Risk selection and risk adjustment in competitive health insurance markets

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RISK SELECTION AND RISK ADJUSTMENT IN
COMPETITIVE HEALTH INSURANCE MARKETS

by

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I would like to dedicate this work to my wife Ashley who always encouraged me to continue when things got rough and my son Soren who can always put a smile on my face, even when my simulated maximum likelihood code won’t converge.
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RISK ADJUSTMENT AND RISK SELECTION
IN COMPETITIVE HEALTH INSURANCE MARKETS

(Order no.             )

TIMOTHY JAMES LAYTON
Boston University Graduate School of Arts and Sciences, 2014

Major Professor: Randall P. Ellis, Professor of Economics

ABSTRACT

In most markets, competition induces efficiency by ensuring that goods are priced according to their marginal cost. This is not the case in health insurance markets. This is due to the fact that the cost of a health insurance policy depends on the characteristics of the consumer purchasing it, and asymmetric information or regulation often precludes an insurer from matching the price an individual pays to her expected cost. This disconnect between cost and price causes inefficiency: When the premiums paid by consumers do not match their expected costs, consumers may sort inefficiently across plans. In this dissertation, I study the effects of policies used to alleviate selection problems. In Chapter 1, I develop a model to study the effects of risk adjustment on equilibrium prices and sorting. I simulate consumer choice and welfare with and without risk adjustment in the context of a Health Insurance Exchange. I find that when there is no risk adjustment, the market I study unravels and everyone enrolls in the less comprehensive plan. However, diagnosis-based risk adjustment causes over 80 percent of market participants to enroll in the more comprehensive plan. In Chapter 2, we study an unintended consequence of risk adjustment: upcoding. When payments are risk adjusted based on potentially manipulable
risk scores, insurers have incentives to maximize those risk scores. We study upcoding in the context of Medicare, where private Medicare Advantage plans are paid via risk adjustment but Traditional Medicare is not. We find that when the same individual enrolls in a private plan her risk score is 5% higher than if she would have enrolled in Traditional Medicare. In Chapter 3, we study two forms of insurance for insurers: Reinsurance and risk corridors. Protecting insurers from risk can lower prices and improve competition by inducing entry into risky markets. It can also induce inefficiencies by causing insurers to manage risk less carefully. We use simulations to compare the power of reinsurance and risk corridors to protect insurers against risk while limiting efficiency losses. We find that risk corridors are always able to limit insurer risk with the lowest efficiency cost.
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<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>ACA</td>
<td>Affordable Care Act</td>
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<tr>
<td>ACO</td>
<td>Accountable Care Organization</td>
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<td>CARA</td>
<td>Constant Absolute Risk Aversion</td>
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<td>CMS</td>
<td>Center for Medicare and Medicaid Services</td>
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<td>ER</td>
<td>Emergency Room</td>
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<td>ESI</td>
<td>Employer-sponsored Health Insurance</td>
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<td>FFS</td>
<td>Fee-for-Service</td>
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<tr>
<td>FPL</td>
<td>Federal Poverty Level</td>
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<tr>
<td>HCC</td>
<td>Hierarchical Condition Category</td>
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<tr>
<td>HHS</td>
<td>Department of Health and Human Services</td>
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<tr>
<td>HMO</td>
<td>Health Maintenance Organization</td>
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<tr>
<td>MA</td>
<td>Medicare Advantage</td>
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<tr>
<td>OOP</td>
<td>Out-of-Pocket</td>
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<tr>
<td>PFFS</td>
<td>Private Fee-for-Service</td>
</tr>
<tr>
<td>PPO</td>
<td>Preferred Provider Organization</td>
</tr>
<tr>
<td>RA</td>
<td>Risk Adjustment</td>
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<tr>
<td>SCHIP</td>
<td>State Children’s Health Insurance Program</td>
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<td>US</td>
<td>United States</td>
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CHAPTER ONE:

IMPERFECT RISK ADJUSTMENT, RISK PREFERENCES, AND SORTING IN COMPETITIVE HEALTH INSURANCE MARKETS

Section 1: Introduction

The question of whether competition improves efficiency in health insurance markets is at the center of the recent reform of the US health care system. Efficiency is achieved when consumers purchase goods that they value more than the cost of those goods. In most markets, competition induces efficiency by insuring that goods are priced according to their marginal cost. In many health insurance markets, however, competition does not ensure that the price of a product (an insurance plan) is equal to its cost. This is due to the fact that the cost of the product depends on the characteristics of the consumer purchasing it, and asymmetric information or regulation often precludes an insurer from matching the price an individual pays to her expected cost. This disconnect between cost and price results in two kinds of inefficiency. On the supply side, when an insurer’s revenues and costs for enrolling an individual do not match in predictable ways, insurers are incentivized to inefficiently manipulate their contracts in order to “cream-skim” consumers with lower expected costs (Rothschild and Stiglitz 1976, Glazer and McGuire 2000, Ellis and McGuire 2007). On the demand side, when the premiums paid by consumers do not match their expected costs, consumers may sort inefficiently across plans (Akerlof 1970, Einav et al. 2010). Due to competitive pressures and a relatively unrestricted contract space, the Health Insurance Exchanges (Exchanges) established by

1 In fact, in the US the Affordable Care Act (ACA) prohibits virtually all variation in health insurance premiums across consumers, forcing insurers to charge one price to all consumers, no matter their expected costs.
the ACA are likely to experience much more serious supply-side and demand-side selection problems than in other settings such as the employer and Medicare markets more typically studied in the literature. In fact, some recent research suggests the potential for complete market unraveling in an Exchange-like setting (Handel et al. 2013).

These selection problems are widely recognized among economists. However, with respect to the demand-side selection problems, the health economics literature has largely focused on only three solutions: restricting the contract space, subsidizing adversely selected plans, and allowing premiums to vary by expected cost (Cutler and Reber 1998, Einav et al. 2010, Bundorf et al. 2012, Geruso 2013, Handel et al. 2013). In this paper, I study an additional solution to the demand-side adverse selection problem: Risk adjustment. Risk adjustment has been implemented in some form in almost every individual health insurance market in the world, including the new state Exchanges. Risk adjustment transfers costs from plans that attract a relatively unhealthy mix of enrollees to plans that attract a relatively healthy mix of enrollees. It works by first using sophisticated algorithms to predict consumers’ health care costs and then reallocating premium revenues to plans based on those predicted costs, effectively pooling all costs that are predicted by the algorithm among all plans in a market. While it has long been recognized that risk adjustment has the potential to ameliorate insurers’ incentives to engage in cream-skimming by inefficiently manipulating contracts to attract healthy

---

2 In the US, risk adjustment is used in some form in Medicare Advantage, Medicare Part D, the new state Health Insurance Exchanges, and many state Medicaid Managed Care programs. Risk adjustment is also used in some form in the health insurance markets of the Netherlands, Switzerland, Germany, Israel, and Belgium.
enrollees (Glazer and McGuire 2000, Glazer and McGuire 2002, Brown et al. 2012, McGuire et al. 2013a, 2013b, Newhouse et al. 2013), the effect of risk adjustment on health plan pricing and consumer sorting across plans has been largely overlooked.\(^3\)

The importance of risk adjustment in the context of equilibrium pricing of health plans can be described with a simple observation: With no risk adjustment, in a competitive equilibrium each plan’s price is determined by the mix of consumers it enrolls; however, with perfect risk adjustment, where all costs are fully pooled across plans, each plan’s price no longer reflects the cost profile of its enrollees. In markets where some plans are adversely selected, this shift in prices could be quite large, and any large shift in prices is likely to result in consumers re-sorting across plans, affecting the overall level of efficiency in the market. In the first part of this paper, I develop a simple theoretical model to show how risk adjustment affects prices in a competitive equilibrium. The model shows that risk adjustment causes plan prices to reflect the portion of costs of each plan’s enrollees that are not predicted by the risk adjustment model ("residual costs"), while the costs predicted by the model ("predicted costs") are pooled across all plans. I then use a series of graphical representations, building on those presented in Einav et al. (2010) and Einav and Finkelstein (2011), to develop intuition for how risk adjustment affects and welfare. The intuition provided by these figures provides a major contribution of this paper.

\(^3\) A few notable recent papers beginning to explore this topic are Glazer, McGuire, and Shi (2013), Shi (2013), and Handel, Hendel, and Whinston (2013). Glazer, McGuire, and Shi (2013) derive a risk adjustment model that maximizes the fit of the payment system to costs while simultaneously inducing plans to set premiums in a welfare-maximizing way. Shi (2013) studies the interaction between risk adjustment and age-based premium variation in the context of an Exchange. Handel, Hendel, and Whinston (2013) study the tradeoff between adverse selection and reclassification risk in an Exchange and briefly introduce a form of perfect risk adjustment.
In practice, risk adjustment is imperfect and results in some portion of costs being pooled across plans. Risk adjustment policies differ not only in the proportion of costs that are pooled, but also in which costs are pooled. For example, demographic-based risk adjustment results in the pooling of individual costs that are predictable by consumer demographics. Diagnosis-based risk adjustment, on the other hand, results in the pooling of individual costs that are predictable by consumer diagnoses. Diagnosis-based risk adjustment can actually be broken down further into “prospective” and “concurrent” risk adjustment. Prospective risk adjustment results in the pooling of costs that are explained by diagnoses from the prior year, while concurrent risk adjustment results in the pooling of costs explained by diagnoses from the current year. The model and the graphical representation below show that the effect of a particular form of risk adjustment on equilibrium prices depends on the correlation between demand and the costs predicted by the risk adjustment model. Consider a case where individuals are required to choose one of two health plans, and one of the plans is adversely selected. In this case, if there is no correlation between demand and predicted costs, then there will be no difference between equilibrium prices and sorting with or without risk adjustment. However, if predicted costs are positively (negatively) correlated with demand for that plan, risk adjustment will cause the prices of the two plans to converge (diverge), resulting in more (fewer) consumers choosing the adversely selected plan. In many cases, if risk adjustment causes the prices to diverge and fewer consumers to choose the adversely selected plan, it will decrease welfare. This finding mimics for demand-side selection problems the finding of Brown et al. (2012) that imperfect risk adjustment can worsen supply-side selection.
problems. The finding also implies that in order to accurately simulate competitive equilibria in health insurance markets with and without imperfect risk adjustment, the correlation between preferences and “predicted costs” must be taken into account along with the correlation between preferences and total costs used in previous studies (Glazer et al. 2013, Handel et al. 2013, Shi 2013). Preference heterogeneity presents the potential that these two correlations need not be identical.4

In the second part of this paper, I investigate the efficiency consequences of plan risk adjustment empirically by estimating the joint distribution of demand, total costs, and predicted costs using administrative health insurance claims data from a large employer. Following the implications of the model, I allow for correlation between preferences and predicted costs along with correlation between preferences and total costs. For employees at this firm, I recover the joint distribution using a structural model of health insurance choice similar to other models in the literature (Cohen and Einav 2007, Handel 2013, Geruso 2013). I then use this distribution to simulate plan prices and consumer sorting under various forms of risk adjustment in the context of a Health Insurance Exchange where prices are set competitively and all consumers choose between a Bronze plan and a

4 In settings where plans are vertically differentiated and differ only in cost sharing, the correlation between demand and predicted costs is likely to be captured in the correlation between demand and total costs, making the joint distribution of demand and total costs somewhat adequate for simulation of equilibrium under risk adjustment. However, in horizontally differentiated settings similar to that studied by Bundorf et al. (2012), the relationship between preferences, total costs, and predicted costs is less clear, making estimation of this distribution more important. Additionally, as discussed below, when comparing risk adjustment models, the correlations between preferences, total costs, and the additional costs predicted by one model over another is what is important, and these correlations are not easy to predict ex-ante, again making estimation necessary.
Platinum plan. I use these simulations to compare efficiency with no risk adjustment and efficiency under a number of risk adjustment models that could potentially be used in the Exchanges.

I replicate the result of Handel et al. (2013) that with no risk adjustment, the market fully unravels, and all consumers enroll in the less comprehensive Bronze plan. Interestingly, I find that while demographic-based risk adjustment does weaken the relationship between demand and costs (i.e. flattens the incremental average cost curve), its effects are not large enough to undo market unraveling. However, diagnosis-based risk adjustment, similar to that being implemented in the Exchanges, eliminates much of the correlation between total costs and demand and almost fully undoes market unraveling, resulting in over 80% of market participants enrolling in the more comprehensive Platinum plan. Moreover, when risk adjustment is combined with reinsurance, as it is in the Exchanges, virtually all variation in plan costs across consumers is eliminated and close to 100% of the market enrolls in the Platinum plan. Welfare calculations indicate that the welfare consequences of risk adjustment in this setting are far from trivial, with risk adjustment improving welfare by over $800 per person, per year, or around 20% of

---

5 In the Exchanges, plans are divided into tiers based on their actuarial value. The tiers are called (from least to most comprehensive) Bronze, Silver, Gold, and Platinum.

6 Risk adjustment models can largely be grouped into three categories: demographic, prospective, and concurrent. Demographic models use only age and gender to predict costs. Prospective and concurrent models use diagnosis groups from health insurance claims and, sometimes, utilization. Prospective models use variables from time t-1, while concurrent models use variables from time t, to predict costs in time t. The HHS-HCC model chosen by HHS for use in the Exchanges is a concurrent model. There is some controversy about this decision given that the concurrent variables are potentially more endogenous to spending than the prospective variables.
total health care costs among employees of the firm I study. Interestingly, I find that in both environments concurrent risk adjustment models, which explain a substantially larger portion of the variance in consumers' costs, result in only a slightly better equilibrium than prospective models, with incremental welfare gains of only $1-$10. I argue that this is due to the fact that the extra costs explained by concurrent models are not likely to be predictable, and therefore are not likely to be correlated with demand.

These findings represent an important contribution to the literature on adverse selection in markets for health insurance. Risk adjustment, a policy meant to limit incentives for plans to cream-skim healthy enrollees, also has a large and important effect on equilibrium prices and sorting in competitive health insurance markets. In fact, in the setting studied here, it proves critical for the market to function efficiently. Additionally, when combined with reinsurance, market unraveling is completely undone. This suggests that risk adjustment may play a much more important role in these markets than was previously assumed and should be taken much more seriously among economists as a solution to not just supply-side selection problems, but also selection problems coming from the demand-side. These findings also suggest that because risk adjustment can almost completely undo market unraveling, it is unwise to ignore it in any empirical

---

7 This is a huge welfare improvement. It is worth noting that it is especially large compared to the calculations of welfare loss from adverse selection found elsewhere in the literature (Cutler and Reber 1998, Einav et al. 2010, Geruso 2013). It is important to note, however, that in all of these other settings, the plans consumers were choosing from were quite similar in terms of cost sharing. Here, the plans have huge differences in cost sharing, reflecting the huge differences in cost sharing found across tiers in the Exchanges. Simulations with plan options that are more similar to the options available in the settings studied in other papers found welfare results similar to the results from those papers, suggesting that if the estimated structural demand and cost parameters from those papers were used to study the Bronze-Platinum setting studied here, they would find similar results.
study of the markets where it is being used, such as Medicare Part D and the Exchanges, as it is likely to have large and important effects on plan pricing.

The paper proceeds as follows. Section 2 develops a simple model of a competitive health insurance market with risk adjustment and presents the graphical framework to provide intuition for the relationship risk adjustment, prices, and sorting, focusing on the importance of the correlation between demand and predicted and residual costs. Sections 3 discusses the data used for estimation. Section 4 outlines the structural empirical model used to the joint distribution of demand, total costs, and predicted costs. Section 5 presents the results of the simulations of equilibrium under risk adjustment, and Section 6 concludes.

**Section 2: Theoretical Framework**

The model I develop in this paper builds on those developed in Einav et al. (2010a) and Bundorf et al. (2012). The key innovation is that total costs are divided into two components: predicted costs and residual costs. In the model individuals are required to choose one of two insurance contracts. Everyone faces the same price for each contract. One of the contracts provides enhanced coverage (contract E) and the other provides basic coverage (contract B). As in Bundorf et al. (2012), consumers are distinguished by their health risk, $\theta$, and preferences, $\epsilon$. Let $v^j(\theta_i, \epsilon_i)$ represent consumer $i$’s valuation of plan $j$ in dollars, so that $\Delta v(\theta_i, \epsilon_i) = v^E(\theta_i, \epsilon_i) - v^B(\theta_i, \epsilon_i)$ represent consumer $i$’s willingness-to-pay for Plan E over Plan B. Let $P$ represent the difference in the price for Plan E and the price for Plan B. Therefore, individual $i$ chooses to purchase
Plan E if and only if $\Delta \nu(\theta_i, \epsilon_i) \geq P$. This leads to the following demand for Plan E and Plan B where $N$ equals the total number of individuals in the population:

$$D^E = \int 1(\Delta \nu(\theta_i, \epsilon_i) \geq P) dF(\theta, \epsilon)$$

$$D^B(P) = N - D^E(P)$$

where $F(\theta, \epsilon)$ is the joint distribution of health risk and preferences and $1(\cdot)$ is equal to one if the argument between the parentheses is true and zero otherwise.

Next, I describe how plans set $P$. First, let $c^j(\theta_i)$ represent the expected monetary cost to plan $j$ of enrolling an individual with health risk $\theta_i$. Second, assume that insurers set prices in perfect competition. While this is not likely the case in my empirical setting where the employer is able to arbitrarily set employee contributions, it is a convenient benchmark and potentially a good description of the Exchanges. In competition, insurers will set prices equal to average cost. Therefore, I describe the average costs of plans E and B as follows:

$$AC^E(P) = E[c^E(\theta) \mid \Delta \nu(\theta_i, \epsilon_i) \geq P]$$

$$AC^B(P) = E[c^B(\theta) \mid \Delta \nu(\theta_i, \epsilon_i) < P]$$

In equilibrium, the premium differential $P$ will then be equal to the difference between E and B’s average costs:

$$P^* = \Delta AC(P) = AC^E(P) - AC^B(P)$$

The expressions show that two factors cause the premium differential, $P^*$, to vary. To see the first factor, let us assume that the individuals enrolling in Plan E and Plan B are

---

8 It is possible that such a premium will not exist. In this case, as shown in Handel et al. (2013) in equilibrium all individuals will enroll in Plan B if $\Delta AC(P)$ is always greater than $\theta$ for all values of $\theta$ and in Plan E if $\Delta AC(P)$ is always less than $\theta$ for all values of $\theta$ in the population. In these cases $P^*$ will be equal to $AC^B(P)$ and $AC^E(P)$, respectively.
identical. Now, if the cost to Plan E from enrolling individual i is different from the cost to Plan B from enrolling the same individual, i.e. $c^E(\theta_i) \neq c^B(\theta_i)$, $P^*$ will reflect that cost difference. Plan costs for enrolling the same individual could differ for a variety of reasons including differences in plan generosity, moral hazard, administrative costs, etc.

To see the second factor, let us now assume the cost to Plan E from enrolling individual i is identical to the cost to Plan B from enrolling the same individual, i.e. $c^E(\theta_i) = c^B(\theta_i)$. Now, if the individuals enrolling in Plan E and Plan B are identical, the average cost for each plan will also be identical, and $P^* = 0$. However, if the individuals enrolling in Plan E are sicker (and thus higher cost) than the individuals enrolling in Plan B, Plan E’s average cost will be larger than Plan B’s and the premium differential will be positive, $P^* > 0$. Thus, in addition to reflecting differences in plan costs, $P^*$ also reflects the relationship between demand for E and total individual health care costs. It is precisely this relationship between price and the correlation between demand and total costs that results in adverse selection.

Section 2.0.1: Risk Adjustment

I now augment the model by adding risk adjustment. To incorporate these policies into my model, I first introduce the concept of a “risk score.” Risk adjustment starts with by a regulator choosing a set of variables to predict market enrollees’ total costs. These variables often include indicators for age-by-gender cells and groups of diagnoses. Each of these variables is assigned a weight. The weights are assigned via a linear regression of current costs on the chosen set of variables in a large sample of individuals. The weights are combined with information on the market enrollees’ actual experience to produce
individual-level risk scores, \( r_i \), for each enrollee.\(^9\) Risk adjustment is then implemented through a series of plan-specific transfers dictated by some variant of the following formula:

\[
T_j(P) = \left( \frac{\bar{R}_j}{\bar{R}} - 1 \right) \bar{P}
\]

In formula \( \bar{R}_j \) represents the average risk score of plan j’s enrollees, \( \bar{R} \) is the average risk score of all enrollees in the market, and \( \bar{P} \) is the average premium in the market.\(^10\) The formula ensures that the transfers will be budget neutral and that plans with higher average risk scores receive positive transfers, lowering their average cost, and plans with lower average risk scores receive negative transfers, raising their average cost.

The formula can also be translated into individual transfers. Effectively, for individual \( i \) plan \( j \) receives a transfer from the regulator equal to \( r_i \bar{P} \) and pays the regulator \( \bar{P} \). With these risk adjustment transfers, the residual plan cost, or plan cost net of risk adjustment, from enrolling individual \( i \) is a function of both total cost risk, \( \theta \), and the risk score, \( r \), and is defined as

\(^9\) For simplicity, I assume that an individual’s risk score is invariant to his choice of plan. In the Exchanges, this is actually not the case. Risk scores are explicitly different for different plan tiers, with risk scores being systematically higher in plans with higher actuarial values. This is due to the fact that HHS estimated different models for each tier, assuming that in different tiers, plans cover different portions of total costs. I do not account for this possibility in the model, but I do use the HHS risk scores that vary across plans in the simulations of the HHS risk adjustment model. Risk scores could also vary across plans due to coding differences across plans (Geruso and Layton 2014). For simplicity, I abstract from this type of risk score variation here.

\(^10\) Note that all of these values other than the market average risk score are functions of \( P \) because they will change as \( P \) changes and consumers re-sort across plans. Additionally, note that here (and in the Exchanges) transfers depend on average plan risk scores rather than average plan costs as they do in Handel et al. (2013).
where $c_R^I(\theta_i, r_i)$ are the costs not predicted by the risk adjustment model ("residual costs") and $c_P^I(\theta_i, r_i) = \frac{r_i}{R} \bar{P} - \bar{P}$ are the costs explained by the risk adjustment model ("predicted costs"). This implies that average costs for Plan E can now be rewritten as

$$AC^E_{RA}(P) = E[c^E_R(\theta, r) \mid \Delta v(\theta, \epsilon) \geq P]$$

And for contract B

$$AC^B_{RA}(P) = E[c^B_R(\theta, r) \mid \Delta v(\theta, \epsilon) < P]$$

This implies the following new premium differential

$$P^* = E[c^E_R(\theta, r) \mid \Delta v(\theta, \epsilon) \geq P] - E[c^B_R(\theta, r) \mid \Delta v(\theta, \epsilon) < P]$$

As before, $P^*$ reflects differences in the cost to Plan E from enrolling individual $i$ and the cost to Plan B from enrolling the same individual. However, whereas before $P^*$ also reflected the relationship between demand for Plan E and total individual health care costs, it now reflects only the relationship between demand and residual individual health care costs. Thus, if only the 10-15% of costs explained by risk adjustment model are correlated with demand while the residual costs are totally independent of demand, risk adjustment will cause $P^*$ to no longer be affected by the relationship between demand and individual health care costs. In this case, even though under risk adjustment only 10-15% of costs are pooled, the price differential will reflect only differences in plan costs. More formally, if residual costs do not vary with $\Delta v(\theta, \epsilon)$ there will be no relationship

\[11\] Note that it is entirely possible that predicted costs exceed total costs, $c^I_P(\theta_i, r_i) > c^I(\theta_i)$. This could happen if the risk adjustment model over-predicts an individual's costs.
between the premium differential and costs, and the equilibrium premium differential $P^*$ simplifies to

$$P^* = \Delta AC = E[c^E_k(\theta, r)] - E[c^B_k(\theta, r)]$$

the difference between the average cost of the entire population in Plan E and the average cost of the entire population in Plan B, or the average incremental cost for the entire population. More generally, if residual costs are less (more) strongly correlated with demand than are total costs, $P^*$ will be smaller (larger) with risk adjustment than without. While it may seem impossible for residual costs to be more strongly correlated with demand than are total costs, heterogeneity in $\epsilon$ makes this entirely possible. This would occur in a setting where the average total cost of Plan E is relatively higher than the average total cost of Plan B, but Plan B has a higher relative risk score than Plan E. The intuition for this concept will hopefully be made clearer in the figures in the next section. For now I suggest that the concept is similar to that described in Finkelstein and McGarry (2006) where preference heterogeneity can cause advantageous selection rather than adverse selection. Here, there are also multiple dimensions of cost, and preference heterogeneity can cause there to be adverse selection on total costs but advantageous selection on predicted costs, resulting in a stronger relationship between demand and residual costs than demand and total costs, and causing adverse selection to be worse with risk adjustment than without. Even if preference heterogeneity is not strong enough to cause risk adjustment to worsen adverse selection, it is clearly important to take correlations between preferences and predicted costs into account when simulating equilibria with risk adjustment.
Section 2.0.2: Efficiency

Efficiency requires that an individual enroll in Plan E if and only if her willingness-to-pay for Plan E over Plan B exceeds the incremental social cost of enrolling her:

$$\Delta v(\theta_i, \epsilon_i) \geq \Delta c(\theta_i) = c^E(\theta_i) - c^B(\theta_i).$$

Note that risk adjustment does not affect the efficiency criteria. This is because the social cost of enrolling individual $i$ in plan $j$ is invariant to any transfers of costs across plans: Individual $i$ will always cost the market more in Plan E than in Plan B. Risk adjustment just changes how those costs are distributed across plans in the market.

Recall that individuals sort across plans according to their willingness-to-pay, $\Delta(\theta, \epsilon)$. At the same time, efficiency requires them to sort according to their incremental marginal cost, $\Delta c(\theta)$. It is important to note that in this environment whether there is risk adjustment or not, there is only one tool to induce sorting, and thus affect welfare: the uniform price differential, $P$. Risk adjustment affects efficiency by altering the equilibrium value of $P$, thus causing market participants to re-sort between plans. As noted above, the direction of this re-sorting depends on the correlation between demand and predicted costs. The welfare consequences of this re-sorting depends on the joint distribution of $\Delta v(\theta_i, \epsilon_i)$ and $\Delta c(\theta_i)$.\(^\text{12}\)

\(^\text{12}\) In addition to making it unclear how risk adjustment will affect sorting, the potential for preference heterogeneity also makes it unclear ex-ante what optimal sorting looks like (Bundorf et al. 2012). However, a treatment of this issue is beyond the scope of the paper. Instead, I just suggest that the effect of risk adjustment on welfare is unclear ex-ante. A thorough study of risk adjustment in such an environment is a promising and interesting direction for future research.
Section 2.1 Graphical Description

In order to provide intuition for how risk adjustment affects equilibrium prices and sorting, I now describe the theoretical model developed above in a series of figures. Assume, again, that all individuals must choose one of two plans. Plan E is more comprehensive than Plan B but there is no moral hazard. The right panel of Figure 1.1A replicates Figure 1 of Einav et al. (2010). The x-axis describes enrollment in Plan E with enrollment increasing to the right. The y-axis describes the difference between the premium of Plan E and the premium of Plan B. This figure describes the “textbook” case of adverse selection. The demand curve lies everywhere above the incremental marginal cost curve, implying all individuals value Plan E more than their incremental marginal cost of enrolling in Plan E, or in other words it is optimal for everyone to enroll in Plan E. This could be due to risk aversion or some other preferences. Additionally, the incremental average and marginal cost curves are downward sloping, implying that Plan E is adversely selected.

The competitive equilibrium will be at Point A, where the demand curve crosses the incremental average cost curve. However, because all individuals value Plan E more than their incremental cost, efficiency requires that all individuals enroll in Plan E. This will only occur if is set below Point B. This is the textbook adverse selection problem.

13 For these figures to be entirely accurate, consumers must be required to choose between Plan E and Plan B, but Plan B must actually provide no coverage at all (uninsurance) yet have a price equal to the average plan cost of the enrollees in Plan B. While in the typical case, this “premium” for Plan B would always be equal to zero, with risk adjustment transfers, it will be non-zero. While this case is not realistic, it is very convenient, and the intuition is generalizable to the case where Plan B does provide some level of coverage.
As shown in the model above, risk adjustment results in each plan's prices reflecting the residual costs rather than the total costs of its enrollees. In the right panel of Figure 1.1A, the incremental average cost curve reflects total costs. The left panel of Figure 1.1A breaks the incremental average cost curve into two curves representing incremental predicted and residual costs. Because total costs are equal to the sum of predicted and residual costs, the slope of the incremental total average cost curve, $\beta$, is the sum of the slope of the incremental predicted cost curve, $\beta^P$, and the incremental residual cost curve, $\beta^R$: $\beta = \beta^P + \beta^R$. The figure shows the slopes of the incremental average cost curve and the incremental predicted cost curve. In the case described in the figure, demand for Plan E is positively correlated with both predicted and residual costs, implying that Plan E will be adversely selected on both predicted and residual costs. Risk adjustment effectively sets $\beta^P = 0$, by pooling these costs across plans. As in the model above, this implies that the slope of the incremental average risk adjusted cost curve is equal to the slope of the residual cost curve, $\beta^{RA} = \beta^R$. This is shown in Figure 1.1B. The price differential no longer reflects the relationship between demand and predicted costs. Instead, the price only reflects the relationship between demand and residual costs. In this case, this results in a flatter incremental average risk adjusted cost curve, and a new competitive equilibrium emerges at Point C where the demand curve crosses the incremental average risk adjusted cost curve. In this new competitive equilibrium, with risk adjustment a larger portion of the individuals in the market enroll in Plan E, in this case implying improved efficiency.\footnote{It is not always optimal for more individuals to enroll in the more comprehensive plan. Preference}
(i.e. predicted and residual costs are positively correlated with demand), risk adjustment
will always result in a larger portion of the market enrolling in the more comprehensive
plan. Figure 1.1C shows how the competitive equilibrium is affected by “perfect” risk
adjustment, where total costs are perfectly predicted and pooled. It is interesting to note
that in this case if $\beta^r = 0$ (the case where demand and residual costs are independent)
imperfect risk adjustment will result in the same result as perfect risk adjustment. This
suggests that the relevant metric for determining the effectiveness of a risk adjustmen
t policy is not how well it explains total costs. Instead, it is most important for risk scores
to explain the correlation between demand and total costs as fully as possible because as
the relationship between predicted costs and total costs increases, $\beta^N$ goes to zero. This
suggests that risk adjustment models that explain additional costs that are unlikely to be
correlated with demand (i.e. unpredictable acute costs) may be no better than models that
do not explain such costs.

Figure 1.2A again describes the textbook case of adverse selection. However, in
this case, while Plan E is still adversely selected on total costs, it is advantageously
selected on predicted costs and adversely selected on residual costs. In this case $\beta^p >
0$, $\beta^r < 0$, and $\beta < 0$. Figure 1.2B shows the effects of risk adjustment on equilibrium
prices and sorting. Because $\beta^p > 0$ the incremental average risk adjusted cost curve is
actually steeper than the incremental average cost curve. This results in fewer individuals

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heterogeneity and moral hazard or administrative costs can cause some individuals’ incremental
marginal cost to exceed their incremental willingness-to-pay (Einav and Finkelstein 2011, Bundorf et
al. 2012). In this textbook case, however, the incremental willingness-to-pay of all individuals is
assumed to exceed their incremental marginal cost, making it optimal for the entire market to enroll
in the more comprehensive plan.
enrolling in Plan E, in this case causing the equilibrium to be less efficient. It is clear that if $\beta_p$ is positive and large (i.e. predicted costs are strongly, negatively correlated with demand), risk adjustment can even lead to a complete unraveling of the market where everyone enrolls in Plan B.

While it may seem unlikely that there could be advantageous selection on pooled costs, there are plausible scenarios where this could occur. This is due to there being both multiple dimensions of “costs” and preferences. Consider the following example. Reinsurance, a policy that reimburses plans for the costs of high cost individuals, is a form of risk adjustment where predicted costs are the costs of individuals above the reinsurance threshold and residual costs are all other costs. Assume that reinsurance is implemented in a health insurance market, implying costs above the reinsurance cutoff are pooled. Let there be two types of individuals: Risky and safe. Risky individuals value more comprehensive insurance less than safe individuals. They are also more likely to engage in risky activities such as snowboarding or rock climbing that result in large acute health care costs. Safe individuals value more comprehensive insurance more than risky individuals. Let’s also assume that safe individuals tend to go to the doctor a lot due to a mild case of hypochondria. In this example, the costs of the safe individuals will be moderately high but not high enough to trigger reinsurance payments. The costs of risky individuals will be very low for most but extremely high for a few individuals who incur large acute costs due to their risky behaviors. These large payments will trigger reinsurance payments. In this example, the average cost of safe individuals will likely be much higher than the average cost of risky individuals. Safe individuals will also be more
likely to enroll in the comprehensive plan, implying that the comprehensive plan is adversely selected on total costs. However, because safe individuals are much less likely than risky individuals to incur costs high enough to trigger reinsurance payments, the comprehensive plan will be advantageously selected on predicted costs. This case will be similar to the one described in Figure 1.2, and risk adjustment will fewer rather than more individuals to choose the adversely selected and more comprehensive plan. Risk adjustment models that predict only acute costs would produce a similar outcome in this setting.

This case also illustrates why when risk adjustment is imperfect some payment models may be better than others, and why better “fit” does not always imply higher welfare. Consider the case of two risk adjustment models, Model A and Model B. Under Model A (Model B), predicted and residual costs are described as $c_{p,A}(\theta_i, r_i)$ and $c_{r,A}(\theta_i, r_i)$ and $c_{p,B}(\theta_i, r_i)$ and $c_{r,B}(\theta_i, r_i)$, respectively. Now, assume that Model A explains all of the costs explained by Model B, plus an additional portion of costs, i.e. 

$$c_{p,A}(\theta_i, r_i) = c_{p,B}(\theta_i, r_i) + d(\theta_i, r_i)$$
$$c_{r,A}(\theta_i, r_i) = c_{r,B}(\theta_i, r_i) - d(\theta_i, r_i)$$

This implies that Model A “fits” total costs better than Model B in the r-squared sense so that 

$$\sum c_{R,A}(\theta_i, r_i)^2 < \sum c_{R,B}(\theta_i, r_i)^2$$

Now, the slope of the incremental average cost curve can be described as the sum of either the slopes of Model A's incremental predicted and residual cost curves or Model B's incremental predicted and residual cost curves:

$$\beta = \beta^{R,A} + \beta^{P,A} = \beta^{R,B} + \beta^{P,B}$$

Additionally, the slope of Model A's incremental residual cost curve can be described as the difference of the slope of Model B's residual cost curve and the slope of the curve describing the additional costs explained by Model
A: $\beta^{RA} = \beta^{RB} - \beta^d$. This implies that the incremental average risk adjusted cost curve will be equal to $\beta^{RA,A} = \beta^{RA} = \beta^{RB} - \beta^d$ under Model A and $\beta^{RA,B} = \rho^{N,B}$ under Model B, and the difference in the slope of the incremental average risk adjusted cost curves under Model A and under Model B will be equal to $-\beta^d$. This implies that if $\beta^d > 0$ ($\beta^d < 0$), the incremental average cost curve will be flatter under Model A (Model B). Thus, in order to compare two models, again the portion of total costs explained by the model, or the “fit” of the model, is not the relevant metric. Instead, it is the correlation between demand and the additional costs that are explained by Model A that determines whether Model A results a flatter incremental average risk adjusted cost curve and additional enrollment in the adversely selected plan. In the textbook case, if those additional costs are positively correlated with demand (i.e. $\beta^d > 0$), then Model A will result in a more efficient equilibrium than Model B, and if they are negatively correlated with demand, Model B will result in a more efficient equilibrium than Model A.

An environment in which Model A has a better fit and yet $\beta^d < 0$ is not at all implausible. Consider the comparison of prospective and concurrent risk adjustment models. In general, prospective models explain chronic costs (Model B) and concurrent models explain chronic costs and acute costs (Model A). Here, $d(\theta_t, \tau_t)$ represents acute costs, and $\beta^d > 0$ implies adverse selection on acute costs and $\beta^d < 0$ implies

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15 Recall that prospective models are estimated by regressing costs in year $t$ on diagnoses from year $t-1$ and concurrent models are estimated by regressing costs in year $t$ on diagnoses from year $t$. This implies that prospective models are likely to explain costs that are predictable from year to year (chronic costs) and concurrent models are likely to explain costs that are explainable by diagnoses (chronic and acute costs).
advantageous selection on acute costs. If the same assumptions hold as in the reinsurance example above to make more comprehensive plans advantageously selected on acute costs, then in this case $\beta^d < 0$ and concurrent risk adjustment will lead to a steeper incremental average risk adjusted cost curve and a fewer individuals enrolling in the adversely selected plan, despite concurrent models achieving substantially better fit. Perhaps more likely, if $\beta^d = 0$ (i.e. demand is unrelated to acute costs) prospective and concurrent risk adjustment will result in identical equilibrium sorting, prices, and welfare, despite the concurrent model explaining much more of the variance in total costs than the prospective model. In the empirical part of this paper, I show that it is in fact the case that the extra costs explained by concurrent models are relatively uncorrelated with demand.

Even if more comprehensive plans are adversely selected on both pooled and non-pooled costs as in Figure 1.1, in practice, the assumptions of the textbook case may not hold. For example, it is likely that there will be moral hazard, implying that it may not be efficient for all individuals to enroll in the more comprehensive plan. Costs may also differ across plans for other reasons such as differences in administrative costs. There may also be preference heterogeneity (Glazer and McGuire 2011; Bundorf et al. 2012; Geruso 2013). In all of these cases the explanation of how risk adjustment affects prices and sorting given here will remain true: If predicted costs are positively (negatively) correlated with demand, risk adjustment will result in more (fewer) individuals choosing the adversely selected plan. However, the efficiency consequences of this re-sorting of individuals across plans may be different because in some of these cases it may not be optimal for all individuals to enroll in the more comprehensive plan. This will be
especially important in cases where plans are horizontally differentiated as in Bundorf et al. (2012). I also point out that while the Figures 1.1 and 1.2 may not be fully realistic, they make clear the concept that in order to simulate competitive equilibria with risk adjustment, one needs to take into account not just the correlation between demand and total cost, but also the correlation between and predicted costs. As discussed above, due to potential preference heterogeneity, these two correlations need not be identical. This is a new concept that has not previously be recognized. In the next section I use data from a large employer to recover this joint distribution and then simulate equilibria under different forms of risk adjustment.

Section 3: Data and Setting

I estimate the joint distribution of preferences, total costs, and predicted costs using data from a large employer in the Truven Marketscan Database during 2006-07. During this period, the firm offered its employees a choice of two PPO plans: a basic plan (Plan B) and a more comprehensive, enhanced plan (Plan E). Around 50,000 employees

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16 It seems apparent that similar to the figures in Einav et al. (2010), the figures here show that the demand and cost curves, along with the predicted and residual cost curves, present sufficient statistics for the welfare analysis of plan risk pooling policies. The only assumptions that have to be made are that individuals’ choices reflect their preferences and that plan behavior is not a function of plan risk adjustment (i.e. there is no upcoding or alterations of the set of contracts offered). In environments where risk adjustment is already being used, given exogenous variation in prices, along with data on plan average costs, enrollment, and average risk scores, these curves can all be estimated relatively easily. In environments where risk adjustment is not being used, given additional data on individual level insurance claims, predicted and residual cost curves for different counterfactual plan risk pooling policies can be estimated, and the welfare consequences of the counterfactual policies can be calculated. However, the potential for large changes in equilibrium prices and sorting suggests that the assumptions of linear demand and cost curves, while likely valid locally, may be invalid in this context. This will become apparent in the empirical exercise below. An additional issue with this estimation strategy is that the incremental average cost curve shown in the figure is not the relevant curve for finding the equilibrium price when Plan B offers greater than zero coverage.

17 This is the same employer used by Geruso (2013).
enrolled in these plans during the time period, along with 76,000 dependents. For all individuals in the data, I observe their plan choice and administrative health insurance claims for each year during which they enroll in a plan. As is common in this type of data, I do not observe employees who choose not to enroll in a plan. Fortunately, due to the high subsidies offered by employers and the market failures present in the individual market, less than 20% of individuals forgo coverage offered to them by their employer (Kaiser Family Foundation 2013).

In order to simplify estimation, I limit the sample in the following ways. First, I only include employees who enroll no dependents. This permits me to avoid issues stemming from combining each family member’s distribution of costs, without really taking away from the simulations of the effects of risk adjustment. Perhaps more importantly, it also allows me to avoid making assumptions about the family structure of the employee premium contribution which is not available in the data. Second, I only include each employee’s choice from 2007. In order to estimate switching costs, I require information on each employee’s prior plan. This requirement implies that I cannot use choices from 2006.18 Third, I limit the sample to employees who are enrolled for the full 365 days of 2006 and 2007. As described below, in order to estimate each employee’s distribution of expected out-of-pocket costs, I require information on utilization and diagnoses from the year prior to plan choice. If this information is incomplete, the

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18 Data from this firm are present in the Marketscan database for 2005 and 2008. However, in 2005, employees are offered more than just these two plans and it is not entirely clear that the plans are consistent from year-to-year. This raises concerns about my ability to estimate switching costs accurately using 2006 choices, so I leave the 2006 choices out. For 2008, estimation results seem to indicate that my estimates of the employee contribution to the premium were fairly inaccurate, skewing some of the results. Implausibly large estimates of switching costs in 2008 (higher than $5,000) also caused concern. For these reasons, I also leave out choices from 2008.
estimates of future costs will be biased. Finally, I drop any employee not enrolled in the first month of 2007 and any employee who changed plans in the middle of 2007.

The left columns of Table 1.1 shows observed characteristics of the employees in the sample. I note that the Marketscan database includes minimal demographic information about the employees in order to protect the privacy of Truven's clients. The average age among the employees in my sample is around 42, and 60% of the employees are male. About 10% of the individuals in the sample are defined as “new” employees, meaning they were not enrolled in a plan during 2006. As discussed below, this will be important for estimating switching costs. The average total annual health care costs among the employees in the sample is around $4,000.

The two PPO plans offered by this employer differ only in cost sharing, and the contracts remained constant throughout the sample period. The cost-sharing parameters of each plan are found in left columns of Table 1.2. For medical costs, Plan E has a lower deductible, coinsurance rate, and out-of-pocket maximum. With respect to other costs from ER visits and prescription drugs, cost sharing is identical in the two plans. The main differences between the plans are the cost sharing parameters for medical claims and the plan premiums. Unfortunately, neither the premiums nor the employee

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19 As discussed below, in order to estimate switching costs, I require the presence of new enrollees who were not previously enrolled in a plan. Therefore, I do include enrollees not enrolled at all during the prior year. For these new enrollees, the distribution of expected out-of-pocket costs is estimated using information on utilization and diagnoses from the current year, so I require that they remain enrolled for all 365 days of the current year. This implies that the condition for remaining in the sample is that the enrollee be enrolled for either 365 days of the prior year and one month of the current year (to allow me to observe plan choice) or 365 days of the current year.

20 All of these parameters apply only to providers in the plan’s network. Claims from out-of-network providers are covered much less generously. However, there are very few of these claims, and they are not consistently and clearly identified, so I largely ignore them here.
contribution to the premiums are available in the data. Because the employee contribution is a critical piece of the empirical model described below, I follow Kowalski (2013) and Geruso (2013) and estimate the contribution from the data. I discuss the estimation process in the following section. Here I just note that while it may seem quite difficult to estimate the employee contribution, most employers follow a rule that bases premiums for year $t$ on average costs in each plan in year $t - 1$. I observe the universe of claims from year $t - 1$, so I can calculate premiums according to this rule. Additionally, I note that for the sake of the empirical model, all that matters is the difference in employee contributions for Plan E and Plan B, not their actual values. This makes the estimation of contributions easier because certain unobserved costs such as the administrative load will likely be the same for the two plans.

Section 3.1 Cost Model Sample

In order to estimate the choice model discussed below, I need to construct an estimate of each individual’s distribution of expected costs. As discussed in Section 4.2.3 below, estimation of this distribution is likely to be more accurate with a larger dataset. Because the firm sample is relatively small, in order to estimate the cost model I augment the sample using data on 845,000 additional individuals from the Marketscan Database to form the cost model sample. The cost model sample consists of a random sample from the sample of all individuals in Marketscan from 2006-07 enrolled in a PPO plan for at least 300 days of year $t$ and year $t + 1$. The characteristics of the cost model sample are found in column 4 of Table 1.1. While the means of the variables in the table differ for these two samples, as discussed below, the ranges of risk scores and ages are more
relevant for comparing the samples. Additionally, the cost model sample will be validated by comparing costs predicted by the cost model to actual costs among the employees in the sample.

Section 4: Empirical Model

As discussed above, in order to simulate equilibrium prices and sorting under risk adjustment, I require the joint distribution of demand, total costs, and predicted costs. In this section, I will discuss how I recover each component of this distribution.

Section 4.1: Total Costs and Predicted Costs

Because my data include the universe of health insurance claims for each individual in the sample, I observe total costs. I also observe predicted costs in the data. As discussed above, predicted costs are the costs explained by individuals' risk scores. Risk scores are assigned using the following formula:

\[ r_i = \delta x_i \]

\( x_i \) represents a vector of “risk adjusters,” or variables that describe an individual’s health status. \( \delta \) represents a vector of risk adjustment weights. Different risk adjustment models use different groups of variables. The models I use in the simulations include dummy variables for age-by-sex cells and a set of 394 “Hierarchical Condition Categories,” or HCCs developed by Verisk Health. HCCs indicate whether an individual has one of 394 health conditions that have an effect on medical costs. They are groups of diagnoses and are based on health insurance claims. When the diagnoses are from the prior (current) year, the model is referred to as a “prospective” (“concurrent”) model. HCCs are also used in the models developed by HHS and CMS for the Federal Exchange, Medicare
Advantage, and Medicare Part D. In addition to the Verisk models, I also simulate equilibria under the HHS-HCC model being implemented in the Exchanges. The HHS-HCC model is a concurrent model.

The risk adjustment weights, $\delta$, are estimated using a large sample of insurance claims from the Marketscan database. First, total annual costs, $C_i$, are regressed on the risk adjusters:

$C_i = \beta x_i + \epsilon_i$

The coefficients from the regression, $\hat{\beta}$, are then normalized by dividing by the average cost in the estimation sample: $\delta = \frac{\hat{\beta}}{\hat{c}}$. This implies that an individual who would be predicted to have average costs in the estimation sample will be assigned a risk score of 1.0.

In practice, individuals are assigned HCCs using diagnoses from their health insurance claims. Because I observe the health insurance claims for each employee in my sample, I also observe their HCCs. I calculate each individual's risk score by combining these HCCs with the pre-estimated weights for the Verisk and HHS-HCC risk adjustment models. The critical assumption here is that individuals would receive the same diagnoses in a setting with or without risk adjustment.$^{21}$

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$^{21}$This assumption would be violated if plans respond to risk adjustment by “upcoding” or by increasing utilization in order to increase the number of diagnoses and thus extract a larger risk adjustment transfer (see Geruso and Layton (2014) for an example of this in Medicare). While this type of behavior is likely, it is unlikely that it would dramatically alter individuals' risk scores and the joint distribution estimated here. Additionally, if plans are identical and all individuals are equally “upcode-able,” upcoding will result in the market average risk score increasing in tandem with the plan average risks scores. Because risk adjustment transfers are based on normalized risk scores, this would result in precisely the same normalized risk scores as the setting with no upcoding.
Section 4.2 Demand

While employees' costs can be observed in the data, demand is unobservable and must be estimated. Conceivably, demand could be non-parametrically estimated by observing how employees respond to an exogenous shift in plan prices (Einav et al. 2010). However, because there is no variation in prices in my data, in order to estimate preferences, I must specify a structural model of health plan choice and use the model to estimate demand using a method similar to that used in Cohen and Einav (2007). Fortunately, the two plans at the firm I study are vertically differentiated in that they differ only in cost sharing, making the assumption that the structural model fully characterizes the employees' choices more easily justified. I start by assuming that employees make choices based on the following Von-Neuman Morgenstern expected utility function:

\[ U_{ij} = \int f_{ij}(OOP)u_i\left(W_i, OOP, P_j, 1_{ij,t-1}\right)dOOP \]

Four variables enter into the employee’s utility function: \( f_{ij}(OOP) \), employee \( i \)'s distribution of expected out-of-pocket costs if enrolled in plan \( j \); \( W_i \), employee \( i \)'s wealth; \( P_j \), plan \( j \)'s premium; and \( 1_{ij,t-1} \), an indicator for whether employee \( i \) was enrolled in plan \( j \) during the previous period. The additional factor affecting individual choice is the shape of \( u_i \). I assume that employees’ preferences follow the constant absolute risk aversion (CARA) formulation. Let \( x_i \) represent the ex-post consumption level of individual \( i \). The CARA assumption implies that

\[ u_i = -\frac{1}{\gamma_i(Y_i, Z_i)} e^{-\gamma(Y_i, Z_i)x_i} \]
The shape of each individual's CARA utility function is defined by her coefficient of absolute risk aversion, $\gamma_i$, with larger values of $\gamma_i$ implying higher levels of risk aversion. I define $x$ as follows:

$$x_i = W_i - P_j - OOP + \eta(Y_i)1_{j=t-1} + \epsilon_{ij}$$

The employee’s consumption is a function of initial wealth, the plan premium, expected out-of-pocket costs, a switching cost incurred if the employee chooses a different plan in year $t$ than in year $t - 1$, and an i.i.d. preference shock, $\epsilon_{ij}$, with mean $\mu_\epsilon$ and variance $\sigma_\epsilon^2$. Because the two plans employees of the firm can choose between vary only in their financial characteristics, I argue that this specification comes quite close to fully characterizing employee choice. With all of the components of this model, I can determine each individual's choice of plan under different levels of the price differential from the model above $P$. This will allow me to determine each individual's demand for Plan E, the third component of the joint distribution required for simulation of competitive equilibria with risk adjustment. As most of the components of the model are unobserved, they require some form of estimation. I now discuss how I estimate each component.

**Section 4.2.1: Plan Premiums: $P_j$**

As discussed above, the data do not include any information about the employee contribution to the premium so I must estimate it. Most employers follow a simple pricing rule based on the average cost of individuals enrolled in a plan during the prior year (see Handel (2013) and Geruso (2013)). I assume that for the firm I study, the

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22 The assumption of CARA utility makes $W_i$ irrelevant, implying no income effects.
premiums for employees without dependents are equal to the average cost of the employees enrolled in each plan during the prior year plus some loading factor, \( P_t^f = AC_{t-1}^f + \alpha \). I calculate \( AC_{t-1}^f \) using the claims data from the prior year. I then assume that the employer sets the employee contributions equal to 20% of the full premium of each plan (Kaiser Family Foundation 2013). Note that for estimation of the choice model it is not important for the premiums of each plan to be accurately estimated. Instead, it is just important that the premium differential \( P \) be correct. Given the assumptions, this premium differential is:

\[
P_t = 0.2(AC_{t-1}^E - AC_{t-1}^B)
\]

To address the possibility that \( P_t \) is incorrectly estimated, I also include a plan specific intercept for Plan E in \( x_{ij} \). Because all individuals pay the same prices, this intercept will capture both any idiosyncratic preference for Plan E and any bias in the estimate of \( P \).

**Section 4.2.2: Switching Costs: \( \eta_i \)**

There is extensive empirical evidence that individuals face substantial switching costs when choosing to move between health plans (Sinaiko and Hirth 2011, Handel 2013, Polyakova 2013). There are many reasons for this phenomenon such as the time and hassle costs of researching a new plan and switching, attachment to a network of providers, or just pure inattention or laziness.\(^{23}\) Here, the source of the switching cost is unimportant. It is included in the model to allow simulation of equilibrium sorting where all individuals face an active choice, as in the first year of operation of the Exchanges. In order to separate switching costs from persistent heterogeneity in preferences, I follow

\(^{23}\) See Handel (2013) for a thorough discussion of potential sources of inertia.
Handel and Kolstad (2013) by exploiting the fact that some employees in the data were not previously enrolled in a plan. While I do not observe why these enrollees are enrolling for the first time, I know that they should not face a switching cost when making their choice. To account for observable differences between new and old enrollees, I allow $\eta$ to vary with observable demographic characteristics. Specifically, I assume that

$$\eta_i = \eta_0 + \eta_1 age_i + \eta_2 female_i$$

Effectively, I compare the choices of new and old enrollees with similar demographics and cost risk to estimate the switching costs.

As discussed above, this $\eta_i$ is identified by comparing the choices of new and old enrollees. If these enrollees are identical with respect to any relevant unobserved characteristics, then the differences in the patterns of their choices identify the size of the switching cost. If there is no switching cost, then the choices should be similar. However, if there are switching costs, individuals previously enrolled in Plan E should be more likely to choose Plan E than otherwise identical individuals not previously enrolled in either plan. The important assumptions here are that new and old enrollees are similar with respect to unobserved variables that affect risk preferences and that there is sufficient variation in the observed characteristics (age and gender) among the new enrollees such that there is a new enrollee similar to every old enrollee. Columns 2 and 3 of Table 1.1 show that while the mean age is lower among the new enrollees, the range of the ages of new enrollees is almost identical to that of old enrollees.
Out-of-Pocket Cost Distributions: $F_{ij}(OOP)$

As discussed, the model requires an estimate of each employee’s distribution of expected out-of-pocket costs in each plan, $F_{ijt}(OOP)$. I construct this distribution directly from data in the cost model sample described above. To obtain a distribution of expected total costs for each employee, I first divide the full Marketscan sample into cells of employees with similar health status in year $t-1$. The cells are based on predictive measures of each individual’s medical cost risk generated by sophisticated predictive modeling software developed by Verisk Health and used by health insurers and large employer to predict the costs of their enrollees.\(^{24}\) The software uses information such as diagnoses and utilization found in insurance claims data from year $t-1$ to generate individual-level medical risk scores, $\lambda_i$, describing each individual’s medical cost risk in year $t$. These risk scores are different from the risk scores used for risk adjustment described above. The risk adjustment risk scores are based only on information about diagnoses and demographics. The medical risk scores used here are based on the entire set of information available in the health insurance claims. This includes past utilization and spending in addition to the diagnoses and demographics used to generate the risk adjustment risk scores. In order to ensure that the estimates of each employee's cost distributions are as precise as possible, I split the sample into 1,000 cells based on medical cost risk. To ease computation, I take a random sample of 1,000 individuals from each medical cost risk cell. For all of the individuals in a given cell, I fit a lognormal

\(^{24}\) I note that I sort individuals into cells based only on predictions of medical cost risk and not predictions of prescription drug cost risk because the plans do not vary with respect to cost-sharing for prescription drugs, making those costs irrelevant to the employee's choice. I do, however, incorporate predictions of prescription drug costs in the counterfactual simulations below.
distribution with a point mass at zero to the actual medical costs of the individuals in the cell in year $t$ and allow the lognormal parameters to vary with age and gender. The lognormal parameters plus the point mass at zero fully describe the estimates of each employee’s distribution of expected medical costs. I then use the simple cost-sharing rules for each plan to map each employee’s expected total medical costs to expected out-of-pocket costs to form $F_{ij}(OOP)$.

I use the cost model sample rather than the smaller choice model sample to construct $F_{ij}(OOP)$ because there is a tradeoff between cell size and the number of cells. With a larger number of cells I capture more of the private information about individuals’ future costs. However, larger cells necessarily imply fewer individuals in each cell, resulting in less accurate estimation of the parameters describing $F_{ij}(OOP)$. Using the larger cost model sample avoids this tradeoff by increasing the total number of individuals in the sample. The cost of using the cost model sample rather than the choice model sample to estimate $F_{ij}(OOP)$ is the requirement of an additional assumption: Individuals in the cost model sample and the choice model sample are similar with respect to any relevant variables not used to form the cells. Given the large amount of sophisticated information used to form the cells and the large number of cells, I argue that this assumption is reasonable. Additionally, in Table 1.1 I show that the range of risk scores is similar for the cost model and estimation samples, implying that there are

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25 As mentioned above, there is no cost-sharing for ER and preventive visits. Because the prediction software predicts total medical risk, rather than medical risk other than ER and preventive visits, I cannot separately predict an employee’s use of these services. Instead, I ignore the fact that they are priced differently and combine them with other medical spending. In practice, these services make up a relatively small portion of spending and have a small impact on inferences about the distribution of $F_{ij}(OOP)$. 
similar individuals in the samples. Table 1.1 also shows that for the estimation and simulation samples the average expected cost produced by the cost model is quite similar to the average realized cost among employees in the sample, implying that the estimates are not systematically biased.

**Risk Preferences: \( \gamma_i \)**

Each individual’s coefficient of absolute risk aversion, \( \gamma_i \), is the final component of the choice model. I estimate this parameter as follows. Because the two plans available to the employees in my sample differ only in cost sharing, if the employees are all risk neutral and \( F_{ij}(OOP) \) and \( P_j \) are known, their optimal choices can easily be recovered by calculating the mean of each employee’s distribution of expected costs in each plan, adding that mean to each plan’s premium, and then comparing the two sums. Whichever plan has the lower total cost (premium plus out-of-pocket costs) would be the optimal choice. Call this choice the risk-neutral optimal choice. The intuition behind the identification of \( \gamma_i \) is that under the assumption that \( F_{ij}(OOP) \) is observed, an employee’s deviation from the risk-neutral optimal choice describes her level of risk aversion (Cohen and Einav 2007). For example, if an employee faces higher total cost in Plan B than in Plan E, but she chooses Plan E anyway, she must be risk averse, and the size of the cost difference identifies the extent of her risk aversion. This method is also used by Handel (2013) and Geruso (2013).

I estimate a random coefficient distribution for \( \gamma_i \) with mean \( \mu_\gamma(Y_i, Z_i) \) and normally-distributed variance \( \sigma_\gamma^2 \), where \( \nu_i \) represents the random component of \( \gamma \). To ensure the joint distribution of demand, total costs, and predicted costs is fully
characterized, I allow $\mu_Y$ to vary with a set of demographic variables, $Y_i$, along with employees’ total medical risk scores (total costs), $\lambda_i$, and risk adjustment risk scores (predicted costs), $r_i$, to allow for heterogeneity in risk preferences. Specifically, I assume that $\mu_Y(Y_i, Z_i)$ can be described as follows:

$$
\gamma_i(Y_i, Z_i) = \beta_0 + \beta_1 \text{age}_i + \beta_2 \ln(\lambda_i) + \beta_3 \text{age} \times \ln(\lambda_i) + \beta_4 \ln(\eta)
$$

Allowing $\gamma_i$ to vary with $\lambda_i$ is motivated by previous research that has shown that the correlation between risk preferences and cost risk can influence the degree and direction of selection in equilibrium (see Finkelstein and McGarry (2006), Cohen and Einav (2007), Einav et al. (2013), and Handel et al. (2013)). The inclusion of $r_i$ in the risk preference equation is motivated by the graphical analysis above. Recall that the equilibrium consequences of risk adjustment depend on the relationship between demand and predicted and residual costs. Thus, in order to accurately simulate equilibrium prices and sorting under risk adjustment, it is critical that the model fully capture these relationships. Because demand is a function of $\gamma_i$, it is necessary to allow $\gamma_i$ to vary by the risk scores that determine predicted and residual costs. In fact, if this correlation is not allowed for in the estimation of $\gamma_i$, the situation described in Figure 1.2 would be missed in the simulations.

Section 4.2.5: Limitations

While this demand specification characterizes the choices of consumers quite nicely, it does rely on a few important assumptions. First, I assume that when making their choices between the two plans, employees are using the same distribution of expected out-of-pocket costs that I assign to them. While it is possible that individuals
know more than what I am able to predict, it is unlikely that they know much more. On the other hand, it is also possible that individuals know much less than the model suggests. To deal with this problem, in the appendix I test the sensitivity of the parameter estimates to the specificity of the information available to consumer. I also suggest that some portion of any misspecification of expected out-of-pocket costs may be absorbed by coefficient of absolute risk aversion. While this may seem undesirable, recall that for accurate simulation of competitive equilibria under risk adjustment, it is the joint distribution of demand, total costs, and predicted costs that is required, not the joint distribution of risk preferences, out-of-pocket costs, total costs, and predicted costs. As long as the willingness-to-pay is characterized in some way in the demand model, whether through the estimate of the individual's out-of-pocket cost distribution or her coefficient of absolute risk aversion, the simulations will provide accurate results. This still leaves open the possibility that rather than just using limited information in a rational manner, individuals actually use sophisticated information but they do so irrationally. There is evidence for this type of behavior (Handel and Kolstad 2013, Abaluck and Gruber 2011). It is important to note, however, that “mistakes” may also be captured as risk preferences in this model. Again, this is not a problem for using the joint distribution of demand, total costs, and predicted costs to simulate competitive equilibria with and without risk adjustment. However, it does present a problem for inference about welfare consequences of risk adjustment because the area below the demand curve and above the price may not actually represent consumer surplus (Spinnewijn 2013).
Section 4.2.6: Estimation

Because the random components of the model, $\sigma^2_e$ and $\sigma^2_p$, are assumed to be normally distributed, I estimate the parameters of the model using a random coefficients probit simulated maximum likelihood approach similar to the method used by Handel (2013) and Geruso (2013) and outlined in Train (2009). Estimation begins by fixing the parameter vector, $\Phi$, and taking a draw from each of the distributions of the random components of the model, $\epsilon^s$ and $\nu^s$. Next, $Q$ draws are then taken from each employee's total cost distribution and run through each plan's cost-sharing parameters to simulate $F_{ij}(OOP)$ for each employee $i$ and plan $j$. Each employee's expected utility from plan $j$ is then estimated by averaging the CARA utility function over the $Q$ draws from $F_{ij}(OOP)$:

$$E[U_{ij}] = \frac{1}{Q} \sum_{q=1}^{Q} \exp\left(-\gamma^s_i(Y_i Z_i)(P_j + OOP_{ij})^q + \eta(Y_i)1_{ij,t-1} + \epsilon_{ij}^s\right)$$

where

$$\gamma^s_i(Y_i Z_i) = \beta_0 + \beta_1 \text{age}_i + \beta_2 \ln(\lambda_i) + \beta_3 \text{age} \times \ln(\lambda_i) + \beta_4 \ln(\eta_i) + \nu^s_i$$

$$\eta(Y_i) = \eta_0 + \eta_1 \text{age}_i + \eta_2 \text{female}_i$$

Given the draws of the random components of the model, $\epsilon^s$ and $\nu^s$, and the expected utility estimates for each plan they imply, I could simulate each employee's choice by comparing the expected utility for Plan E and Plan B and assigning employee $i$ to the plan with higher expected utility, an accept-reject simulator. However, the accept-reject simulator can cause problems in the estimation process due to flat portions of the likelihood function where no employees choose to move from one plan to the other and undefined portions of the log-likelihood function due to some individuals having a zero
probability of enrolling in one of the plans. Both of these problems could potentially be solved by including a larger number of draws of the random components; however, for both issues to be fully resolved, the number of necessary draws would approach infinity, which would be computationally impossible. Instead, I use a smoothed accept-reject simulator. The simulator I use was developed by Handel (2013) and simulates probability that the employee will choose each plan according to the following function:

\[
R^s_{ij}(j = j^*) = \frac{1}{\sum_j \left( -E[U^s_{ij}] \right)} \left( \frac{1}{\sum_j \left( -E[U^s_{ij}] \right)} \right)^\tau
\]

The form of the simulator ensures that the estimated probability increases (decreases) when the accept-reject simulator would increase (decrease) and that the probability lies between zero and one. As the smoothing parameter, \( \tau \), becomes large, the simulator becomes identical to the accept-reject simulator.

The probability of choosing each plan is calculated for each draw, \( s \), of the random components. To find the simulated probability that the employee chooses plan, \( j \), given the draw from the parameter distribution, I average over the smoothed values,

\[
P_{ij}(\Phi) = \frac{1}{S} \sum_{s=1}^{S} R^s_{ij}
\]

The simulated log-likelihood function is then defined as
\[ SLL(\Phi) = \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{J} d_{ij} \ln P_{ij}(\Phi). \]

\( d_{ij} \) is equal to one if the employee actually chose plan \( j \) and zero otherwise. The likelihood function is quite intuitive in that it will achieve its maximum where the simulated probability that each employee chose plan \( j \) is as close to one as possible when the employee actually chose plan \( j \) and as close to zero as possible otherwise. I use standard numerical techniques to find the parameter vector, \( \Phi \), that maximizes the likelihood function. In the actual estimation I set \( Q = 50, S = 75, \) and \( \tau = 2 \).

**Section 4.2.7: Model Results**

Table 1.3 presents the results from the choice model discussed above. The estimates of the coefficient of absolute risk aversion are similar to estimates in the health insurance literature (Geruso 2013, Handel 2013). The average estimate of the coefficient of absolute risk aversion is \( 6.9 \times 10^{-4} \) and the median estimate is \( 6.8 \times 10^{-4} \). To aid interpretation, this level of risk aversion implies that the average employee in the sample would be indifferent between a gamble where she will win $100 or lose $94 with equal probability and the status quo. Perhaps more importantly, the estimates imply that risk aversion is negatively correlated with total medical cost risk, positively correlated with prospective risk adjustment risk scores, and negatively correlated with concurrent risk adjustment risk scores. If taken literally, this implies that controlling for prospective and concurrent risk scores, employees with high levels of total medical cost risk have lower levels of risk aversion. This result is similar to the finding of Handel et al. (2013). However, as discussed above, it is possible that the expected out-of-pocket cost
distributions are miss-specified, resulting in biased estimates of the coefficient of absolute risk aversion. If this is the case the correlations could represent real relationships between risk aversion and total costs and risk scores or they could represent the misspecification of the expected out-of-pocket cost distribution.

The estimated switching costs are quite large, with the mean and median switching costs being around $4,800. To put this in context, this is around 126% of the total average health care costs among the employees in the sample. These estimates are substantially larger than other estimates found in the literature (Handel 2013, Handel and Kolstad 2013). This could be due to large switching costs in this population or to some form of model misspecification. Estimating the model using data from other years produces similarly large estimates. However, as discussed above, accurate estimates of switching costs are not critical for the simulations below. Instead, the joint distribution of active choice demand, total costs, and predicted costs is what is required. The switching costs are just estimated to ensure that the estimates of risk preferences are not contaminated by employee inertia. Given that the estimates are so similar to other estimates in the literature, the potentially biased estimates of switching costs here are somewhat unimportant.

Given the assumption of CARA utility and the estimates of employee risk aversion ($\gamma_i$) and the expected out-of-pocket cost distribution ($f_{ij}(OOP)$), I can now recover each employee's relative willingness-to-pay for one plan, $j$, over another plan, $j'$, where the plans are vertically differentiated in that they differ only in cost sharing. This
provides the final component of the joint distribution of total costs, predicted scores, and demand.

**Section 5: Counterfactual Simulations**

In order to simulate competitive equilibria with and without risk adjustment, I first expand the sample to form a new simulation sample. The simulation sample includes all single-coverage employees from 2005-07. The sample is restricted in the same ways as the choice model sample described above (i.e. must be enrolled for all 365 days of the year, etc.). For this sample, total costs and risk scores for each plan are calculated or estimated as described in Section 4. Summary statistics for this simulation sample can be found in the final column of Table 1.1.

I simulate competitive equilibria with and without risk adjustment in an environment similar to the Exchanges currently being established throughout the United States. Specifically, each individual is required to choose either a Bronze plan or a Platinum plan where the two plans are vertically differentiated in that they only differ in cost sharing. The Platinum plan is much more comprehensive than the Bronze plan. Plan cost sharing is described by standard non-linear price schedules where individuals pay the full cost of all care received up to a deductible, then some portion of each additional dollar of care up to an out-of-pocket maximum. The exact price schedules can be found in the last two columns of Table 1.2. The simulated Platinum (Bronze) plan has a deductible of $0 ($4500) a coinsurance rate of 20% (20%) and an out-of-pocket maximum of $1500 ($6500). The cost-sharing parameters were chosen using the 2014 version of the actuarial value calculator provided by the Department of Health and
Human Services. The choice to use the most and least comprehensive plans available on the Exchange in the simulation was deliberate. In order to capture the most accurate picture of adverse selection on the Exchange, the simulation must include these two options.

One additional component is required to complete the joint distribution of demand, total costs, and predicted costs. Demand is a function of two factors: risk preferences and the distribution of expected out-of-pocket costs. Risk preferences are assigned to each individual according to the estimated parameters from the model above, found in Table 1.3. The distributions of expected out-of-pocket costs for the new Platinum and Bronze plans are estimated using techniques similar to those described in Section 4. The key difference is that under the Platinum and Bronze plans, cost sharing for prescription drug utilization is not assumed to be identical in the two plans. Instead, the cost-sharing parameters described above are applied to total health care costs, the combination of prescription drug costs and medical costs. Therefore, in order to construct the distributions of expected out-of-pocket costs for the Platinum and Bronze plans, I first need to estimate each individual's distribution of expected total health care costs, rather than the distributions of total medical costs used to estimate the choice model. I do this by dividing the cost model sample discussed above into 1000 cells based on total cost risk instead of medical cost risk, where total cost risk is generated using a sophisticated

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26 This is the calculator that all insurers are required to use to ensure that their plans meet the actuarial value requirements of the ACA. The calculator can be found at http://www.cms.gov/CCIIO/Resources/Regulations-and-Guidance/Downloads/av-calculator-final.xlsm

27 In practice, most consumers will choose between 4 tiers of plans with varying levels of comprehensiveness. However, the competitive equilibrium in this environment would be quite complex and extremely difficult to model while not providing much additional intuition.
predictive model analogous to the one used to generate medical cost risk. I then follow
the procedure outlined above to complete the construction of the expected out-of-pocket
cost distributions, here using the Platinum and Bronze cost-sharing parameters rather than
the Enhanced and Basic plan parameters used above. The combination of risk preferences
and the expected out-of-pocket cost distribution allow me to calculate each individual's
expected utility under plan \( j \) by taking \( Q \) draws from the estimated \( F_{ij}(OOP) \) and using
the following expression

\[
E[U_{ij}] = \sum_{q=1}^{Q} e^{-\gamma_i(P_j + OOP_i^q)}
\]

I can then determine which plan \( i \) will choose given a price differential \( P \), providing the
final component of the joint distribution: Demand. Note that in the simulations
consumers are assumed to pay the full incremental cost of enrolling in the Platinum plan
rather than the subsidized cost assumed in the choice model. The subsidized cost was
used to estimate the choice model because it is likely to correspond closely with the price
the employees of the firm actually faced. The full incremental cost is used in the
simulations because this is the price that will be faced by individuals purchasing coverage
through the Exchanges.

Section 5.1: Welfare

In order to assess the welfare consequences of risk adjustment, I follow Einav et al.
(2010) and use a certainty equivalent concept. The certainty equivalent, \( e_{ij} \), is defined as
the value, \( e \), that makes individual \( i \) indifferent between paying \( e \) and facing the
uncertain loss under insurance plan $j$. I calculate the certainty equivalent for individual $i$ under plan $j$ by finding the value of $e_{ij}$ that makes the following expression true

$$-\frac{1}{\gamma_i} e^{-\gamma_i e_{ij}} = \int e^{\gamma_i (P_j + OOP_i)} dF_{ij}(OOP).$$

The certainty equivalent is convenient because it provides a way to determine $i$’s valuation of the insurance plan in dollars. Given an individual's certainty equivalent under each plan, I can calculate individual $i$’s willingness-to-pay for the Platinum plan by subtracting $e_{ip}$ from $e_{iB}$: $WTP_{ip} = e_{ip} - e_{iB}$. The willingness-to-pay for the Platinum plan incorporates the difference in out-of-pocket costs paid by $i$ and the difference in uncertainty under the two plans. It also represents consumer surplus from $i$ moving from the Bronze plan to the Platinum plan.

Total welfare, however, must also account for changes to producer surplus. Because the difference in out-of-pocket costs under the two plans just represents a transfer from the insurer to the consumer, it does not affect total welfare. Only the decreased uncertainty will impact total welfare. Thus, the change in total welfare from $i$ moving from the Bronze plan to the Platinum plan is

$$\Delta W_i = WTP_{ip} - \left( c_i^p - c_i^F \right)$$

Where $c_i^j$ is the plan cost from enrolling $i$ in plan $j$, making $(c_i^p - c_i^F)$ $i$’s incremental marginal cost. $\Delta W_i$ essentially represents the incremental welfare improvement from moving $i$ from the Bronze to the Platinum plan. This implies that the change in total welfare resulting from a move from a setting with no risk adjustment to a setting with risk adjustment is equal to
\[
\Delta \text{Welfare} = \sum_{i=1}^{N} \Delta W_{i} \mathbf{1}(E[U_{ip}^{RA}] > E[U_{ip}^{RA}]) - \sum_{i=1}^{N} \Delta W_{i} \mathbf{1}(E[U_{ip}^{NRA}] > E[U_{ip}^{NRA}])
\]

Where \( E[U_{ij}^{RA}] \) is \( i \)'s expected utility under plan \( j \) given the equilibrium prices with risk adjustment and \( E[U_{ij}^{NRA}] \) is \( i \)'s expected utility under plan \( j \) given the equilibrium prices without risk adjustment. The intuition for this measure is that welfare only changes when individuals move from one plan to another, and when an individual moves, welfare either increases or decreases by \( \Delta W_{i} \), depending whether \( i \) is moving from Bronze to Platinum or Platinum to Bronze.

Section 5.2 Correlations

As discussed in Section 2, the effect of risk adjustment on equilibrium prices and sorting depends critically on the correlations between demand, total cost, and predicted cost. In this section, I present evidence of these correlations in the simulation sample. To do so, I first group members of the sample into 50 quantiles of “willingness-to-pay” for the Platinum plan over the Bronze plan. To construct these groups, I use the expected utility model described in Section 4 to calculate for each individual \( i \) the difference between her expected utility in the Platinum plan and her expected utility in the Bronze plan where both premiums are set to zero.

Figure 1.3 shows the correlation between demand and total costs, with the quantile of willingness-to-pay on the x-axis and the average total cost for the group on the y-axis. It is clear that total costs are increasing with demand. This Figure shows that the slope of the incremental average total cost curve, \( \beta \) from section 2.1, is downward sloping, implying that the Platinum plan will be adversely selected.
Next we move to the correlations between predicted and residual costs. I show these correlations for four risk adjustment models: an age/sex risk adjustment model including only demographic variables, and prospective and concurrent diagnostic risk adjustment models. In each model predicted costs are determined by first regressing total costs on the risk score. The predicted values from this regression are the predicted costs and the residuals from the regression are the residual costs. The left panels of Figures 1.4A-1.4C show the correlation between demand and predicted costs, and the right panels show correlations between demand and residual costs.

It is clear that the predicted costs from all of the models are positively correlated with demand, implying that in all three settings the slope of the incremental predicted cost curve, $\beta^p$, is downward sloping, or in other words the Platinum plan is adversely selected on predicted costs. As expected, the correlation between demand and prospective and concurrent predicted costs is stronger than the correlation between demand and demographic predicted costs. Additionally, for all forms of risk adjustment, there is a positive correlation between demand and residual costs, implying that the incremental residual cost curve, $\beta^r$, is also downward sloping. This suggests that even after risk adjustment, the Platinum plan will be adversely selected.

Interestingly, with prospective and concurrent risk adjustment, there appears to be no correlation between demand and residual costs for everyone except for a few extremely high cost cases with highest willingness-to-pay. In other words, the incremental average risk adjusted cost curve is flat for everyone except for the highest spenders. This suggests that when prospective or concurrent risk adjustment is combined
with reinsurance, which compensates plans for the highest spenders, the correlation between demand and costs may be completely eliminated. Additionally, it is interesting to note that the correlation between demand and residual costs is quite similar for prospective and concurrent risk adjustment, implying that despite explaining a much larger portion of total costs (40% vs. 15%), concurrent risk adjustment may not do much better than prospective in terms of flattening the cost curve and inducing more enrollees to choose the Platinum plan.

Section 5.3: Equilibrium

In order to simulate equilibrium prices and sorting in this environment, I first need to establish an equilibrium concept. Handel et al. (2013) show that in this setting, the competitive equilibrium can be found using the following algorithm where willingness-to-pay is bounded between $\Delta w$ and $\bar{\Delta w}$, $P^P$ and $P^B$ represent the premium of the Platinum and Bronze plans, $P = P^P - P^B$, $AC^P(P)$ and $AC^B(P)$ represent the average plan costs of enrollees in the Platinum and Bronze plans given price differential $P$, $AC^E$ and $AC^B$ represent the average plan costs of the entire population in the Platinum and Bronze plans, and $\Delta AC(P) = AC^P(P) - AC^B(P)$:

1. If $\Delta AC(P) < P \forall P$ then the entire market enrolls in the Platinum plan and $P^P = AC^E$

2. If $\exists P$ such that $P = \Delta AC(P)$ then the equilibrium value of $P$ is equal to $P^* = \min(P: P = \Delta AC(P))$ and consumers sort according to willingness-to-pay
3. If $\Delta AC(P) > P \ \forall P$ then the entire market enrolls in the Bronze plan and $P^B = AC^B$

Figure 1.5 illustrates the equilibrium search with no risk adjustment. $P$ is on the x-axis. The light blue line represents the 45-degree line, and the orange line represents $\Delta AC(P)$. If there is an interior equilibrium, it will be where $\Delta AC(P) = P$. It is clear that there is no interior equilibrium in this setting and that $\Delta AC(P) > P$ for all values of $P$. This implies that in equilibrium, the entire market enrolls in the Bronze plan and $P^B = AC^B$. This is also known as market unraveling and is the same result found by Handel et al. (2013). In this setting, the correlation between demand and total costs, i.e. adverse selection, is so strong that there is no price differential at which any part of the market enrolling in the Platinum plan would result in a competitive equilibrium where both plans earns zero profits.

Section 5.3.1: Risk Adjustment

With risk adjustment, the equilibrium concept remains the same, but the relevant plan average costs change. Risk adjustment is implemented by assuming the regulator gives each plan the following transfer

$$T_j(P) = \left( \frac{\bar{R}_j}{\bar{R}} - 1 \right) \bar{P}$$

where as in section 2, $\bar{R}_j$ represents the average risk score of the enrollees in plan $j$, $\bar{R}$ represents the average risk score in the entire market, and $\bar{P}$ represents the average premium in the market. With risk adjustment, equilibrium is where the premium differential is equal to the incremental average risk adjusted cost. In other words,
equilibrium is now where the premium differential is equal to the incremental average cost net of risk adjustment transfers,

\[ AC_{RA}^j(P) = AC^j(P) + T_j(P) \]

The algorithm for finding the competitive equilibrium remains the same, except \( \Delta AC(P) \) is replaced with \( \Delta AC_{RA}(P) \). Note that \( AC^j = AC_{RA}^j \) for both plans because when the entire market is enrolled in the same plan \( T_j = 0 \).

I simulate four types of risk adjustment: demographic based on age-by-sex cells, prospective and concurrent diagnostic based on HCCs, and the HHS-HCC model being implemented in the Exchanges.\(^{28}\) Figures 1.5 and 1.6 illustrate the equilibrium search under these four forms of risk adjustment. Again, the light blue line represents the 45-degree line and the orange line represents \( \Delta AC(P) \). The dark blue, grey, and gold lines represent \( \Delta AC_{RA}(P) \) under demographic, prospective, and concurrent risk adjustment, respectively. Under demographic risk adjustment, \( \Delta AC_{RA}(P) > P \) for all values of \( P \) and the entire market still enrolls in the Bronze plan. In other words, demographic risk adjustment has no effect on equilibrium prices or sorting in this setting. However, under both prospective, concurrent, and HHS-HCC risk adjustment \( \Delta AC_{RA}(P) \) crosses the 45-degree line, implying that there exists an interior equilibrium. This can be seen more.

\(^{28}\) The transfer for HHS-HCC risk adjustment is slightly different from the formula used for the other forms of risk adjustment. It is

\[ T_j(P) = \left( \frac{\bar{R}_j}{\bar{R}} - \frac{AV_j}{\bar{AV}} \right) P \]

where \( AV_j \) is the actuarial value of plan \( j \) \( \bar{AV} \) is the enrollment-weighted average actuarial value in the market. Additionally, under the HHS-HCC model an individual’s risk score is different in the Platinum plan than in the Bronze plan, with the Platinum risk score being higher than the Bronze risk score. The reasons for these two adjustments are unclear, but I use them in order to simulate the true policy.
clearly in Figure 1.6. With both forms of diagnostic risk adjustment there are in fact multiple points where \( P = \Delta AC_{RA}(P) \). Recall that according to the algorithm, the competitive equilibrium value of \( P, P^* \), is the smaller value of \( P \) for which \( P = \Delta AC_{RA}(P) \). According to the algorithm then, under prospective risk adjustment \( P^* = $1,031 \), under concurrent risk adjustment \( P^* = $890 \), and under HHS-HCC risk adjustment \( P^* = $1,819 \).

Figure 1.7 illustrates the equilibrium allocations of individuals across plans in a more familiar way, similar to the graphical representation above. In this figure, enrollment in the Platinum plan is on the x-axis. Again, the orange, dark blue, gray, gold, and green lines represent the incremental average cost curve under no risk adjustment, demographic risk adjustment, prospective risk adjustment, concurrent risk adjustment, and HHS-HCC risk adjustment, respectively. The light blue line reflects demand or willingness-to-pay for the Platinum plan relative to the Bronze plan. For prospective, concurrent, and HHS-HCC risk adjustment, the equilibrium price \( P^* \) is where the grey, gold, and green incremental average risk adjusted cost curves cross the light blue demand curve. The equilibrium price and Platinum enrollment under HHS-HCC risk adjustment are highlighted with the dashed lines. Recall that with no risk adjustment or demographic risk adjustment, the entire market enrolls in the Bronze plan. The figure shows that under prospective, concurrent, and HHS-HCC risk adjustment, a substantial portion of the market, over 60% for HHS-HCC risk adjustment and over 80% for the others, will enroll in the Platinum plan.
The results of these simulations can also be found in Table 1.4. The table clearly shows that diagnostic risk adjustment compresses the premiums of the Platinum and Bronze plans and undoes a substantial portion of market unraveling. Changes in welfare due to risk adjustment are also found in Table 1.4. The welfare calculations suggest that individuals in this market would place a high value on diagnostic risk adjustment, almost $700 per person per year for HHS-HCC risk adjustment and more than $800 per person per year for the others. This suggests huge welfare gains from risk adjustment, around 20% of average total health care costs in this population.

It is also interesting to note that the effects of prospective and concurrent risk adjustment are quite similar, despite the concurrent model explaining a substantially larger portion of individuals' total costs. This is largely due to the fact that there is little correlation between demand and the extra costs explained by the concurrent model. This is an important and fairly intuitive finding. If the extra costs explained by the concurrent model are unpredictable acute costs, they are unlikely to affect an individual's plan choice.

Section 5.3.2: Reinsurance

The ACA implements a reinsurance program during the first three years of the Exchanges existence. The program reimburses health plans for 80% of an enrollee's plan costs above a threshold of $60,000 and below a cap of $250,000. Insurers are expected to

---

29 This could be partially due to the fact that the specification of $f_{ij}(OOP)$ is based on predictions of future costs using past information. If consumers have private information about future costs beyond what can be explained by the sophisticated predictive models used here (childbirth could fit in this category), the extra costs explained by concurrent models may be more highly correlated with demand, and concurrent risk adjustment may have a larger incremental effect over prospective risk adjustment. However, the allowed correlation between risk aversion and concurrent risk scores should pick at least some of this misspecification of $f_{ij}(OOP)$. 
purchase private coverage for costs exceeding $250,000, with a coinsurance rate of 85%. Reinsurance is also used in the Medicare Part D program. Because reinsurance essentially transfers costs from plans with more extremely high cost enrollees to plans with fewer high cost enrollees, it can be thought of as a form of risk adjustment where the predicted costs are costs above the reinsurance threshold and residual costs are all other costs. Recall that Figures 1.5 and 1.6 showed that diagnostic risk adjustment almost entirely eliminates the correlation between demand and costs for everyone except for the most expensive enrollees. This suggests that when risk adjustment is combined with reinsurance, adverse selection problems could be reduced even further.

To explore this possibility I simulate equilibrium prices and sorting with each form of risk adjustment combined with reinsurance. I simulate reinsurance by assuming that for each enrollee, plans receive a payment equal to 85% of any plan costs exceeding $60,000 within a year. The simulated reinsurance program is funded with a uniform per capita actuarially fair premium equal to the expected per capita reinsurance payment in the market. The equilibrium results with reinsurance are found in Table 1.4 and in Figure A1.1 in the appendix. The Figure and Table show that even with reinsurance, when there is no risk adjustment or demographic risk adjustment, the market still fully unravels and everyone enrolls in the Bronze plan. With diagnostic risk adjustment, however, the incremental average risk adjusted cost curves are even flatter than they were without reinsurance. The flattening of the curves is especially apparent for the highest cost/highest willingness-to-pay enrollees at the far right of the figure. The results in the table indicate that when concurrent risk adjustment is combined with reinsurance, market
unraveling is entirely undone, with the premium differential shrinking enough to induce 100% of market participants to enroll in the Platinum plan. Similarly, with prospective and HHS-HCC risk adjustment, result in 94% and 83% of enrollees choosing the Platinum plan, respectively. However, the additional welfare gains from reinsurance when combined with prospective and concurrent risk adjustment, around $20-$30, while non-trivial are small relative to the gains from diagnostic risk adjustment. The additional gains from reinsurance when combined with HHS-HCC risk adjustment are more substantial, around $150. This finding complements the finding of Zhu et al. (2014) that when combined with risk adjustment, reinsurance can substantially weaken plans' incentives to cream skim healthy enrollees.

Section 5.3.3: Age-based Pricing

The ACA allows for premiums in the Exchanges to vary by age as long as they remain within a 3:1 ratio. Because age-based pricing causes the prices paid by enrollees to be closer to their expected costs, this policy has the potential to undo some of the adverse selection problems resulting from uniform pricing that I study in this paper. This suggests that the effects of risk adjustment may not be as large in practice due to this regulation. In fact, Shi (2013) finds that welfare in a simulated Exchange is highest when risk adjustment is combined with age-based prices. To study this question, I implement age-based pricing as it is implemented in the Federal Health Insurance Exchange. In the Federal Exchange, plans submit one price that applies to a 21 year old. An individual's price is this price multiplied by an age-specific weight assigned by HHS. For example, the weight for a 25 year-old is 1.004, the weight for a 40 year-old is 1.278, and the weight
for a 64 year-old is 3.0.\footnote{This is different from the age-based pricing studied by Shi (2013) in that HHS forces insurers to use their age curve rather than allowing insurers to set their own age-based prices according to age-specific expected costs. I choose to use the fixed age-curve approach because this is the approach used in the Exchanges in every state. While the alternative approach is interesting, and was used in Massachusetts prior to the ACA, the concept of equilibrium is much more complex due to multiple age-based risk pools and is beyond the scope of this paper.} In practice, risk adjustment combined with mandated age-curve may “over-compensate” for costs correlated with age and cause plan revenues for an individual to be less correlated with costs than without the mandated age-curve.

The results from simulations including the HHS-mandated age-curve can be found in Table 1.5 and Figures A1.2 and A1.3 in the appendix. Interestingly, the results are largely unchanged from the uniform price case. The bolded case in Table 1.5 with the age-curve, reinsurance, and HHS-HCC risk adjustment is the full policy being implemented in the Exchanges. It is clear that this policy goes a long way toward undoing the problems cause by adverse selection with 83\% of the market enrolling in the Platinum plan, resulting in a welfare gain of over $800.

**Section 6: Discussion**

Adverse selection presents a large problem for competitive health insurance markets like the Exchanges created by the ACA. The negative effects of adverse selection occur both on the demand-side and the supply-side, and they have the potential to be quite important in the setting provided by the Exchanges due to the relatively unrestricted nature of the contract space. The potential ability of risk adjustment to fix supply-side selection problems has been known for quite some time (Glazer and McGuire 2000). The effects of risk adjustment on demand-side selection problems, however, are relatively unexplored. This is true, despite the fact that if risk adjustment is perfect, it will
completely eliminate these demand-side selection problems. In this paper, I study the
effects of risk adjustment on demand-side selection problems in a setting where contracts
are fixed and insurers compete on price to enroll consumers. I show that in this
environment, imperfect risk adjustment causes plan prices to be based only on costs that
are not predicted by the risk adjustment model rather than total costs. This could
ameliorate or exacerbate adverse selection problems, depending on the correlation
between demand and predicted costs. I then use data from a large employer to estimate
the joint distribution of demand, total costs and predicted costs. I use this distribution to
simulate equilibrium prices, sorting, and welfare in an Exchange-like environment where
consumers choose between a Bronze plan and a more comprehensive Platinum plan. I
find that without risk adjustment, the market completely unravels due to adverse selection
and the entire market enrolls in the Bronze plan. With risk adjustment based on prior
diagnoses, however, market unraveling is almost entirely undone, and over 80% of
market participants choose the Platinum plan. This results in a welfare gain of over $800
per person, per year. I also find very small incremental gains from concurrent risk
adjustment over prospective risk adjustment, despite the concurrent model explaining a
substantially higher portion of the variance in total costs.

The tradeoff between choice and adverse selection is a recurring theme among
health economists. In the absence of choice, there is no potential for adverse selection
because the costs of all consumers are combined in one risk pool. However, there is also
no potential for efficiency gains from competition or from accommodating preference
heterogeneity. Risk adjustment presents an opportunity to limit adverse selection
problems by pooling a portion of consumers' costs across plans while still allowing choice and competition. Even the imperfect forms of risk adjustment studied in this paper, appear to be able to eliminate a substantial portion of the welfare loss caused by adverse selection in a competitive environment similar to the Exchanges.

While the results in this paper are compelling, they are limited by some important caveats. First, the estimates of consumer preferences used in the simulations are based on a highly parametric structural model. Because the data do not include any premium variation (or even the premiums themselves!), I am unable to non-parametrically estimate an individual's willingness-to-pay for insurance. While the setting in which the individuals choose plans is quite simple and potentially easily characterized, the process by which consumers make choices in the real world is complex. There is evidence of important behavioral frictions in health plan choice (Abaluck and Gruber 2011, Handel 2013, Handel and Kolstad 2013), and although I attempt to control for perhaps the most important of these, inertia, in my estimation, it is controlled for imperfectly and makes up only one of many potential frictions. Additionally, the preference estimates and simulated choices here depend on the assumption that I correctly characterize individuals' distributions of expected out-of-pocket costs. This assumption seems extreme in that individuals may know more or less about their future health care utilization than is predictable by the sophisticated algorithms I use to estimate their expectations. However, the sophisticated nature of the algorithm does lend some credibility to the estimated expectations, especially given that little is known about the true form of these expectations. These limitations in estimating consumer preferences, combined with the
importance of these preferences described by the model and figures in Section 2, suggest that the effects of risk adjustment on equilibrium prices, sorting, and welfare may differ from those found here.

Additionally, throughout this study, the assumptions of a strong mandate and no moral hazard were maintained. If there were moral hazard, equilibrium pricing and sorting results would likely be similar, but the welfare consequences of risk adjustment would likely not be so extreme. This is due to the fact that with moral hazard it would not be optimal for the entire market to enroll in the Platinum plan. This possibility is related to the discussion of moral hazard in Einav and Finkelstein (2011). Additionally, if the mandate is weak and consumers can opt out of the market, the equilibrium consequences of risk adjustment could be quite different. As shown in the simulations, risk adjustment raises the premium of the Bronze plan. If the mandate is weak, this could easily result in healthy consumers dropping out of the market entirely, potentially resulting in the entire market unraveling. This issue is beyond the scope of this paper, but presents a promising area for future research. Here, I just point out that a large portion of the individuals participating in the Exchanges will be receiving subsidies that are based on the price of the second-cheapest Silver Plan. This implies that for a large segment of the market, the absolute prices of the Bronze and Silver Plans don’t actually matter; all that matters is the difference between the Bronze or Silver Plan price and the Platinum plan price, and this is what is simulated in this paper.

Despite the potential limitations, however, consumer choice is likely to follow similar patterns to those shown in the counterfactual simulations. Therefore, the effect of
risk adjustment on equilibrium prices, sorting, and welfare while perhaps not perfectly estimated, is likely to be substantial. This is true not only in the Exchanges but also in Medicare Part D where premiums are set competitively, some portions of the contracts are fixed, and demand is correlated with predicted costs (Polyakova 2014). When combined with its potential beneficial effects on supply-side selection problems (Glazer and McGuire 2000), this makes risk adjustment a powerful tool for ameliorating adverse selection problems and improving welfare within competitive insurance markets. As these markets mature and data becomes available, it will be interesting to observe the correlations between demand, costs, and predicted costs and the effects of risk adjustment in practice.
Notes: Right panel describes setting where consumers required to choose between 2 insurance contracts. Enrollment in plan E is on x-axis and price differential is on y-axis. Blue line represents incremental average cost curve, green represents incremental marginal cost curve, red represents demand curve. Competitive equilibrium is at point A. Efficiency requires that everyone enroll in plan E. Left panel splits incremental average cost curve into two components: Residual costs and predicted costs.
Figure 1.1B: Equilibrium sorting with adverse selection and imperfect risk adjustment

Notes: Right panel describes setting where consumers required to choose between 2 insurance contracts. Enrollment in plan E is on x-axis and price differential is on y-axis. Top blue line represents incremental average cost curve and red represents demand curve. Bottom blue line represents incremental average cost curve with risk adjustment. Competitive equilibrium with no risk adjustment is at point A. Equilibrium with risk adjustment is at point C. Efficiency requires that everyone enroll in plan E. Risk adjustment improves efficiency. Left panel splits incremental average cost curve into two components: Residual costs and predicted costs. With risk adjustment predicted costs are pooled across plans, so the predicted cost curve is flat, and the incremental average cost curve with risk adjustment reflects only the correlation between residual costs and demand for E.
Nest: Right panel describes setting where consumers required to choose between 2 insurance contracts. Enrollment in plan E is on x-axis and price differential is on y-axis. Top blue line represents incremental average cost curve and red represents demand curve. Middle blue line represents incremental average cost curve with imperfect risk adjustment. Bottom blue line represents incremental average cost curve with perfect risk adjustment. Competitive equilibrium with no risk adjustment is at point A. Equilibrium with imperfect risk adjustment is at point C and equilibrium with perfect risk adjustment is at point D. Efficiency requires that everyone enroll in plan E. Imperfect risk adjustment improves efficiency, and perfect risk adjustment results in additional efficiency improvements. Left panel shows that in this case all costs are predicted costs. With risk adjustment predicted costs are pooled across plans, so the incremental average cost curve with risk adjustment is flat.
Notes: Right panel describes setting where consumers required to choose between 2 insurance contracts. Enrollment in plan E is on x-axis and price differential is on y-axis. Blue line represents incremental average cost curve and red represents demand curve. Competitive equilibrium is at point A. Efficiency requires that everyone enroll in plan E. Left panel splits incremental average cost curve into two components: Residual costs and predicted costs. In this case demand and residual costs are positively correlated (adverse selection) and demand and predicted costs are negatively correlated (advantageous selection). Such a result could occur due to preference heterogeneity.
Figure 1.2B: Equilibrium sorting with adverse selection and adverse risk adjustment

Notes: Right panel describes setting where consumers required to choose between 2 insurance contracts. Enrollment in plan E is on x-axis and price differential is on y-axis. Bottom blue line represents incremental average cost curve and red represents demand curve. Top blue line represents incremental average cost curve with risk adjustment. Competitive equilibrium with no risk adjustment is at point A. Equilibrium with risk adjustment is at point E. Efficiency requires that everyone enroll in plan E. In this case, risk adjustment decreases efficiency. Left panel splits incremental average cost curve into two components: Residual costs and predicted costs. In this case demand and residual costs are positively correlation (adverse selection) and demand and predicted costs are negatively correlated (advantageous selection). Such a result could occur due to preference heterogeneity. Because of negative correlation between predicted costs and demand, risk adjustment results in a steeper incremental average cost curve.
Figure 1.3: Correlation between Willingness-to-Pay for Platinum and Total Cost

Notes: Figure shows correlation between total cost and willingness-to-pay for Platinum over Bronze Plan for employees at large firm for choice years 2006-08. Expected utility for Platinum and Bronze plans calculated using choice model described in paper. Individuals in sample grouped into 50 groups based on difference in expected utility. Group number is on the x-axis with 0 being the group with the lowest willingness-to-pay and 50 the highest. Average realized costs for the group are on y-axis. Cost increasing in willingness-to-pay suggests that Platinum Plan will be adversely selected.
Figure 1.4A: Correlation between Demand and Predicted and Residual Costs (Demographic)

Figure 1.4B: Correlation between Demand and Predicted and Residual Costs (Prospective)

Figure 1.4C: Correlation between Demand and Predicted and Residual Costs (Concurrent)

Notes: Figures show correlation between willingness-to-pay for the Platinum plan and predicted and residual costs in sample under 3 types of risk adjustment: Demographic (age and gender), Prospective Diagnostic, and Concurrent Diagnostic. Expected utility for Platinum and Bronze plans calculated using choice model described in paper. Individuals in sample grouped into 50 groups based on difference in expected utility. Group number is on the x-axis in all figures with 0 being the group with the lowest willingness-to-pay and 50 the highest. In the figures on the left, costs predicted by the risk adjustment model are on the y-axis. In the figures on the right, residual costs are on the y-axis. There is a positive correlation between demand and predicted costs in all cases, implying that risk adjustment will weaken the correlation between demand and costs. Prospective and concurrent risk adjustment almost completely eliminate correlation between demand and costs for all but the most expensive groups.
Figure 1.5: Equilibrium Search – Price Differential and Incremental Average Cost under Different Types of Risk Adjustment

Notes: Figure shows search for equilibrium in setting where sample individuals required to choose between Bronze and Platinum Plans. Light blue line is the 45-degree line. Orange line represents incremental average cost (IAC) curve with no risk adjustment, blue line represents IAC with demographic risk adjustment, gray line represents IAC with prospective risk adjustment, gold line represents IAC with concurrent risk adjustment, and green line represents IAC with HHS-HCC risk adjustment. IAC with no and demographic risk adjustment is everywhere above 45-degree line implying complete market unraveling where everyone enrolls in Bronze plan. Prospective, concurrent, and HHS risk adjustment IACs cross 45-degree line, implying an interior equilibrium exists. Equilibrium is at lowest P where IAC crosses 45-degree line. Concurrent results in the lowest price differential. Prices, enrollment, and welfare can be found in Table 1.4.
Figure 1.6: Equilibrium Search (Zoomed)

Notes: Figure shows search for equilibrium in setting where sample individuals required to choose between Bronze and Platinum Plans. Light blue line is the 45-degree line. Orange line represents incremental average cost (IAC) curve with no risk adjustment, blue line represents IAC with demographic risk adjustment, gray line represents IAC with prospective risk adjustment, gold line represents IAC with concurrent risk adjustment, and green line represents IAC with HHS-HCC risk adjustment. IAC with no and demographic risk adjustment is everywhere above 45-degree line implying complete market unraveling where everyone enrolls in Bronze plan. Prospective, concurrent, and HHS risk adjustment IACs cross 45-degree line, implying an interior equilibrium exists. Equilibrium is at lowest P where IAC crosses 45-degree line. Concurrent results in the lowest price differential. Prices, enrollment, and welfare can be found in Table 1.4.
Figure 1.7: Equilibrium Price Differentials and Sorting under Different Types of Risk Adjustment

Notes: Figure shows equilibrium in setting where sample individuals required to choose between Bronze and Platinum Plans. Light blue line is the demand curve. Orange line represents incremental average cost (IAC) curve with no risk adjustment, blue line represents IAC with demographic risk adjustment, gray line represents IAC with prospective risk adjustment, gold line represents IAC with concurrent risk adjustment, and green line represents IAC with HHS-HCC risk adjustment. Enrollment in Platinum Plan is on x-axis. IAC with no and demographic risk adjustment is everywhere above 45-degree line implying complete market unraveling where everyone enrolls in Bronze plan. Prospective, concurrent, and HHS risk adjustment IACs cross 45-degree line, implying an interior equilibrium exists. Equilibrium is at lowest P where IAC crosses 45-degree line. Concurrent results in the lowest price differential. Equilibrium price and enrollment in Platinum are highlighted by dotted lines. Prices, enrollment, and welfare can be found in Table 1.4.
### Table 1.1: Summary Statistics

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<th>Simulation Sample</th>
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### Summary Statistics

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Notes: Summary statistics for Estimation Sample, Cost Model Sample, and Simulation Sample. All samples come from Truven Marksetscan dataset from choice years 2006-08. Estimation and Simulation Samples are from one large firm in Marksetscan dataset where employees choose between 2 PPO plans. Samples are restricted to single-coverage employees enrolled for all 365 days of the year prior to and year of plan choice to ensure that costs can be predicted using full set of information. Estimation sample is restricted to employees from choice year 2007. Cost model sample is formed by first taking all individuals in Marksetscan during at least 300 days of both 2006-2007. Then, total cost risk scores are generated from prior health claims using Verisk Health DxCG predictive modeling software. Marksetcan sample is divided into 1000 cells based on total cost risk scores from year 1. Cost Model Sample is constructed by taking a random sample of 1000 individuals from each cell. Lognormal distribution with point mass at zero fit to costs in year 2 for each cell. Expected costs calculated by finding mean of the estimated distribution. Prospective and concurrent risk scores generated using Verisk Health DxCG risk adjustment software using diagnoses and demographics from year 1.
### Table 1.2: Cost-sharing Parameters for Firm and Simulation Plans

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**Drug copay**

- Generic = $10
- Brand = $5

<table>
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<th>Included in medical deductible, coinsurance, OOP max</th>
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</thead>
</table>

**Notes:** Table shows cost-sharing parameters for plan options at the firm and for plan options in the Exchange simulations. Firm parameters are used to create \( f_i(OOP) \) for estimation of the choice model, simulation parameters are used to create \( f_i(OOP) \) for Bronze and Platinum plans in the simulations. Under all plans, consumers pay the full cost of care up to the deductible, then they pay the coinsurance rate up to the out-of-pocket max. Beyond the out-of-pocket max, the consumer pays nothing. For the firm plans, drug coverage is not part of the price schedule, but coverage is identical in the two plans. For the simulations, drug spending is included with other medical spending in the non-linear price schedule. In the firm plans, ER visits and preventive visits are free of charge, but these visits make up only a small portion of total medical expenditures, so they considered to be priced with other medical spending.
### Table 1.3: Choice Model Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Parameter Std Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enhanced Shifter</td>
<td>-824.74</td>
<td>317.22</td>
</tr>
<tr>
<td>Switching Cost - Intercept</td>
<td>527.31</td>
<td>773.66</td>
</tr>
<tr>
<td>Switching Cost - Age Coeff</td>
<td>104.91</td>
<td>30.36</td>
</tr>
<tr>
<td>Switching Cost - Fem Coeff</td>
<td>-708.95</td>
<td>370.41</td>
</tr>
<tr>
<td>CARA - Intercept</td>
<td>8.4e-4</td>
<td>1.5e-4</td>
</tr>
<tr>
<td>CARA - Predicted Cost Coeff</td>
<td>-1.6e-4</td>
<td>7.4e-5</td>
</tr>
<tr>
<td>CARA - Age Coeff</td>
<td>-4.7e-6</td>
<td>1.5e-6</td>
</tr>
<tr>
<td>CARA - Age*Pred Cost Coeff</td>
<td>1.9e-6</td>
<td>1.3e-6</td>
</tr>
<tr>
<td>CARA - Fem Coeff</td>
<td>-2.5e-5</td>
<td>-3.3e-5</td>
</tr>
<tr>
<td>CARA - Pros Risk Coeff</td>
<td>4.6e-5</td>
<td>3.4e-5</td>
</tr>
<tr>
<td>CARA - Conc Risk Coeff</td>
<td>-2.0e-5</td>
<td>9.8e-6</td>
</tr>
<tr>
<td>CARA - Std Dev</td>
<td>-3.4e-4</td>
<td>-1.0e-4</td>
</tr>
<tr>
<td>Preference Shock - Std Dev</td>
<td>876.11</td>
<td>653.04</td>
</tr>
<tr>
<td>Mean CARA</td>
<td>6.9e4</td>
<td></td>
</tr>
<tr>
<td>Median CARA</td>
<td>6.8e4</td>
<td></td>
</tr>
<tr>
<td>Mean Switching Cost</td>
<td>4745.36</td>
<td></td>
</tr>
<tr>
<td>Median Switching Cost</td>
<td>4828.82</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Results from simulated maximum likelihood estimation of choice model described in the paper. Enhanced shifter is a plan-specific intercept for the Enhanced Plan. Switching costs are estimated by comparing the choices of switchers and those of new enrollees of similar age and gender. CARA intercept represents the coefficient of absolute risk aversion for a zero year-old with total predicted cost and risk adjustment risk scores of zero. Predicted cost coefficient describes how CARA parameter varies with total predicted cost, $\lambda_p$. Pros and conc risk coefficients describe how CARA parameter varies with risk adjustment risk scores. Mean CARA parameter implies that average individual in the sample would be indifferent between the status quo and a lottery that offered $100 with 50% probability and $95 with 50% probability.
Table 1.4: Equilibrium Prices, Sorting, and Welfare with Uniform Pricing

<table>
<thead>
<tr>
<th>Risk Adjustment</th>
<th>Price Differential</th>
<th>Bronze Price</th>
<th>Platinum Price</th>
<th>% in Platinum</th>
<th>Change in Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>n.a.</td>
</tr>
<tr>
<td>Age/sex Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>$0</td>
</tr>
<tr>
<td>Prospective Risk Adjustment</td>
<td>$1,082</td>
<td>$2,403</td>
<td>$3,483</td>
<td>80%</td>
<td>$829</td>
</tr>
<tr>
<td>Concurrent Risk Adjustment</td>
<td>$952</td>
<td>$2,501</td>
<td>$3,453</td>
<td>82%</td>
<td>$838</td>
</tr>
<tr>
<td>HHS Risk Adjustment</td>
<td>$1,819</td>
<td>$1,978</td>
<td>$3,797</td>
<td>65%</td>
<td>$695</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Risk Adjustment</th>
<th>Price Differential</th>
<th>Bronze Price</th>
<th>Platinum Price</th>
<th>% in Platinum</th>
<th>Change in Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>n.a.</td>
</tr>
<tr>
<td>Age/sex Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>$0</td>
</tr>
<tr>
<td>Prospective Risk Adjustment</td>
<td>$149</td>
<td>$3,222</td>
<td>$3,365</td>
<td>94%</td>
<td>$861</td>
</tr>
<tr>
<td>Concurrent Risk Adjustment</td>
<td>n.a.</td>
<td>n.a.</td>
<td>$3,380</td>
<td>100%</td>
<td>$862</td>
</tr>
<tr>
<td>HHS Risk Adjustment</td>
<td>$872</td>
<td>$2,566</td>
<td>$3,438</td>
<td>83%</td>
<td>$843</td>
</tr>
</tbody>
</table>

Notes: Table shows equilibrium price differential (price of Platinum – price of Bronze), prices, proportion enrolled in Platinum plan, and change in welfare from no risk adjustment case to case with indicated type of risk adjustment. Bottom panel adds reinsurance where reinsurance reimburses 65% of an individual’s plan costs above $60,000 and is funded with an actuarially fair per capita premium. Equilibrium found using algorithm described in the text. If there is no interior equilibrium, there is no price differential, and only the price of the plan in which the entire market enrolls is shown. Types of risk adjustment include age/sex which uses only demographic variables to predict costs, prospective and concurrent which use prior and current diagnosis groups, respectively, to predict costs, and HHS which is a concurrent model that uses a different set of diagnosis groups and allows for higher risk scores for Platinum enrollees and a penalty factor for the Platinum plan. Welfare calculated by the certainty equivalent concept discussed in the paper.
Table 1.5: Equilibrium Prices, Sorting, and Welfare with Age-based Pricing

<table>
<thead>
<tr>
<th>Adjustment</th>
<th>Avg Price Diff</th>
<th>Avg Bronze Price</th>
<th>Avg Platinum Price</th>
<th>% in Platinum</th>
<th>Change in Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>n.a.</td>
</tr>
<tr>
<td>Age/sex Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>$0</td>
</tr>
<tr>
<td>Prospective Risk Adjustment</td>
<td>$1,095</td>
<td>$2,381</td>
<td>$3,471</td>
<td>81%</td>
<td>$831</td>
</tr>
<tr>
<td>Concurrent Risk Adjustment</td>
<td>$1,048</td>
<td>$2,423</td>
<td>$3,460</td>
<td>82%</td>
<td>$835</td>
</tr>
<tr>
<td>HHS Risk Adjustment</td>
<td>$1,954</td>
<td>$1,867</td>
<td>$3,822</td>
<td>61%</td>
<td>$649</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Adjustment</th>
<th>Avg Price Diff</th>
<th>Avg Bronze Price</th>
<th>Avg Platinum Price</th>
<th>% in Platinum</th>
<th>Change in Welfare</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>n.a.</td>
</tr>
<tr>
<td>Age/sex Risk Adjustment</td>
<td>n.a.</td>
<td>$1,969</td>
<td>n.a.</td>
<td>0%</td>
<td>$0</td>
</tr>
<tr>
<td>Prospective Risk Adjustment</td>
<td>$171</td>
<td>$3,191</td>
<td>$3,367</td>
<td>94%</td>
<td>$860</td>
</tr>
<tr>
<td>Concurrent Risk Adjustment</td>
<td>n.a.</td>
<td>n.a.</td>
<td>$3,380</td>
<td>100%</td>
<td>$862</td>
</tr>
<tr>
<td>HHS Risk Adjustment</td>
<td>$969</td>
<td>$2,481</td>
<td>$3,446</td>
<td>83%</td>
<td>$840</td>
</tr>
</tbody>
</table>

Notes: Table shows equilibrium price differential (price of Platinum – price of Bronze), prices, proportion enrolled in Platinum plan, and change in welfare from no risk adjustment case to case with indicated type of risk adjustment. Bottom panel adds reinsurance where reinsurance reimburses 65% of an individual’s plan costs above $60,000 and is funded with an actuarially fair per capita premium. In all cases, prices vary by age according to the HHS age curve. Equilibrium found using algorithm described in the text. If there is no interior equilibrium, there is no price differential, and only the price of the plan in which the entire market enrolls is shown. Types of risk adjustment include age/sex which uses only demographic variables to predict costs, prospective and concurrent which use prior and current diagnosis groups, respectively, to predict costs, and HHS which is a concurrent model that uses a different set of diagnosis groups and allows for higher risk scores for Platinum enrollees and a penalty factor for the Platinum plan. Welfare calculated by the certainty equivalent concept discussed in the paper. Case in bold represents the full pricing policy currently being implemented in the Exchanges.
CHAPTER TWO

RISK SELECTION, RISK ADJUSTMENT, AND MANIPULABLE MEDICAL CODING: EVIDENCE FROM MEDICARE

with Michael Geruso

Section 1: Introduction

Risk adjustment is the primary mechanism used to counteract distortions caused by adverse selection in competitive insurance markets. It is used in nearly all US markets for public and private health insurance, including Medicare Advantage, Medicare Part D, many privatized state Medicaid programs, and the ACA exchanges. Risk adjustment modifies payments to insurers on the basis of a consumer’s expected costs, estimated using information that includes prior diagnoses from insurance claims. For instance, a consumer coded with a history of diabetes generates a larger than average payment for the insurer. This capitation payment is independent of actual treatment the enrollee receives, compensating the insurer for attracting a patient with high expected costs, while still forcing the insurer to internalize the marginal costs of providing care. In this way, risk-adjustment escapes the incentive problems created by fee for service payments, but discourages “cream skimming,” in which insurers avoid high cost consumers by distorting their menu of services, inefficiently rationing services demanded by high-risk individuals (Frank et al. 2000, Glazer and McGuire 2000). Risk adjustment also has the effect of weakening the connection between premiums and the risk pool of a plan’s draw of enrollees, decreasing the likelihood of market unraveling due to adverse selection,

31 In regulated private insurance markets, such as the Health Insurance Exchanges created by the ACA, risk adjustment often works via a system of mandated ex-post transfers between private insurers related to the average risk score of their pools of enrollees.
which has been documented in numerous settings in which risk adjustment was absent (e.g. Bundorf et al. 2013, Geruso 2013, Handel 2013, Handel et al. 2013, Einav et al. 2010, Fang et al. 2008, Buchmueller and DiNardo 2002, Cao and McGuire 2002, Cutler and Reber 1998).

Implicit in the theory of risk adjustment is the assumption that consumers have risk scores that are invariant to the insurer with whom they are enrolled. But in all real world payment systems, it is the insurers themselves who report the diagnoses that determine enrollee risk scores, suggesting the potential for manipulation, or at least heterogeneity in coding practices. Therefore, even when successful in counteracting cream-skimming and adverse selection, risk adjustment creates its own distortion: It rewards insurers who would code the same patient more intensively. These coding incentives constitute an important but underexplored problem in the regulation of public and private health insurance markets. For publicly funded programs like Medicare and Medicaid, differences in coding between the public and private options create an implicit subsidy that distorts the choice that beneficiaries face between public and private insurance, and impacts the total size of public spending. Discussion of risk adjustment and coding is largely absent from discussions of adverse selection (see, for example, Einav and Finkelstein 2011), despite the fact that risk adjustment is the most widely utilized policy tool for combating the price distortions caused by selection.

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32 See for example Pope et al (2004) describes among the principles guiding the creation the CMS HCC risk adjustment used in Medicare Advantage. These principles include requirements that, “The diagnostic classification should not reward coding proliferation,” and “Discretionary diagnostic categories should be excluded from payment models.”
We define “upcoding” broadly as the practice by which different insurers would produce different risk scores, and therefore extract different payments, for the same individual. This could happen in many ways. For example, insurers can (and sometimes do) pay their providers using a risk adjustment payment model similar to the one the insurer itself faces, aligning provider and insurer incentives to code patients intensively. Insurers are in a good position to manipulate coding in this way: They have full knowledge of the publicly-posted risk-scoring algorithms that convert diagnosis codes to risk scores and, ultimately, payments. Plans may also differ in coding practices for an entirely different set of reasons, such as differences in practice patterns or electronic medical record adoption that may be unrelated to coding incentives.

The extent of coding differences across insurers is largely unknown because in most data, upcoding is observationally equivalent to adverse selection. An insurer might report an enrollee population with higher than average risk scores either because the consumers choosing its plan are in worse health (selection) or because for the same individual, the insurer uses coding practices that result in higher risk scores (upcoding). Because of this central identification difficulty, there has been limited empirical work on the extent of upcoding in any US health insurance market. Two exceptions are Silverman and Skinner (2004) and Dafny (2005), which exploit changes over the 1990s in how

33 We note that this definition of upcoding is deliberately broad. Another term for our definition of upcoding that would have a more neutral connotation is “coding heterogeneity,” as our definition of upcoding encapsulates all sources of variation in risk scoring across plans, whether the variation is intentional or unintentional. We use this broad definition due to the fact that in our model the effect of coding differences on costs (the focus of this paper) does not depend on the source of these differences.
Traditional Medicare compensated hospitals on the basis of diagnosis, showing that hospital coding patterns changed to track the reimbursement changes.\footnote{Song et al. (2010), find that traditional Medicare enrollees who move from a “low intensity” region to a “high intensity” region exhibit substantial increases in their Traditional Medicare risk scores. While not direct evidence of upcoding, this strongly suggests that risk scores are not fixed for an individual.}

In this paper, we develop a general method for separating upcoding from selection, applicable to any market for public or private health insurance. The core insight of our approach is novel, but straightforward: We note that if the same individual would generate a different risk score under insurer A than insurer B and if we observe a change in market share of the two insurers, then we should also observe changes to the observed \textit{market-level} average of the risk score. Such a pattern could not be rationalized by selection, because selection can affect only the sorting of risk types across health plans within the market, not the overall market-level distribution of reported risk types. Our model primitives correspond closely to empirical moments that are readily observable in most insurance markets: the market-level average-risk score and market shares. Our approach thus contrasts with attempts to identifying upcoding by following individual switchers across plans (see for example, Government Accountability Office 2013). Data on risk scores for the same individual enrolled in different plans are rarely available, and identification via plan switching requires that consumers change plans for reasons unrelated to changes in their health.\footnote{When data on individual risk scores are available, rarely can researchers follow the same individual from one plan to another. Even in large state all-payer datasets, individual identifiers usually change when individuals move from one plan to another because they are originally assigned by the insurers rather than the database managers.} Our method does not require this identifying assumption.
We apply our framework to analyze upcoding in Medicare Advantage (MA) from 2006 to present. Medicare Advantage (also known as Medicare Part C) is comprised of private plans from which Medicare beneficiaries can choose in lieu of traditional fee-for-service Medicare (TM). Premiums are heavily subsidized with funds that would otherwise pay for the beneficiary’s Traditional Medicare services. MA is an ideal setting for applying our framework, both because MA is the largest risk-adjusted health insurance market in the US, with annual tax expenditure exceeding $100 billion, and because it is widely believed among researchers and regulators that upcoding is a persistent and important phenomenon among plans competing in the MA market.\textsuperscript{36}

Whether coding should be systematically more intensive in private Medicare plans than under Traditional Medicare, is \textit{a priori} ambiguous. On one hand the risk adjustment payment system incentivizes intensive coding, but on the other, the managed care plans that make up much of Medicare Advantage typically control costs by limiting utilization, which would tend to reduce the encounters necessary for generating diagnoses.

We exploit the large and geographically heterogeneous changes to MA penetration that occurred beginning in the mid 2000s in response to the Medicare

\textsuperscript{36} CMS and the GAO have released reports that investigate this question, but their methods do not adequately separate “upcoding” from selection (CMS 2010; GAO 2012). Nonetheless, the Center for Medicare and Medicaid Services (CMS) subtracts a 3.41\% upcoding deflation factor when determining payments to private plans in the Medicare Advantage program, under the assumption that private plans code the same patients more intensively than do doctors performing services under the Traditional Medicare program (CMS 2010). The GAO study chose a cohort of individuals enrolled in MA during 2007. It compared the growth in risk scores in the MA cohort to a cohort of FFS enrollees, controlling for observables. They then concluded that there was evidence of upcoding in MA and calculated the overpayment to be from 4.8\% to 7.1\%. Unbiased identification of the estimates, however, would require that any differences between the control group (FFS enrollees) and the treatment group (MA enrollees) would have to be orthogonal to the risk score, conditional on the control variables. In other words, the study assumes no quantitatively important selection, which we show empirically is incorrect. We also point out that the GAO study measures difference in risk score growth over time. We note that this is not the policy relevant parameter. Instead the relevant parameter is the difference between the risk score an individual received in MA and the score she would have received in FFS that we highlight here.
Modernization Act in order to examine whether market-level observed risk co-varies with MA penetration over time. Using the rapid within-county changes in penetration that occurred over our short panel, we find that a 10 percentage point increase in MA penetration leads to a 0.4 percentage point increase in the average risk score in a county. This implies that MA plans generate risk scores for their enrollees that are on average 4% larger that what those same enrollees would have generated under TM. We show that it is difficult to rationalize this result by the alternative explanation that true county-level population health was changing contemporaneously with these penetration changes. We also exploit an institutional feature of Medicare Advantage that causes risk scores to be based on prior year diagnoses. This yields sharp predictions on the timing of effects that offer several falsification tests of our identification in the spirit of an event study.

In this paper we make four important contributions to the literature on adverse selection and the public finance of healthcare. First, ours is the first paper to model the implications of differential coding patterns across insurers. While there has been substantial research on the statistical aspects of diagnosis-based risk adjustment models, little is known about whether the clinical indicators used are robust to manipulation or about the distortionary implications of coding heterogeneity.\textsuperscript{37} This is an important omission in the literature, since risk adjustment features prominently in the recent US healthcare reform. We create a framework to show how differences in coding may cause excess public spending and always cause implicit subsidies across health plans that

\textsuperscript{37} See van de Ven and Ellis (2000) and Ellis and Layton (2013) for reviews of the literature on risk adjustment. A couple of recent papers, McGuire et al. (2013) and Glazer, McGuire, and Shi (2013), develop a model of risk adjustment in the new state Health Insurance Exchanges, showing how to use risk adjusted payments to maximize the “fit” of the payment system while simultaneously minimizing the welfare losses from inefficient sorting due to adverse selection.
distort consumers’ choices—in our case between Traditional Medicare and MA. This coding distortion along the public-private insurance choice margin has not been previously recognized. A non-obvious result that emerges from our modeling is that for many policy questions regarding the public finance of health insurance and regulatory incidence, it is not necessary to take a stand as to which insurer’s coding regime is the “correct” reference coding or to identify the pathways by which coding regimes diverge. In our empirical setting, this means that it doesn’t matter whether physicians under Traditional Medicare pay too little attention to coding or whether MA insurers pay too much attention to coding. It also doesn’t matter whether the coding differences are a response to the incentive to upcode or due to other factors.

Second, we provide a simple and intuitive method for estimating the presence, direction, and extent of coding differences across plans in selection markets. Our method is widely applicable and has minimal data requirements, and may be particularly useful in analyzing risk adjustment in the ACA Exchanges in the future. It may also be useful for separating selection and other outcomes in other contexts where, within a geographic market, a fixed population chooses between public and private providers of a service. For example, our method could be used to estimate causal effects of charter schools on graduation rates and test scores in a way that is robust to endogenous sorting of students across schools.

38 Private insurers in individual markets have historically kept claims records proprietary. State all-payer databases make this data available, but individual identifiers often change when an individual moves from one insurer to another, making it impossible to track individuals’ risk scores across plans. Therefore, upcoding in the Exchanges, may need to be analyzed using only market-level data, or, at best, without the ability to follow individuals between plans.
Third, we provide the first econometric evidence of upcoding in MA. We find that risk scores in MA are about 4 percent of the mean higher than they would have been in FFS Medicare for the same beneficiary. While Medicare Advantage enrollees look healthier than FFS enrollees because of selection, in reality they are *even healthier* than they look. While, similar to Brown et al. (2012), we cannot perform a full welfare analysis of this coding difference, we note that the public spending implications are significant. Medicare is the costliest public health insurance program in the world, and a significant fraction of US government spending. Absent a coding correction, our estimates imply excess payments of around $4 billion to Medicare Advantage plans annually.\(^{39}\) This subsidy distorts Medicare beneficiaries’ choice of health insurance away from Traditional Medicare, effectively providing a larger voucher for purchasing an MA plan than for purchasing Traditional Medicare. We also note that increasing the competitiveness of the MA market would have no effect on this margin of distortion.

More broadly, our empirical results yield important insights into the potential for coding heterogeneity in other markets. Risk adjustment is the core of modern healthcare payment reform. In the ACA Exchanges, for example, a nearly identical risk adjustment algorithm will be used to enforce *ex post* transfers among insurers.\(^{40}\)

Finally, our findings contribute to the growing policy literature on the broader welfare impacts of the Medicare Advantage program. Besides the benefits of expanding choice, one popular argument in favor of Medicare Advantage is that it might create

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\(^{39}\) We estimate that in 2010, the government paid private Medicare plans about $97 billion

\(^{40}\) The presence of upcoding in Exchanges would imply that the mandated RA transfers partly reward coding intensity, rather than merely compensate adversely selected plans for higher cost patients. This incentivizes insurers to divert resources toward coding at the cost of services valued by consumers.
important spillover effects on Traditional Medicare. Studies of physician and hospital behavior in response to the growth of managed care (see for example, Baker (1996), Glied (2002), Glazer and McGuire (2002), and Frank and Zeckhauser (2007)) suggest the possibility of positive externalities in which the existence of managed care plans lowers costs for all local insurers. Indeed, Baicker et al (2012) find that the expansion of MA resulted in lower hospital costs in Traditional Medicare. Our findings indicate that these benefits of MA do not come without costs. Any positive spillovers should be balanced alongside the additional cost (and deadweight loss of taxation) of enrolling a beneficiary in MA due to both positive selection and upcoding.

The outline for the remainder of the paper is as follows. In Section 2, we provide reduced form, suggestive evidence of coding differences between MA and TM, by comparing coding patterns in the two market segments using micro claims data. In Section 3, we derive a general expression for the implicit subsidy caused by coding differences and provide a graphical explanation of our method for estimating upcoding in the presence of selection. In Section 4, we discuss our data and empirical setting. Section 5 presents results, and section 6 discusses several implications of our findings for policy and economic efficiency. Section 7 concludes.

**Section 2: Upcoding in Practice**

What does upcoding look like in practice? Risk adjustment models include large numbers of explanatory variables, consisting mostly of dummy variables indicating whether an individual received a diagnosis code that maps to a particular diagnosis
These diagnoses are generated during encounters between providers and patients, and recorded in claims that are sent to insurers.

At the extreme, insurers can commit outright fraud by adding diagnosis codes to a patient’s records with no medical basis. But a more subtle (and legal) approach is simply to dedicate more resources to carefully and meticulously coding every eligible diagnosis. As mentioned above, insurers can construct contracts with providers to incentivize coding. In addition, insurers purchase commercial software that has the sole function of scanning medical records and determining for each individual the most lucrative combination of codes consistent with their health state. In some cases these software products, which are aimed at gaming the risk adjustment algorithms, are designed and marketed by the very same organizations that developed the risk scoring algorithms used by regulators. Other strategies may include requiring patients to come in each year for an “evaluation and management visit,” which is inexpensive to the insurer, but during which codes can be added which otherwise would have gone undiscovered. Insurers may also choose to selectively contract with providers that code more aggressively.

The most popular of these groupings of diagnoses are Hierarchical Condition Categories (HCCs), Diagnosis-related Groups (DRGs), and Adjusted Clinical Groups (ACGs).

For example, in United States v. Janke 2009, a Florida-based Medicare Advantage insurer was found to be fraudulently adding diagnosis codes to claims, resulting in average overpayments of $3,015 per enrollee for around 10,000 enrollees.

Section 3: Identifying Upcoding

Section 3.1: Risk Adjustment

We begin by briefly describing a model of risk-adjusted payments to health plans/providers. A regulator pays plans risk adjusted payments from a fund, or enforces transfers between plans. The fund can be financed via tax revenues or via fees assessed to health plans by the regulator. We consider the case of two health plans, though the extension to several plans is straightforward. The plans receive a payment from the regulator for each individual they enroll. The payment to plan $j$ for enrolling individual $i$ is equal to the individual’s risk score, $r_i$, multiplied by some benchmark payment, $B$, set by the regulator: $R_i^j = r_i \times B$. The benchmark payment can be equal to average actual costs in the full population of enrollees, as in the ACA exchanges, or some statutory amount, as in Medicare Advantage. The risk score $r_i = x_i \hat{\beta}$ is calculated by multiplying a vector of risk adjusters, $x_i$, by a vector of risk adjustment coefficients, $\hat{\beta}$. The risk adjusters typically consist of a set of dummy variables for demographic groups (usually age-by-sex cells) and a set of dummy variables for diagnosis groups. Diagnosis groups are mapped from the diagnosis codes contained in health insurance claims. The data used to generate $x_i$ can originate from the prior year’s insurance claims (a prospective model) or the current year’s claims (a concurrent model). The implicit assumption in the theory...

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44 These are the two most common ways risk adjustment is funded in practice with the former being used in Medicaid, Medicare Advantage, Germany, Israel, and the Netherlands and the latter being used in Switzerland and the Exchanges in the United States. Medicare Part D uses a combination of the two. For details on the various mechanisms for implementing the risk adjusted payments, see van de Ven and Ellis 2000.

45 In MA, $B$ is set by a complex formula that is partially tied the average cost of enrolling a beneficiary in Traditional Medicare in the local area.
of risk-adjustment is that $x_i$ does not vary according to the plan in which a consumer is enrolled. The risk adjustment coefficients, $\beta$, are usually estimated from a regression of actual treatment costs on the risk adjusters in some reference population.\(^{46}\)

**Section 3.2: Upcoding**

We define upcoding as differences in coding practices across plans that would lead to two plans generating distinct risk scores for the same individual. If the risk score is a characteristic of a consumer-plan pair, then risk adjustment compensates plan characteristics, and not solely consumer characteristics. Because $B$ and $\beta$ are set by the regulator and fixed across insurers, upcoding can arise only from differences in the recording of diagnoses on claims that map to the risk score. Formally, we relax the fixed risk scoring assumption by allowing the risk adjusters, $x_i'$, for individual $i$ to vary by plan. It is straightforward to show that the difference between the risk adjusted payment for individual $i$ if she enrolls in plan $j$ and the payment if she enrolls in plan $j'$ is:

$$y_i^j = R_i^j - R_i^{j'} = B\beta(x_i^j - x_i^{j'})$$

Thus, plan $j$ would receive a subsidy, $y_i^j$, for enrolling individual $i$, the size and direction of which is determined by the intensity of its coding. In the case of Medicare Advantage, if MA insurers would assign more (or more generously reimbursed) diagnoses to patients, this is equivalent to providing a voucher for the purchase of MA that is in excess of the

\(^{46}\) For example, if $C_i$ were actual costs for individual $i$, and the estimating equation were $C_i = \delta X_i + \epsilon_i$, then $\hat{\beta} = \delta / C$. The choice of reference population is not important for analyzing the effects of coding differences across plans.
Traditional Medicare voucher by the amount: $B\tilde{\beta}(x_{i}^{MA} - x_{i}^{TM})$. In the empirical exercise, we operationalize the risk score for individual $i$ in plan $j$ as equal to the “true risk” plus a plan-specific coding factor: $r_{i}^{j} = r_{i} + \alpha_{j}$.

We think about the plan-specific coding factor, $\alpha_{j}$, as coming from plan profit maximization where plan $j$’s profits are defined as follows:

$$\pi_{j} = \sum_{i=1}^{N} \left\{ \phi_{ij}(\lambda_{j}) \left[ B \cdot (r_{i} + \alpha_{j}(\lambda_{j}, \eta_{j})) - m_{ij}(\lambda_{j}) - c_{j}(\eta_{j}) \right] \right\}$$

In this expression, $\phi_{ij}(\lambda_{j})$ represents the probability that individual $i$ will enroll in plan $j$ and $m_{ij}(\lambda_{j})$ represents individual $i$’s utilization of medical care, both as decreasing functions of the shadow price of medical care, $\lambda_{j}$, chosen by the plan. Additionally, $\eta_{j}$ represents the coding intensity chosen by the plan and $c_{j}(\eta_{j})$ is the cost to the plan of increased coding intensity. We model the plan-specific coding factor, $\alpha_{j}(\lambda_{j}, \eta_{j})$, as a decreasing function of the shadow price of medical care ($\alpha_{\lambda} < 0$) and as an increasing function of coding intensity ($\alpha_{\eta} > 0$). This is because an individual’s risk score can change due to shifts in the “extensive margin” (increased encounters with physicians that can result in additional diagnoses) or the “intensive margin” (increased number of diagnoses from each visit). Let $\lambda_{j}^{*}$ and $\eta_{j}^{*}$ be the values of $\lambda_{j}$ and $\eta_{j}$ that maximize plan $j$’s profits. In our operationalization of the risk score for individual $i$ in plan $j$ we think of

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47 In the ACA Exchanges risk-adjusted payments will be based on a relative risk score, rather than an absolute risk score. In the appendix, we show that if we assume the additive coding factor the implicit subsidy in this case is decreasing in the proportion of individuals enrolled in plan $j$.

48 One could also allow $\lambda_{j}$ to vary across services as in Glazer and McGuire (2002). While this would have important implications for the structure of optimal risk adjustment when the fixed risk scoring assumption does not hold, it is not important for the effects of risk adjustment on costs (the focus of this paper), so we abstract from it here.
\( \alpha_j \) as being equal to \( \alpha_j(\lambda_j, \eta_j^*) \). This shows that coding differences can come first from heterogeneous costs of coding intensity across plans, but differences can also come from differences across plans in the relationship between the shadow price of medical care and utilization and differences in the relationship between the shadow price and enrollment. Additionally, it is important to note for our empirical exercise that in one segment (MA) plans are both profit maximizing and subject to risk adjusted payments, while in the other segment (FFS), neither of these are true.

The vulnerability of a risk adjustment regime to manipulation can vary depending on the risk adjusters chosen by the regulator. In the extreme, risk adjusters based solely on easily observable demographic variables such as age and gender could not be heterogeneously coded across plans.\(^{49}\)

### 3.3 Identifying Upcoding in Selection Markets

The central difficulty of identifying upcoding arises from selection on risk scores. At the health plan level, average risk scores can differ across plans competing in the same market either because of coding practice differences for identical patients, or because patients with systematically different health conditions are attracted to different plans. At the individual level, the counterfactual risk score that a person would generate in another plan is unobservable.\(^{50}\)

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\(^{49}\) This is the intuition for risk adjusters based on diagnoses rather than utilization, since the former are arguably less likely to vary across plans than the latter.

\(^{50}\) Even examining switchers, who enroll in plan A one year and plan B the next, is problematic for identifying coding differences between plans because the switching behavior could be motivated by an unobserved (to the econometrician) health trajectory, which would have a direct effect on coded conditions and therefore risk scores.
Our solution to the identification problem is based on the recognition that within a large geographic market, the total population distribution of health conditions (among all enrollees in all health plans) should not change much year-to-year. Thus if the average risk score in the entire market changes in response to a net shifting of individuals between health plans within the market, it is indicative of differences in coding practices between the plans.

Figure 2.1 provides the graphical intuition for this idea. We depict two plans, labeled A and B, which are intended to correspond roughly to TM and MA. All consumers are enrolled in one plan or the other. Consistent with our application below, we assume that plan B (like Medicare Advantage) is advantageously selected, meaning that lower risk individuals prefer it.51

We begin in the top panel of Figure 2.1 by assuming no upcoding. The panel shows 3 curves: average risk in A (A Risk), average risk in B (B Risk), and the average risk of all enrollees in the market (Total Risk). The proportion of individuals enrolled in B (B penetration) increases along the horizontal axis. The downward slope of the A Risk curve and the B Risk Curve indicate that A is adversely selected, and that B is advantageously selected. For example, the plan B average risk at low levels of plan B market share is low because the few beneficiaries choosing B are especially low risk. Because the panel depicts only selection and not upcoding, the total risk averaged over both plans (i.e. the market) is constant, regardless of plan B market share.

51 For the purposes of our model, we offer no explanation for why lower risk individuals choose MA first and why the marginal MA enrollee is higher risk than the other MA enrollees. Nonetheless, this is a common assumption and the existing evidence supports it. See for example, Newhouse et al (2012) and Brown et al. (2012).
The bottom panel of Figure 2.1 incorporates upcoding. We add a new curve, B Risk^A, which is the counterfactual average risk of plan B enrollees under plan A coding practices. We shift the B Risk^B curve up to indicate that coding practices in B are such that individuals receive higher risk scores than they would have under A coding practices. This is a graphical depiction of our notion of upcoding, and makes no assumptions about the source of coding differences. Note that the distance between the B Risk^A curve and the A Risk^A curves is the selection effect and the distance between the B Risk^B curve and the B Risk^A curve is the coding difference effect.

While the vertical difference between the B Risk^B curve and the B Risk^A is the appropriate theoretical construct, it is unlikely that the counterfactual B Risk^A curve would ever be observable. Fortunately, the bottom panel of Figure 2.1 suggests an alternative way to identify coding differences. Comparing the top and bottom panels of Figure 2.1 shows that if and only if there are coding differences between A and B, the slope of the total risk curve will no longer be equal to zero. Instead, if the same individual would receive a higher risk score in B than in FFS, the Total Risk curve will be upward sloping. This is true whether or not one of the plans is adversely selected. The implication is that with variation in market share that is exogenous to the underlying population health, we can identify the presence of coding differences between A and B as a non-zero slope of the total risk curve. Further, the slope of the curve identifies the extent of coding differences and allows calculation of the implicit subsidy caused by the risk-adjusted payment system.
The figure assumes that the B and A average risk curves are linear for tractability. However, identifying the existence of coding differences depends only on the assumption that variation in market share is exogenous to the risk scores. Under any assumptions about selection and any assumptions about the distribution of health states in the population, upcoding will manifest as a non-zero slope of the total risk curve. Estimating the magnitude of coding differences via the slope of the total risk curve requires only the additional assumption that the upcoding factor is uniform across enrollees, again regardless of the shapes or even signs of the plan-specific risk curves. We assume that upcoding is uniform across enrollees in the empirical section, but acknowledge that this is a local approximation, since we have no method for identifying heterogeneity in how individual enrollees are coded when using aggregate, market-level data. We also note that this assumption is similar to other linearity assumptions made in the public finance literature when calculating policy-relevant parameters (for example, see Einav and Finkelstein 2011).

**Section 4: Data and Setting**

*Section 4.1: MA Plans*

We now apply our insight for separately identifying selection and upcoding to the case of Medicare. Individuals who are eligible for Medicare can choose between the traditional fee-for-service (FFS) plan offered by the government or coverage through a private plan chosen in the Medicare Advantage (MA) market. Many of the plans available in the MA market charge no additional premium for enrollment. They are attractive to Medicare enrollees because they offer more comprehensive financial
coverage, such as lower deductibles and coinsurance rates, and additional benefits, such as dental care. The tradeoff faced by beneficiaries selecting an MA plan is that most of these plans are managed care plans. They restrict enrollees to a particular network of doctors, and may impose gatekeeping to specialists via referral requirements.

The government pays MA plans a fixed amount (capitation payment) for each individual they enroll, which is a function of a base or benchmark rate determined by the individual’s county of residence and a person-specific adjustment determined by her risk score, as in Section 3. (See the appendix for details on the exact payment formula.) Plans receive higher payments for enrolling individuals with higher risk scores. The county-specific benchmarks are tied to the average cost of individuals enrolled in FFS Medicare in that county, though Congress and CMS have made many ad-hoc adjustments over time. Risk scores are determined using the CMS-HCC risk adjustment model, which includes indicators for age and sex cells and indicators for a series of diagnosis groups known as Hierarchical Condition Categories (HCCs) (Pope et al. 2004).

Section 4.2: Data

Tracing the curves in Figure 2.1 requires observing market-level risk scores across a range of MA penetration levels. The Center for Medicare and Medicaid Services (CMS) provides publicly available data on the enrollment by county by contract in

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52 Plan payments are actually a function of MA risk relative to FFS risk. This means that any payment differences are due to differential coding in MA vs. FFS, i.e. $\alpha_{MA} \neq \alpha_{FFS}$. See the appendix for a discussion of why equilibrium coding would differ between FFS and MA.

53 Over the time period we study, county base rates were set as the maximum of the relevant (urban/rural) payment floor, the TM costs of TM enrollees in the county according to a five year moving average lagged three years, a 2% update over the prior year, and a variable update determined by national TM cost growth. Payments to plans were further adjusted from the county rate according to a bidding scheme. For more details on the determination of county-level payments over this period, see Baicker et al (2013).
Medicare Advantage plans.\textsuperscript{54,55} For traditional Medicare enrollees, CMS reports enrollment by county. We combine this information to construct county-level MA penetration. For each county-year, we also observe the average FFS risk score and the MA average risk score. We construct the total market risk score as an enrollment-weighted average of the FFS and MA risk scores.

We exploit the fact that MA actually consists of around 3000 separate geographic markets defined by county boundaries, each with distinct menus of MA plan offerings, prices, and penetration rates. For most of our analysis, we collapse all MA plans together, and consider the markets as divided between the MA and FFS segments. The top of Table 2.1 lists penetration rates for all of Medicare Advantage, over the time period of our data.\textsuperscript{56} The units of observations are counties, and our sample reflects data for 3,133 counties.\textsuperscript{57} We note these statistics are representative of counties, not individuals, since our unit of analysis is the county-year. Table 2.1 shows that average within-county MA penetration increases substantially during our short, 5-year time period. In the top panel of Figure 2.3, we put this growth in historical context, charting the rapid growth in MA that began in the mid 2000s. In the bottom panel, we plot the histogram of differences between county-level MA penetration in 2006 and penetration in 2010. There is substantial variation in penetration changes and it is largely positive.

\textsuperscript{54} A contract covers a single insurer and may include one or several health plans.\textsuperscript{55} See the appendix for the web sources for the data\textsuperscript{56} 2006 and 2010 are the first and last years for which data is on risk scores is available.\textsuperscript{57} We eliminate Los Angeles County because in one dataset the county has two SSA county codes while others it only has one. Because it is unclear to us how to merge these data for Los Angeles, we drop it from the sample. We also eliminate any SSA counties that do not have a corresponding FIPS county code (mostly counties in Puerto Rico) to facilitate merging of control variables.
This growth in penetration over the mid to late 2000s is widely attributed to the Medicare Modernization Act of 2003, which, among other changes, increased base payment rates in many counties and added a prescription drug benefit that was highly complimentary to Medicare Advantage plans (see for example, Gold 2009). In Figure 2.4, we show that this MA penetration growth, while geographically heterogeneous was not obviously limited to only certain regions or to urban areas. The figure shades each county according to its quartile of penetration changes.

Table 2.1 also shows that, consistent with previous evidence, risk scores are lower in MA than in FFS—though we show evidence below that they are nonetheless inflated via upcoding. The lower risk scores among MA plans are suggestive of advantageous to selection into MA on risk score.

Section 4.3: Empirical Framework

We approach identification in two ways. First, to control for any unobserved local factors--such as physician practice styles, medical infrastructure, or health behaviors--that could simultaneously affect population health and MA, we estimate fixed effects models of the form

$$totrisk_{ct} = \beta_0 + \beta_1 MApen_{ct-1} + \beta_3 X_{ct} + \theta_s S_{st} + \gamma_c + \delta_t + \epsilon_{ct}$$

(1)

where \(totrisk\) is the total market-level risk, \(\gamma_c\) and \(\delta_t\) are county and year fixed effects, \(S_{st}\) represents a set of state-specific time trends, and \(X_{ct}\) is a vector of time-varying county characteristics capturing shifts in demographics (age), economic conditions (unemployment, median income, and uninsurance rates), and health care infrastructure
(number of hospitals, skilled nursing facilities, and hospital beds). $y_c$ captures all unobserved properties of the local market that are fixed over our short panel and $S_{st}$ captures all unobserved state factors that vary linearly over time. $MApen_{ct-1}$ represents the MA penetration rate in county $c$ at time $t - 1$. The coefficient of interest is $\beta_1$, on this lagged MA penetration, rather than contemporaneous penetration. This is because of an institutional feature in which risk scores are calculated based on the prior year’s medical history.

Our second approach to identification exploits this institutional feature of how risk scores are calculated in Medicare Advantage. We illustrate the timing in Figure 2.2. The individual’s risk score that is used for payment throughout year $t + 1$ is based on diagnoses from the enrollment period between $t$ and $t + 1$. This implies, for example, that if an individual moves to MA in year $t$, the risk score for her entire first year in MA will be based on diagnoses she received while in TM in the prior plan year. Therefore, while the risk pools of the MA and TM market segments will change contemporaneously in response to a change in MA penetration (as consumers are reshuffled from one segment to another while retaining their old risk scores), the overall market level risk should remain constant. After the first year of MA enrollment, the risk score of the switcher will be updated to include diagnoses she received while enrolled in her first year...

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58 Data for the control variables comes from the SEER dataset at the National Cancer Institute (age) and the Area Resource File (all other controls).
of MA coverage. Therefore, coding differences between plans are revealed as changes to market-level risk, but only with a one year lag.\textsuperscript{59}

Because of this timing, a positive coefficient on lagged penetration ($\beta_1$) indicates more intensive coding in MA relative to FFS. In contrast, the coefficient on contemporaneous penetration should be equal to zero. We add a contemporaneous MA penetration term to equation (1),

\[ totrisk_{stc} = \beta_0 + \beta_1 MApen_{ct-1} + \beta_2 MApen_{ct} + \beta_3 X_{ct} + \theta_st + \gamma_c + \delta_t + \epsilon_{ct} \]  

and test whether $\beta_2$ is equal to zero.

This is a powerful placebo test, revealing any source of contemporaneous correlation between penetration and county risk that could contaminate our results. If $\beta_2$ is different from zero, this would suggest that there is some factor correlated with MA penetration and true underlying population health reflected in risk scores.\textsuperscript{60} If $\beta_2$ is not different from zero, it supports our identifying assumption that there are no time-varying county characteristics that are correlated with $totrisk_{ct}$ and $MApen_{ct-1}$ other than the ones that we control for in $X_{ct}$.

In addition to allowing the data the opportunity to falsify our identifying assumption, we argue that this assumption is plausible. On the supply side, it implies that insurers don’t base their decision to enter a county, or base changes to their product

\textsuperscript{59} The switcher case is the easiest to illustrate, but exactly the same pattern holds for shifts in the choice patterns of new beneficiaries.

\textsuperscript{60} Appropriate instruments could also be used to find plausibly exogenous variation in MA penetration. We attempted to use the instruments developed by Afendulis et al. (2013) and Baicker et al. (2013) but neither were well-suited to our data and time period. Because the Afendulis et al. instrument is non-time-varying, many of our observations are effectively eliminated, reducing our power by enough that our estimates, though consistently positive, are too noisy to make any conclusions. The Baicker et al. instrument is time-varying but does not vary enough during our time period to function well.
characteristics and prices on year-to-year changes in the average health of the county.

This seems sensible, given that the dramatic penetration growth over our period appears to be driven by regulatory changes to Medicare embodied in the Medicare Modernization Act of 2003. We would spuriously estimate upcoding effects in MA only if insurers expanded market share by lowering prices or increasing benefits in places where the population was simultaneously becoming sicker or older. (Later, we show in a series of “randomization tests” that penetration changes do not predict demographic changes in the county).

In terms of consumer choice, our assumption implies that individuals’ demand for MA does not increase as the average health in the county declines. This seems plausible, given that it has been widely documented that MA plans predominately attract lower risk enrollees.

Perhaps the strongest argument in support of our identification strategy is that true underlying population health, reflected especially in prevalence of chronic conditions that form the basis for risk scoring, is unlikely to change sharply within a county (i.e. year-to-year), while changes in reported risk due to coding will change instantaneously in the second year of MA enrollment for the mechanical reason described above.

Although estimating selection is not our primary goal, it is important to note that the timing in the selection regressions is different. In contrast to the market level risk, MA and FFS specific risk should change contemporaneously with changes in penetration due to selection, as shown in Figure 2.2. This is because if, say, a high risk-score enrollee switches from MA to FFS, his higher risk score immediately contributes to the new FFS
average. MA and FFS risk may additionally change with a lag if enrollees switch in anticipation of future health shocks, making \( t + 1 \) effects on TM and MA average risk ambiguous. To examine this and simultaneously evaluate whether MA is advantageously selected on the margin of penetration expansion, we run the following regressions of segment-specific risk scores on penetration:

\[
MA_{risk} = \beta_0 + \beta_1 MA_{pen} + \beta_2 MA_{pen_{t-1}} + \beta_3 X_{ct} + \theta_S S_{st} + \gamma_c + \delta_t + \epsilon_{ct} \tag{3}
\]

\[
FFS_{risk} = \beta_0 + \beta_1 MA_{pen} + \beta_2 MA_{pen_{t-1}} + \beta_3 X_{ct} + \theta_S S_{st} + \gamma_c + \delta_t + \epsilon_{ct} \tag{4}
\]

**Section 5: Results**

We begin in Table 2.2 by reporting results on selection. We estimate the slopes of the MA and FFS risk curves, following equations (2) and (3). In the first three columns, the dependent variable is county-level average FFS risk. In the second three it is MA risk. The three specifications for each outcome differ by the inclusion of controls. All columns include state time trends and county and year fixed effects. Columns (2) and (5) add controls for economic conditions and narrow age bins, and columns (3) and (6) add controls for health care infrastructure. (See table notes for details.) In most specifications, the estimates of the slopes of the MA and FFS risk curves are positive and significant.

Thus we find, consistent with previous evidence in Brown et al (2011) and Newhouse et al (2012), that Medicare Advantage is advantageously selected on the risk score. An effect size of 0.05 on FFS average risk, indicates that a 10% increase in MA penetration leads to an increase in the FFS average risk score of around 0.004-0.005.\(^{61}\)

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\(^{61}\) While the FFS results are quite similar to the findings of Newhouse et al. (2012), our MA result may seem to contradict their finding that individuals switching into MA get healthier as MA penetration increases (see Newhouse et al. appendix). We point out that in reality our analysis is quite different. Instead of measuring
MA, the magnitudes are larger than FFS, perhaps reflecting that marginal enrollees represent a greater share of the smaller MA risk population. These slopes provide evidence of advantageous selection into MA on the risk score, consistent with the figure in Section 3. Importantly, any selection on the risk score is compensated for. However, in order for risk adjustment to have any effect at all, there must be selection on the risk score, so it is important to know whether this type of selection exists (Layton 2014).

Table 2.3 reports our main upcoding results. The coefficient of interest is on lagged MA penetration. In column 1 we present estimates of the baseline model controlling for state time trends and county and year fixed effects. The coefficient on lagged MA penetration indicates that a county going from 0% to 100% MA penetration would cause an increase in the total average risk score by 0.04 points, or about half a standard deviation. This implies that an individual’s risk score in MA is about 4% higher than it would have been in FFS. In columns 2 and 3, we control for time-varying observable county characteristics. The coefficient on lagged MA penetration is largely unaffected. Table 2.3 also shows that coefficient estimates for contemporaneous penetration (MA Pen) support our placebo test. Unlike the case in the selection regressions in Table 2.2, here the contemporaneous coefficients are not statistically different from zero in almost all specifications. These coefficients imply that the health of changes in county-level MA average risk correlated with changes in MA penetration, they measure changes in the risk scores of individuals switching into MA correlated with changes in MA penetration.

We note that the “selection” we estimate here is different from most discussions of selection in the economics literature. We estimate selection on a risk score rather than selection on costs net of premiums, implying nothing about selection on uncompensated costs and welfare losses from that selection. See Einav and Finkelstein (2010) for a useful summary of this topic.

See Layton (2014) for a useful discussion of this important point. Basically, the effects of risk adjustment on equilibrium sorting across plans depend on the slopes of the “predicted” cost curve and the “residual” cost curve. In these regressions we measure the slope of the “predicted” cost curve. We cannot measure the slope of the “residual” cost curve due to data constraints.
the population was not drifting in a way that is predicted by contemporaneous or even lagged changes in penetration.

Columns 4-6 repeat the specifications in columns 1-3, controlling for PFFS penetration. PFFS plans are quite different from other MA plans. During our sample period they did not have networks or negotiate rates with providers. Instead PFFS plans acted exactly like FFS Medicare, reimbursing Medicare providers for any services provided to their enrollees at Medicare rates. At the same time, much of the variation in MA penetration during our sample period comes from increases in PFS enrollment. Due to these important differences and concerns that potentially endogenous PFFS penetration may be driving our results, we separate out the effect of PFFS plans and all other MA plans. The coefficients in columns 4-6 represent the effect of changes in the penetration rate of all MA plans except for PFFS plans on market risk. Interestingly, when controlling for PFFS penetration separately, the contemporaneous coefficients move closer to zero and the lagged coefficients increase slightly. This implies that rather than driving our results, if anything, PFFS penetration attenuates them.

We can extend the placebo test further by examining additional leads and lags, but are somewhat limited by our short panel. In Table 2.4, we included a variety of lead and lag combinations, under the intuition that upcoding effects should only be reflected in the coefficient on one-year-lagged penetration, while significant coefficients on contemporaneous effects or any other leads or lags would provide evidence of

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64 In 2011, PFFS plans were required to establish rates and Medicare providers were no longer required to accept Medicare rates from PFFS plans.
confounding trends. Standard errors increase slightly and the sample size varies from specification to specification because of the short panel, but the patterns are consistent with a true causal effect. We argue that because population variables tend to change gradually rather than discretely, the precisely timed response with a lag of one-year is more consistent with a mechanical coding effect than an impulse change in true population health.

In Table 2.5 we restrict the sample by eliminating counties with small shifts in MA penetration (column 1) and eliminating counties with relatively large shifts in MA penetration (column 2). These results indicate that much of the effect is coming from counties with large shifts in MA penetration. Because large shifts in MA penetration are much more likely to be due to supply-side factors (since large, rapid shifts in local population demographics and health are rare), we take this as further evidence that the positive coefficient on MA penetration is not due to spurious changes in demand due to health. In columns 3 and 4 we separate the sample into urban and rural counties. We do this because MA plan payments vary according to this definition. The effect seems to be larger in rural counties, but it is still positive for urban counties and statistically indistinguishable from the rural estimate. The estimate for urban counties is less precise because much of the time-variation in MA penetration occurs in rural counties during our sample period.

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65 It is possible that “upcoding” effects get larger the longer an individual is in MA. This would result in positive coefficients for all lags of MA penetration. We do not find evidence of this, suggesting that the upcoding effect is instantaneous and constant.
Finally, we test the “randomization” of our changes to MA penetration by evaluating whether they predict changes in demographic makeups of counties. These results are presented in Table 2.6. Column 1 shows that there is a weak relationship between lagged penetration and the proportion of individuals eligible for Medicare due to their age. Columns 2-5 represent a more important falsification test. Because risk scores include a demographic component that increases with age, our results could be explained by a correlation between lagged MA penetration and aging of the Medicare population. The coefficients on lagged MA penetration in columns 2-5 show the relationship between the proportion of individuals in each Medicare-eligible age group and MA penetration. All of the coefficients are close to zero, implying no relationship between MA penetration and the age distribution of individuals eligible for Medicare within a county.

Section 6: Discussion

We have so far ignored the possibility that coding differences from one plan may “spill over” onto the risk scores of a population enrolled in another plan. This could occur, for example, because providers often see patients from a mix of different health plans. Therefore, if an MA health plan managed to influence a provider’s coding or practice patterns, it could impact the risk scores of all individuals served by the provider, including those insured under TM.66 We discuss spillovers at length in the appendix, but here we briefly note that while spillovers may affect our estimate of the implicit subsidy due to upcoding, they do not affect our estimate of the presence, direction, or extent of coding differences between MA and TM.

66 This would be unlikely if the coding of diagnoses were done at the health plan level, rather than the provider level or if “upcoding” consists of plans selectively contracting with providers that code aggressively.
To put the size of our parameter estimates in context, recall that the subsidy to Medicare Advantage is equal to the upcoding factor multiplied by the county benchmark rate ($\alpha_{MA}B_{ct}$). In 2010, the average annual value of $B$ was about $10,500.\textsuperscript{67} Given our estimate of $\alpha_{MA} = 0.04$, this implies a subsidy of about $419 per MA enrollee in 2010, or a total potential subsidy of about $4 billion. Since Medicare Advantage has different penetration rates across regions of the country and in urban versus rural areas, this implies impacts that are unequal geographically. For illustration, Figure 2.5 plots MA penetration by county in 2011. The Great Lakes region and the West appear to reap the largest per capita gains from the subsidy. From the consumer choice perspective, this subsidy effectively generates a voucher for the purchase of an MA plan that is higher than the implicit Traditional Medicare voucher, distorting consumer choice toward the private option.

While we document the impact on public spending and the choice distortion, it is difficult to take a stance on the welfare consequences of these subsidies. We can, however, say something about the costs of risk adjustment. Brown et al. (2013) estimate that shifts in selection caused by the implementation of risk adjustment led to a $30 billion “differential payment,” or subsidy in our terminology, to MA plans. We argue that their estimate of the cost of risk adjustment is incomplete because it does not account for the subsidy generated by coding differences between TM and MA plans. Instead, the cost of risk adjustment is the combination of our estimate of increased costs due to coding differences and their estimate of increased costs due to selection. While our estimate of a

\textsuperscript{67} We estimate $B$ as the total amount paid to MA plans (about $124 billion) divided by the total MA enrollment (about 12 million). Payment and enrollment estimates are from MEDPAC (2012).
$4 billion subsidy from coding differences is significantly smaller than their estimate of the $30 billion subsidy from selection, it is far from a trivial cost of risk adjustment. Speaking more generally about the welfare impact of a subsidy to MA plans, it may be the case that it is welfare improving to pay MA plans more than the cost of enrolling beneficiaries in TM, if the MA plans use the extra payments to provide additional benefits. Further, benefits of MA may not accrue privately to enrollees. For example, Baicker, Chernew, and Robbins (2012) find that the existence of MA creates local spillovers that lower hospital spending for Traditional Medicare patients. Nonetheless, from both a public costs and welfare perspective, evaluating such positive externalities requires understanding the magnitude of the hidden subsidy to MA, which creates both additional public costs and creates deadweight loss due to taxation. That is the main goal of this paper.

**Section 7: Conclusion**

In this paper, we provide a theoretical framework for thinking about the effects of upcoding on plan payments and an empirical framework for estimating upcoding in the presence of selection. In the context of recent changes to payments structures in US health insurance markets, this paper provides a framework for analyzing the implicit transfers between health plans in the Exchanges due to risk adjustment. Researchers can easily adopt our method of estimating upcoding using the slope of the total market risk curve, given exogenous variation in enrollment across plans.

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68 See Hall (2011) which estimates the return on government spending in MA to be 96-186%
Our estimates show quantitatively important subsidies to Medicare Advantage due to coding differences. One apparent solution to this unintended subsidy and price distortion is simple: As long as the upcoding factor can be determined, the regulator can deflate payments to market segments or specific plans by the relevant upcoding factor. Indeed, CMS currently deflates payments to all MA plans uniformly. However, this solution requires CMS to constantly estimate upcoding and may be impractical at the insurer or plan level, rather than at the market segment level we examine here (all of MA). Currently, CMS is considering abandoning the deflation of MA risk scores, and instead attempting to address upcoding by including MA claims in the estimation of the risk adjustment coefficients. Our model clearly shows that including MA enrollees in the estimation sample will not change the upcoding problem. A change in the estimation sample simply changes the coefficients $\hat{\beta}$, but the upcoding problem stems from differences in the diagnoses those coefficients multiply, $x_i^f$.

Ultimately, risk adjustment addresses a very important problem: adverse selection and the many margins of distortion it can create. In a second-best world in which adverse selection is an inherent feature of competitive insurance markets, the solution to the upcoding problem is not to abandon risk adjustment. However, the focus in the risk adjustment literature on maximizing “fit” of payments to expected costs is the wrong objective function. Glazer and McGuire (2000) argue that risk adjustment systems should be focused on the incentives faced by insurance plans, rather than fit. Applying that insight to our results suggests that an important dimension of incentives is the incentive to manipulate coding. Further, we argue that to ensure that risk adjustment does not
inappropriately subsidize one plan over another, attention should be paid not just to the potential manipulability of risk adjusters, but also to how much they may naturally vary across plans for any reason whatsoever.

The optimal (second best) payment policy almost certainly includes risk adjustment, but with adjustments that reflect both predictiveness of costs and susceptibility to coding heterogeneity. For instance, “Diabetes” may optimally receive a larger weight than under the current system, while “Diabetes with acute complications” may optimally receive a lower weight than currently, since the former may be less susceptible to differential coding by different plans. Given the large role that risk adjustment is scheduled to play in the current health reform taking place in the United States, development of such optimal payment policies that take differential coding into account is potentially of great importance.
Notes: The horizontal axis measures the market share of plan B. The vertical axis measures average risk for each level of market share, either associated with a particular plan or overall in the market. All consumers choose either plan A or plan B. "Total Average Risk" is the average of observed risk scores taken over the entire market, regardless of plan choice. The dashed curve in the bottom panel is the counterfactual risk curve that would result from scoring Plan B enrollees according to Plan A diagnosis practices.
Figure 2.2: Timing Illustration: Coding Effects Occur with a Lag in Medicare

Notes: This diagram highlights the timing of changes to segment-specific (TM vs MA) average risk and market level average risk in response to a change in MA penetration. For the first year in either MA or TM, a switcher carries forward a risk score based on his last year in the other segment. Therefore, upcoding effects should not be apparent for the first plan year following the change in enrollment. The dashed curves after period $t+1$ for the MA and TM average risk curves indicate that changes in segment-specific average risk in the years following the switch are ambiguous.
Figure 2.3: Growth in Medicare Advantage (MA) Penetration

Notes: The top panel displays national trends in MA penetration, where the unit of observation is the Medicare beneficiary. Source: Kaiser Family Foundation, 2013. The bottom panel displays a histogram of within-county changes in penetration from 2006 to 2010, using the main estimation sample. The unit of observation here is the county.
Figure 2.4: Geographic Heterogeneity in MA Penetration Growth

Notes: MA penetration growth by quartile, from 2006 to 2010. Darker regions experienced the largest positive change in MA penetration.
Figure 2.5: Implicit Transfer Across Geography Due to Upcoding

Notes: MA penetration by quartile as of 2010. Darker regions have the highest MA penetration.
<table>
<thead>
<tr>
<th></th>
<th>2006</th>
<th></th>
<th>2010</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
<td>SD</td>
</tr>
<tr>
<td>MA Penetration</td>
<td>0.069</td>
<td>0.093</td>
<td>0.140</td>
<td>0.118</td>
</tr>
<tr>
<td>MA Penetration (pop weighted)</td>
<td>0.165</td>
<td>0.151</td>
<td>0.237</td>
<td>0.145</td>
</tr>
<tr>
<td>Total Market Avg Risk</td>
<td>0.957</td>
<td>0.072</td>
<td>0.944</td>
<td>0.075</td>
</tr>
<tr>
<td>FFS Avg Risk</td>
<td>0.959</td>
<td>0.073</td>
<td>0.954</td>
<td>0.076</td>
</tr>
<tr>
<td>MA Avg Risk</td>
<td>0.901</td>
<td>0.141</td>
<td>0.876</td>
<td>0.099</td>
</tr>
<tr>
<td>Medicare Eligibles (≥ 65)</td>
<td>11530</td>
<td>28890</td>
<td>12547</td>
<td>31015</td>
</tr>
<tr>
<td>Fraction of Population ≥ 65</td>
<td>0.152</td>
<td>0.041</td>
<td>0.159</td>
<td>0.042</td>
</tr>
<tr>
<td>Among Population ≥ 65, age:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>65 – 69</td>
<td>0.292</td>
<td>0.039</td>
<td>0.312</td>
<td>0.040</td>
</tr>
<tr>
<td>70 – 74</td>
<td>0.238</td>
<td>0.019</td>
<td>0.237</td>
<td>0.019</td>
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<tr>
<td>75 – 79</td>
<td>0.197</td>
<td>0.015</td>
<td>0.182</td>
<td>0.014</td>
</tr>
<tr>
<td>80+</td>
<td>0.273</td>
<td>0.046</td>
<td>0.269</td>
<td>0.047</td>
</tr>
</tbody>
</table>

Summary statistics for the beginning and end period of our county panel. The unit of observation is the county, and means are county-weighted unless otherwise noted.
Table 2.2: Selection Results: Effect of Penetration Changes on FFS and MA Risk

<table>
<thead>
<tr>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dep Var: Avg Risk in FFS</td>
<td>Dep Var: Avg Risk in MA</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA Pen</td>
<td>0.051*</td>
<td>0.061**</td>
<td>0.061**</td>
<td>0.148*</td>
<td>0.197**</td>
<td>0.198**</td>
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<tr>
<td></td>
<td>(0.021)</td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.063)</td>
<td>(0.039)</td>
<td>(0.039)</td>
</tr>
<tr>
<td>MA Pen t-1</td>
<td>0.035*</td>
<td>0.035*</td>
<td>0.034*</td>
<td>0.050</td>
<td>0.042</td>
<td>0.042</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.034)</td>
<td>(0.035)</td>
<td>(0.035)</td>
</tr>
<tr>
<td>Year FE s</td>
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<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>County FE s</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>State Trends</td>
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<td>✔</td>
<td>✔</td>
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<td>✔</td>
</tr>
<tr>
<td>Age Bins</td>
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<td>✔</td>
<td>✔</td>
<td>✔</td>
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</tr>
<tr>
<td>Econ Controls</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
<td>Health Infrastructure</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
<td>✔</td>
</tr>
<tr>
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<td>✔</td>
<td>✔</td>
</tr>
</tbody>
</table>

Observations | 12232 | 12228 | 12228 | 11240 | 11240 | 11240 |

Regressions of average reported FFS and MA risk scores in the market (county) on Medicare Advantage (MA) penetration. MA Pen t-1 indicates penetration in the county in the prior plan year. Observations are county-years. In Columns (1) through (3), the dependent variable is average FFS risk in the county. In Columns (4) through (6), the dependent variable is average MA risk over all MA plans and insurers in the county. Economic controls include county income, poverty rate, unemployment rate, and unemployment rate. Health infrastructure includes number of skilled nursing facilities, skilled nursing facility beds, number of hospitals, and number of hospital beds. Health outcomes include inpatient days per capita and outpatient visits per capita. Standard errors in parentheses are clustered at county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. 


Table 2.3: Upcoding Results: Effect of Penetration on County Aggregate Risk

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Market Risk</td>
<td>Market Risk controlling for PFFS</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA Pen (t)</td>
<td>0.027+</td>
<td>0.024</td>
<td>0.024</td>
<td>0.003</td>
<td>-0.002</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>MA Pen (t-1)</td>
<td>0.046**</td>
<td>0.040**</td>
<td>0.039**</td>
<td>0.051*</td>
<td>0.044*</td>
<td>0.043*</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.015)</td>
<td>(0.015)</td>
<td>(0.022)</td>
<td>(0.021)</td>
<td>(0.021)</td>
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</table>

Year FEs: ✓ ✓ ✓ ✓ ✓ ✓ ✓ County FEs: ✓ ✓ ✓ ✓ ✓ ✓ ✓ State Trends: ✓ ✓ ✓ ✓ ✓ ✓ ✓ Age Bins: ✓ ✓ ✓ ✓ ✓ ✓ ✓ Econ Controls: ✓ ✓ ✓ ✓ ✓ ✓ ✓ Health Infrastructure: ✓ ✓ ✓ ✓ ✓ ✓ ✓ Health Outcomes: ✓ ✓ Controls for PFFS Pen: ✓ ✓ ✓ ✓

Observations: 12498 12418 12418 12498 12418 12418 12418

Regressions of average reported risk scores in the market (county) on Medicare Advantage (MA) penetration. MA Pen \(t-1\) indicates penetration in the county in the prior plan year. Controls are as described in the Table 2 notes. Observations are county-years. Columns (4) through (6) control separately for contemporaneous and lagged Private Fee For Service (PFFS) penetration. Standard errors in parentheses are clustered at county level. + \(p < 0.1\), * \(p < 0.05\), ** \(p < 0.01\).
Table 2.4: Falsification Test: Leads and Lags

<table>
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<tbody>
<tr>
<td></td>
<td>2007-2010</td>
<td>2008-2010</td>
<td>2008-2010</td>
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<tr>
<td>MA Pen $t+1$</td>
<td>-0.009</td>
<td>-0.021</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.013)</td>
<td></td>
</tr>
<tr>
<td>MA Pen</td>
<td>0.026+</td>
<td>-0.012</td>
<td>-0.015</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td><strong>MA Pen $t-1$</strong></td>
<td>0.039**</td>
<td>0.044+</td>
<td>0.045*</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.023)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>MA Pen $t-2$</td>
<td></td>
<td>-0.005</td>
<td>-0.009</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.017)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Year FEs</td>
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<td>✓</td>
</tr>
<tr>
<td>County FEs</td>
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<td>Health Outcomes</td>
<td>✓</td>
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Observations 12418 9313 9313

Regressions of average reported risk scores in the market (county) on Medicare Advantage (MA) penetration. MA Pen $t+1$ indicates penetration in the county in the prior plan year. MA Pen $t-1$ indicates penetration in the county in one plan year in the future. Observations are county-years. The data include penetration from 2005 through 2011 and market risk from 2005 through 2010. The length of the panel determines the sample size in each column. Controls are as described in the Table 2 notes. Standard errors in parentheses are clustered at county level. $+ p < 0.1$, $* p < 0.05$, $** p < 0.01$. 
Table 2.5: Heterogeneity in Upcoding Results

<table>
<thead>
<tr>
<th></th>
<th>(1) $\Delta &gt; .06$</th>
<th>(2) $\Delta &lt; .06$</th>
<th>(3) Urban/Rural</th>
<th>(4) Urban/Rural</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA Pen $t-1$</td>
<td>0.001</td>
<td>0.055***</td>
<td>0.036*</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.019)</td>
<td>(0.018)</td>
<td>(0.028)</td>
</tr>
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<td>Year FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>County FEs</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>State Trends</td>
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<tr>
<td>Age Bins</td>
<td>✓</td>
<td>✓</td>
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<td>Econ Controls</td>
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Observations: 6174  6244  9469  2949

Observations of average reported risk scores in the market (county) on Medicare Advantage (MA) penetration. MA Pen $t-1$ indicates penetration in the county in the prior plan year. Controls are as described in the Table 2 notes. Observations are county-years. In columns (1) and (2), sample split at median by within-county change in MA penetration between 2006 and 2010. In columns (3) and (4), sample split by urban/rural. Standard errors in parentheses are clustered at county level. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$. **
Table 2.6: Test of Randomization

<table>
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<th>(2) Conditional on &gt; 65</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>65 - 69 70 - 74 75 - 79 80+</td>
<td></td>
</tr>
<tr>
<td>MA Pen t</td>
<td>0.007**</td>
<td>0.016*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>MA Pen t-1</td>
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</tr>
<tr>
<td></td>
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<td>(0.008)</td>
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<td>Year FEs</td>
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<tr>
<td>County FEs</td>
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</tr>
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<tr>
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<td>12418</td>
<td>12418</td>
</tr>
</tbody>
</table>

Dependent variables are the fraction of the county population in the indicated age bin. MA Pen t-1 indicates penetration in the county in the prior plan year. Controls are as described in the Table 2 notes. Standard errors in parentheses are clustered at county level. + p < 0.1, * p < 0.05, ** p < 0.01.
CHAPTER THREE

RISK CORRIDORS AND REINSURANCE IN HEALTH INSURANCE EXCHANGES:
INSURANCE FOR INSURERS

with Thomas G. McGuire and Anna D. Sinaiko

Section 1: Introduction

As of October 1, 2013, new state-based or federally-facilitated health insurance exchanges have opened their virtual doors for U.S. citizens and legal residents who are not eligible for employer-sponsored or public coverage to purchase health insurance. These Exchanges represent the most significant policy initiative to increase access to health insurance since the creation of Medicare and Medicaid in 1965. Their success will depend on, among other things, how insurance plans are paid, and in particular how plans are protected against the risk of enrolling some extraordinarily expensive enrollees, whether due to random variation, adverse selection, or other market problems.

There are four primary tools to protect health plans against the financial risk associated with adverse selection: pricing of health plan premiums, risk adjustment, reinsurance, and risk corridors. Each of these tools ameliorates selection problems differently. Age-based pricing of health plan premiums matches revenues for an individual more closely to expected costs. Risk adjustment redistributes revenues from plans with healthier than average enrollees to plans with sicker than average enrollees. Reinsurance pools the costs of the sickest enrollees across plans. Risk corridors redistribute revenues from plans earning large profits to plans incurring large losses.\(^{69}\)

\(^{69}\) One could add the individual mandate to this list, a requirement designed to ensure both low and high-risk individuals participate in the risk pool.
Much has been written about premium pricing and risk-adjustment (McGuire et al. 2013, Glazer et al. 2013, Shi 2013). Here our focus is on reinsurance and risk corridors. Fundamentally, these policies act as insurance for insurers. They protect insurers from the potential losses that could occur if they enroll an unexpectedly unhealthy group of enrollees. However, as with other forms of insurance, the risk protection from reinsurance and risk corridors likely comes at a cost: When insurers are protected from bad outcomes, they may not try as hard to avoid them, i.e. moral hazard. The best form of insurance for insurers, then, would be the one that reduces insurer risk as much as possible while limiting efficiency losses from moral hazard. In this paper, we simulate the distribution of costs faced by an insurer competing in a Health Insurance Exchange. We then use the simulated cost distribution to evaluate the potential of the reinsurance and risk corridor policies enacted through the Affordable Care Act (ACA) to reduce the risk faced by insurers in the Exchanges. We then develop a framework for thinking about efficiency losses from these policies and empirical measures of that efficiency loss. We use these measures and the simulated cost distribution to compare the power of reinsurance and risk corridors generally to reduce insurer risk with as little efficiency loss as possible.

Insurers reduce risk faced by individuals by taking on individual risk and pooling that risk. It may seem odd then to seek to reduce the risk faced by insurers. However, if there is too much risk, risk-averse insurers will avoid entering a market, reducing competition. Risk-averse insurers will also charge higher premiums to compensate for the risk they are taking on, driving up prices in the market, potentially driving healthy
consumers out of the market, leading to adverse selection problems (Cutler and Reber 1998, Einav et al. 2010, Hackmann et al. 2013). Given that it may be desirable to reduce insurer risk, it is important to evaluate the ability of different policies to accomplish that goal.

When considering optimal policies for reducing the risk faced by insurers, an analogy can be drawn to the principles of optimal health insurance set forth by Arrow (1963) and Zeckhauser (1970). Briefly, if insurer risk-aversion mimics individual risk aversion in that it is based on diminishing marginal utility of profits, a policy that reimburses insurers for all costs beyond a certain loss threshold (i.e. full coverage after a deductible) is the optimal policy. Similarly, if there is some moral hazard (i.e. insurer behavior changes in the presence of the risk reducing policy), partial coverage after a deductible will be optimal. The implication of this result is that in the absence of moral hazard, risk corridors, which mimic the “full coverage after a deductible” policy will be preferred to reinsurance. The intuition for this claim is as follows: Risk corridor payments apply only when a plan’s total costs are in the tails of the total cost distribution whereas with reinsurance plans receive payments in every part of the cost distribution. Because risk is reduced most quickly by eliminating the tails of the distribution, risk corridors are likely to reduce insurer risk more efficiently than reinsurance.

The paper will proceed as follows. In Section 2 we provide an explanation of the various risk reducing policies being implemented in the ACA Health Insurance Exchanges. In Section 3 we set forth a conceptual framework outlining an optimal insurer risk reducing policy and how to think about the efficiency consequences of reinsurance.
and risk corridors. In Section 4 we provide details about a series of simulations we run to first assess the ability of the proposed reinsurance and risk corridor policies to reduce insurer risk and second compare the efficiency of reinsurance and risk corridors. We also describe the dataset of individuals likely to enroll in an Exchange plan that we construct from the Medical Expenditure Panel Survey (MEPS). In Section 5 we present the results of our simulations. In Section 6 we discuss the results and their limitations.

Section 2: Policy Background

Reinsurance. Private reinsurance has been available in the health insurance market for many years, and government-sponsored reinsurance has been implemented at the national level (e.g. the Medicare Part D program) and the state level (e.g. New York, Idaho). Typically, private reinsurance policies cover only the highest cost cases, while government-sponsored reinsurance reimburses costs starting at much lower thresholds (Bovbjerg et al., 2008; Swartz, 2006). In Part D for example, Medicare subsidizes 80% of any spending on prescription drugs above an enrollee’s out-of-pocket maximum. This has been a non-trivial amount; in 2012 Medicare’s reinsurance payments to plans amounted to $14.8 billion, 24% of total Medicare payments to prescription drug plans.

Previous empirical research has largely used simulation (as opposed to evaluations of existing programs) to test the extent that reinsurance reduces a plan’s potential losses from enrolling high-risk individuals. In an SCHIP-eligible population, Sappington et al. (2006) simulated plan profits under varying reinsurance parameters, and find that public reinsurance with an attachment point of $10,000, much lower than the attachment point being implemented in the Exchanges, reduced average plan losses by 40
percent. However, Dow et al. (2010) used data from a Medicare population to
demonstrate that even with reinsurance, incentives to avoid enrolling high cost patients
remain as insurers could still expect to lose $5,400 per individual in the top one percent,
and $1,700 per individual in the top three percent of spenders.

Section 1341 of the ACA creates a reinsurance program for the first three years of
the Exchanges, from 2014 to 2016. For 2014, this program will reimburse 80 percent of
individual market health plans’ annual costs of care for enrollees who incur spending
above an “attachment point” of $60,000 and up to a $250,000 cap (HHS, 2012). Plans
are expected to have commercial reinsurance covering costs above $250,000. All
covered claims, not just claims for the federally determined essential health benefits, will
be eligible for reinsurance (Winkleman et al., 2012). This program will be financed by a
small reinsurance premium, determined as a percentage of premiums and set annually
that will be assessed for all covered lives in non-grandfathered health plans in the United
States, including some self-funded plans. A state may collect additional contributions
to provide funding for its administrative expenses or additional reinsurance payments.

Risk Corridors Risk corridors, also known as aggregate stop-loss reinsurance, have also
existed for quite some time in both the private and public sectors (Bovbjerg et al., 2008;
Swartz, 2006). In the private sector, some reinsurance contracts include both individual
and aggregate (i.e. risk corridor) protection (Bovbjerg et al., 2008). In the public sector,

70 The per-capita “reinsurance tax” was set to be 95% of total market premiums in 2014
equivalent to $65 per covered life), 60% in 2015 and 35% in 2016. Recent policy changes have
resulted in a delay in collection of these funds from insurers to the period 2015-17. In 2014 the
transitional reinsurance program will be funded with government revenues.
Arizona’s “Healthcare Group” program, which began in the mid-1980s, included a risk corridor-like policy that reimbursed health plans for costs exceeding an aggregate medical loss ratio of 86 percent annually (AcademyHealth 2007). Symmetric risk corridors that limit plans’ profits or losses are also included as part of Medicare payments to prescription drug plans in Part D, where after risk-adjustment and reinsurance payments for expenditures by high cost individuals, a plan’s losses or profits can trigger risk corridor payments or collections (MedPAC 2012). There, payments to plans for greater than expected costs are financed by recouping funds from plans with greater than expected profits, and the expected net cost of the program to Medicare is zero. The Medicare Shared Savings and Pioneer Accountable Care Organization (ACO) Programs also include payment models incorporating a risk corridor feature. Under the Shared Savings Program, ACOs can choose between a one-sided and two-sided arrangement. Under the one-sided arrangement, ACOs will be allowed to share up to 50% of savings in excess of a minimum loss ratio (Boyarsky and Parke 2012). Under the two-sided model, ACOs will be allowed to share in 60% of savings, but they will also be liable for up to 60% of costs above expectation. Similar to the Exchange risk corridor program, if provider groups have exceedingly low revenues (high savings to Medicare), Medicare will reimburse some portion of the loss, and if the group has exceedingly high revenues, Medicare will extract some portion of the excess.

Under Section 1342 of the ACA, a symmetric risk corridor program was established for the marketplaces to operate from 2014-16 and help plans manage high risks enrolled during the early years of the Exchanges. Under this program a “target
amount” of expenditures will be calculated for each health insurer’s covered risk pool, which is equal to their total premiums collected minus an allowed amount for administrative costs and profits. If a plan’s actual expenditures for medical care for its enrollees are greater than the target by at least 3 percent, the plan will receive a payment from the risk-corridor program. In contrast, if a plan’s actual medical care expenditures are lower than the target by 3 percent or greater the plan must make a payment to the risk corridors program.

Section 3: Insurance Principles

In conventional theory, the firm is risk neutral, the rationale being that a large number of owners/investors are assumed to be able to protect themselves against any firm-specific risk by diversification in their investment portfolio. In practice, however, while firms are owned by shareholders who can diversify away risk, they are managed by individuals. When managers are risk-averse and their incomes are tied to the value of the firm, firms may act as if they are risk-averse. The optimal manager contract involves some portion of pay being tied to firm performance, with the exact portion being determined by the trade-off between motivating managers to maximize the value of the firm and changes to firm behavior stemming from manager risk aversion (Fama and Jensen 1983). Additionally, the correlation between manager pay and firm value has increased dramatically in recent years, largely due to the prevalence of stock options (Hall and Liebman 1998). Given that a high correlation between manager pay and firm

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71 See Rothschild and Stiglitz 1976 for justification of this assumption in the context of insurance. For an argument justifying this assumption in the context of the risk of pharmaceutical patent litigation, see Bulow (2004).
value implies that managers indeed face a great deal of risk, the assumption that firms behave as though they are risk neutral seems somewhat questionable.\textsuperscript{72} For firms in the insurance industry the role of risk and potential risk aversion take on special significance. Insurers can use the law of large numbers to reduce the risk of large losses: the variance of an insurer’s costs (i.e. insurer risk) decreases with the number of uncorrelated risks it enrolls. This property is what gives rise to insurance. An insurer can pool the risks of many risk-averse individuals, improving welfare while simultaneously decreasing its own uncertainty with each additional enrollee. With an infinite number of enrollees, insurance can eliminate all risk. However, insurers do not have infinitely large enrollment pools. Therefore, managers at insurance companies still face risk, especially when entering new markets such as the Exchanges where there is greater uncertainty about the distribution of risks from which they are drawing. Moreover, managers at health insurance companies also face the risk of mispricing insurance policies or selecting an unexpectedly high cost group of enrollees.\textsuperscript{73} These types of risk cannot be eliminated by increasing the size of the pool.

In this paper, we assume that the firms potentially participating in health insurance Exchanges act as though they are risk averse. We give three justifications for this assumption. First, as discussed above, while owners can hedge away risk, firm managers are likely to be making the decisions regarding the pricing of contracts and

\textsuperscript{72} Conceivably, managers could hedge against the risk present in their pay packages on their own. However, given that changes in firm value are quite large (Hall and Liebman (1998) report a standard deviation of changes in firm value of around 32\% or about $700 million), it seems likely that liquidity constraints will prevent them from fully hedging against this kind of risk.

\textsuperscript{73} As has become obvious in recent months, insurers also face political risk where policies and regulations that affect the risk pool can change after insurers set prices.
whether or not to enter new markets. Because managers’ pay is largely tied to firm value (Hall and Liebman 1998), the firm’s choices are likely to reflect manager risk aversion. Second, the loading factor (the difference between medical claims paid by the insurer and premium revenue) has been estimated to be around 40% higher for very small groups than for very large groups (Gruber 1998). While this difference could be due to large fixed costs of insuring a group of individuals, at least some portion of it also likely reflects the fact that small risk pools are by definition riskier to insure than large pools.

Second, there is a long line of research in the actuarial literature about how to calculate a “risk premium” in order to incorporate it into the loading factor on an insurance policy (see Kahane (1979), and Christofides and Smith (2001) for some examples of this literature). Most of these studies relate the “cost” of risk to be priced into the insurance premium to the standard deviation of the cost distribution, a measure we will use later.

We measure insurer risk in two ways. The first we characterize as the conventional form of risk aversion, similar to individual risk aversion where individuals’ utility functions exhibit diminishing marginal utility in income. In this case risk is related to the variance of the distribution of potential outcomes. This possibility is motivated by the fact that traditionally risk-averse managers make pricing decisions under a reward structure that penalizes losses and rewards profits. The second form of insurer risk aversion we consider could be more accurately described as “large loss aversion.” This type of risk aversion is motivated by the managers or owners/investors facing a large penalty for being forced to declare bankruptcy or for depleting the insurer’s reserves. In this case risk is related to the probability of large losses.
We define potential outcomes for insurers using the distribution of expected costs of the insurer’s enrollees. When constructing costs, we include only medical and pharmaceutical expenditures and any transfers coming through the various policies we analyze. We ignore factors such as administrative costs, risk premia, etc. because these costs are largely predictable and will be priced into the premium set by an insurer. The predictability of these factors implies that they affect only the mean of the expected cost distribution, which is unrelated to our measures of insurer risk. We treat the mean of the cost distribution as the insurer’s expected cost per enrollee, and we assume that any outcome below this expected cost results in insurer “profits” and any outcome above this cost results in insurer “losses.” Figure 3.1 illustrates this cost distribution. Essentially, every year an insurer receives a draw from this distribution. If an insurer receives a draw from the left side of the distribution, it will earn unexpected profits in that year. On the other hand, if the insurer receives a draw from the right side of the distribution, it will experience unexpected losses.

A risk neutral insurer will only care about the mean of the cost distribution. A risk averse insurer, on the other hand, makes choices based on other moments of the distribution. No matter the form that insurer risk aversion takes, whether conventional risk aversion or “large-loss aversion,” insurer risk aversion implies that insurers are willing to pay to have their risk reduced. If insurer risks can be pooled in a similar way as are individual risks, and at a cost lower than the insurers’ willingness-to-pay, total surplus

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74 This definition of “profits” and “losses” comes from an assumption that insurers price their insurance policies at the average expected cost of potential enrollees. Such pricing is implied by the assumption of perfect competition.
can be increased. This provides motivation for policies that reduce the risk faced by insurers. Additional motivation comes from the possibility that when insurers are risk averse, they may be hesitant to enter markets with a great deal of uncertainty, such as the Exchanges, potentially limiting competition.\textsuperscript{75} Risk-averse insurers will also require larger risk premiums, increasing prices paid by consumers, and possibly driving lower risk consumers out of the Exchanges, reducing welfare (Einav et al. 2010). Given these motivations for reducing insurer risk, we now explore the optimal way to do so.\textsuperscript{76}

The seminal papers establishing the theory of insurance in health economics are Arrow (1963) and Zeckhauser (1970). Arrow established that with a limited budget, the optimal insurance policy is full coverage after a deductible. In Arrow’s model, individuals have diminishing marginal utility in non-medical consumption and there is uncertainty about their future health status and, thus, their medical expenses. Under these assumptions, individuals value an extra dollar of coverage against medical expenses more as the potential expense gets larger. Therefore, coverage for large expenses provides larger welfare gains than coverage for small expenses. Ellis and McGuire (1988) and Keeler et al. (1988) apply this principle to the design of outlier payments for hospitals paid via prospective payment. However, as Zeckhauser (1970) points out, full coverage after a deductible is not always the optimal insurance policy. In his paper, he formalizes

\textsuperscript{75} This is precisely the stated purpose of the risk-reducing policies such as reinsurance and risk corridors that are present during the first three years of the Exchanges’ existence.

\textsuperscript{76} Risk adjustment is another policy related to insurer risk that is often discussed along with risk corridors and reinsurance. However, while risk adjustment has important effects on the mean of an insurer’s distribution of expected costs, its effects on the variance of the distribution are minimal. Because all of our measures of risk are based in some way on the variance of the cost distribution and are unrelated to the mean of the distribution, we abstract from risk adjustment through much of this paper. All of the important results that come out of our simulations are robust to the inclusion of risk adjustment. Those results are available on request from the authors.
the trade-off between risk protection and moral hazard in insurance. Insurance provides both welfare gains through risk protection and welfare losses through moral hazard. This implies that optimal coverage is a deductible followed by coverage equal to a coinsurance rate that is a function of the price elasticity of demand for medical care.

In the context of protecting health insurers from risk, if we assume no moral hazard, Arrow’s principle of the optimality of full coverage after a deductible would imply that it is inefficient to use reinsurance to provide risk protection. Reinsurance provides the plan with protection from the risk that an individual incurs high costs. While this type of protection will decrease the variance of the insurer’s profit distribution and decrease the probability of a large loss, it is not the most efficient way to do so. Under reinsurance, some plans whose ex-post outcomes are in the left hand side of the cost distribution (positive profits) will receive reinsurance payments if they have one or two high cost cases and many low cost cases. At the same time, some plans whose ex-post outcomes are in the right hand side of the cost distribution (negative profits) will receive no reinsurance payments if they have many cases whose costs are only slightly above what was expected. A more efficient policy would mimic Arrow’s optimal insurance policy of full coverage after a deductible by only reimbursing plans incurring large losses (i.e. outcomes in the far left tail of the profit distribution). This type of policy would use fewer dollars to provide larger reductions in the variance of the profit distribution and the probability of a large loss. This is exactly what risk corridors do.
Section 3.1: Efficiency Loss

Similar to other forms of insurance, risk protection from reinsurance and risk corridors is likely to come at the cost of moral hazard, i.e. changes in insurer behavior due to the protection provided by the policies. When considering the optimal form of risk protection, and when comparing the power of reinsurance and risk corridors to reduce insurer risk, the efficiency losses from moral hazard must also be considered. While some sort of efficiency loss seems inevitable, the source of the loss is unclear in the context of these policies. To give some concreteness to this issue, we use the following framework.

A plan faces $s$ states of the world, where a state of the world represents a single draw from the insurer’s cost distribution. In each state, a proportion $\alpha$ of a population of $N$ potential enrollees enrolls in the plan. Let $p_{ls}$ be the probability that individual $i$ enrolls in the plan in state of the world $s$. At the beginning of each period, (before the state of the world is revealed) the health plan chooses a level of utilization management effort, $e_i$, for each potential enrollee. An individual’s utilization is a function of $e_i$. A plan chooses the effort levels to maximize the following expected profit function:

$$E[\pi] = \sum_i \sum_s p_{ls} [r_{ls}(x_i(e_i)) - x_i(e_i) - c_i(e_i)]$$

where $x_i(e_i)$ represents average enrollee utilization of medical care in dollars as a function of effort, $r_{lsk}(x_i(e_i))$ represents average plan revenues under policy $k$ possibly as a function of utilization, and $c_i(e_i)$ represents the cost of effort. Risk corridors and reinsurance affect the plan’s behavior by altering the relationship between revenues and utilization, $\frac{\partial r_{lsk}}{\partial x_i} = r'_{lsk}$. If $r'_{lsk} = 1$, then under policy $k$ in state of the world $s$, each
additional dollar spent by individual $i$ is fully reimbursed by the regulator. Let $r_0' = 0$ be the relationship between revenues and utilization with no cost-sharing policy and fully prospective payment. Thus, if risk corridors reimburse the plan for all costs incurred by the plan beyond a threshold of plan costs, then $r_{ls,rc}' = 1$ for all individuals in the states of the world where that threshold is crossed and zero otherwise. Likewise, if reinsurance reimburses a plan for all costs incurred by individual $i$ beyond some threshold of individual costs, then $r_{ls,re}' = 1$ in every state of the world for each individual whose costs cross that threshold and zero otherwise. If we assume that $r_{ls,k}' = 0 \forall i, s, k$ is optimal, efficiency loss can be described as a function of $r_{ls,k}' - r_0' = r_{ls,k}'$. Because plans choose effort levels at the beginning of the period, prior to knowing the state of the world, in reality it is each individual’s expected level of $r', r_{ls,rc}' = \sum_s p_{is} r_{ls,rc}'$, that actually matters for plan behavior, so we define efficiency loss as $L_t(\tilde{r}_{ls,rc}')$.

We note that there is no analytical solution suggesting that one policy is “better” than the other in terms of efficiency. Reinsurance affects plans’ incentives for only a few people but in all states of the world. Additionally, reinsurance affects plans’ incentives for the individuals for whom “effort” is likely to be most beneficial. Risk corridors, on the other hand, affect plans’ incentives for all enrollees but only in a few states of the world. Fortunately, our framework provides a useful method for comparing the efficiency loss from each policy. In the appendix, we show that under our assumptions, the difference between the efficiency loss from reinsurance and the loss from risk corridors is approximately proportional to the following expression:
\[ \sum_i \frac{dx_i}{d\eta_i'} (\bar{\eta}_{l,re}'^2 - \bar{\eta}_{l,rc}'^2). \]

This implies that the efficiency loss from a given reinsurance policy is greater than the loss from a given risk corridor policy if and only if \( \sum_i \frac{dx_i}{d\eta_i'} (\bar{\eta}_{l,re}'^2) < \sum_i \frac{dx_i}{d\eta_i'} (\bar{\eta}_{l,rc}'^2) \). Thus, if we can construct measures of \( \sum_i \frac{dx_i}{d\eta_i'} (\bar{\eta}_{l,re}'^2) \) and \( \sum_i \frac{dx_i}{d\eta_i'} (\bar{\eta}_{l,rc}'^2) \), we can determine which policy results in a larger loss of efficiency. We now turn to discuss the methods for constructing and testing these measures.

**Section 4: Data and Methods**

In this section, we will first present the dataset we use to analyze reinsurance and risk corridors and then discuss the construction of the insurer’s simulated cost distribution under each policy. We also present our measures of risk and efficiency loss. As a preview, in the base case with no reinsurance or risk corridors, we construct this distribution by drawing 10,000 random groups of 5,000 “enrollees” from a pool of potential exchange participants. The average cost for each of these draws represents a potential state of the world for the insurer, and we calculate our risk measures using this simulated cost distribution. We then apply reinsurance and risk corridors to the distribution and recalculate our risk measures under each policy to determine how each policy affects insurer risk. We also calculate our measures of efficiency loss under each policy to allow comparisons of the power of reinsurance and risk corridors to reduce insurer risk with as little efficiency loss as possible.
Section 4.1: Data on the Exchange Population and Health Care Spending

The Medical Expenditure Panel Survey (MEPS) is a large, nationally representative survey of the civilian non-institutionalized U.S. population with information on approximately 33,000 individuals annually. We identify an Exchange-eligible population following methods in McGuire et al. (2012). Pooling MEPS data from Panels 9 (2004/5) through 14 (2009/10), we select a population of individuals and families eligible for enrollment in Exchanges based on income, insurance, and employment status. Specifically, we select adult, non-elderly individuals (aged 18-64) in households earning at least 138 percent of the federal poverty level (FPL) and children in households with income of at least 205 percent of FPL. Selection criteria into the Exchange population, as defined by the ACA, include individuals living in households in which an adult was: ever uninsured, a holder of a non-group insurance policy, self-employed, employed by a small employer, or paying an out-of-pocket premium for their employer-sponsored health insurance (ESI) plan that is deemed to be unaffordable. If an individual meets the selection criteria in at least one of the two survey years, she is part of the sample. The dataset comprises 44,210 “Exchange-eligible” individuals, 11,773 of whom have only one year of data and 32,437 of whom have two years of data, generating a total sample size of 76,647 person-years.

The MEPS includes data on total expenditures on health care for each individual during each year. It also includes information such as diagnoses from all of the medical events that result in those expenditures (i.e. office visits, hospital stays, prescriptions filled, etc.). We use these diagnoses and expenditures to implement reinsurance and risk
corridors as we discuss in the following sections. We also use the costs to construct the insurer profit distribution using simulations discussed in Section 4.4. It is well-known that MEPS data understate health expenditures (Sing et al., 2002; Aizcorbe et al., 2012; Zuvekas and Olin, 2009). Discrepancies are driven both by underreporting of healthcare utilization and under-representation of high-expenditure cases due to the exclusion of patients who are institutionalized or hospitalized longer than 45 days. Zuvekas and Olin (2009) suggest that total expenditures be inflated by a factor of 1.09 for individuals with an inpatient claim and by a factor of 1.546 for all other individuals. We adopt this correction, inflating expenditures of the individuals in our sample as directed.

Section 4.2: Reinsurance

Reinsurance reimburses insurers for some portion of the costs incurred by high cost enrollees. Our methods for modeling reinsurance mimic the methods used in our previous work (Zhu et al. 2014). More formally, let $x_i$ be individual $i$’s total annual cost to the insurer. Now let $\hat{x}$ be the reinsurance threshold above which costs are reimbursed. Finally, let $\delta$ be the rate at which costs are reimbursed. The reinsurance payment received by the insurer when enrolling individual $i$, $re_i$, is defined as follows:

$$re_i = \begin{cases} 0 & \text{if } x_i < \hat{x} \\ \delta(x_i - \hat{x}) & \text{if } x_i \geq \hat{x} \end{cases}$$

For simplicity, we assume that plans’ paid claims are equal to total claims; in other words, we assume that the plan covers all health care costs incurred by an individual during a given year. We also assume that reinsurance is funded through a per capita
actuarially fair reinsurance fee collected for each Exchange enrollee.\textsuperscript{77} The fee, denoted \( ref \), is assumed to be equal to the average reinsurance payment for the entire population:

\[
ref = \frac{1}{N} \sum_{t} re_{t}
\]

This ensures that similar to risk corridors, reinsurance will be budget neutral. In practice, a reinsurance policy may have multiple thresholds with different reimbursement rates. For example, the reinsurance policy proposed for the Exchanges that we explore below reimburses 80% of costs between $60,000 and $250,000 and 85% of costs between $250,000 and $2,000,000.\textsuperscript{78}

\textit{Section 4.3: Measures of Risk}

We use two measures of insurer risk. First, we use the standard deviation of the expected cost distribution, where risk is increasing in the standard deviation. This is similar to how the risk faced by a traditionally risk averse individual would be measured. Importantly, this measure captures both “upside” and “downside” risk, as both are undesirable to a traditionally risk averse insurer. Second, we use the “value at risk.” Value at risk is a measure of risk used in finance, and is defined as the Yth percentile of

\textsuperscript{77} Note that this is different from how reinsurance will be funded in practice (described in section 2). We do this to allow for an “apples-to-apples” comparison of reinsurance and risk corridors by forcing them both to be “self-funding.”

\textsuperscript{78} The true Exchange reinsurance policy actually only covers 80\% of costs between $60,000 and $250,000. However, the policy stops at $250,000 because most insurers are expected to purchase private reinsurance in addition to the public reinsurance available in the Exchange. Private policies typically cover 85\% of costs between $250,000 and $2,000,000. See Zhu et al. (2014) for a discussion of the public and private reinsurance policies.
the expected cost distribution. This measure allows us to characterize the probability of a large loss. In our case, larger values of the value at risk imply higher risk.

Section 4.4: Cost Distributions

We first construct the insurer’s cost distribution for the case of no reinsurance and no risk adjustment. Because insurers do not know who will enroll in their plans nor the future realization of each individual’s cost distribution, ex ante they face a number of potential states of the world. They could enroll an unexpectedly healthy group of individuals, an unexpectedly sick group of individuals, or just an average group of individuals. The cost distribution, \( f(c) \), describes an insurer’s average cost per enrollee in each state and the probability of those states. In order to construct the cost distribution we first fix the size of the plan to be \( Q \) enrollees. We then take \( M \) random samples of \( Q \) individuals from our sample of \( N \) Exchange-eligible individuals. For each random sample, we calculate the average expenditure of the \( Q \) chosen individuals, \( \bar{x}_m \). In the case of no reinsurance, we define average cost as being equal to average expenditure for each sample, \( \bar{x}_m = \bar{c}_m \). We use these random samples to simulate the insurer’s average cost distribution which in this case is equal to the insurer’s average expenditure distribution. Given a large enough \( M \) this simulated cost distribution represents all of the states of the world an insurer would face in an exchange, from the possibility of only enrolling the sickest individuals to the possibility of only enrolling individuals who use no health care at all. It is this cost distribution that forms the basis of our measures of risk discussed above.
In order to incorporate reinsurance, for each sample $m$ we also calculate the average reinsurance payment, $\bar{re}_m$, for the $Q$ individuals randomly chosen in resample $m$, where $re_i$ is calculated as defined above, based on the parameters of the specific reinsurance policy being simulated. We use these simulated values to construct the joint distribution of average expenditure and average reinsurance payments. We use this distribution to calculate the reinsurance fees used to finance these policies. We define the reinsurance fee, $ref$, to be equal to the mean of the average reinsurance payment distribution:

$$ref = \int \bar{e}h(\bar{x}, \bar{e})d\bar{e}$$

We use the draws of expenditures and reinsurance payments plus the definition of reinsurance fees to calculate plan costs with and without reinsurance for each sample. Again, when there is no reinsurance, costs are equal to expenditures, $\bar{c}_m = \bar{x}_m$. With reinsurance, plan costs are equal to expenditures minus any reinsurance payments plus the reinsurance fee: $\bar{c}_m = \bar{x}_m - \bar{re}_m + ref$. Recall that reinsurance is constrained to be budget neutral. This implies that while in most cases $\bar{c}_m \neq \bar{x}_m$, the mean of the average cost distribution, $\bar{c} = \int cf(c)dc$, will be the same with and without reinsurance.

Section 4.5: Risk Corridors

Risk corridors transfer money to an insurer if the sum of covered health care costs of the insurer’s enrollees are greater than a fixed percent of a target. In the risk corridor

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79 While our simulations result in a discrete cost distribution, in our notation we treat the distribution as though it is continuous because with enough draws, our discrete distribution will equal the continuous distribution in the limit.
policy proposed for the Exchanges, the target is defined as an insurer’s total premium revenues minus some combination of administrative costs and profits. To simplify, we define the target as the mean of the average expenditure distribution.\(^8\) Thus, if an insurer’s realized average per capita cost is greater than the expected average expenditures (the target), the risk corridor will reimburse the insurer for a portion of its costs according to the risk corridor cost-sharing parameters.

More formally, let \(\overline{c}\) continue to be the insurer’s average costs, defined for the cases with and without reinsurance above. Let \(p\) be the mean of the plan’s average expenditure distribution and, thus, the target. Now we introduce three new parameters:

\[\alpha = \frac{\overline{c}}{p},\] the percent of the target paid out in costs; \(\overline{a}\), the upper threshold; and \(\theta\), the portion of costs reimbursed. Note that reinsurance fees are included in \(\overline{c}\). The risk corridor gives the insurer the following transfer if the insurer’s \(\alpha\) is greater than \(\overline{a}\):

\[\text{trans}(\alpha) = \theta(\overline{c} - \overline{a}p) \quad \text{if} \ \alpha > \overline{a}\]

Now suppose that the risk corridor reimburses plans for 50% of costs above 108% of the target. In this case, \(\overline{a} = 1.08\) and if for a given plan \(\alpha > 1.08\) then the plan will receive a transfer of \(0.5(\overline{c} - 1.08p)\).

Risk corridors can be funded through an actuarially fair uniform fee, denoted \(rcf\), similar to the reinsurance and risk adjustment fees, or through an upside risk transfer. We refer to these as one-sided and two-sided risk corridors, respectively. For one-sided risk corridors, only factors that involve uncertainty impact risk corridor payments and our risk measures. Administrative costs and profits affect the level of outcomes but not the other moments of the outcome distribution (i.e. variance), so they don’t matter for risk corridor payments or for our risk measures. This assumption could also by justified by assuming perfect competition and no administrative costs.
corridors, we define $\alpha$ to incorporate the risk corridor fee, $\alpha^1 = \frac{\bar{c} + rcf}{p}$, to enforce budget neutrality. We define the fee as being equal to the average expected transfer given the simulated distribution of $\alpha$, $g(\alpha)$ where $\alpha$ is a function of expenditures and reinsurance payments:

$$rcf = (\alpha^1)g(\alpha^1)$$ (1)

Note that because the transfer is a function of $\alpha^1$, $rcf$ is a function of $\alpha^1$. Recall that $\alpha^1$ is also a function of $rcf$. This implies that for each $\bar{c}$ there is an equilibrium value for $rcf$ that causes (1) to hold. In practice, for each risk corridor policy we analyze, we find the value of $rcf$ that causes transfers to be equal to $rcf$ on average, enforcing budget neutrality.

For two-sided risk corridors, the risk corridor transfer looks the same but the fee changes. The fee is not charged to all plans. Instead, it is charged to plans whose realized costs are below a fixed percentage of the target. In other words, plans with unexpectedly low costs transfer money to the regulator while plans with unexpectedly high costs get transfers from the regulator. To formalize this we introduce an additional transfer. We define a new parameter, the lower threshold, $\underline{\alpha} = 1 - (\bar{\alpha} - 1)$. The lower threshold is just the upper threshold reflected to the other side of the target. The new transfer is defined as

$$trans = -\theta (ap - \bar{c})$$
Note that if the profit distribution is symmetric, the two-sided risk corridor is budget neutral: The transfers cancel each other out in expectation. Similar to reinsurance, risk corridors can have multiple thresholds with different reimbursement rates between each threshold. For example, the proposed risk corridor policy for the Exchanges reimburses 50% of costs between 103% and 108% of the target and 80% of costs beyond 108% of the target. In our simulations, we account for this non-linear reimbursement policy.

Section 4.6: Measures of Efficiency Loss

As discussed in Section 3, in order to compare the efficiency loss of our simulated risk corridor and reinsurance policies we need to construct measures of $\sum_i \frac{dx_i}{dr_i} (\bar{r}_{i,rc})^2$ and $\sum_i \frac{dx_i}{dr_i} (\bar{r}_{i,rc})^2$. We start by assuming that the effect of a one unit increase in $r'$ on utilization is proportional to an individual’s costs relative to the average cost in the population: $\frac{dx_i}{dr_i} = \frac{x_i}{\bar{x}} = \beta_i$. $\beta_i$ can easily be calculated for each individual. We now turn to the construction of $\bar{r}_{ik}^2$ for each individual and policy. We begin with reinsurance. For simplicity, let reinsurance reimburse an insurer for all of an individual’s costs above the reinsurance threshold (i.e. $\delta = 1$). In this case $\bar{r}_{i,re}'^2 = 1$ for all individuals whose costs exceed the reinsurance threshold and $\bar{r}_{i,re}'^2 = 0$ for all other individuals. This implies that in our comparisons of efficiency loss under reinsurance and risk corridors, the appropriate measure to use for efficiency loss from reinsurance is

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81 Because the insurer’s cost distribution is a distribution of sample means, the central limit theorem implies that the cost distribution should be approximately normal. In practice, because our simulated distributions are not constructed with an infinite number of draws, our simulated distributions are not quite symmetric. They are, however, very close to symmetric.
\[ \sum_i \frac{dx_i}{dr_i}(\bar{r}_{i, re}^2) = \sum_i \beta_i(\bar{r}_{i, re}^2) = \beta \]

where \( \beta \) is equal to the portion of total costs in the population spent on individuals whose costs exceed the reinsurance threshold. The intuition for this measure is that under reinsurance, a plan’s incentive to invest in costly effort to restrain the spending of individuals whose costs exceed the reinsurance threshold goes to zero. Because the effect of reducing effort is proportional to an individual’s costs, the total efficiency loss should be proportional to the costs spent on individuals whose costs cross the reinsurance threshold.

Next, we move to risk corridors. Similar to reinsurance, let risk corridors reimburse an insurer for all costs above the risk corridor threshold. In this case \( r_{is, rc} = 1 \) for all individuals in the states of the world where the risk corridor threshold is crossed and \( r_{is, rc} = 0 \) otherwise. This implies that for individual \( i \) the expected value of \( \bar{r}_{is} \) is the proportion of states of the world in which individual \( i \) is enrolled in the plan that the risk corridor threshold is crossed: \( \bar{r}_{is} = \sum_s p_{is} r_{is} = \theta_i \). This implies that in our comparisons of efficiency loss under reinsurance and risk corridors, the appropriate measure to use for efficiency loss from risk corridors is

\[ \sum_i \frac{dx_i}{dr_i}(\bar{r}_{i, rc}^2) = \sum_i \beta_i(\bar{r}_{i, rc}^2) = \sum_i \beta_i \theta_i^2. \]

The intuition for this measure comes from the fact that risk corridors limit an insurer’s incentive to invest in costly effort to restrain the costs of individual \( i \) and the extent to which the policy affects the insurer’s incentives regarding a particular individual depends
on how often that individual is present in the plan when the plan crosses the risk corridor threshold. Note that $\theta_l$ is likely to be larger for high cost individuals because an insurer is more likely to cross the risk corridor threshold when enrolling high cost individuals.

For one-sided risk corridors, the threshold is only crossed when plans experience higher-than-expected costs. With two-sided risk corridors, however, the threshold is crossed when plans experience either higher than expected costs or lower than expected costs. In each case, the plan is not responsible for any portion of the marginal dollar spent on an individual. In the case of higher than expected costs, the plan is reimbursed for the full dollar. In the case of lower than expected costs, on the other hand, the plan is charged a dollar for each dollar of savings it achieves. In both cases, $r' = 1$. This implies that

$$\theta_l^{(2-sided)} = 2\theta_l^{(1-sided)}.$$

One of the assumptions involved in the derivation of these measures is worth discussing here. As discussed above, in order to operationalize $\frac{dx_l}{dr_l}$, we assume that the effect of a one unit increase in “effort” has a larger effect on utilization for high cost enrollees than low cost enrollees. Formally, we assume that $\frac{dx_l}{de_l} = \frac{x_l}{x}$. Again, we think about “effort” as utilization management. This is likely to be more productive for high cost enrollees because there is so much more utilization that can be managed. On the other hand, utilization management is unlikely to have any effect on enrollees who already use little or no care. There is evidence for this in the literature (Commonwealth Fund 2012).
Section 5: Results

We now discuss the results from the simulations. First, we simulate insurer risk under current policies for the Exchanges. Second, we compare efficiency under reinsurance and risk corridors, showing that for a given level of risk-reduction, risk corridors always incur lower efficiency losses. Third, we discuss the optimality of two-sided vs. one-sided risk corridors.

Section 5.1: Current Policy

As discussed in Section 2, during the first three years of the Exchanges existence, reinsurance and risk corridor policies will be in force. We simulate the effects of each of these policies on insurer risk as measured by the standard deviation of the profit distribution and the value at risk. We simulate each proposed policy on its own and combined in the full package of risk reducing policies. We adapt our general framework to the actual policies being implemented in the Exchanges. Both the ACA reinsurance and risk corridor policies are slightly more complicated than those modeled above in that they have multiple thresholds and the portion of costs reimbursed varies across thresholds. In the Exchanges risk corridor transfers are defined as follows:

\[
\begin{align*}
\text{trans} & = \begin{cases} 
0, & \text{if } \alpha_k < 1.03 \\
0.5(c_k - 1.03p_n), & \text{if } 1.03 \leq \alpha_k < 1.08 \\
0.025p_n + 0.8(c_k - 1.08p_n), & \text{if } \alpha_k > 1.08 
\end{cases}
\end{align*}
\]

Similarly, reinsurance payments will be paid according to the following definition:
Table 3.2 contains our three risk measures (the standard deviation, 99th percentile, and 95th percentile of the cost distribution) under every combination of proposed policies for a small plan with $N = 5,000$. Similar tables for a large ($N = 20,000$) can be found in the appendix. The results suggest that both risk corridors and reinsurance significantly reduce all measures of insurer risk. Interestingly, the risk reductions caused by risk corridors and reinsurance are quite similar, with reinsurance reducing the standard deviation slightly more than risk corridors and risk corridors usually decreasing the value at risk slightly more than reinsurance.

By comparing the first and last columns of the table, we can observe the effects of the current ACA policy for the Exchanges (reinsurance and risk corridors) on insurer risk. The policy dramatically decreases insurer risk, with a reduction of the standard deviation by more than a third and the value at risk measures by about $100$, or close to one standard deviation of the cost distribution. Figure 3.2 shows the full distribution of the insurer’s expected costs under each combination of policies. The figure makes it clear that the policies tighten the distribution significantly, both on their own and when implemented together.

Figure 3.3 begins to describe how reinsurance and risk corridors differ. The cost distribution is divided into 20 equally sized groups according to the insurer’s draw from the distribution. For example, the first bars, labeled “0”, represent the states of the world in which the insurer draws a cost in the bottom 5% of the cost distribution. This implies

$$
re_i = \begin{cases} 
0 & \text{if } x_i < 60,000 \\
0.8(x_i - 60,000) & \text{if } 250,000 > x_i \geq 60,000 \\
152,000 + 0.85(x_i - 250,000) & \text{if } x_i \geq 250,000
\end{cases}
$$


that the bars on the left represent cases where the insurer earns large profits and the bars on the right represent cases where the insurer incurs large losses. The blue bars represent the average reinsurance payment for the cases in a given group. The orange bars represent the average risk corridor transfer. The figure illustrates the fact that insurers receive reinsurance payments in virtually all states of the world, including states in the far left part of the cost distribution where the insurer is already earning large profits. However, insurers receive larger reinsurance payments in cases where they are incurring large losses. Risk corridors, on the other hand, only transfer money to insurers in cases where they are incurring large losses. They also transfer money away from insurers in cases where they are earning large profits. When it comes to risk, these tail-cases are the most important, so it appears that risk corridors should be able to reduce risk more efficiently than reinsurance. However, risk corridors affect insurer incentives to invest in costly effort for all individuals while reinsurance only affects insurer incentives for a few high cost individuals. Thus, there seems to be a tradeoff where risk corridors affect insurer incentives for all individuals but only in a few cases while reinsurance affects insurer incentives in all cases but only for a few individuals. In the next set of simulations, we use our measures of efficiency loss to quantify this tradeoff and determine which policy delivers greater risk reduction with less efficiency loss.

Section 5.2: Risk Corridors vs. Reinsurance

We now compare efficiency loss under risk corridors and reinsurance. The purpose of this section is to quantitatively describe the principles we discussed in Section 3. To do this, we use the simple definition of a risk corridor that we outline in the
methods section above. This definition sets $\theta = 1$, so the corridor provides “full coverage after a deductible.” Similarly, we define reinsurance as a policy that reimburses plans for 100% of an individual’s costs above some reinsurance threshold, i.e. we set $\delta = 1$. To compare the effects of the two policies, we simulate a large number of cutoffs for both risk corridors and reinsurance. For reinsurance, we allow the cutoff to vary from $10,000 to $250,000. For risk corridors, we allow the cutoff to vary from 101% to 130% of the target. We allow risk corridors to be either two-sided or one-sided. For each simulation, we calculate each of the risk measures and the measure of efficiency loss for that policy, as described in Section 4. We then compare the efficiency loss required to achieve a given level of each risk measure.

Figure 3.4 shows the results for all of the risk measures. The top panel shows the standard deviation of the cost distribution. The standard deviation is on the x-axis and the efficiency loss is proportional to the measures shown on the y-axis. This allows us to compare efficiency loss under reinsurance and risk corridors by finding a desired level of risk on the x-axis and then tracing upward to find the efficiency loss required to achieve that level of risk under each policy. For example, if a standard deviation of $85 is the desired level of risk, all policies will achieve this level with an efficiency loss proportional to 0.2. Interestingly, the figure shows that for all levels of risk, all three policies result in similar efficiency losses. This implies that for traditionally risk averse insurers, the choice of risk-reducing policy is unimportant; both policies can achieve similar amounts of risk reduction at a similar cost in terms of efficiency.
The bottom panels of Figure 3.4 describe insurer risk using the value at risk measure: the 95th and 99th percentiles of the cost distribution. Again, the x-axis shows the risk measure and the value shown on the y-axis is proportional to the efficiency loss required in order to achieve the given level of risk under each policy. For these risk measures, risk corridors can always achieve a given level of risk reduction with a lower efficiency cost. This is not surprising given that risk corridors effectively eliminate the right tail of the cost distribution while reinsurance just shrinks it. The differences in efficiency loss between reinsurance and risk corridors are also non-trivial. For example, the efficiency loss from the reinsurance policy required to bring the 95th percentile of the cost distribution down to $3,465 is more than twice (five times) as large as the loss from a two-sided (one-sided) risk corridor policy that achieves a similar amount of risk reduction.

It is also unsurprising that with respect to the value at risk, one-sided risk corridors are always able to achieve a given level of risk with less efficiency loss than two-sided risk corridors, given that two-sided risk corridors compensate the plan for the marginal dollar if its costs are higher than expected or lower than expected. In the case of the standard deviation of the cost distribution, there is a tradeoff between the higher efficiency loss from two-sided risk corridors and increased risk reduction because two-sided risk corridors reduce the standard deviation from the left and right tails of the cost distribution, while one-sided risk corridors only affect the right tail. The fact that the 1-sided and 2-sided risk corridor lines lie on top of one another in the standard deviation plot in Figure 3.4 suggests that these two competing factors cancel each other out,
resulting in equal risk reduction with equal efficiency loss for 1-sided and 2-sided corridors. This tradeoff does not exist, however, for the cases of the 99th and 95th percentiles of the cost distribution because these measures are unaffected by the left tail of the distribution.

**Section 6: Discussion**

The simulations illustrate the power of risk corridors to reduce insurer risk with a low incentive cost, especially relative to reinsurance. First, we find that the combination of risk reduction policies slated for implementation in the Exchanges dramatically reduces the amount of risk faced by insurers. Both reinsurance and risk corridors contribute to this dramatic decrease in risk, though the second set of simulations shows that the contribution of reinsurance likely comes at a much larger incentive cost than that of the risk corridors. While risk corridors and reinsurance result in similar efficiency loss for a given level of the standard deviation of the cost distribution, risk corridors are clearly the more efficient tool for reducing the risk of large losses. Additionally, taking all of the risk measures into account, one-sided risk corridors are always weakly superior to both reinsurance and two-sided risk corridors. This is because risk corridors eliminate only the extreme events that have the largest impact on insurer risk, and one-sided risk corridors eliminate the more important extreme events (e.g. large losses) without the additional efficiency costs resulting from two-sided risk corridors. Reinsurance, on the other hand, is a very imprecise tool for reducing insurer risk, and often results in transfers to plans that are already earning profits.
Throughout the paper we have highlighted our results focusing on a small plan of around 5,000 enrollees. The appendix contains the results for a larger plan where the results are similar. However, the magnitude of the effects of both reinsurance and risk corridors on insurer risk are much smaller for the larger plan. This is due to the fact that larger plans face less risk. Due to the law of large numbers, risk diminishes as enrollment increases.

The results for small and large plans can be interpreted in a variety of ways. Instead of plan size, these results could be seen as describing the effects of insurer experience in the market. As an insurer participates in the market, its ability to forecast costs may improve, shrinking the variance of the cost distribution. In this case instead of results for small and large plans the results could be interpreted as representing novice and experienced insurers. Insurer “risk” does not necessarily have to refer to the risk of enrolling high cost individuals. Risk could instead refer to political uncertainty where insurers are unsure about how the policy environment might change between the time when prices are set and when costs are incurred. Insurers in the Exchanges were in fact victims of this type of risk when policies were changed after prices were set to allow insurers to continue plans that did not meet the requirements of the Affordable Care Act through 2014.

We have shown that risk corridors are “better” at reducing insurer risk than reinsurance, where “better” is defined as achieving the same risk reduction with less efficiency loss. However, there are other measures of incentive costs for which this result will not hold. For example, if we assume that a unit of effort reduces each individual’s
utilization by exactly the same amount, i.e. $\frac{dx_i}{de_i} = g$ where $g$ is a constant that is identical for all individuals, reinsurance often performs better than risk corridors in terms of efficiency. However, we believe that our assumption that the effect of effort on utilization is proportional to an individual’s costs relative to the average cost in the population, $\frac{dx_i}{de_i} = \beta_i$, is much more reasonable than assuming that a unit of utilization management would lower a high cost individual’s costs by the same amount in dollars as an individual using little or no care.

The superiority of risk corridors may not hold when considering other effects of the policies. For instance, the two policies have quite different implications for insurers’ incentives to engage in inefficient selection of low-risk enrollees. Reinsurance effectively redistributes costs from high cost individuals to low cost individuals. This weakens insurer incentives to select low cost individuals, because their costs are more similar to those of high cost individuals. Risk corridors, on the other hand, do not affect the heterogeneity of costs across the population of potential enrollees. Under risk corridors, high cost individuals are still much more costly to the plan than low cost individuals, so the plan will still engage in inefficient selection.\textsuperscript{82} This suggests that when there is the potential for selection the optimal amount of reinsurance depends on the power of

\textsuperscript{82}Risk corridors can affect selection incentives if the contribution of low cost individuals to the variance of the distribution is different from the contribution of high cost individuals. If this is the case, then risk corridors do affect the incentives of risk-averse insurers to inefficiently select low cost individuals because they will seek to do so for two reasons: (1) to shift the mean of the cost distribution to be as small as possible and (2) to decrease the variance of the distribution as far as possible. Because risk corridors affect the variance of the distribution and the effects of selection efforts on the variance of the distribution, they can affect selection incentives. However, selection incentives via the variance of the distribution are likely to be second-order to the incentives via the mean of the distribution.
reinsurance to reduce selection incentives. Some evidence suggests that reinsurance is quite good at improving the fit of a payment system but has little effect on predictive ratios that describe plans' incentives to inefficiently ration particular services (Zhu et al. 2014). This suggests that while the optimal amount of reinsurance may be small, it is probably greater than zero.

Risk corridors and reinsurance may also differ in how they affect insurer pricing incentives. When individuals face large “switching costs” for moving from one plan to another, insurers may optimally choose to engage in “invest then harvest” strategies where they compete to be the “loss leader” in the first year of the operation of the market in order to gain market share (Ericson 2014). In subsequent years, insurers can then ratchet up the price of their policies because consumer switching costs cause price sensitivity to be quite low. Risk corridors may make such strategies more attractive to insurers by limiting the losses incurred by underpricing policies during the first year of enrollment. Two-sided risk corridors, on the other hand, may limit the attractiveness of these strategies by transferring money away from insurers earning large profits, reducing the surplus insurers can extract by ratcheting up prices in later years.

While we show that risk corridors can dramatically reduce insurer risk, they may have additional unintended consequences. While the implications of these unintended consequences are outside the scope of this paper, they present opportunities for future research. Additionally, while this paper lays out the conceptual framework behind the need for risk corridors, empirical evidence on their effects in practice is needed. Given that risk corridors have been implemented in Medicare Part D and are currently being
implemented in the Exchanges, there will be excellent opportunities for studying the effects of this policy in practice in the near future.
Figure 3.1: Insurer’s Distribution of Expected Costs

Notes: This figure illustrates the expected cost distribution faced by insurers. Possible realizations of per capita costs are on the x-axis, and the density is on the y-axis. The expected cost is the mean of this distribution. We assume that prices are set such that any outcome to the left of the mean (lower than expected costs) result in positive profits and any outcome to the right of the mean (higher than expected costs) result in losses.
Figure 3.2: Insurer’s Distribution of Expected Costs under Proposed Policies

Notes: The blue distribution displays the distribution of average costs approximated by taking 10,000 draws of 5,000 individuals from the population of exchange-eligible individuals we create from MEPS data. The red and teal distributions display the distributions of average costs net of reinsurance payments or net of risk corridor payments approximated using the same draws from the exchange population. The maroon distribution displays the distribution of average costs net of both reinsurance and risk corridor payments. All distributions are estimated using kernel densities. Both reinsurance and risk corridors are modeled to match the policies proposed for the Exchanges.
Figure 3.3: Average Risk Corridor and Reinsurance Payments in Each Quantile of Insurer’s Distribution of Expected Costs

Notes: Each blue (orange) bar represents the average reinsurance (risk corridor) payment to a plan taking a draw from one of 20 pieces of the cost distribution. The cost distribution is approximated by taking 10,000 draws of 5,000 individuals from the exchange-eligible population we build using MEPS data. Each draw results in a realization of average cost for the plan. The first bars (labeled group 0) represent the average payments for the bottom 5% of realizations of average cost, i.e., the plans with realized costs furthest below expected cost. The second bars represent payments for realizations of average cost falling in the 5-10 percentile range, and so on. Both reinsurance and risk corridors are modeled to match the policies proposed for the Exchanges.
Figure 3.4: Risk and Efficiency Loss under Reinsurance and Risk Corridors

Notes: Each figure shows the specific measure of the risk of the cost distribution on the x-axis and a value proportional to the efficiency loss required for the policy to achieve that level of risk on the y-axis. To determine the efficiency loss necessary for a given policy to achieve a particular level of risk, first find the level of risk on the x-axis and then trace upward to find the efficiency loss. If policy A's curve is everywhere above policy B's (as in the case of reinsurance over risk corridors in the bottom 2 figures), Policy A is always less efficient than policy B. The joint distribution of risk and efficiency loss shown in the figures for each policy is derived as follows: (1) a cost distribution is approximated by taking 10,000 draws of 3,000 individuals from the Exchange-eligible population we construct from MEPS data and calculate the average cost for each draw; (2) reinsurance payments and fees are calculated for reinsurance policies that reimburse the plan for all of an individual’s costs above thresholds ranging from $10,000 to $250,000 for all draws; (3) risk corridors payments and fees are calculated for 1- and 2-sided risk corridor policies with upper thresholds ranging from 101-130% of the “target”; (4) risk corridor or reinsurance payments or fees are applied to the cost distribution; (5) standard deviation, 95th percentile, and 99th percentile of new cost distribution are calculated and recorded; (6) policy-specific measure of efficiency loss is calculated as laid out in text and recorded.
### Table 3.1: Summary Statistics of the Full Population

<table>
<thead>
<tr>
<th>Values in table are means unless otherwise noted</th>
<th>N=76647</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
</tr>
<tr>
<td>Age 0-18</td>
<td>0.16</td>
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<tr>
<td>Age 19-34</td>
<td>0.33</td>
</tr>
<tr>
<td>Age 35-44</td>
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<tr>
<td>Age 45-64</td>
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</tr>
<tr>
<td>Male</td>
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<tr>
<td>Married</td>
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<tr>
<td><strong>Race</strong></td>
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</tr>
<tr>
<td>Black, non-Hispanic</td>
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</tr>
<tr>
<td>Hispanic</td>
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</tr>
<tr>
<td>Other</td>
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<tr>
<td><strong>Education</strong></td>
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</tr>
<tr>
<td>Less than high school</td>
<td>0.19</td>
</tr>
<tr>
<td>High school</td>
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</tr>
<tr>
<td>Some college</td>
<td>0.15</td>
</tr>
<tr>
<td>College degree</td>
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</tr>
<tr>
<td><strong>Employment status</strong></td>
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<tr>
<td>Continuously employed</td>
<td>0.64</td>
</tr>
<tr>
<td>Continuously unemployed</td>
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<tr>
<td><strong>Income</strong></td>
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<tr>
<td>Family income</td>
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<tr>
<td>Total annual expenditures</td>
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</tr>
<tr>
<td><strong>Medical</strong></td>
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<tr>
<td><strong>Insurance Status</strong></td>
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<td>Expensive ESI</td>
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<td>Self Employed</td>
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<tr>
<td>Medicaid</td>
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<td>Small Group ESI</td>
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<td><strong>Health Status</strong></td>
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<tr>
<td>Excellent</td>
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</tr>
<tr>
<td>Very good</td>
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<td>Fair</td>
<td>0.08</td>
</tr>
<tr>
<td>Poor</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Notes: Statistics calculated for Exchange-eligible population constructed from panels 9-14 of the MEPS. We select adult, non-elderly individuals in households earning at least 138% of FPL and children in households with income of at least 205% of FPL. We include households where an adult is ever uninsured, a holder of a non-group insurance policy, self-employed, employed by a small employer, or paying an out-of-pocket premium for their employer-sponsored health insurance (ESI) plan that is deemed to be unaffordable. If an individual meets the selection criteria in at least one of the two survey years, she is part of the sample. The dataset comprises 44,210 “Exchange-eligible” individuals, 11,773 of whom have only one year of data and 32,437 of whom have two years of data, generating a total sample size of 76,647 person-years.
<table>
<thead>
<tr>
<th>Risk Measure</th>
<th>Base Case</th>
<th>Reinsurance Only</th>
<th>2-sided Risk Corridor Only</th>
<th>Reinsurance and 2-sided Risk Corridor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard Deviation</td>
<td>$138.00</td>
<td>$100.74</td>
<td>$104.89</td>
<td>$85.21</td>
</tr>
<tr>
<td>95th Percentile of Cost Distn</td>
<td>$3,559.65</td>
<td>$3,492.51</td>
<td>$3,491.99</td>
<td>$3,458.42</td>
</tr>
<tr>
<td>99th Percentile of Cost Distn</td>
<td>$3,670.62</td>
<td>$3,570.17</td>
<td>$3,523.46</td>
<td>$3,497.25</td>
</tr>
</tbody>
</table>

Notes: Each column represents a different set of policies and each row represents a moment of the insurer’s cost distribution under those policies. The distribution cost distribution in the base case is approximated by taking 10,000 draws of 5,000 individuals from the population of exchange-eligible individuals we create from MEPS data. The cost distributions under reinsurance, risk corridors, and both reinsurance and risk corridors are approximated by starting with the base case distribution and then calculating the reinsurance and risk corridor transfers and fees according to the parameters proposed for implementation in the Exchanges.
APPENDIX

Appendix A: Application to Exchanges

As mentioned in the text, in the state Health Insurance Exchanges, plan payments are a function of relative risk scores instead of absolute risk scores. Plan $j$’s relative risk score is equal to the average absolute risk score of all of plan $j$’s enrollees divided by the average absolute risk score of all of the enrollees in the market. To formalize this for the case of two plans, let $r^j$ be plan $j$’s average absolute risk score and let $\theta$ be the portion of individuals in the market enrolled in plan $j$. As above, $r^j = r + \alpha_j$ where $r$ represents the “true risk” of plan $j$’s enrollees and $\alpha_j$ is the plan-specific coding factor. Now define plan $j$’s relative risk score as

$$rr^j = \frac{r^j}{\theta r^j + (1 - \theta)r^{j'}}$$

Now, in the exchanges a plan’s per capita payment is equal to $R^j = B \cdot rr^j$. If we let the market be large and we normalize $r$ such that $\alpha_j = 0$, then we can characterize the implicit subsidy/transfer to plan $j$ as

$$\gamma^j = B \left( \frac{r^j - r^{j'}}{\theta r^j + (1 - \theta)r^{j'}} \right) = B \left( \frac{\alpha_j}{r + \theta \alpha_j} \right)$$

Note that as the portion of individuals enrolled in plan $j$ increases, the subsidy to plan $j$ decreases. In other words, upcoding becomes less profitable as plan $j$’s market share increases. The intuition for this result is simple. With a payment system based on a relative risk score, plan $j$’s subsidy is based on the difference between plan $j$’s coding
and average coding in the market. As plan $j$’s market share increases, these two values converge and the subsidy decreases.
Appendix B: Institutional Detail on MA

B.1 MA Payment formula

To apply the model we develop in Section 3, let plan \( j' \) be FFS Medicare and let plan \( j \) be MA. Unlike \( j' \) in the model, payments to FFS Medicare are not risk-adjusted. The government just pays the bills of the patients in FFS Medicare; there is no capitation payment. Payments to MA plans, on the other hand, are based on a relative risk score that is a modified version of the risk score introduced in Section 3. The government’s stated goal is to pay MA plans \( B \) (the county benchmark or base rate) for enrolling an individual with an average FFS risk score and to increase or decrease that payment proportionally with expected cost. In order to accomplish this, the MA relative risk score is calculated as follows:

\[
rr_{i}^{MA} = \frac{r_{i}^{MA}}{\frac{1}{N^{FFS}} \sum_{i \in FFS} r_{i}^{FFS}} = \frac{r_{i}^{MA}}{\bar{r}_{i}^{FFS}}^{\text{83}}
\]

Plans are then paid a sum equal to the county benchmark multiplied by the relative risk score for enrolling individual \( i \):

\[
\hat{p}_{i}^{MA} = rr_{i}^{MA} * B
\]

For sake of exhibition, we also define an analogous FFS relative risk score:

\[
rr_{i}^{FFS} = \frac{r_{i}^{FFS}}{\frac{1}{N^{FFS}} \sum_{i \in FFS} r_{i}^{FFS}} = \frac{r_{i}^{FFS}}{\bar{r}_{i}^{FFS}}
\]

---

83 Because \( \bar{r}_{i}^{FFS} \) is not known at the beginning of the year when MA plans submit their bids (see below) CMS linearly extrapolates \( \bar{r}_{i}^{FFS} \) using data from the 5 most recent years for which data is available. Here, we assume that this extrapolation is correct. Any error in the extrapolation would affect the implicit subsidy, with positive errors decreasing over payment and negative errors increasing overpayment.
The fixed risk score assumption would imply that any individual $i$ would receive the same risk score in MA that she would receive in FFS: $rr_i^{FFS} = rr_i^{MA}$. If there is “upcoding” in MA (i.e. $r_i^{FFS} = r_i, r_i^{MA} = r_i + \alpha_{MA}$ and $\alpha_{MA} > 1$), then

$$rr_i^{MA} = \frac{r_i^{MA}}{\sum_{l \in FFS} r_i^{FFS}} = \frac{r_i + \alpha_{MA}}{r_i} = 1 + \alpha_{MA}$$

$$rr_i^{FFS} = 1$$

$$\gamma_i = B(rr_i^{MA} - rr_i^{FFS}) = \alpha_{MAB}$$

In the upcoding case, the government is overpaying MA plans, and the overpayment is equal to $\alpha_{MAB}$. Additionally, if there is heterogeneity in coding practices within MA (i.e. HMOs upcode while PFFS plans don’t), then the government is subsidizing some private plans more than others. Our main goal is to determine $\alpha_{MA}$ and, thus, the average overpayment from the government due to upcoding.

B.2 MA vs. FFS coding incentives

As discussed in the text, in MA plan-specific coding factors are generated through profit maximization where profits are characterized as,

$$\pi_j = \sum_{i=1}^{N} \left\{ \phi_{ij}(\lambda_j) \left[ B \cdot (r_i + \alpha_j(\lambda, \eta_j)) - m_{ij}(\lambda_j) - c_j(\eta_j) \right] \right\}$$
For profit maximizing plans $\alpha_f$ will be equal to $\alpha_f(\lambda_f^*, \eta_f^*)$. Thus, for MA, $\alpha_{MA} = \alpha_{MA}(\lambda_{MA}, \eta_{MA})$. However, the process for generating the FFS coding factor, $\alpha_{FFS}$, is quite different. Importantly, FFS is not profit maximizing and does not involve risk adjusted payments. While $\alpha_{FFS} = \alpha_{FFS}(\lambda_{FFS}, \eta_{FFS})$, $\lambda_{FFS}$ and $\eta_{FFS}$ are not set via profit maximization. Instead they are set by lawmakers to satisfy political incentives. The profit maximizing and politically incentivized $\lambda$ and $\eta$ are likely to be quite different, producing different values of $\alpha$ for MA and FFS. In fact, there may be little incentive for lawmakers to do much of anything to affect $\eta_{FFS}$, so this will just be set by the incentives provided to physicians through their organizations, through the incentive to pass information from one physician to another, through the incentive to keep good records on patients in order to minimize future diagnostics, or, for the case of hospitals, through the DRG payment system.
Appendix C: Spillovers

As discussed in the text, the source of coding differences between MA and FFS is unknown. If coding differences are due to MA plans selectively contracting with providers that code more aggressively or if all providers in a plan’s network only see patients enrolled in the plan, coding spillovers would be unlikely. However, providers often see patients from a mix of different health plans. Therefore, if a health plan managed to influence a provider’s coding or practice patterns, it could impact the risk scores of all individuals served by the provider, including those insured under different plans. This would be plausible if, for instance, providers tended to maintain similar practice and coding patterns across all of their patients regardless of insurer.

In the context of our empirical example, it is common for physicians to treat both MA and traditional FFS Medicare patients, suggesting the possibility of these types of spillovers. Here, we show how spillovers affect our calculation of the subsidy caused by a risk adjusted payment system. We allow spillovers to vary in two characteristics: completeness and direction. First, we assume that spillovers are “bidirectional,” meaning that coding practices spill from \( j \) to \( j' \) and from \( j' \) to \( j \). To formalize this we define a “spillover factor” for an individual enrolled in plan \( j \) as an enrollment weighted average of plan \( j \)’s coding factor and plan \( j' \)’s coding factor, \( \bar{\alpha} = \theta \alpha_j + (1 - \theta)\alpha_{j'} \), where \( \theta \) is the proportion of the population enrolled in plan \( j \). Second, we allow spillovers to be “incomplete,” meaning the risk score for individual \( i \) in plan \( j \) is a weighted average of the plan-specific coding factor and the spillover factor: \( r_i^j = r_i + \delta \alpha_j + (1 - \delta)\bar{\alpha} \), where

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\(^{84}\) This would be unlikely if the coding of diagnoses were done at the health plan level, rather than the provider level.
δ is a “completeness factor.” It is easy to show that when spillovers are complete (i.e. δ = 1), \( r_i^j = r_i^{f_i} \) and γ = 0, i.e. there is no subsidy even with \( \alpha_j > \alpha_{f_i} \). However, if we allow spillovers to be incomplete (i.e. δ < 1) and we again normalize \( \alpha_{f_i} = 0, \gamma_i = B\delta \alpha_j \). In other words, the subsidy is decreasing in the completeness of the spillovers, and our approximation of the subsidy, \( \gamma_i = B\alpha_j \), represents an upper bound for the actual subsidy.

In our empirical example, coding spillovers are likely to be quite incomplete. While plan payments in MA are a function of relative risk scores, the risk scores are relative to absolute FFS risk in the entire country. In many counties, there is little or no MA penetration, implying that providers in these counties will have little incentive to adopt coding practices incentivized by MA plans. This will cause \( \alpha_{MA} \) and \( \alpha_{FFS} \) to be quite different even if spillovers are large in counties with high MA penetration. If payments were based on within-county MA absolute risk relative to within-county FFS absolute risk, spillovers could present a larger problem.

With respect to our ability to identify \( \alpha_{MA} \) in the presence of coding spillovers, Figure C1 shows what happens to our graphical representation of coding differences when complete, bidirectional spillovers are present. The green lines represent the average risk score in FFS and MA when there are complete, bidirectional spillovers. Note that the FFS risk curve with spillovers is everywhere above the FFS risk curve without spillovers and the MA risk curve with spillovers is everywhere below the MA risk curve without spillovers. This is due to FFS coding pulling MA risk down and MA coding pulling FFS risk up. Also note that the total average risk curve is unchanged from the case with no
spillovers, implying that $\alpha_{MA}$ is still identifiable from the slope of the total risk curve. As spillovers become more incomplete, the risk curves with spillovers will converge to the risk curves without spillovers. Therefore, while the possibility of coding spillovers presents a potential problem for estimating $\gamma$, it does not present a problem for estimating the existence or direction of coding differences.
Appendix D: Web sources for CMS data

<table>
<thead>
<tr>
<th>Variable</th>
<th>File</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>MA risk scores by county</td>
<td>Plan Payment Data for 2006-2011</td>
<td><a href="http://www.cms.gov/Medicare/Medicare-Advantage/Plan-Payment/Plan-Payment-Data-Items/CMS1256180.html?DLPage=1&amp;DLSort=0&amp;DLSortDir=ascending">http://www.cms.gov/Medicare/Medicare-Advantage/Plan-Payment/Plan-Payment-Data-Items/CMS1256180.html?DLPage=1&amp;DLSort=0&amp;DLSortDir=ascending</a></td>
</tr>
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</table>
Appendix E: Derivation of efficiency loss measures

In order to derive our measures of efficiency loss from reinsurance and risk corridors, we start by defining the setting in which insurers act. Let there be a population of $N$ individuals, indexed by $i$. Also let there be $S$ potential states of the world, where a state of the world is defined as an allocation of individuals to a plan and, thus, a plan average cost. At the beginning of the period, before discovering the state of the world, the insurer chooses a utilization management “effort” level, $e_i$, for each of the $N$ individuals. After choosing the effort levels, the plan draws an allocation of enrollees and discovers the average cost. The plans choose the effort levels to maximize the following expected profit function:

$$E[\pi] = \sum_i \sum_s p_{ls} [r_{ls}(x_i(e_i)) - x_i(e_i) - c_i(e_i)]$$

where $p_{ls}$ is the probability that if individual $i$ is enrolled that she is enrolled in state $s$ (i.e. $p_{ls} = P_l(state = s \mid enroll)$), $x_i$ represents individual $i$’s utilization in dollars as a function of the plan’s level of effort, $r_{ls}$ represents plan revenues potentially as a function of utilization, and $c_i(e_i)$ represents the cost of effort. Profit maximization implies the following

$$\sum_s p_{ls} \frac{dc_i}{de_i} = \sum_s p_{ls} \frac{dx_i}{de_i} \left( \frac{\partial r_{ls}}{\partial x_i} - 1 \right), \forall i$$

With no reinsurance or risk corridors $\frac{\partial r_{ls}}{\partial x_i} = r'_{ls} = 0 \ \forall i$. Both of these policies change $\frac{\partial r_{ls}}{\partial x_i}$ to no longer be equal to zero for some individuals and states of the world. This results in profit maximizing insurers choosing a new set of $e_i$s in equilibrium, which alters utilization and welfare. We assume that efficiency is maximized when $r'_{ls} = 0 \ \forall i, s$. This
implies that the efficiency loss from policy $k$ can be described as a function of the individual’s expected value of $r'$ given that she is enrolled, $\bar{r}_{isk}' = \sum_s p_{is} r_{isk}', L(r_{isk}')$, where $r_{isk}'$ represents $\partial r_{is} / \partial x_i$ under policy $k$. Now, if we take a Taylor expansion of $L(r_{isk}')$ around $r' = 0$, we find that the total efficiency loss under policy $k$ can be approximated as

$$L_i(\bar{r}_{isk}') = \frac{1}{2} \frac{\partial^2 L_i}{\partial r_{ik}^2} (\bar{r}_{isk}')^2.$$

This implies that the average difference in efficiency loss under reinsurance and risk corridors can be approximated as:

$$\frac{1}{2N} \sum_i \frac{\partial^2 L_i}{\partial r_{ik}^2} (\bar{r}_{is,rc} - \bar{r}_{is,rc}) = \frac{1}{2N} \sum_i \alpha_i (\bar{r}_{is,rc}^2 - \bar{r}_{is,rc}^2).$$

Effectively, the difference in efficiency loss is equal to the weighted average of the difference of the squared expected values of $r'$ under each policy across the population.

The weight can be further broken down as follows:

$$\alpha_i = \frac{\partial^2 L_i}{\partial r_{ik}^2} = \frac{\partial L_i}{\partial x_i} \frac{d^2 x_i}{dr_{ik}^2} + \frac{\partial^2 L_i}{\partial x^2} \frac{dx_i}{dr_{ik}^2}.$$

Now, let’s assume that the relationship between the efficiency loss and a change in utilization is the same for everyone (i.e., $\frac{\partial L_i}{\partial x_i} = \frac{\partial L}{\partial x}$ and $\frac{\partial^2 L_i}{\partial x^2} = \frac{\partial^2 L}{\partial x^2}$ for all $i$). Let’s also assume that the response of cost to changes in $r'$ is constant so that $\frac{d^2 x}{dr_{ik}^2} = 0$. This implies that the average difference in efficiency loss can be described as

$$\frac{1}{2N} \frac{\partial^2 L_i}{\partial x_i^2} \sum_i \frac{dx_i}{dr_{ik}} (\bar{r}_{is,rc}^2 - \bar{r}_{is,rc}^2)$$

which is proportional to
\[ \sum_{t} \frac{dx_i}{d\tau_i} \left( \bar{r}_{ls,rc}^2 - \bar{r}_{ls,rc}^2 \right). \]
Figure A1.1: Equilibrium search with Reinsurance

Notes: Figure shows search for equilibrium in setting where sample individuals required to choose between Bronze and Platinum Plans and there is reinsurance. Light blue line is the 45-degree line. Orange line represents incremental average cost (IAC) curve with no risk adjustment, blue line represents IAC with demographic risk adjustment, gray line represents IAC with prospective risk adjustment, gold line represents IAC with concurrent risk adjustment, and green line represents IAC with HHS-HCC risk adjustment. IAC with no and demographic risk adjustment is everywhere above 45-degree line implying complete market unraveling where everyone enrolls in Bronze plan. Prospective, concurrent, and HHS risk adjustment IACs cross 45-degree line, implying an interior equilibrium exists. Equilibrium is at lowest P where IAC crosses 45-degree line. Concurrent results in the lowest price differential. Prices, enrollment, and welfare can be found in Table 1.4.
Figure A1.2: Equilibrium search with age-based pricing

Notes: Figure shows search for equilibrium in setting where sample individuals required to choose between Bronze and Platinum Plans and premiums are age-rated using the HHS age curve. Light blue line is the 45-degree line. Orange line represents incremental average cost (IAC) curve with no risk adjustment, blue line represents IAC with demographic risk adjustment, gray line represents IAC with prospective risk adjustment, gold line represents IAC with concurrent risk adjustment, and green line represents IAC with HHS-HCC risk adjustment. IAC with no and demographic risk adjustment is everywhere above 45-degree line implying complete market unraveling where everyone enrolls in Bronze plan. Prospective, concurrent, and HHS risk adjustment IACs cross 45-degree line, implying an interior equilibrium exists. Equilibrium is at lowest P where IAC crosses 45-degree line. Concurrent results in the lowest price differential. Prices, enrollment, and welfare can be found in Table 1.5.
Notes: Figure shows search for equilibrium in setting where sample individuals required to choose between Bronze and Platinum Plans, premiums are age-rated using the HHS age curve, and there is reinsurance. Light blue line is the 45-degree line. Orange line represents incremental average cost (IAC) curve with no risk adjustment, blue line represents IAC with demographic risk adjustment, gray line represents IAC with prospective risk adjustment, gold line represents IAC with concurrent risk adjustment, and green line represents IAC with HHS-HCC risk adjustment. IAC with no and demographic risk adjustment is everywhere above 45-degree line implying complete market unraveling where everyone enrolls in Bronze plan. Prospective, concurrent, and HHS risk adjustment IACs cross 45-degree line, implying an interior equilibrium exists. Equilibrium is at lowest P where IAC crosses 45-degree line. Concurrent results in the lowest price differential. Prices, enrollment, and welfare can be found in Table 1.5.
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