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Towards Optimizing Co-Insurance Levels for Statin Treatment of Heart Disease

Shuyi Wang
Statistical Consultant II, Alliance Data

Aurélie C. Thiele
Associate Professor, Southern Methodist University

Abstract

Objectives. To investigate a Value-Based Insurance Design (VBID) approach for heart disease treatment where low-risk and high-risk health insurance enrollees have different cost-sharing parameters, to provide incentives to increase medication adherence and health outcome.

Study Design. We propose a methodology based on a Markov Chain to model transitions between health states, which has not been used in the context of health insurance design. We also conduct sensitivity analysis to analyze how key parameters influence the optimal coinsurance levels.

Data Sources. We use data published in the literature.

Principal Findings. (i) Preventing low-risk patients from turning into high-risk patients is more important in keeping total cost down than preventing high-risk patients from having a heart attack. (ii) The VBID approach yields the greatest cost benefits when the heart attack cost is about 175 times the cost of medicine. (iii) VBID cost savings and optimal cost-sharing levels are very sensitive to medicine effectiveness when the rate of reduction in heart attack is less than 14%.

Conclusions. While VBID is appealing in theory, its practical usefulness is highly uncertain due to the sensitivity to model parameters, which are difficult to estimate accurately.

Keywords. Value-Based Insurance Design, heart disease, Markov Chains.

Literature Review

The issue of appropriate cost-sharing between patients and payers has been the focus of significant attention in the healthcare community, by payers, policy-makers and patient advocates alike. A widely accepted notion is that higher cost-sharing by patients in Value-Based Insurance Design (VBID) can help insurance companies control their costs by providing an incentive for patients to avoid unnecessary or wasteful use of services, and is counterbalanced by more affordable insurance premiums; however, when high-risk patients need treatment, increases in deductibles, copayments, and coinsurance rates due to the implementation of VBID shift a greater part of the financial burden from payers to enrollees. Thus, higher cost-sharing for sick enrollees may motivate certain patients to postpone needed care, especially for slowly-progressing conditions such as heart disease or chronic illnesses. In this paper, we investigate the potential of differentiated cost-sharing to incentivize patients to seek treatment before their condition deteriorates and also maintain the payer's financial stability.

The link between patients' financial cost and health resource usage was first investigated in the 1970s in a landmark RAND study known as the Health Insurance Experiment (Newhouse [14]). Key findings included that increased cost-sharing led to decreased health services utilization. Specifically, on average participants with cost-sharing had one to two fewer doctor visits each year and 20 percent fewer hospital admissions than those with no financial contribution. [14]

Goldman et al. [7] reported that, when copayment was doubled, patients with diabetes reduced their anti-diabetes drugs by 23 percent and patients with hypertension reduced their anti-hypertension medication by 10 percent. Tamblyn et al. [32] found that when cost-sharing increased, elderly and poor people used less medication, leading to a 6.8 percent net increase in adverse events for elderly people and a 12.9 percent net increase for poor people.

Value-Based Insurance Design (VBID) was first introduced in Fendrick et al. [5]. The goal of VBID is to align the value of the medical services provided with patients' incentives to encourage medication adherence and the early use of high-value services via appropriate cost-sharing. The authors show that for patients with asthma, diabetes or gastric disorders, doubling the cost-sharing leads to a 17 percent increase in emergency visits and a 10 percent increase in hospitalizations. Chernew et al. [2] find that the implementation of VBID decreased the use of nondrug health care services, offsetting the cost associated with increased drug spending. Goldman et al. [8] find that, for high and medium risk patients, the proportion of full compliance falls by 6 percent to 10 percent when cost-sharing levels of cholesterol-lowering drugs increase from $10 to $20. Maciejewski et al. [10] argue that even a modest cost-sharing increase for Veterans Affairs patients with diabetes or hypertension can be important for medication adherence.

Heart Disease Treatment

Every year, heart disease kills about 600,000 people in the United States, which represents 1 in every 4 deaths, and coronary heart disease is the most common type of heart disease, killing nearly 380,000 people annually [13]. 720,000 heart attacks occur in the United States each year, of which 515,000 are a first heart attack for the patient [6].

Statin is considered an effective medicine to reduce the risk of heart attack. Sokol et al. [21] shows that adhering to statin treatment could reduce hospitalization risk by 12 percent. Schultz et al. [18]

show that higher prescription cost-sharing is correlated with lower statin adherence rate. Ellis et al. [4] find that 50% of patients whose average monthly statin cost-sharing was less than $10 discontinued treatment (stopped refilling their medication) by the end of the follow-up period (3.9 years), while 50% of those who paid, respectively, between $10 and $20 or strictly more than $20 discontinued by 2.2 and 1.0 years.

Towards Optimizing Co-Insurance for Heart Disease Treatment

In what follows, we present a Markov Chain approach to model disease progression and ultimately to minimize the overall total cost to the payer. Markov Chains are a well-studied class of stochastic models describing possible sequences of events where the probability of each event only depends on the state attained by the chain after the previous event, and not the sequence of earlier events that led to that state (Ross [16]). Markov Chains have been used in multiple studies on medical decision making, as reviewed below, but to the best of our knowledge have not been implemented in the context of VBID.

Maillart et al. [11] consider an observable Markov Chain model to compare various breast cancer screening policies. Shechter et al. [19] consider the optimal timing of HIV therapy with an infinite-horizon Markov Decision Process model, when the objective is to maximize quality-adjusted life years (QALYs) over the patient's lifetime. Denton et al. [3] present a Markov Chain model to find the optimal time to initiate statin for Type 2 Diabetes patients in order to prevent cardiovascular events. The objective is to maximize the monetary rewards for QALYs minus costs of statin treatment and cardiovascular events and the decision is revisited each year. Mason et al. [12] propose a Markov Decision process to improve diabetes patients' adherence to medication. The decision variable is the timing to perform adherence-improving interventions. The objective is a combination of maximizing patient's quality-adjusted time to the first adverse health event and minimizing costs of treatment.

We contribute to the literature in the following ways:

- Our model focuses on the healthcare financing area, instead of medical operations. The decision variables are patients' coinsurance levels, i.e., the percentage of the medication cost that they have to pay (the health payer will pay the remainder), and the objective is to minimize the total cost from the payer's standpoint.
- We incorporate the fact that people with different risk levels have different probabilities to develop negative events and thus assign its own set of decision variables to each group.
- We discuss how to approach uncertainty on future payoffs and patients' price response function using simple robust optimization techniques and sensitivity analysis.
- We argue that Markov Chains provide an important tool to better understand and design incentives for high-risk heart disease patients through appropriate cost-sharing.
- We design and analyze two models based on Markov Chains: the first one (the "traditional model") does not consider the risk category of the patients when they enter the system while the second model (the "VBID model") incorporates the fact that patients have different risk levels and thus different transition probabilities between medical states. The traditional model serves as a benchmark to show the advantages and disadvantages of VBID.

Traditional Insurance Design

Disease progression in our simplified model can be described as follows. The patient is diagnosed with being at risk for a heart attack and is prescribed medication. Medication adherence depends on the coinsurance level, denoted *x*, and other factors, so that medication adherence is never 100% even if the medication is free. Let *a(x)* be the proportion of patients that will be adherent, i.e., take their medication.

We introduce the following notation. Per time period:

- If patients take their medication, then only a fraction t_1 will indeed have a heart attack in the next time period, a fraction s_1 will remain at their current "at risk" health status and the remaining fraction $1 - t_1 - s_1$ will have a natural death.
- If patients are not adherent to their medication, then a fraction t_2 will have a heart attack in the next time period, a fraction s_2 will remain at their current "at risk" health status and the remaining fraction $1 - t_2 - s_2$ will have a natural death.
- If patients have a heart attack, a fraction *d* of them will pass away and *1-d* of them will survive and be at risk for another heart attack.

We assume $t_1 < t_2$ (adherence makes a heart attack less likely) and $t_1 + s_1 > t_2 + s_2$ (adherence makes death less likely).

In our simplified model, we model adherence as a yes/no state, although more complex models could incorporate the extent of medication adherence through the proportion of days covered. Further, we assume that a patient's adherence level is constant, i.e., an adherent patient always remains adherent and a non-adherent patient always remains non-adherent. All the patients prescribed medication against heart attacks start in the "at risk" state.

This model of disease progression is represented in Markov Chain format in Figure 1. The nodes represent health states for the patient and the arcs represent transition from a state to another. The values on the arcs represent the probability of each transition.

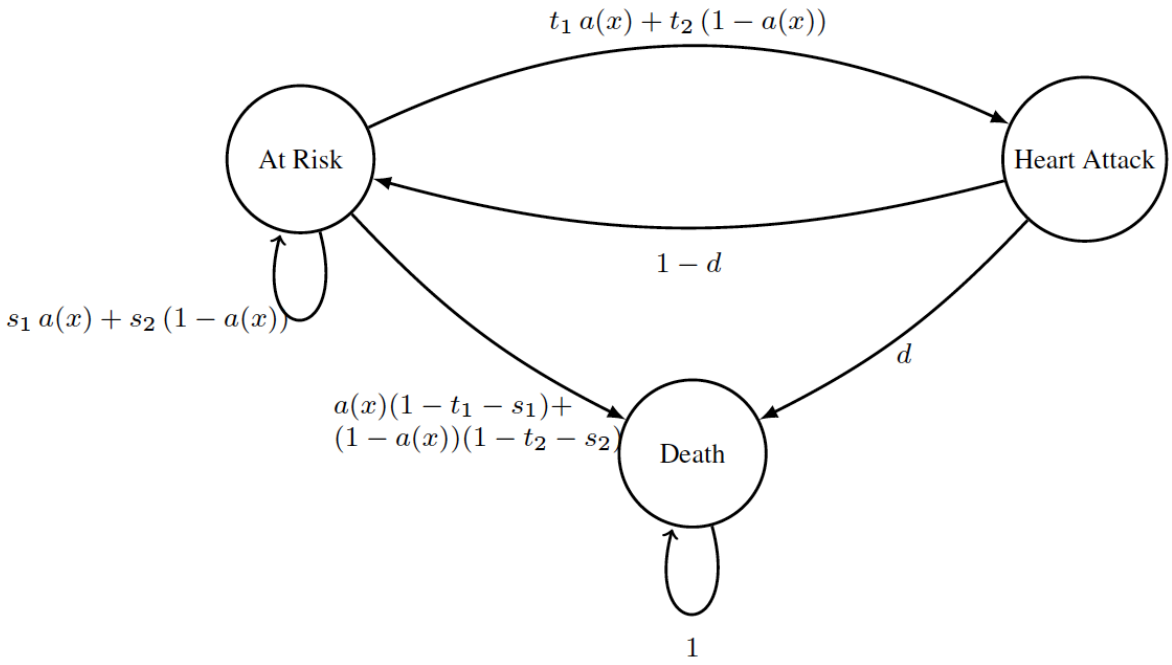

Figure 1 Markov-Chain model of disease progression in the no-VBID case.

Our goal is to minimize the steady-state cost to the payer per time period. We assume that patients have at most one heart attack per time period, which is a standard assumption in Markov Chain literature. In addition, let us define the following parameters:

- c_1 : the total (patient + payer) drug cost per patient per time period,
- c_2: the total cost of a heart-attack-related hospital stay per patient per time period,
- *p*: the fraction of the cost hospital stay paid by the patient,
- *r*: the number, in millions, of people diagnosed with being at risk of a heart attack per time period,
- *R*: the number of people at risk of a heart attack in steady state per time period,
- *T*: the number of people having a heart attack per time period,
- *A*: the penalty factor for a fatal heart attack.

For the sake of clarity, we assume that patients who have a heart attack all incur the same treatment cost, and that non-adherent patients do not take their medicine at all. The fact that non-adherent patients might take a small amount of medicine and the adherent patients may not be completely adherent can easily be incorporated by modifying the adherence function.

The objective function, from the payer's perspective, is formulated as the sum of the cost for drugs, hospital stays and penalty for patient death:

$$\min(1 - x)c_1 Ra(x) + (1 - p)c_2 T + AdT$$

We must now estimate *R* and *T*. Using classical Markov Chain analysis to compute the steady state of a Markov Chain (see Ross [16] and Wang [25] for details), the payer's problem can be written as:

$$min_{0\le x\le 1}\frac{(1-x)c_1 ra(x)+(1-p)c_2 r[t_2-a(x)(t_2-t_1)]}{1-[s_2+(1-d)[t_2-a(x)(t_2-t_1)]+a(x)(s_1-s_2)]}$$

While the objective function is quite complex, the minimization problem is only over one variable in a bounded interval and thus can be approached through a line search or by enumerating a finite number of potential values. This is particularly appropriate in health insurance where the coinsurance level typically only takes discrete values in 5% increments between 0 and 100%.

Value-Based Insurance Design Model

Next, we model the heterogeneity of the population with respect to patients' risk of developing heart disease. We group people into high risk and low risk and assign its own cost-sharing level to each group. This represents the core idea of Value-Based Insurance Design.

Using notations similar to those earlier, we assume that a fraction $a^l(x^l)$ of the low-risk people will adhere to their medication and $1-a^l(x^l)$ of them will not, where $a^l(x^l)$ is a function of the cost-sharing level x^l. If patients take their medication, in the next period s_1^l will remain low risk, h_1^l of them will become high risk and n_1^l of them will have a natural death. If patients do not take their medication, s_2^l of them will remain low risk, h_2^l of them will transit to high risk, t_2^l of them will have a heart attack and n_2^l of them will have a natural death. Similar notations are used for the high-risk patients, with a superscript *h* rather than *l*. This model of disease progression is represented in Markov Chain format in Figure 2. Again, the nodes represent the states of patients' health and the arcs represent transitions between health states, with the number near the arcs being transition probabilities.

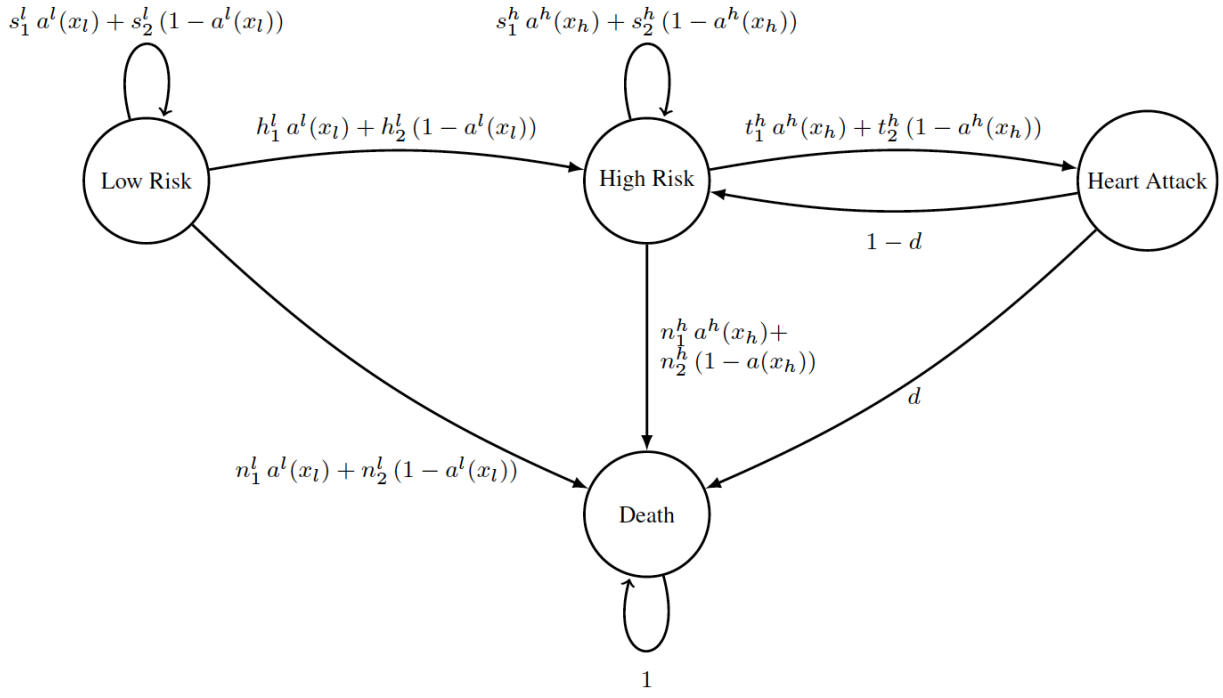

Figure 2 Markov-Chain of disease progression in the VBID case

Then we can minimize the total average cost in the long run as:

$$min_{0\le x_l\le 1, 0\le x_h\le 1}(1-x_l)c_1^l L(x_l,x_h)a^l(x^l) + (1-x^h)c_1^h H(x_l,x_h)a^h(x^h) + (1-p)c_2 T(x_l,x_h) + AdT(x_l,x_h)$$

where:

- c_1^l is the medication cost of low-risk patients in each period
- $L(x_l,x_h)$ the number of low-risk patients in the steady state of the Markov chain
- c_1^h is the medication cost of high-risk patients
- $H(x_l,x_h)$ is the number of high-risk patients in the steady state of the Markov Chain
- c_2 is the heart attack cost
- p is the proportion of heart attack cost paid by the patient
- $T(x_l,x_h)$ is the number of heart attacks in the steady state of the Markov Chain
- A is the penalty factor for a fatal heart attack.

Again, while the objective function above is quite complex, the minimization problem can be solved by discretizing the feasible set, which is the unit square, for reasonable values of the coinsurance levels.

Numerical Experiments

In this section, we illustrate how our model can be applied in practice, using parameter values drawn from the literature and provided in Table 1.

Table 1 Parameter Estimates for VBID

Parameter	Estimate	Source	Parameter	Estimate	Source
$\boldsymbol{h_1^l}$	6.9%	[34]	t_1^h	10.20%	[30]
$\boldsymbol{n_1^l}$	2%	[27]	n_1^h	2%	[27]
$\boldsymbol{s_1^l}$	91.10%	=1-5.3%-6.9%-2%	s_1^h	87.80%	=1-10.2%-2%
$\boldsymbol{h_2^l}$	9.9%	[34]	t_2^h	13.20%	[30]
$\boldsymbol{n_2^l}$	2%	[27]	n_2^h	2%	[27]
$\boldsymbol{s_2^l}$	88.10%	=1-7.6%-2.3%-2%	s_2^h	84.80%	=1-13.2%-2%
$\boldsymbol{c_2}$	30,000	[39]	c_1^l	432	[38]
d	0.143	[39]	c_1^h	804	[38]

We now estimate the adherence function. Grohol [9] states that 76.2 percent of those patients whose out-of-pocket prescription cost was $20 or more for a month's worth of statin drugs were non-adherent, compared with 49.4 percent of patients whose monthly prescription co-pay was less than $10, and that the response function is the same for both high-risk patients and low-risk patients. Thus, we estimate the adherence function as:

$$a(x) = \frac{1}{1+e^{-0.66+0.0055x}}$$

with $a(x) = a^l(x) = a^h(x)$.

We follow Shepherd [20] to describe the enrollee pool. Every year, the insurance company adds to its insurance pool 5% of its current population. If the company uses a traditional insurance model and does not classify its members as high risk and low risk, then it will rely on the weighted average estimates of the parameters for its whole population as shown in Table 2 (obtained using the assumptions in [20] of 6,595 low-risk members and 4,159 high-risk members).

Table 2 Parameter Estimation of Traditional Insurance Design

Parameter	Estimate	Parameter	Estimate
$\boldsymbol{t_1}$	3.94%	t_2	5.10%
$\boldsymbol{n_1}$	2%	n_2	2%
$\boldsymbol{s_1}$	94%	s_2	92.90%
$\boldsymbol{c_1}$	575.87	c_2	30,000
D	0.143		

In our numerical study, the optimal cost-sharing level in the traditional insurance design is 100%, which means that it would be mathematically optimal to make patients pay their medication in full, and the optimal cost would be 41.5 million dollars. (In practice, patients would leave the payer to join another insurance company. More realistically, the mathematical model suggests that the payer should make the cost-sharing level for the patient as high as the market will allow.) For the VBID insurance design, the optimal cost-sharing level for low-risk enrollees is 61% and for high-risk enrollees it is 78%, meaning that low-risk people shoulder a much lower relative burden of the medication cost. The optimal cost of VBID design is 38.9 million dollars, which is 6.7% lower than the optimal cost of traditional insurance design.

Sensitivity Analysis

In this section, we conduct sensitivity analysis on the following factors: (i) the cost of adverse outcomes, (ii) medicine effectiveness at preventing adverse outcomes, (iii) consumers' responsiveness to lower copayments. We look at how these factors influence cost savings generated by VBID and the optimal cost-sharing levels.

The Cost of Adverse Outcomes

Figure 3 and Figure 4 show how the cost of adverse outcome influence VBID cost savings and optimal copayment, respectively.

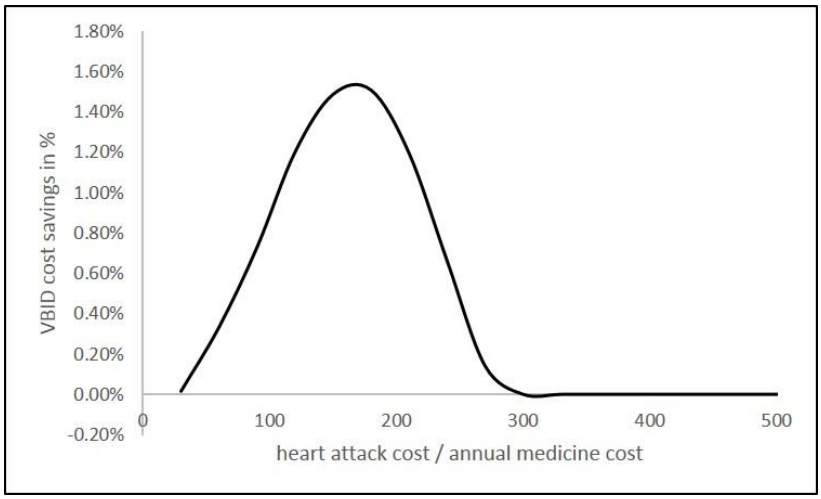

Figure 3 Sensitivity analysis of heart attack cost on VBID cost savings

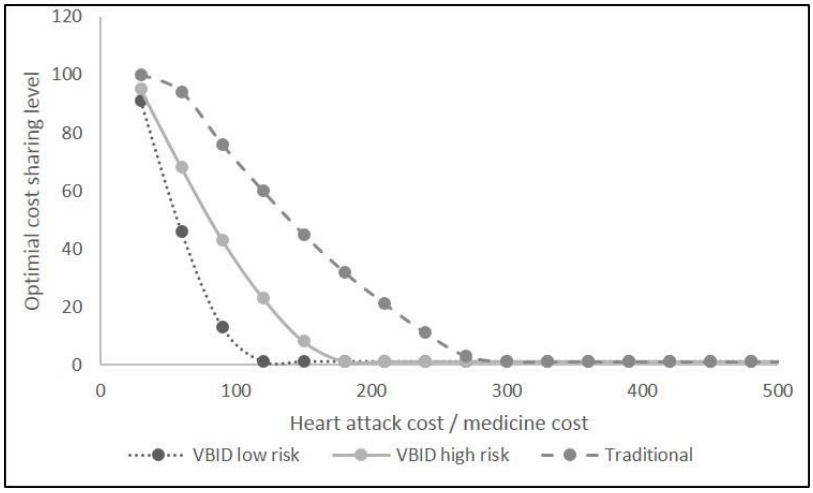

Figure 4 Sensitivity analysis of heart attack cost on VBID optimal cost-sharing

As the heart attack cost increases from zero, VBID cost savings increase too. This is because a higher heart attack cost represents a more severe consequence of not taking medication as prescribed. Since VBID insurance design separates patients as high risk and low risk, and then builds upon more accurate estimates of the transition probabilities between each state and the consequence of non-adherence for each group, it generates more savings when the heart attack cost begins to increase, at which point traditional insurance design does not emphasize the consequence of non-adherence. However, when the heart attack cost is very high and the adverse outcome has a large impact on the total cost, the traditional insurance model will also encourage patients to take their medication with a low cost-sharing level. At this point, it is best to reduce heart attacks as much as possible and thus both high-risk patients and low-risk patients will have a zero optimal copayment in the VBID model. This explains why VBID cost savings have a negative relationship with the heart attack cost after the heart cost exceeds 180 times the medicine cost and why VBID cost savings become zero after the heart attack cost exceeds 300 times the medicine cost.

Medicine Effectiveness at Preventing Adverse Outcome

In our example, medicine effectiveness is measured by the difference in likelihood of having a

heart attack of high-risk adherent and high-risk non-adherent patients. We present those results in Figures 5 and 6.

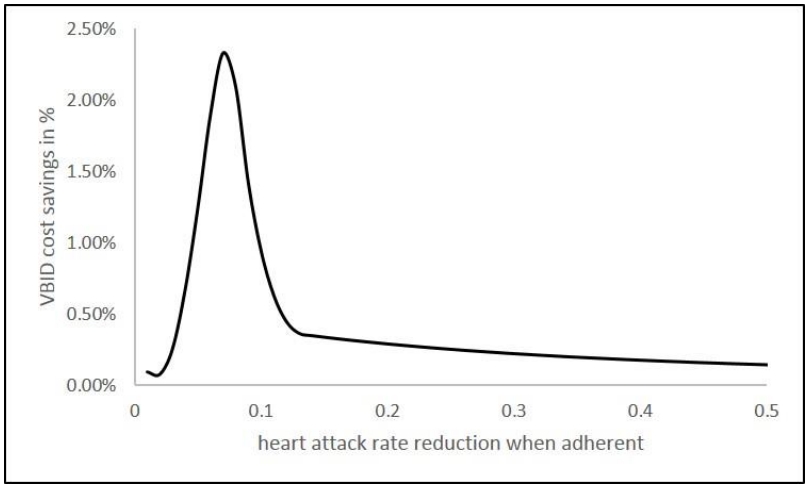

Figure 5 Sensitivity analysis of medicine effectiveness on VBID cost savings

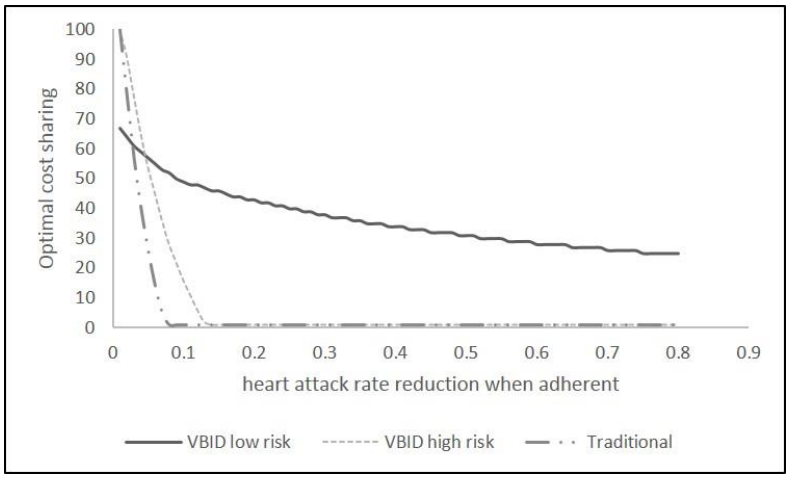

Figure 6 Sensitivity analysis of medicine effectiveness on VBID optimal cost-sharing

As for the heart attack cost, medicine effectiveness has a positive relationship with VBID cost savings at the beginning and then has a negative impact on VBID cost savings. When the medicine has no effect on reducing the heart attack rate for high-risk patients, the optimal cost-sharing level for high-risk patient is 100%, meaning that high-risk patients need to pay the zero-value medicine in full if they want to purchase it. Since the medicine still can help prevent low-risk patients from having their condition worsen and thus turning into high-risk patients, the optimal cost-sharing level for low-risk patients is around 70%. At this point, the optimal cost-sharing level in traditional insurance design is 100% and the VBID cost-sharing level is very low around 0.07%. As the medicine becomes more effective, both optimal cost-sharing levels for high-risk and low-risk patients decrease and the VBID optimal high-risk cost-sharing level decreases much faster than the VBID optimal low-risk cost-sharing level, which matches intuition since the increasing benefit is for high-risk patients.

At the same time, the optimal cost-sharing level in the traditional model decreases and reaches zero first, compared to all the other optimal cost-sharing levels. This is because the traditional insurance model does not differentiate between high-risk and low-risk patients and does not have an accurate estimate of transition probabilities between states. VBID cost savings reach a maximum of 2.33% when the medication reduces heart attacks by 7% among high-risk patients. At this point, the optimal high-risk cost-sharing level is 36% in VBID and low risk 53% in VBID, while the traditional optimal cost-sharing level is 5%. After that, as the medicine becomes more effective at preventing heart attacks, traditional optimal cost-sharing drops to zero first and then VBID's high-risk optimal copayment drops to zero, as VBID's low risk optimal slowly approaches zero, which results in a reduction in VBID cost saving.

Consumers' Responsiveness to Lower Copayments

We study consumers' responsiveness to lower copayments in Figure 7 and Figure 8. Patients' sensitivity towards copayment is modeled by β_1 in the adherence function $a(x) = \frac{1}{1+e^{\beta_0+\beta_1 x}}$. When consumers are not sensitive to changes in copayment, there is no point in decreasing copayment since a low copayment will not improve the medication adherence rate. Hence both the VBID model and traditional model give an optimal copayment of 100% and the VBID cost saving is zero. As patients become more sensitive to price change, optimal cost-sharing levels in the VBID model start to decrease first while the traditional insurance model still advocates a 100% optimal cost-sharing level. At this stage, VBID cost savings increase sharply. Then the traditional optimal copayment starts to decrease too and VBID cost savings decreases at the same time.

Conclusions

To the best of our knowledge, our paper is the first to consider Markov Chains in the context of Value-Based Insurance Design. We investigate the optimal coinsurance levels to minimize the total cost from the payer's standpoint in the presence of different risk groups for the statin treatment of heart disease. We find that, while VBID has much potential in theory, its practical gains are highly dependent on accurate estimates of the problem parameters to select coinsurance levels appropriately.

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