Does risk adjustment make risk selection less profitable?

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Abstract

This paper analyzes insurers' incentives for risk selection, when it is costly to obtain information on a potential enrollee's risk type. The effects of a conventional risk adjustment scheme, which compensates for observable differences in expected costs, are considered. Initially, the regulator and the insurer observe the same information, which can be used as a risk adjuster. Risk adjustment causes the insurer to accept consumers with "unfavorable" characteristics, but also to screen out high-risk types within each cost group more aggressively. That is, insurer incentives to acquire information are increasing in the quality of the risk adjustment system. Surprisingly, the welfare effects are ambiguous: while low-risk consumers are always better off under risk adjustment, high-risk individuals may face a higher probability of being "dumped". The results particularly contradict the view that it may be efficient to implement only simple (e.g., age-sex) risk adjustment models.

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1 Introduction

Risk selection belongs to the most heavily debated issues in health economics of the last years. One of the main reasons is that many countries have implemented social health insurance systems which, on the one hand, rely on competition, but, on the other hand, are aimed at treating high- and low-risk individuals equally. To reach this goal, insurers are prohibited from setting differentiated premiums based on consumers' risk categories. This regulation, however, gives incentives for cream skimming, i.e., for direct and indirect risk selection. By direct selection, we understand insurers' attempts to accept only those applicants for whom expected costs are below revenue, based on insurer information. Indirect selection, which is closely related to the phenomenon of adverse selection, implies that the insurer attracts low-risk consumers by rationing some services more than others.

In order to avoid cream skimming, insurers are required to enroll all applicants regardless of their risk type and to offer a regulated benefit package. Further, risk adjustment schemes, whereby premium payments to insurers are adjusted to reflect the expected costs of individual enrollees, have been introduced to reduce potential profits from cream-skimming. Currently, risk adjustment is used in over 20 countries (e.g. Australia, Germany, the Netherlands, Switzerland, Israel and the US). However, there is still concern that insurers will use more subtle tools to select profitable enrollees. In particular, existing risk adjustment models, which can only imperfectly predict future health care use, may not reduce incentives for cream-skimming sufficiently. Empirical studies show that insurers may still make substantial profits if they can exploit private information to select "preferred" risks (Van Vliet, 1992; Shen and Ellis, 2002).

This paper analyzes how risk adjustment changes the incentives for cream-skimming, when it is costly for the insurer to discover the likely treatment costs of a potential enrollee. A central result is that the insurer's incentive to acquire information is increasing in the quality of the risk adjustment scheme. This has interesting implications: On the one hand, risk adjustment causes insurers to accept consumers with "unfavorable" observable characteristics (e.g., elderly people), when these variables are corrected for. On the other hand, insurers will try even harder to screen out high risks within each cost group. The welfare effects are ambiguous: while low-risk consumers always benefit from the introduction of a risk adjustment system (or the refinement of an existing scheme), high-risk individuals may face an even higher probability of being "dumped". Under welfare aspects, this is alarming, because, arguably, risk adjustment is intended to make those individuals in a society who face the highest health risks better off.

The results are derived in a model where a regulator seeks to secure health insurance coverage for a consumer population. Initially, the regulator and the insurer are equally informed, i.e., they can observe a signal on a consumer's risk type. The regulator decides whether the capitation payments to the insurer are adjusted for this signal. At the enrollment stage, the insurer can exert effort to find out a consumer's true risk type. Whether informed or not, the insurer may reject, with some probability, an applicant with whom he would make an expected loss. In practice, insurers may look into patients' medical histories, existing diagnoses, or make detailed investigations of family health histories or local environmental risks. Even if they are not permitted to ask questions related to an applicant's health status, insurers may obtain this type of information through contact with medical providers or insurance agents.

The paper which is most closely related to ours is by Sappington and Lewis (1999). The authors consider the regulatory problem of preventing an insurer from acquiring information in order to practice cream skimming. They also find that it may not be optimal to use all statistical information on a consumers likely treatment costs. However, they consider a regulatory framework where payments are based on the insurer's report on an individual's risk type, rather than a "conventional" risk-adjustment scheme.

In the literature on risk adjustment, insurers' superior information is recognized as a major source of risk selection and resulting inefficiencies.[1] Empirical studies (Newhouse et al., 1989; van Vliet, 1992; Ellis and McGuire, 2006) suggest that at most 20 percent of the variance in individuals' annual health care costs can be predicted by statistical models. This finding is in

[1]That is, apart from adverse selection, which is due to asymmetric information between consumers and insurers. This is analyzed by Glazer and McGuire (2000).

accordance with economic intuition, because there would hardly be a market for health insurance if individual utilization could be predicted with certainty beforehand. However, while some part of individual health care costs will remain subject to purely random variation, insurers may be able to make a better prediction than the regulator. Part of the asymmetric information is due to the fact that some variables which could be used as risk adjusters may not be appropriate to be included in the payment formula.[2]

Previous studies have estimated the profits which a superiorly informed insurer could make by rejecting unprofitable enrollees. Shen and Ellis (2002) use data from a private health insurer to compare potential selection profits under different, currently used risk adjustment models, when the insurer can use alternative information sets to predict individuals' costs. The authors find that although risk adjustment reduces the maximum profits attainable from selection, all current methods still leave substantial gains. Further, the proportion of applicants whom the insurer would like to reject is particularly high under the best-performing adjustment model (the average cost group model). A weakness of this approach is that it does not consider any costs of risk selection.

The rest of the paper is structured as follows. The model is presented in the next section. Section 3 shows the central result that risk adjustment may *increase* insurers' incentives for risk selection. Section 4 considers the introduction of cost-sharing to mitigate the effects of an existing, imperfect risk adjustment system. In section 5, it is demonstrated that the basic result extends to a continuous cost distribution. Finally, section 6 concludes.

[2] Van de Ven and van Vliet (1992) summarize the criteria for a "good" risk adjuster.

2 Model

Three basic kinds of players exist in the model: consumers, a regulator and an insurer. There are two types of consumers: high risk individuals and low risk individuals, indexed by $i = h, l$. Let the proportion of type i be p_i, where $p_h = 1 - p_l$. Consumers differ in the type-specific distribution of health care costs. For our purposes, it is sufficient to distinguish the expected costs of health care over a certain time period. These are denoted by k_i, where $k_h > k_l$.

The regulator cannot observe a consumer's risk type, nor insurer-level costs, but instead only observes a binary signal on an individual's type. If he receives information of the individual being a high risk type, let $s = D$ (for "diagnosis"), otherwise $s = N$. In general, the signal might be anything from a readily observable characteristic (age, sex) to a clinical diagnosis. Here, we assume that s can be initially observed by the insurer as well. If risk adjustment is introduced on an individual basis, this is always the case, since the insurer can observe the payments he receives for a consumer. The signal is positively correlated with the underlying risk type. That is, the probability of facing a high risk type given $s = D$ is higher than if an N - signal were observed: $p_{h|D} > p_{h|N}$. The expected costs conditional on observing $s = D, N$ are denoted by $k_s = p_{h|s}k_h + p_{l|s}k_l$.

Under conventional risk adjustment, the regulator will estimate a model using only the observed signals. Through a transfer system, the insurer will receive, for each insured consumer, the average costs conditional on those signals. To analyze the effects of introducing such a "statistical" risk adjustment system (or of adding a new variable to an existing system), it is assumed that the insurer simply receives an amount k_s. In the case without risk adjustment, the insurer receives the average cost $\overline{k}$.

The insurer exerts an informational effort and subsequently chooses whom he wishes to admit. With probability a, he learns an applicant's true risk type and shuns high risks; with probability $1-a$, he knows only the signal s.[3]

[3]This type of "binary" information acquisition has been introduced by Aghion and Tirole (1997). In the context of risk selection, a similar technology is used by Eggleston (1999).

The variable a can be interpreted as selection effort, which causes a utility cost $f(a)$. The effort cost function $f(a)$ is convex. Risk selection can take place even without full information: if there is no risk adjustment, the insurer will try to avoid all individuals who show a D-signal, i.e., for whom the expected costs are above the average. To keep the model as simple as possible, it is assumed that consumers who cause an expected loss (i.e., D-types or h-types, depending on the insurer's information) can be dumped with an exogenous probability $1-t$, but must be accepted ("treated", in case the insurer is also a provider of medical care) with probability $t \in [0,1)$.

There are two variants:

Assumption 1: The insurer observes s before deciding on his effort level a_s. Thus he will learn the cost type with probability a and will still only observe s with probability $1-a_s$.

Assumption 2: The insurer cannot observe s before choosing an effort level. After his investigations, he will always observe s, but the true cost type can be observed only with probability a.

We define some expressions: $k_s \equiv p_{h|s}k_h + p_{l|s}k_l$ as the expected costs, given the signal. That is, $k_D > k_N$. The average cost is $\overline{k} = p_h k_h + p_l k_l = p_D k_D + p_N k_N$.

3 Information acquisition

3.1 No risk adjustment

The case without risk adjustment will be labelled by OV (for "omitted variable"). Under Assumption 1, the insurer chooses the level of information a_s^{OV} conditional on the observed signal to maximize expected profits. If signal D is observed and no other information is available, the insurer will want to "dump" the individual to avoid expected losses $\overline{k} - k_D$. Thus, he might erroneously reject a low risk individual, which can be avoided under full information. For $s = D$, the insurer's expected profit is

$$a_D^{OV}\left[p_{h|D}\,t(\overline{k} - k_h) + p_{l|D}(\overline{k} - k_l)\right] + (1 - a_D^{OV})\;t(\overline{k} - k_D) - f(a_D^{OV}) \qquad (1)$$

As mentioned, the insurer will still accept a loss-making individual with probability t. If $t = 0$, only low risk individuals and those who show an N-signal (without further information) are accepted. Now, consider the expected profit upon observation of $s = N$:

$$a_N^{OV}\left[p_{h|N}\,t(\overline{k} - k_h) + p_{l|N}(\overline{k} - k_l)\right] + (1 - a_N^{OV})\;(\overline{k} - k_N) - f(a_N^{OV}) \qquad (2)$$

In contrast to the D-type, more information is, on average, detrimental from the consumer's point of view. With probability $a_N^{OV} p_{h|N}$, he will turn out to be a high risk type and may be rejected. We can already understand what drives information acquisition in the OV system. Under incomplete information, risk selection is based on the signal. When fully informed, the insurer can make a more accurate decision, i.e., reject high risk individuals instead of those who *seem* to be high risks. The more these groups overlap, the more likely will his decision be unchanged, and the lower is his incentive to become informed. The intuition becomes more clear when looking at the first-order conditions, which can be written as

$$f'(a_D^{OV}) = p_h p_l \frac{p_{D|l}}{p_D}\,(1-t)(k_h - k_l) \qquad (3)$$

$$f'(a_N^{OV}) = p_l p_h \frac{p_{N|h}}{p_N}\,(1-t)(k_h - k_l) \qquad (4)$$

The incentive to acquire information is increasing in the "dumping probability" $(1-t)$ and in the financial benefit from correcting a wrong decision $(k_h - k_l)$. It is also increasing in the probability that the observed signal would have led to the rejection of a low risk individual $p_{l|D} = \frac{p_l p_{D|l}}{p_D}$, or to the admission of a high risk individual $p_{h|N} = \frac{p_h p_{N|h}}{p_N}$. These events can be defined as type 1 and type 2 error, respectively.[4] Finally, for a given signal distribution, the marginal benefit from information is maximal at $p_h = p_l = \frac{1}{2}$, where the initial uncertainty on the risk type is highest.

The results are similar under Assumption 2. Here, the level of information a^{OV} cannot be conditioned on the signal value. The first-order condition can be obtained by taking the average with respect to the signal distribution (p_D, p_N) of the right hand sides of equations (3) and (4):

$$f'(a^{OV}) = p_h p_l (p_{D|l} + p_{N|h})(1-t)(k_h - k_l) \tag{5}$$

3.2 RA system

Introducing a risk adjustment scheme has the advantage that there will be no more discrimination against $D-$type individuals. In the following, it will be shown that incentives to acquire information are higher under risk adjustment.

Now consider the case with RA based on D.

$$a_D^{RA} \left[p_{h|D}\, t(k_D - k_h) + p_{l|D}(k_D - k_l) \right] - f(a_D^{RA}) \tag{6}$$

It is instructive to compare (6) to the corresponding expression (1) in the case without risk adjustment. The intuition why the level of information acquisition is higher under risk adjustment can be clarified most easily for the case of unrestricted risk selection $(t = 0)$, although the result will continue to hold for all $t < 1$. Without further information, the expected profit from an individual who shows signal D is zero, both in the OV and in the RA system. If the insurer becomes informed, he will accept only the low-

[4]With respect to the null hypothesis that the individual is a low risk type, e.g., a type 1 error implies that the hypothesis is wrongly rejected.

cost types. The benefit from "filtering out" these types is *higher* under risk adjustment, because $k_D - k_l > \overline{k} - k_l$, that is, because the transfer is higher. In conclusion, avoiding a type 1 error is rewarded more in the RA system.

For the N type, the expected profit is

$$a_N^{RA}\left[p_{h|N}\, t(k_N - k_h) + p_{l|N}(k_N - k_l)\right] - f(a_N^{RA}) \tag{7}$$

Again, we can compare this to the maximization problem in the OV system (2) by setting $t = 0$.

Here, the "untypical" consumer has characteristics Nh and will be rejected under full information. If the true type remains undiscovered, the insurer incurs a loss which is higher under risk adjustment than in the OV system, since $(k_N - k_h) < (\overline{k} - k_h)$. That is, the incentive to avoid a type 2 error is also higher in the RA system.

The intuition is confirmed by the first-order conditions:

$$f'(a_D^{RA}) \;=\; p_h p_l \frac{p_{D|h} p_{D|l}}{(p_D)^2}(1-t)(k_h - k_l) \tag{8}$$

$$f'(a_N^{RA}) \;=\; p_h p_l \frac{p_{N|h} p_{N|l}}{(p_N)^2}(1-t)(k_h - k_l) \tag{9}$$

Equation (8) contains the probability of a correct rejection, $p_{h|D} = \frac{p_h p_{D|h}}{(p_D)}$, instead of p_h in the case without risk adjustment. Similarly, equation (9) can be obtained from equation (4) by replacing p_l with the probability of a correct enrollment $p_{l|N} = \frac{p_l p_{N|l}}{p_N}$. Finally, under assumption 2, the first-order condition takes the form

$$f'(a^{RA}) \;=\; p_h p_l \left(\frac{p_{D|l} p_{D|h}}{p_D} + \frac{p_{N|l} p_{N|h}}{p_N}\right)(1-t)(k_h - k_l) \tag{10}$$

The main result of this section can now be stated:

Proposition 1 *For all $t \in [0, 1)$, the insurer becomes informed with a higher probability in the RA system than in the OV system, given his observation $s = D, N, 0$.*

Proof: By comparing the first-order conditions, because $\frac{p_{D|h}}{p_D}, \frac{p_{N|l}}{p_N} > 1$.

Under assumption 1, the level of information is maximal if the probability of a type 1 or type 2 error is equal to $\frac{1}{2}$. In contrast to the OV system, information does not keep increasing with the error probability, because the risk adjustment payments k_s will also depend on these probabilities. E.g., if $p_{l|D}$ moves close to p_l, k_D will be close to $\overline{k}$.

3.3 Welfare comparison

While risk adjustment eliminates selection based on the information used in the payment scheme, it gives the insurer more incentives to obtain unexploited information. Therefore, the probability of "informed" selection will be higher. Clearly, an l-type individual may only be dumped without risk adjustment, if it is wrongly diagnosed. Surprisingly, h-types do not always benefit from the introduction (or improvement) of a risk adjustment system.

At this point, we limit the analysis to a comparison of "dumping rates" and profits from selection. It is not straightforward to tell what the actual objectives of the regulator - and therefore the welfare function - are. The next section will present a more detailed discussion.

Proposition 2 *The low cost type is unambiguously better off under risk adjustment. The high cost individuals prefer the RA system to the OV system under Assumption 1 if*

$$p_{D|h}a_D^{RA} + p_{N|h}a_N^{RA} < p_{D|h} + p_{N|h}a_N^{OV}$$

and under Assumption 2 if

$$a^{RA} < p_{D|h} + p_{N|h}a^{OV}$$

Insurer profits from risk selection may also be higher under risk adjustment. Consider, for instance, the case of assumption 2. We have

$$\begin{aligned}
\pi^{RA} &= a^{RA}p_h p_l \left(\frac{p_{D|l}p_{D|h}}{p_D} + \frac{p_{N|l}p_{N|h}}{p_N}\right)(1-t)(k_h - k_l) - f(a^{RA}) \\
\pi^{OV} &= a^{OV}p_h p_l(1-t)(k_h - k_l)
\end{aligned}$$

$$+(1-a^{OV})p_h p_l(p_{D|h}-p_{D|l})(1-t)(k_h-k_l)-f(a^{OV})$$

If the insurer could become informed at no cost, risk adjustment would always reduce selection profits. It can be shown that

$$\frac{p_{D|l}p_{D|h}}{p_D}+\frac{p_{N|l}p_{N|h}}{p_N}<1$$

This is the standard assumption. If we allow information to be endogenous to the payment system, the comparison becomes ambiguous. A necessary condition for profits to be higher in the RA system is

$$\frac{p_{D|l}p_{D|h}}{p_D}+\frac{p_{N|l}p_{N|h}}{p_N}>p_{D|h}-p_{D|l}$$

which may or may not be the case.

4 Cost-sharing as a supplement to imperfect risk adjustment

In this section, we will abstract from the possibility that risk adjustment may be completely undesirable. Instead, we consider how an imperfect, statistical risk adjustment system can be improved by introducing partial cost reimbursement. In practice, forms of cost-sharing between the insurer and the regulator are often used as an additional way to reduce incentives for risk selection. Whereas risk-adjusted capitation payments can be calculated on a prospective basis and therefore do not, in general, influence efficiency, a trade-off between selection and incentives for cost control now arises. A central result of this section is that cost-reimbursement is less efficiency-reducing than one would generally expect, as long as overpayments for risk-selecting insurers cannot be avoided otherwise.

If, as in our model, the payments to the insurer equal the expected cost for each consumer category, cream-skimming implies that these payments will be higher than actual expenses. One means to reduce insurer profits would be to systematically reduce the payments for each cost group. There are several problems, however. Firstly, as risk selection is hardly verifiable, insurers might not be willing to consent to these rates which seem to be too low, measured by the population average. Secondly, the incentives for risk selection would be further increased in favor of lower insurer profits. Such a trade-off has been considered by Shen and Ellis (2002b).

Cost-sharing has an advantage here. As the regulator retrospectively reimburses a share of the insurer's expenses, the actual risk structure is taken into account. This makes the trade-off between selection and efficiency more favorable, if the selection profits cannot be taken away from the insurer.

4.1 Derivation of the optimal cost-sharing rate

Several modifications to the model are made. Health care costs $c_i(e)$ now depend on the insurer's cost-reduction effort e. This can be interpreted as the insurer's effort to reduce moral hazard by monitoring health care providers, or in negotiating lower prices. Empirically, an impact of e on treatment expenses has been shown to exist and to be greater (in absolute) or equal for high-cost types than for lower cost groups. For simplicity, it is assumed that $c'_h(e) = c'_l(e) \equiv c'(e) < 0$, and $c''(e) \geq 0$. The effort cost is described by the function $g(e)$, which is strictly increasing and convex, that is, $g'(e) > 0$ and $g''(e) < 0$. We assume constant returns to scale with respect to the number of enrolled consumers, i.e., effort costs are determined on a per capita basis. This is another simplification which has only a quantitative effect on results. Effort can be reasonably assumed to be non-contractible, since it seems to be quite hard to specify the "correct" insurer behavior. On the other hand, medical expenses $c_i(e)$ are observable and contractible.

Our analysis is mainly positive in nature. That is, it is not aimed at finding an optimal scheme to avoid risk selection. Instead, we take the characteristics of the payment system as given. We consider a simple linear payment scheme, where the regulator reimburses a share γ of total expenses to the insurer. As before, the risk-adjusted per capita payment covers the insurer's part of the expected health care costs, based on the observed signal. This is denoted by $\alpha_s = (1-\gamma)[p_{h|s}\, c_h(e) + p_{l|s}\, c_l(e)]$. An important assumption is that profits from cannot be taxed away from the insurer. That is, there are no fixed transfers. This is plausible for many situations where the insurer is an independent legal entity.[5] Without this assumption, the role of cost-sharing would be less important, but the general trade-off between selection and efficiency would be similar.

Assuming that $t = 0$ and that a is independent from s (assumption 2), the insurer's profit function reads:

$$\max_{a,e} \pi = a\, p_l \{p_{D|l}\alpha_D + p_{N|l}\alpha_N - (1-\gamma)c_l(e) - g(e)\} \tag{11}$$
$$+(1-a)\, \{p_D\alpha_D + p_N\alpha_N - (1-\gamma)[p_h c_h(e) + p_l c_l(e)] - g(e)\} - f(a) \tag{12}$$

The first order conditions for the choice of a and e are

$$\begin{aligned} \frac{\partial \pi}{\partial a} &= -p_h[p_{D|h}\alpha_D + p_{N|h}\alpha_N - (1-\gamma)c_h(e)] - f'(a) \\ &= p_h p_l \Big(\frac{p_{D|l}p_{D|h}}{p_D} + \frac{p_{N|l}p_{N|h}}{p_N}\Big)(1-\gamma)[c_h(e) - c_l(e)] - f'(a) = 0 \end{aligned} \tag{13}$$

[5] For example, the social health insurers in Germany cannot be forced by law to reduce their contribution rates subsequent to incurring positive profits.

$$\frac{\partial \pi}{\partial e} = -(1-\gamma)c'(e) - g'(e) = 0 \tag{14}$$

Both variables are decreasing in γ. The intuition is straightforward. Equation (13) is similar to its counterpart (10) above. Equation (14) states that the marginal effort cost equals the marginal reduction (in absolute) of treatment expenses, which is multiplied by the insurer's share $(1-\gamma)$.

At the contracting stage, the insurer chooses γ to maximize consumer welfare. As stated above, it is not clear what the objective function should be. In a social health care system with community-rating, it may well be the case that the government weights the utility of high-risk individuals more than for other groups. In our context, this does not play a role, since only the high types' benefit from health insurance, denoted by w_h, influences the optimal cost-sharing rate. The regulator's problem is

$$\begin{aligned}
\max \quad W &= (1-a)p_h(w_h - \lambda\theta_h) + p_l(w_l - \lambda\theta_l) \qquad (15)\\
s.t. \quad \theta_i &= p_{D|i}\,\alpha_D + p_{N|i}\,\alpha_N + \gamma\, c_i(e), \quad i = h, l\\
\alpha_s &= (1-\gamma)[p_{h|s}\,c_h(e) + p_{l|s}\,c_l(e)], \quad s = D, N\\
\pi &\geq 0\\
&\text{and subject to (13) and (14)}
\end{aligned}$$

where the parameter $\lambda \geq 1$ may reflect a distortionary cost of public funds. The first-order condition takes the form

$$\frac{dW}{d\gamma} = \frac{\partial W}{\partial \gamma} + \frac{\partial W}{\partial a}\frac{da}{d\gamma} + \frac{\partial W}{\partial e}\frac{de}{d\gamma} = 0 \tag{16}$$

In equilibrium, γ will be strictly positive, since it is efficient to distort the effort e away from its first best level, such that cream-skimming a will be also reduced. It can be shown that

$$\frac{\partial W}{\partial \gamma} = \lambda a p_h p_l \left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N} \right) [c_h(e) - c_l(e)]$$

A marginally higher γ increases welfare by the amount of the selection benefit.

5 The continuous case

The example that has been considered so far is quite stylized. Firstly, it has been assumed that there are only two possible risk adjustment groups which differ in the proportion of the underlying cost types. Secondly, the insurer has been able to become perfectly informed on an individual's type. In this section, these restrictions are removed. Instead, we consider a continuous cost distribution, whereby both the insurer and the regulator can use regression models to predict costs. The central result that risk adjustment leads to more information gathering by the insurer remains unchanged. Welfare results, while still ambiguous, turn out to depend on the concrete risk adjustment method and data.

Regression versus cell-based approach

In current practice, most countries do not use the results of a regression analysis to calculate risk-adjusted capitation payments. Cell-based (categorical) approaches, where insureds are assigned to distinct cost groups or "cells", based on the risk adjusters (e.g., 0-10 year-old females, 11-20 year-old males etc.), are far more common. While this method is relatively simple, it has several disadvantages. Among other aspects, the number of observations per cell may become unacceptably low, particularly if many risk adjusters are to be added. This may result in overidentification of the model and inappropriate incentives for cost efficiency, because if individual observations substantially affect average costs in a cell, the insurer's expenses will be virtually fully reimbursed. In contrast, the regression approach generally allows to include more variables.

For the theoretical analysis, it seems most appropriate to consider a regression model due to its generality. Also, it can be shown that the results are not specific to a categorical approach. The following analysis draws on Newhouse et al. (1989) and van Barneveld et al. (2000), whose model is applied to our framework of endogenous information.

5.1 The model

Suppose that both the regulator and the insurer can observe a vector of individual consumer characteristics X_{1i}, which may be used in the risk adjustment formula. Similarly as before, the insurer can expend effort to observe additional variables X_{2i}. For simplicity, the effort a is assumed to be chosen independently from X_{1i} (assumption 2). As our focus is on average profits from risk selection, the index i can be suppressed from now on. The following cost predictions can be calculated, given the available information:

$$\log C = X_1\beta_1 + \epsilon_1 \tag{17}$$
$$\log C = X_1\beta_1 + X_2\beta_2 + \epsilon_2 \tag{18}$$

Health care costs C are lognormally distributed. The error terms ϵ_1 and ϵ_2 are normally distributed with mean zero. The vectors X_1 and X_2 are assumed to be orthogonal, implying that they are uncorrelated. The terms $X_1\beta_1$ and $X_2\beta_2$ have means μ_1 and μ_2 and standard deviations σ_1 and σ_2, respectively. Further, let $\sigma^2 = \sigma_1^2 + \sigma_2^2 + \sigma_3^2$ denote the total variance of $\log C$, where σ_3^2 is the variance of the error term ϵ_2 (thus, $\mathrm{Var}[\epsilon_1] = \sigma_2^2 + \sigma_3^2$).

Based on the properties of lognormal distributions, the unconditional expectation of average health care expenditures equals

$$E(C) = e^{\mu_1 + \mu_2 + \frac{1}{2}\sigma^2} \tag{19}$$

That is, if there is no risk adjustment, the insurer will receive a capitation payment based on (19) for every enrolled consumer. For an individual with characteristics X_1 and X_2, the risk-adjusted capitation payment and the prediction by the superiorly informed insurer are given by equations (20) and (21), respectively:

$$E(C|X_1) = e^{X_1\beta_1 + \mu_2 + \frac{1}{2}(\sigma_2^2 + \sigma_3^2)} \tag{20}$$
$$E(C|X_1, X_2) = e^{X_1\beta_1 + X_2\beta_2 + \frac{1}{2}\sigma_3^2} \tag{21}$$

Comparing these two expressions, the insurer expects an individual to be "profitable" if $X_2\beta_2 < \mu_2 + \frac{1}{2}\sigma_2^2$ or

$$\frac{X_2\beta_2 - \mu_2}{\sigma_2} < \frac{\sigma_2}{2} \tag{22}$$

where the term on the left hand side follows the standard normal distribution, denoted by $\Phi(\cdot)$. Assuming that dumping is always possible, $t = 0$, the probability that a consumer is rejected equals $1 - \Phi(\sigma_2/2)$ in the considered case. Obviously, it is decreasing in σ_2.

This example illustrates an important property of the model: dumping probabilities as well as expected profits from risk selection can be directly linked to the additional variance explainable by the insurer.[6] Such a unique relationship may not exist in reality, of course. In particular, the assumption of normally distributed error terms may be violated. However, the analysis below gives first evidence on how currently used risk adjustment schemes might perform, given their R^2-value.

5.2 Results

Again, we want to answer the question whether risk adjustment based on X_1 is always advantageous, or under which conditions it is more efficient not to use this information. Consider the RA system first. With probability $1 - a$, regulator and insurer are equally informed, such that there will be no gains from risk selection. If the insurer learns X_2, the share of accepted individuals is $\Phi(\sigma_2/2)$, as stated above. This has to be multiplied by the expected profit per consumer, conditional on enrollment, which equals $E(C)\left[1 - \frac{1-\Phi(\sigma_2/2)}{\Phi(\sigma_2/2)}\right]$. Consequently, the first-order condition for information acquisition reads

$$f'(a^{RA}) = E(C)[2\Phi(\sigma_2/2) - 1] \tag{23}$$

In the OV system, the insurer can practice risk selection based on X_1 even without further information. Additional information X_2 can be used to make "finer" selection. Intuitively, the difference in profits, which appears

[6]This can also be expressed in terms of the coefficients of determination of regression equations (20) and (21), since $\sigma_2^2/\sigma^2 = R^2_{Ins} - R^2_{Reg}$.

on the right hand side of the first order condition (24), is not as high as in the RA system.

$$f'(a^{OV}) = E(C)\left\{\left[2\Phi\left(\sqrt{\sigma_1^2+\sigma_2^2}/2\right)-1\right]-\left[2\Phi(\sigma_1/2)-1\right]\right\} \tag{24}$$

Comparing equations (23) and (24) yields the following statement, which is proven in the appendix.

Remark 1 *In the model where health care costs are continuously distributed and cost estimates are regression-based, the insurer gets informed with a higher probability under risk adjustment, $a^{RA} \geq a^{OV}$.*

A less general feature of the model is that the rejection probability depends on the insurer's informational advantage in a specific way. Given that X_2 can be observed, the share of "dumped" consumers is higher under risk adjustment than in the OV system. In the latter case, as there is only one "cost group", within-group variability is high. The lognormal distribution then implies that relatively few individuals will have above average costs from the insurer's point of view. This biases the results somewhat against risk adjustment, which might become undesirable in terms of rejection rates even without the effect caused by endogenous information.[7]

To avoid this effect, it is somewhat more instructive to consider profits. Here, the result from section 3 can be easily confirmed.

Remark 2 *In the "continuous" model, a necessary but not sufficient condition for profits from risk selection to be higher in the RA system than in the OV system is $\sigma_2 > \sigma_1$.*

[7]This has been shown by Shen and Ellis (2002).

6 Conclusion

In practice, it is well known that risk adjustment systems are highly imperfect. Empirical studies leave doubt whether these systems can reduce selection sufficiently. This argument could be strengthened theoretically. Of course, the results are based on the assumption of costly information acquisition. While it seems plausible that some information on new enrollees is only costly to obtain, it is not clear how important the effect is in reality. Other types of selection costs do matter as well. However, even if the result that risk adjustment can create more cream-skimming may be somewhat extreme, the model shows that its benefits should be further questions. It would also be possible to test the performance of current risk adjustment schemes on the basis of our results. This is left for further research.

Another aspect that has not been mentioned yet concerns the observability of information. Within the context of our model, it can be shown that the RA-system always performs better than the OV-system, if the signal is *not* known to the insurer initially. This implies that it is not harmful to publish new information as part of the risk adjustment process. As a consequence, simple schemes based on observable information (e.g. age and gender) should be regarded more critically than more advanced, e.g. diagnosis-based schemes.

Appendix

Information acquisition under Assumption 1

$$\begin{aligned}
f'(a_D^{OV}) &= tp_{h|D}(\overline{k}-k_h)+p_{l|D}(\overline{k}-k_l)-t(\overline{k}-k_D)\\
&= (1-t)p_{l|D}\overline{k}+t(p_{h|D}k_h+p_{l|D}k_l)-tp_{h|D}k_h-p_{l|D}k_l\\
&= (1-t)p_{l|D}(\overline{k}-k_l)=(1-t)p_hp_{l|D}(k_h-k_l),\\
f'(a_D^{RA}) &= tp_{h|D}(k_D-k_h)+p_{l|D}(k_D-k_l)\\
&= tp_{h|D}p_{l|D}(k_l-k_h)+p_{l|D}p_{h|D}(k_h-k_l)\\
&= (1-t)p_{h|D}p_{l|D}(k_h-k_l)\\
f'(a_N^{OV}) &= tp_{h|N}(\overline{k}-k_h)+p_{l|N}(\overline{k}-k_l)-(\overline{k}-k_N)\\
&= tp_{h|N}p_l(k_l-k_h)+p_{l|N}p_h(k_h-k_l)\\
&\quad -[(p_h-p_{h|N})k_h+(p_l-p_{l|N})k_l]\\
&= (k_h-k_l)[p_hp_{l|N}-tp_{h|N}p_l-(p_h-p_{h|N})]\\
&= (1-t)p_{h|N}p_l(k_h-k_l)\\
f'(a_N^{RA}) &= tp_{h|N}(k_N-k_h)+p_{l|N}(k_N-k_l)\\
&= (1-t)p_{h|N}p_{l|N}(k_h-k_l)
\end{aligned}$$

Information acquisition under Assumption 2

$$a^{OV}[p_ht(\overline{k}-k_h)+p_l(\overline{k}-k_l)]+(1-e^{OV})[tp_D(\overline{k}-k_D)+p_N(\overline{k}-k_N)]-f(a^{OV}) \quad (25)$$

$$f'(a^{OV})=[\underbrace{p_ht(\overline{k}-k_h)+p_l(\overline{k}-k_l)}_{\equiv A_1}]-[\underbrace{p_Dt(\overline{k}-k_D)+p_N(\overline{k}-k_N)}_{\equiv A_2}]$$

Rearranging, using Bayes' Rule, yields:

$$\begin{aligned}
A_1 &= tp_h(p_hk_h+p_lk_l-k_h)+p_l(p_hk_h+p_lk_l-k_l)\\
&= tp_hp_l(k_l-k_h)+p_lp_h(k_h-k_l)\\
&= (1-t)p_hp_l(k_h-k_l)\\
A_2 &= tp_D[(p_h-p_{h|D})k_h+(p_l-p_{l|D})k_l]\\
&\quad +p_N[(p_h-p_{h|N})k_h+(p_l-p_{l|N})k_l]
\end{aligned}$$

$$
\begin{aligned}
&= (k_h - k_l)[tp_D(p_h - p_{h|D}) + p_N(p_h - p_{h|N})] \\
&= (k_h - k_l)\left[tp_D\left(p_h - \frac{p_h p_{D|h}}{p_D}\right) + p_N\left(p_h - \frac{p_h p_{N|h}}{p_N}\right)\right] \\
&= (1-t)p_h(p_{D|h} - p_D)(k_h - k_l) \\
&= (1-t)p_h p_l(p_{D|h} - p_{D|l})(k_h - k_l)
\end{aligned}
$$

Using the fact that $1 - p_{D|h} = p_{N|h}$, we directly obtain equation (**??**). In the case with risk-adjustment, the first-order condition is

$$
\begin{aligned}
a^{RA} \quad & \Big\{tp_h[p_{D|h}k_D + (1-p_{D|h})k_N - k_h] \\
& +(1-p_h)[p_{D|l}k_D + (1-p_{D|l})k_N - k_l]\Big\} - f(a^{RA})
\end{aligned}
$$

$$
f'(a^{RA}) = tp_h\underbrace{[p_{D|h}k_D + (1-p_{D|h})k_N - k_h]}_{A_3} + p_l\underbrace{[p_{D|l}k_D + (1-p_{D|l})k_N - k_l]}_{A_4}
$$

Rearranging, using Bayes' rule:

$$
\begin{aligned}
A_3 &= p_{D|h}(p_{h|D}k_h + p_{l|D}k_l) + p_{N|h}(p_{h|N}k_h + p_{l|N}k_l) - p_{D|h}k_h - p_{N|h}k_h \\
&= p_{D|h}[p_{l|D}(k_l - k_h)] + p_{N|h}[p_{l|N}(k_l - k_h)] \\
&= (k_l - k_h)p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)
\end{aligned}
$$

$$
\begin{aligned}
A_4 &= p_{D|l}[p_{h|D}k_h + p_{l|D}k_l - k_l] + p_{N|l}[p_{h|N}k_h + p_{l|N}k_l - k_l] \\
&= (k_h - k_l)(p_{D|l}\ p_{h|D} + p_{N|l}\ p_{h|N}) \\
&= (k_h - k_l)\ p_h\left(\frac{p_{D|l}p_{D|h}}{p_D} + \frac{p_{N|l}p_{N|h}}{p_N}\right)
\end{aligned}
$$

Substituting A_3 and A_4 in the above FOC yields equation (10).
QED

Appendix to Section 4

$$
\begin{aligned}
&p_{D|h}\alpha_D + p_{N|h}\alpha_N \\
&\quad = (1-\gamma)[p_{D|h}(p_{h|D}c_h(e) + p_{l|D}c_l(e)) + p_{N|h}(p_{h|N}c_h(e) + p_{l|N}c_l(e))] \\
&\quad = (1-\gamma)\left[p_h\left(\frac{p_{D|h}^2}{p_D} + \frac{p_{N|h}^2}{p_N}\right)c_h(e) + p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)c_l(e)\right] \\
&\quad \equiv (1-\gamma)\hat{c}_h(e)
\end{aligned}
$$

$$
\begin{aligned}
&p_{D|l}\alpha_D + p_{N|l}\alpha_N \\
&\quad = (1-\gamma)\left[p_h\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)c_h(e) + p_l\left(\frac{p_{D|l}^2}{p_D} + \frac{p_{N|l}^2}{p_N}\right)c_l(e)\right] \\
&\quad \equiv (1-\gamma)\hat{c}_l(e)
\end{aligned}
$$

$$
\begin{aligned}
\frac{da}{d\gamma} &= \frac{\partial a}{\partial \gamma} = -\frac{1}{f''(a)}\, p_h p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)[c_h(e) - c_l(e)] \\
\frac{de}{d\gamma} &= \frac{\partial e}{\partial \gamma} = \frac{c'(e)}{(1-\gamma)c''(e) + g''(e)}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial W}{\partial \gamma} &= -\lambda(1-a)p_h[c_h(e) - \hat{c}_h(e)] - \lambda p_l[c_l(e) - \hat{c}_l(e)] \\
&= -\lambda(1-a)p_h\left[\left(1 - \frac{p_h p_{D|h}^2}{p_D} - \frac{p_h p_{N|h}^2}{p_N}\right)c_h(e) - p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)c_l(e)\right] \\
&\quad -\lambda p_l\left[\left(1 - \frac{p_l p_{D|l}^2}{p_D} - \frac{p_l p_{N|l}^2}{p_N}\right)c_l(e) - p_h\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)c_h(e)\right] \\
&= -\lambda(1-a)p_h p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)[c_h(e) - c_l(e)] \\
&\quad -\lambda p_h p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)[c_l(e) - c_h(e)] \\
&= \lambda a p_h p_l\left(\frac{p_{D|h}p_{D|l}}{p_D} + \frac{p_{N|h}p_{N|l}}{p_N}\right)[c_h(e) - c_l(e)] \\
\frac{\partial W}{\partial a} &= -p_h w_h + p_h\lambda\left[(1-\gamma)\hat{c}_h(e) + \gamma c_h(e)\right]
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial W}{\partial e} &= -\lambda(1-a)p_h\left(\gamma c_h'(e) + (1-\gamma)\sum_s p_{s|h}\left[p_{h|s}c_h'(e) + p_{l|s}c_l'(e)\right]\right)\\
&\quad -\lambda p_l\left(\gamma c_l'(e) + (1-\gamma)\sum_s p_{s|l}[p_{h|s}c_h'(e) + p_{l|s}c_l'(e)]\right)\\
&= -\lambda(1-ap_h)\, c'(e)
\end{aligned}
$$

It can be shown that the problem becomes very tractable, e.g., when assuming quadratic effort costs.

Insurer profits in the continuous case

$$
\begin{aligned}
&E\left[e^{X_1\beta_1 + X_2\beta_2 + \frac{1}{2}\sigma_3^2} | \, (X_2\beta_2 - \mu_2)/\sigma_2 < \sigma_2/2\right]\\
&= e^{\mu_1 + \frac{1}{2}(\sigma_1^2+\sigma_3^2)}\, E\left[e^{X_2\beta_2} | \, (X_2\beta_2 - \mu_2)/\sigma_2 < \sigma_2/2\right]\\
&= e^{\mu_1 + \frac{1}{2}(\sigma_1^2+\sigma_3^2)}\, e^{\mu_2 + \frac{1}{2}\sigma_2^2}\,\frac{1-\Phi(\sigma_2/2)}{\Phi(\sigma_2/2)}\\
&= E(C)\frac{1-\Phi(\sigma_2/2)}{\Phi(\sigma_2/2)}
\end{aligned}
$$

Proof that $a^{RA} \geq a^{OV}$ in the continuous case

The first-order conditions are

$$
\begin{aligned}
f'(a^{RA}) &= E(C)[2\Phi\left(\sigma_2/2\right) - 1]\\
f'(a^{OV}) &= E(C)\left[2\Phi\left(\sqrt{\sigma_1^2+\sigma_2^2}/2\right) - 2\Phi\left(\sigma_1/2\right)\right]
\end{aligned}
$$

Convexity of the effort cost function implies that $a^{RA} \geq a^{OV}$ if

$$
\Phi\left(\sigma_1/2\right) + \Phi\left(\sigma_2/2\right) \geq \Phi\left(\sqrt{\sigma_1^2+\sigma_2^2}/2\right) + \underbrace{\Phi(0)}_{1/2}
$$

We use the fact that $\sqrt{\sigma_1^2+\sigma_2^2} \leq \sigma_1 + \sigma_2$. It is sufficient to show that the left hand side of the inequality is greater or equal than $\Phi\left[(\sigma_1+\sigma_2)/2\right] + \Phi(0)$.

Let $x = \frac{1}{2}\,\sigma_1$, $y = \frac{1}{2}\,\sigma_2$. It can be demonstrated for all $x, y \geq 0$ that

$$\Phi(x) + \Phi(y) \geq \Phi(x+y) + \Phi(0)$$

or, written out:

$$\int_{-\infty}^{x} \frac{e^{-\frac{1}{2}\,u^2}}{\sqrt{2\pi}}\,du + \int_{-\infty}^{y} \dots \geq \int_{-\infty}^{x+y} \dots + \int_{-\infty}^{0} \dots$$

Splitting up the integrals yields

$$\int_{-\infty}^{x} \dots + \int_{-\infty}^{0} \dots + \int_{0}^{y} \dots \geq \int_{-\infty}^{x} \dots + \int_{x}^{x+y} \dots + \int_{-\infty}^{0} \dots$$

which reduces to

$$\int_{0}^{y} \dots \geq \int_{x}^{x+y} \dots$$

This is true because the density function $\frac{1}{\sqrt{2\pi}}\,e^{-\frac{1}{2}\,u^2}$ is strictly decreasing for $u > 0$, and holds with equality if $x = 0$ or $y = 0$.

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