

Robust Risk Adjustment in Health Insurance

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Abstract

Risk adjustment is used to calibrate payments to health plans based on the relative health status of insured populations and helps keep the health insurance market competitive. Current risk adjustment models use parameter estimates obtained via regression and are thus subject to estimation error. This paper discusses the impact of parameter uncertainty on risk scoring, and presents an approach to create robust risk scores to incorporate ambiguity and uncertainty in the risk adjustment model. This approach is highly tractable since it involves solving a series of linear programming problems.

Keywords: Risk adjustment, health insurance, robust risk scores

1. Introduction

Risk adjustment is defined in the Specifications Manual for National Hospital Quality Measures as “a statistical process used to identify and adjust for variation in patient outcomes that stem from differences in patient characteristics (or risk factors) across health care organizations.” [1] The goal of risk adjustment is to reflect that “patients may experience different outcomes regardless of the quality of care provided by the health care organization” due to patient-specific characteristics, such as age or clinical diagnoses [1]. Without appropriate risk adjustment, comparing patient outcomes across organizations can be misleading. For instance, a best-in-class health provider may attract particularly ill patients, who may face dire prognoses and thus may have worse outcomes than patients who are only moderately ill and go to a less-skilled provider. By accounting for existing risk factors, risk adjustment facilitates a more fair and accurate inter-organizational comparison. The broad concepts and applications of risk adjustment are presented in Ellis [2].

Risk adjustment is further defined by the American Academy of Actuaries as “an actuarial tool used to calibrate payments to health plans or other stakeholders based on the relative health of the at-risk populations.” [3] In that context, it extends beyond risk measurement into risk mitigation, and helps ensure that health plans are appropriately compensated for the risks they enroll. Specifically, risk adjustment – when done well – can help remove the incentive for health plans to try not to enroll sicker people, since they will be compensated for those patients’ worse health status.

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McWilliams et. al. [4] show using a regression model that the implementation of the Hierarchical Condition Categories (HCC) model was associated with reduced favorable selection in the Medicare Advantage program. However, they also point out that inadequate risk adjustment would probably cause greater instability in exchange markets than in Medicare Advantage, and lead to competition among exchange plans to attract and retain healthy enrollees, as well as the withdrawal of under-compensated plans. In contrast, Brown et. al. [5] demonstrate that the effect of risk adjustment on government’s cost of providing health insurance is imperfect since risk adjustment can potentially increase the scope for selecting individuals with costs below their capitation payment due to the increase in the variance of medical costs with the risk score.

The Health and Human Services (HHS) official federal risk adjustment models are available in the HHS Notice of Benefit and Payment Parameters for 2014, which was first released as a proposed rule at the end of 2012 [6]. The HHS risk adjustment system uses fifteen weighted least squares regression models: platinum, gold, silver, bronze, and catastrophic for adult, child, and infant, respectively, to compute risk scores. The weight is the fraction of the year enrolled. Each HHS risk adjustment model predicts annual plan liability for an enrollee based on the person’s age, gender, and diagnoses. The risk score of each enrollee is equal to the sum of all the risk weights associated with that patient, with the average risk score over the whole population being scaled to 1.

The enrollment-weighted average risk score of all enrollees in a particular health plan within a geographic rating area (the weights being again the fractions of the year enrolled) are then used as input to the payment transfer formula to determine an issuer’s payment or charge for a particular plan, which is a baseline payment times the plan’s enrollment-weighted average risk score [7]. The HHS risk adjustment model is a concurrent model, where diagnoses from a given period are used to predict cost in the same period. In contrast, a prospective model uses data from a prior period to predict costs in the current period or in the future. By design, both acute and chronic illnesses are emphasized in the concurrent model. In the prospective model, systematic factors, such as aging and chronic illnesses, outweigh acute and one-time conditions [8]. Acute and one-time events are averaged at the age/gender group level in the prospective model (Yi et. al. [9]). The concurrent model is used by HHS because it is more robust to changes in enrollment than the prospective model ([9], [10]). This is particularly useful under the Affordable Care Act since newly enrolled individuals may not have prior claims data. In addition, prescription drugs are not included as a predictor in each HHS risk adjustment model. To evaluate model performance, R^2 and predictive ratios are examined, where the R^2 statistic calculates the percentage of individual variation explained by a model, and the predictive ratio is the ratio of the weighted-mean predicted plan liability for the model sample population to the weighted-mean actual plan liability for the model sample population [9].

Winkelman [11] uses the Mean Absolute Prediction Error (MAPE) as an alternative to measure predictive accuracy, where MAPE is calculated by dividing the sum of absolute errors by the sample size. Glazer and McGuire [12] argue that, in order to address adverse selection and asymmetric information in managed care, risk adjustment should be viewed as a way to set prices for different individuals. They argue for instance that the payment weight on a patient’s age “may be chosen for

its incentive properties and need not – indeed should not – be the same as the coefficient on age from a regression explaining average costs.” Weiner et. al. [13] quantify the impact of biased selection on health plans in the exchange and evaluates mitigation attempts included in the Affordable Care Act of 2010.

Proper risk adjustment is thus very important for payers’ long-term financial viability and for the competitiveness of the health insurance market. Risk adjustment is currently used in the Medicare Advantage (MA) program, the Part D prescription drug program, many state Medicaid programs, the Commonwealth Care program in Massachusetts, and some employer-based plans [3]. The risk weights can be obtained by linear regression, probit regression, or logistic regression, depending on the situation considered; however, estimates of regression coefficients are subject to error. Because risk adjustment in this context involves real money transfers between payers, it is important to develop quantitative methods to incorporate ambiguity and uncertainty in the risk weights. The main contribution of this paper is to present a tractable methodology to create robust risk scores, which determine the amount of money to transfer.

Outline. In Section 2, we present a short example that demonstrates the need for robustifying models of healthcare transfer payments. We present the robust risk adjustment methodology in Section 3 and numerical experiments in Section 4. Section 5 contains concluding remarks.

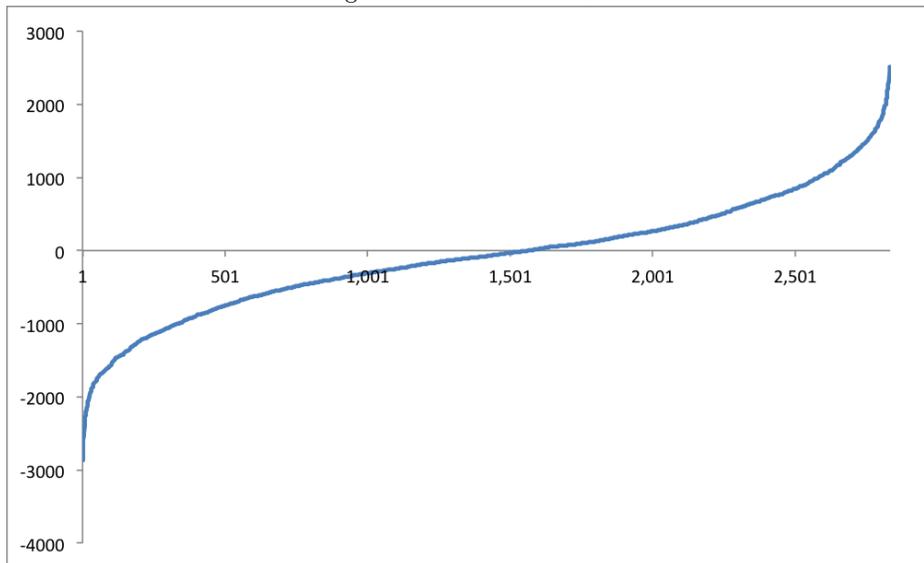
2. Robustness in risk adjustment models

An example to show the need for robustness is based on the Hospital Value-Based Purchasing (VBP) program, established by the Centers for Medicare and Medicaid Services (CMS) [14]. It aims at realigning hospitals’ financial incentives by rewarding those that provide highest-quality care, with quality of care being quantified as the weighted sum of three sets of measures: process measures (13 measures), patient satisfaction measures (8 measures) and mortality rates for heart attacks, heart failures and pneumonia within 30 days of a patient’s leaving the hospital [15]. CMS funds the VBP adjustment scheme by withholding 1% of each hospital’s Medicare payments, and re-distributing this pool of money to the hospitals based on the adjustment factors. Hospitals with the lowest adjustment factors receive little to no money back, and thus their 1% of Medicare payments will be lost to them and reassigned to better performing hospitals. Hospitals with the highest adjustment factors receive payments exceeding their initial 1% contribution to the pool. 1% might be ignored by bigger hospitals, but it can have a significant impact on smaller hospitals or hospitals in precarious financial health. Moody’s estimates the preliminary median operating margins for non-profit hospitals in FY 2013 to be at 2.2%, a decrease compared to FY 2012 [16].

CMS first issued proxy factors in early 2012 and the actual adjustment factors for these 2,894 hospitals were published by CMS in December 2012, both of which are provided in Table 16 of the FY 2013 Final Rule Tables [17]. We investigate the variability between proxy and actual scores as follows. We first compute the rank of each hospital, based on the rank of its adjustment factor, with the hospital having the highest (best) adjustment factor receiving rank 1. We then merge the records under both the proxy and actual systems to compare proxy and actual ranks. The

difference in rank is then computed as the proxy rank minus the actual rank, such that a positive difference represents a gain in ranks following the publication of the final (actual) factors. Figure 1 shows the differences in ranks from most negative to most positive. Because the total number of hospitals is approximately 3,000, hospitals at the extreme left of the graph represent hospitals that had been expected to perform at the top based on proxy numbers and found themselves at the bottom when the actual numbers were published. Similarly, hospitals at the extreme right represent hospitals that had been deemed at the bottom based on the proxy factors and came out on top with the actual factors. The wide fluctuation between the proxy factors and the actual ones has, to the best of our knowledge, not been discussed in the press or elsewhere. The worst rank loss is a drop of 2,866 spots – from rank 21 to rank 2,887 – by the Meadowview Regional Medical Center in Maysville, KY. The highest gain in rank – from rank 2,659 to rank 144 – is an increase of 2,515 by Loretto Hospital in Chicago, IL. 335 hospitals or 11.81% of the hospitals considered lost 1,000 spots or more and 250 hospitals or 8.81% gained 1,000 or more. Such large fluctuations within a few months’ time risk casting doubt on the meaningfulness of the factors and slowing down efforts to move to value-based models, and suggests there is a need to “robustify” factors.

Figure 1: Difference in Rank



3. Robust Risk Scoring

The traditional risk adjustment process, if the weights of the risk factors are known exactly, is as follows:

1. Compute the risk score for each enrollee and scale it such that the average population risk score is one,
2. Compute the average risk score for each insurer (weighted by the fraction of the year each enrollee has been on the plan),

3. Determine the transfer payment as the difference between the insurer’s cost (sum of patients’ risk score times nominal cost) and his revenue (number of patients times capitated payment).

When the weights for the risk factors are not known precisely but estimates (for instance from a regression) and confidence intervals are available, we face the question of how this uncertainty should be incorporated so that payers receive a “fair” transfer payment. We will seek to minimize the *worst-case regret*. Here the worst-case regret is the greatest difference in absolute value between the estimated and actual risk scores computed over all payers and all possible weights for the risk factors within a predefined uncertainty set. It measures the worst-case difference in absolute value between the money transfer that should have taken place between payers if the true weights had been known and the transfer that actually did, based on the actual weights used to compute the risk scores. These weights are the decision variables of the problem.

We will use the following notation:

- K : the number of payers in the market,
- S_k : the set of enrollees of insurer $k = 1, \dots, K$,
- J : the set of conditions incorporated in risk scoring,
- n_{jk} : the number of enrollees of insurer $k = 1, \dots, K$ who have condition $j \in J$,
- N_k : the number of enrollees of plan k ,
- c_{ij} : a binary parameter equal to 1 when individual i ($i \in S_k$, $k = 1, \dots, K$) has condition j ,
- w_j : the incremental risk weight for condition $j \in J$
(to be added to the risk score of individual i if $x_{ij} = 1$).

Insurer k ’s risk score before scaling is obtained by taking the average, over all enrollees, of the risk weights of the factors that affect the enrollee.

$$\frac{1}{N_k} \sum_{i \in S_k} \sum_{j \in J} w_j c_{ij} = \frac{1}{N_k} \sum_{j \in J} w_j n_{jk}.$$

For convenience, we assume that all enrollees have been with the payer the whole year. Adapting the formulation to the case where some patients have joined the health plan during the year involves replacing the average over enrollees by a weighted average where the weights are the fractions of year for each patient. This leads to modified definitions for n_{jk} and N_k . Specifically, if τ_{ik} is the fraction of the year individual i has spent with insurer k , n_{jk} becomes $\sum_{i \in S_k} \tau_{ik} c_{ij}$ and N_k becomes $\sum_{i \in S_k} \tau_{ik}$. Once the n_{jk} and N_k have been thus updated, the models presented below apply immediately.

Risk scores are then scaled so that their population average is 1. Insurer k ’s average risk score after scaling becomes:

$$RS_k = \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \cdot \frac{\sum_{l \in K} N_l}{N_k}.$$

We model the uncertain coefficients w_j , $j \in J$, as belonging to a polyhedral set W . The set W can for instance be a box consisting of confidence intervals for each (independent) factor, or possibly include a budget-of-uncertainty constraint in the spirit of Bertsimas and Sim [18] to bound from

above the total number of parameters that can take their worst-case value. The problem we aim to solve in the decision variables v (the weights we want to give to each factor within the feasible set W) is then:

$$\min_{v \in W} \max_{k \in K} \max_{w \in W} \left| \frac{\sum_{j \in J} v_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} v_j n_{jl}} \frac{\sum_{l \in K} N_l}{N_k} - \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \frac{\sum_{l \in K} N_l}{N_k} \right| \quad (1)$$

Let assume w.l.o.g. that the polyhedral set W is represented as $\{w \mid l \leq w \leq u, Aw = b\}$. Further, let N be the (n_{jk}) matrix, let e be the vector of all ones and let S be the polyhedral set defined as: $\{(x, y) \mid ly \leq x \leq uy, Ax = by, e'N'x = 1\}$. In order to derive a tractable reformulation to Problem (1), we will need the following lemma.

Lemma 3.1. *For all $k \in K$, the fractional optimization problems:*

$$(FP_{-k}) : \min_{w \in W} \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}},$$

and

$$(FP_{+k}) : \max_{w \in W} \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}}.$$

can be solved efficiently by solving the linear programming problems:

$$(LP_{-k}) : \min_{(x,y) \in S} \sum_{j \in J} n_{jk} x_j,$$

and

$$(LP_{+k}) : \max_{(x,y) \in S} \sum_{j \in J} n_{jk} x_j,$$

respectively.

Proof. The proof is in two steps.

(i) For any $w \in W$, let $x_j = \frac{w_j}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}}$ for all j and $y = \frac{1}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}}$. (Recall that y is always positive because the risk weights and the counts are always positive). Then it is immediate that (x, y) is in the set S defined above and we have: $\frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \frac{\sum_{l \in K} N_l}{N_k} = \frac{\sum_{l \in K} N_l}{N_k} \cdot \sum_{j \in J} n_{jk} x_j$.

(ii) For any $(x, y) \in S$, we must have $y > 0$ since $y = 0$ would lead to $x = 0$ (due to $ly \leq x \leq uy$), which would be infeasible (due to $e'N'x = 1$). Let then $w_j = \frac{x_j}{y}$ for all j . Then it is immediate that w is in the set W defined above and the two objectives are equal again.

Therefore, Problem (FP_{-k}) is equivalent to (LP_{-k}) and Problem (FP_{+k}) is equivalent to (LP_{+k}) for all k . \square

Let u_{-k} be the optimal objective of the linear optimization problem (LP_{-k}) and u_{+k} be the optimal objective of the linear optimization problem (LP_{+k}) for all k . It follows from Lemma 3.1 that we have for all k :

$$u_{-k} = \min_{w \in W} \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}}, \quad (2)$$

and

$$u_{+k} = \max_{w \in W} \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}}. \quad (3)$$

The key result of this section is the following theorem.

Theorem 3.1 (Robust risk scoring). *Problem (1) is equivalent to the following linear programming problem:*

$$\begin{aligned} \min \quad & Z \\ \text{s.t.} \quad & Z \geq \frac{\sum_{l \in K} N_l}{N_k} \left(\sum_{j \in J} n_{jk} x_j - u_{-k} \right) \forall k \\ & Z \geq \frac{\sum_{l \in K} N_l}{N_k} \left(u_{+k} - \sum_{j \in J} n_{jk} x_j \right) \forall k \\ & (x, y) \in S. \end{aligned}$$

Proof. We rewrite Problem (1) as:

$$\begin{aligned} \min \quad & Z \\ \text{s.t.} \quad & Z \geq \frac{\sum_{l \in K} N_l}{N_k} \left(\frac{\sum_{j \in J} v_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} v_j n_{jl}} - \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \right), \forall k, \forall w \in W, \\ & Z \geq \frac{\sum_{l \in K} N_l}{N_k} \left(-\frac{\sum_{j \in J} v_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} v_j n_{jl}} + \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \right), \forall k, \forall w \in W, \\ & v \in W, \end{aligned}$$

or equivalently:

$$\begin{aligned} \min \quad & Z \\ \text{s.t.} \quad & Z \geq \frac{\sum_{l \in K} N_l}{N_k} \left(\frac{\sum_{j \in J} v_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} v_j n_{jl}} - \min_{w \in W} \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \right), \forall k, \\ & Z \geq \frac{\sum_{l \in K} N_l}{N_k} \left(-\frac{\sum_{j \in J} v_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} v_j n_{jl}} + \max_{w \in W} \frac{\sum_{j \in J} w_j n_{jk}}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}} \right), \forall k, \\ & v \in W. \end{aligned}$$

We inject Eqs. (2) and (3) and use the transformation $x_j = \frac{v_j}{\sum_{l \in K} \sum_{j \in J} w_j n_{jl}}$ and $y = \frac{1}{\sum_{l \in K} \sum_{j \in J} v_j n_{jl}}$. The rest of the proof is identical to the proof of Lemma 3.1, replacing w by v , and is omitted here. \square

4. Numerical Experiments

To test our approach, we generate a sample with 1,000,000 patients and 10 payers. The base payment is \$2,000. The risk factors and nominal weights are taken from the Federal Register [6]. For illustrative purposes, the confidence interval of each risk factor is symmetric, centered at the nominal weight, and with a relative deviation from the mean selected randomly and up to 30% (i.e., the upper bound is at most 1.3 times the nominal weight.) The uncertainty set is a hypercube

or “box” consisting of the range forecasts for each weight. Table 1 shows the nominal and robust weights as well as the lower and upper bounds of the weights used in the model. Table 2 compares nominal and robust risk scores for each insurer.

Table 1: Nominal Weights vs. Robust Weights

Weight	Nominal Weights	Robust Weights	Lower Bound	Upper Bound
Male,21-24	0.258	0.248556	0.236	0.28
Male,25-29	0.278	0.268399	0.256	0.3
Male,30-34	0.338	0.33028	0.321	0.355
Male,35-39	0.413	0.401163	0.325	0.501
Male,40-44	0.487	0.476333	0.439	0.535
Male,45-49	0.581	0.57234	0.47	0.692
Male,50-54	0.737	0.737519	0.521	0.953
Male,55-59	0.863	0.836877	0.645	1.081
Male,60-64	1.028	1.032386	0.944	1.112
Female,21-24	0.433	0.421584	0.367	0.499
Female,25-29	0.548	0.539729	0.409	0.687
Female,30-34	0.656	0.653322	0.465	0.847
Female,35-39	0.76	0.753436	0.745	0.775
Female,40-44	0.839	0.827146	0.766	0.912
Female,45-49	0.878	0.865029	0.792	0.964
Female,50-54	1.013	1.009959	0.855	1.171
Female,55-59	1.054	1.044461	0.859	1.249
Female,60-64	1.156	1.148513	1.102	1.21
Male, 2-4	0.283	0.276579	0.263	0.303
Male, 5-9	0.196	0.184558	0.143	0.249
Male, 10-14	0.246	0.235474	0.188	0.304
Male, 15-20	0.336	0.324302	0.301	0.371
Female, 2-4	0.233	0.232717	0.229	0.237
Female, 5-9	0.165	0.164905	0.163	0.167
Female, 10-14	0.223	0.217841	0.215	0.231
Female, 15-20	0.379	0.368576	0.321	0.437
Asthma	1.098	1.175946	0.822	1.374
Acute Appendicitis	0.3	0.306364	0.242	0.358
Diabetes	1.331	1.380504	1.195	1.467
Congestive Heart Failure	3.79	3.913027	3.554	4.026
HIV	5.485	4.564919	3.986	6.984
Mental Illness	1.5	1.517435	1.415	1.585

Table 2: Nominal risk scores vs. Robust risk scores

	Insurer 1	Insurer 2	Insurer 3	Insurer 4	Insurer 5
Nominal Risk Score	1.0016391	0.999457	0.998765	0.998804	1.0008784
Robust Risk Score	1.0014636	0.99941	0.998765	0.998892	1.0007269
Change in Risk Score	-0.0175%	-0.0047%	0.0000%	0.0088%	-0.0151%
Nominal money transfer	327820.55	-108611	-246922	-239182	175681.97
Robust money transfer	292720.94	-117951	-246984	-221677	145377.22
Change in money transfer	-10.7070%	8.5988%	0.0250%	-7.3184%	-17.2498%

	Insurer 6	Insurer 7	Insurer 8	Insurer 9	Insurer 10
Nominal Risk Score	1.0001529	1.001036	1.00016	1.000559	0.998548
Robust Risk Score	1.0001534	1.001057	1.000275	1.000555	0.9987026
Change in Risk Score	0.0000%	0.0021%	0.0115%	-0.0004%	0.0155%
Nominal money transfer	30581.801	207150.4	32081.07	111799	-290399.4
Robust money transfer	30675.997	211308.1	55049.92	110959.2	-259479.3
Change in money transfer	0.3080%	2.0071%	71.5963%	-0.7512%	-10.6475%

We can see from Table 2 that although the percentage changes in risk scores are small, the changes in actual money transfers are significant. The reason is that the relative change in risk score is calculated as $\frac{RS-RSN}{RSN}$, while the relative change in actual money transfer is calculated as $\frac{(RS-1) \times N \times C - (RSN-1) \times N \times C}{(RSN-1) \times N \times C}$, or equivalently $\frac{RS-RSN}{RSN-1}$: the numerator stays the same but the denominator is not and this can create significant changes because the risk scores are close to 1 to begin with. In the example above, 4 out of 10 payers observe a relative change in actual money transfer higher than 10% and Insurer 8 sees a 72% increase in payment.

5. Conclusions

In this paper, we have investigated how to mitigate the impact of parameter uncertainty on risk scoring in healthcare. An example related to hospital ranking using adjustment factors was provided to demonstrate the need for robustness. We presented an approach to compute robust risk scores. Our methodology involves solving a series of linear programming problems and thus is highly tractable. Future work includes addressing uncertainty related to the health status of previously uninsured customers entering the system due to the Affordable Care Act of 2010.

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