and insurer. Cost-sharing variations are dropped for Silver plans, so only standard Silver plans are included in the sample. The Uniform Rate Review Data have a two-year lag, so the 2016 - 2019 reports match the 2014 - 2017 plan information respectively.

*The numbers are slightly larger than the sample size reported in Table 3 and Appendix Table C4 because two observations are absorbed by fixed effects.

C2. Robustness Checks

In Section 3.4, I show that the straight-deductible plans have higher total medical expenditure and also receive more risk adjustment payments than other designs, both at plan level or aggregated at insurer level. In this section, I present the robustness check of these results using 1) different control variables; 2) a larger sample from the Medical Loss Ratio filings; 3) use risk premium for the market average population as a measure of plan design.

First, Appendix Table C2 shows the comparison of plan characteristics among straight-deductible plans and the other designs. The two types of plans are similar in terms of network type, whether they are a new plan, and whether launched in rural places. The only difference is that straight-deductible plans are significantly more likely to offer an HSA option. Appendix Table C3 compares the insurers' characteristics among those offering straight-deductible plans and the rest. Consistent with the plan-level comparison, the two types of insurers are similar in terms of offering HMO, national network, operate in rural areas, and the enrollment size. The significant difference is in whether they offer HSA-eligible plans.

Appendix Table C2. Plan Design and Other Plan Characteristics

	Non-Straight-Deductible Plans	Straight-Deductible Plans	Difference
HMO	0.502	0.504	0.002
	(0.500)	(0.500)	(0.018)
National Network	0.327	0.322	-0.005
	(0.469)	(0.467)	(0.017)
HSA Eligible	0.130	0.723	0.593***
	(0.336)	(0.448)	(0.012)
New Plan	0.506	0.488	-0.017
	(0.500)	(0.500)	(0.018)
Fraction of Launched Counties That Are Rural	0.366	0.365	-0.001
	(0.311)	(0.336)	(0.011)
N	6,931	911	7,842

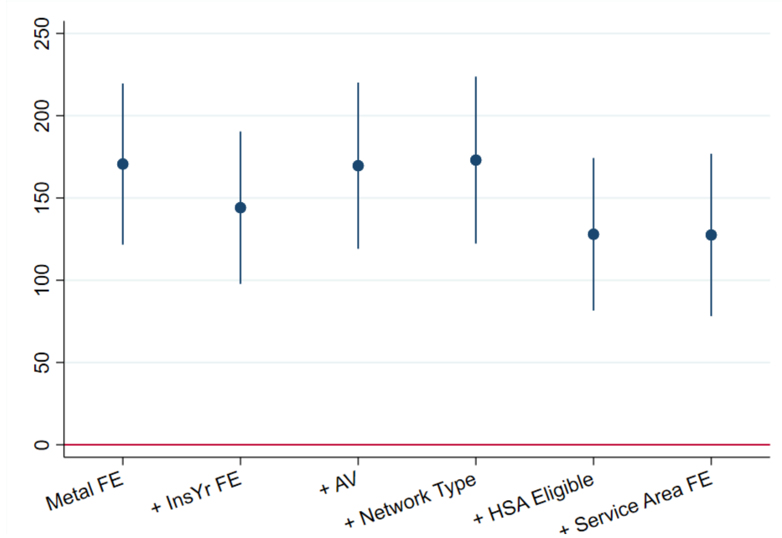
Note: Means and standard errors in parenthesis. *: p<0.1, **: p<0.05, ***: p<0.01. "HMO" stands for stands for health maintenance organization, as opposed to other managed care plan types including preferred provider organization (PPO), exclusive provider organization (EPO) or point of service (POS) plans.

Appendix Table C3. Straight-Deductible Offering and Insurer Characteristics

	Non-Straight-Deductible Plans	Straight-Deductible Plans	Difference
Offering HMO	0.546	0.560	0.014
	(0.499)	(0.497)	(0.035)
Offering National Network	0.240	0.254	0.014
	(0.428)	(0.436)	(0.030)
Fraction Enrolled in HSA-eligible Plans	0.134	0.182	0.048***
	(0.195)	(0.170)	(0.013)
Only Operate in Urban Areas	0.223	0.183	-0.039
	(0.417)	(0.386)	(0.028)
Above Median Enrollment	0.460	0.526	0.066
	(0.499)	(0.500)	(0.041)
Observations	252	367	619

Note: Means and standard errors in parenthesis. *: p<0.1, **: p<0.05, ***: p<0.01. "HMO" stands for stands for health maintenance organization, as opposed to other managed care plan types including preferred provider organization (PPO), exclusive provider organization (EPO) or point of service (POS) plans.

Appendix Figure C1. Total Expenditure per Member Month by Plan Design



Note: The figure shows the slope coefficient of the plan-level regression of average claim costs on whether the plan has a straight-deductible design. The sample includes all plans launched through HealthCare.gov between 2014 and 2017. Each observation is a plan by state. In each line, control variables are added on top of the left model, so for example, in the second line, both the metal fixed effects and insurer by year fixed effects are controlled. "Metal" represents metal tier fixed effects. "InsYr FE" is insurer by year fixed effects; "AV" represents actuarial value of a plan; "Network Type" includes three dummy variables indicating HMO, EPO, POS and PPO (the baseline); "HSA eligible" is a dummy variable indicating whether a plan has a health savings account available; "Service Area FE" include dummy variables indicating the set of counties a plan is launched.

Next, in Appendix Figure C1, I show the plan-level regression of total monthly per member medical expenditure on straight-deductible design. Each line represents the coefficient and its 95% confidence level by adding different control variables. In the first model, only metal tier fixed effects are added; in the second model, I add both metal fixed effects and insurer by year fixed effects, and the other models add more control variables. The coefficients are stable at around $150 for different models.

Appendix Table C4 shows the robustness check of the risk transfers at the insurer-level. All models include year fixed effects and state fixed effects. The fraction of enrollees in health savings account is controlled for all columns. The benchmark result in the paper suggests that insurers offering at least one straight-deductible plan receive about $40 higher risk transfers per member per month. Column (2) further control for fraction of enrollees in different metal tiers and network types for each insurer. The coefficient drops slightly to $34. When using the sample including observations from the Medical Loss Ratio Files, the coefficient is $35.

Second, I impute missing observations using filings from the Medical Loss Ratio reports. Appendix Table C1 Panel B shows the sample size increase. Combining information from the Medical Loss Ratio reports, over 90% of insurers launched a plan have the risk transfers information. Using the larger sample, the estimated differences in risk transfers are similar to using the benchmark sample.

Finally, I examine the robustness of the main results using continuous measure of plan designs. I use two measures to capture the difference in plan designs within a tier: first, I use the relative risk premium calculated as the difference between the risk premium of a plan and the risk premium of the plan with the same expected covered spending for the average population. This measure is 0 for straight-deductible designs, and becomes more positive when the design is more different from a straight-deductible design. Second, I calculate the ratio of deductible over MOOP, which does not depend on the utility functional form, or the shape of the underlying loss distribution. Straight-deductible plans will have a ratio of 1, while all other designs have a value less than 1.

Appendix Table C4. Robustness Check: Risk Transfers at the Insurer-Level

Dep. Var. = Risk Transfers Per Member Month	(1) Baseline	(2) More Controls	(3) MLR Sample	(4) Continuous Plan Design	(5)
Offer Straight-Deductible Plan	40.58	33.89	34.93		
	(13.51)	(12.19)	(11.99)		
Risk Premium				-0.17	
				(0.03)	
Deductible to MOOP Ratio					102.2
					(34.48)
N	617	617	744	617	617
R^2	0.144	0.222	0.122	0.102	0.136
Dep. Var. Mean	-6.201	-6.201	-6.125	-6.201	-6.201
Dep. Var. SD	66.03	66.03	63.41	66.03	66.03

Note: Each observation is an insurer-year. The dependent variable is risk transfers received per member month. "Offer Straight-Deductible Plan" is a dummy variable indicating whether an insurer offers any straight-deductible plan. "Risk Premium" is calculated for each plan for an individual with the 2017 CMS AV Calculator Distribution and CARA utility function (risk aversion level = 0.0004), and averaged within an insurer-year. "Deductible to MOOP Ratio" is calculated for each plan and averaged within an insurer-year. All models include year fixed effects and state fixed effects. The fraction of enrollees in health savings account is controlled for all columns. Column (2) further control for fraction of enrollees in different metal tiers and network types for each insurer. Column (3) impute the missing values using the Medical Loss Ratio Files. Standard errors are clustered at the insurer level.

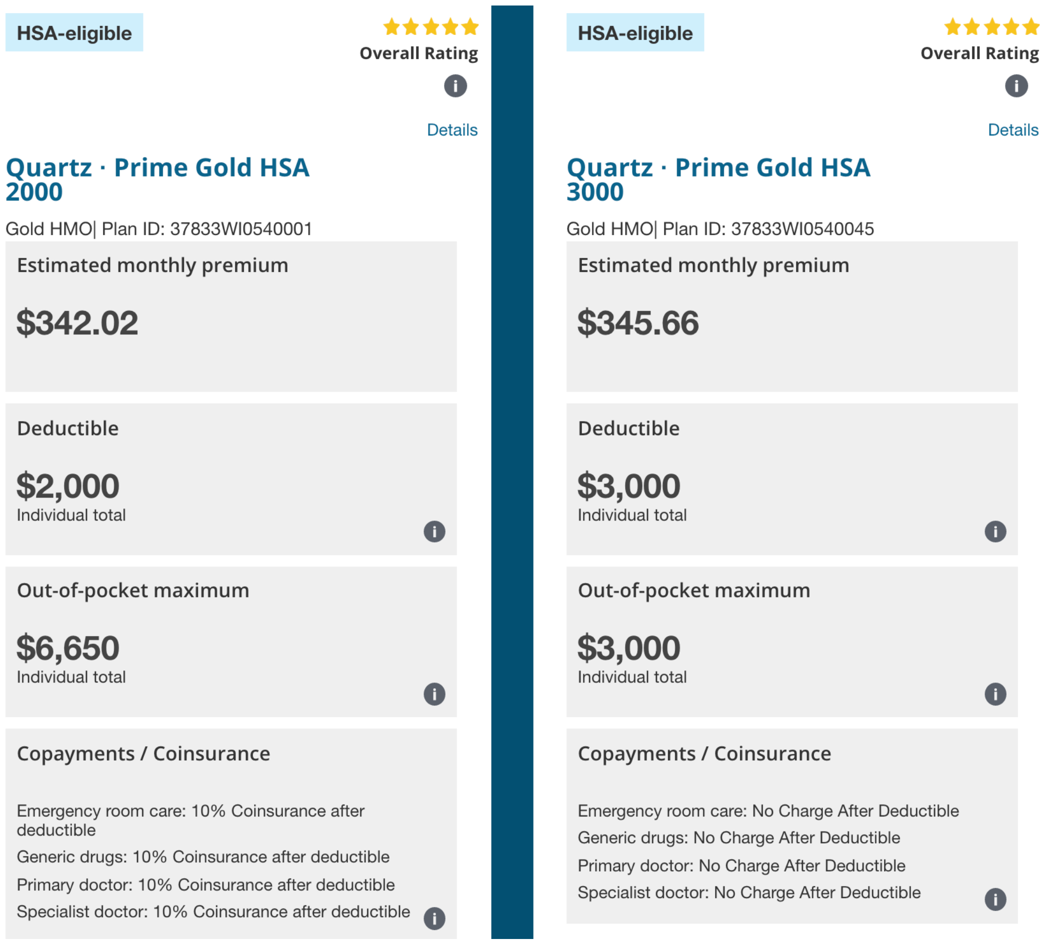
Appendix Table 1. States in the Sample

2014	AK, AL, AR, AZ, DE, FL, GA, IA, ID, IL, IN, KS, LA, ME, MI, MO, MS, MT, NC, ND, NE, NH, NJ, NM, OH, OK, PA, SC, SD, TN, TX, UT, VA, WI, WV, WY
2015	AK, AL, AR, AZ, DE, FL, GA, , IA, IL, IN, KS, , LA, ME, MI, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, OH, OK, OR, PA, SC, SD, TN, TX, UT, VA, WI, WV, WY
2016	AK, AL, AR, AZ, DE, FL, GA, HI, IA, IL, IN, KS, , LA, ME, MI, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, OH, OK, OR, PA, SC, SD, TN, TX, UT, VA, WI, WV, WY
2017	AK, AL, AR, AZ, DE, FL, GA, HI, IA, IL, IN, KS, KY, LA, ME, MI, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NV, OH, OK, OR, PA, SC, SD, TN, TX, UT, VA, WI, WV, WY

Appendix Table 2. List of Essential Health Benefits

Category	Benefit Name
Medical Services	Emergency Room Services, Inpatient Physician and Surgical Services, Imaging (CT/PET Scans, MRIs), Laboratory Outpatient and Professional Services, Outpatient Surgery Physician/Surgical Services, Mental/Behavioral Health and Substance Use Disorder Outpatient Services, Outpatient Facility Fee (e.g., Ambulatory Surgery Center), Occupational and Physical Therapy, Primary Care Visit to Treat an Injury or Illness (exc. Preventive, and X-rays), Specialist Visit, Skilled Nursing Facility, Speech Therapy, X-rays and Diagnostic Imaging.
Drug Tiers	Generics, Preferred Brand Drugs, Non-Preferred Brand Drugs, Specialty Drugs (i.e. high-cost).

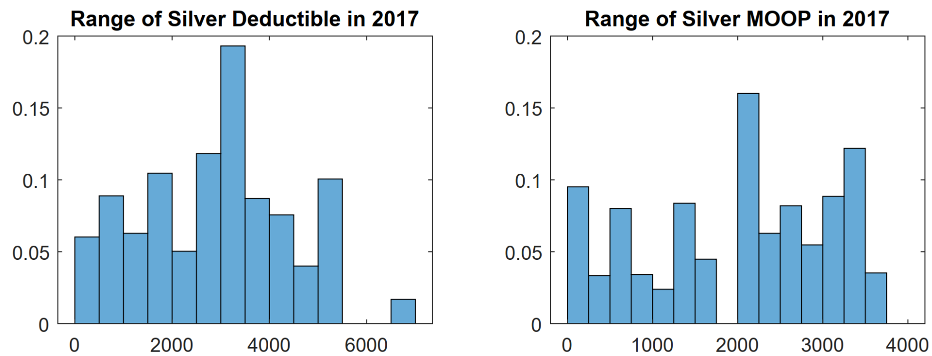
Appendix Figure 1. Illustration of Multiple Financial Attributes of ACA Plans



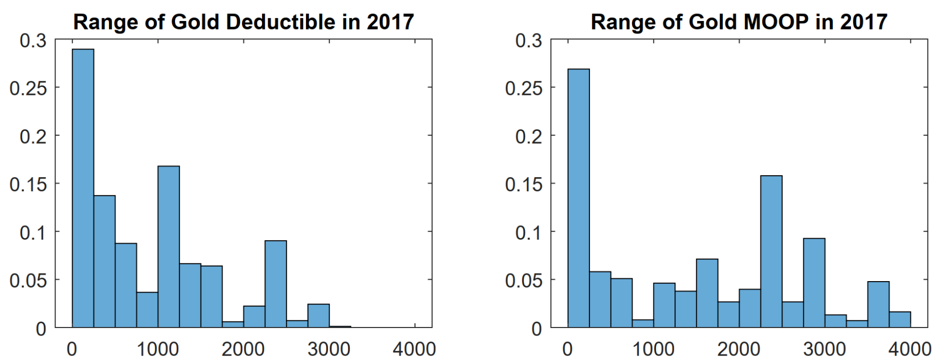
Note: Screenshots from healthcare.gov.

Appendix Figure 2. Deductible and MOOP Variation Within A County

Standard Silver Plan



Gold Plan



Note: Data from 2017 CMS Health Insurance Exchange Public Use Files. I calculate the range of deductible (MOOP) for standard Silver and Gold plans within each county, and then plot the distribution of all counties participated in the Federal Health Insurance Exchange. Plans includes all Exchange qualified health plans offered to individuals through the Health Insurance Exchange. The deductible and maximum out-of-pocket refer to tier-one in-network coverage for an individual, and are cumulative over a year.