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Risk selection and matching in performance-based contracting

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Summary

This paper examines selection and matching incentives of performance-based contracting (PBC) in a model of patient heterogeneity, provider horizontal differentiation and asymmetric information. Treatment effectiveness is affected by the match between a patient's illness severity and a provider's treatment intensity. Before PBC, a provider's revenue is unrelated to treatment effectiveness; therefore, providers supply treatments even if their treatment intensities do not match with the patients' severities. Under PBC, budget allocation is positively related to treatment performance; patient–provider mismatch is reduced because patients are referred more often. Using data from the state of Maine, we show that PBC leads to more referrals and better match between illness severity and treatment intensity. Moreover, we find that PBC has a positive but insignificant effect on dumping. Copyright © 2002 John Wiley & Sons, Ltd.

Keywords incentive contract; performance-based contracting; risk selection; referral; matching; dumping

Introduction

Health insurance covers consumers' financial risks due to illness. Because health status is difficult to verify, second-best insurance contracts fully or partially pay for the consumers' cost of medical treatments. A payment contract between insurer and health care providers determines how treatment costs are reimbursed. Incentive properties of common payment contracts such as cost reimbursement, prospective payment, and capitation have been studied extensively [1–5]. While earlier researchers have concentrated on cost and quality incentives, the potential problem of risk selection is now also regarded as a major issue [6]. Risk selection refers to a provider's incentive to discriminate against consumers who are costly to treat. Dumping of patients, offering expensive patients less desirable care, and limiting amount of care to severely ill patients are consequences of discrimination and selection.

The theoretical and empirical literature in health economics have addressed selection issues [2–14]. It is well recognized that unless the entire cost of treatment is paid for by insurers, providers always have some incentive to serve only less expensive patients. The empirical literature contains evidence of risk selection by health maintenance organizations (HMOs) and hospitals. Many studies have found that health care providers are able to attract or retain good risks. In sum, selection incentives of payment system are critically important for efficient delivery of health services.

In this paper, we study the risk selection properties of performance-based contracting, a recent payment contract innovation. As part of the movement to achieve quality assurance (as advocated by organizations such as the National Committee for Quality Assurance [15,16]),

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performance-based contracting (PBC) adds a new dimension to payment contracts. In its most common form, PBC defines a base compensation and allows an opportunity for additional compensation based on measures of quality of care and treatment outcomes. In the health care industry, performance-based contracts have been implemented and tested by various state governments and managed care organizations. For example, the state of Maine introduced PBC in its contracting with publicly funded substance abuse treatment providers in 1992 [17]. The New Jersey Division of Mental Health and Hospitals started using a Performance Management System to monitor and contract for community mental health services [18]. Beginning from 1987, US Healthcare, a managed care organization, also used and developed the concept of quality-based compensation model for its participating primary care physicians [19,20]. In 1988, the Texas Department of Health initiated a performance-based objectives project to tie contract funds to local health departments to performance measures [21]. Illinois initiated a Quality Incentive Program (QUIP) in its nursing home reimbursement system in 1985 [22].

Performance-based contracting is a familiar concept: the industrial organization literature contains numerous models [23–26]. Generally, problems due to asymmetric information between an agent and a principal are mitigated when contracts based on outcomes can be written to align the agent's incentives. Several empirical studies have presented evidence that quality of care increases when physician income is tied to productivity [27–29]. Nevertheless, what will PBC do to risk selection in the health market? One might be worried that PBC might actually *exacerbate* the risk selection problem. If PBC penalized providers that consistently performed poorly, would PBC lead to more severe adverse selection [17]? By selectively serving patients who are more likely to respond positively from treatment, and therefore implicitly rejecting those who are unlikely to improve, might a provider be able to increase its profits? On the other hand, a provider might be motivated to perform better if rewards were based on outcomes. Which argument tends to be more valid?

We construct a model to study the selection effect of performance-based contracting. The balance of the two effects just discussed will be analyzed in the model, and we subject the model to empirical tests to see which factor is more important. Whereas earlier discussions on selection have considered the unilateral decision of a provider to turn away a patient – a phenomenon called 'dumping' [8] – our model considers the interaction among providers. First, we explicitly model the *referral* of patients among providers. Dumping then becomes a special case in which a patient is sequentially referred from one provider to the next without being treated. Second, we use a *matching* model to address selection issues. Illness severities and treatment intensities vary. Formally, each provider offers a differentiated product and each consumer benefits differently from a provider's product depending on his characteristics. These characteristics represent how well consumers will respond to a given treatment. For example, in the substance abuse and mental health treatments, some patients may respond better with talk therapy while intensive inpatient treatment with therapeutic drugs will be more suitable for others.

In our model, initially providers and patients are matched randomly. Upon seeing a patient, a provider learns the patient's characteristic, and then must decide whether to treat the patient or refer the patient to another provider. The referral decision is key to how PBC encourages providers to make better use of their private information about patient characteristics. Indeed, treatment following random matching implies a high degree of mismatch. Without any mechanism to reward good treatment outcomes, referral by a provider to another is only motivated by a provider's altruistic consideration towards a patient's welfare. PBC, on the other hand, directly relates the financial incentives to treatment decisions and referrals. We show that PBC can raise a provider's degree of altruism: more referrals under PBC are expected in equilibrium. Moreover, the referrals should be associated with better treatment matches between patients and providers. Better referrals also imply less dumping.

The novelty of our account of the impact of PBC stems from the analysis of better matching between providers and clients through referrals. The usual discussion of risk selection concentrates on its adverse side, and dumping has been regarded as a *final* decision by a provider. In practice, a provider may have to refer a patient to another provider when he decides not to supply care. So referrals and dumping may seem to be very hard to distinguish. Must PBC encourage referrals that are in fact dumping? Will PBC encourage referrals that are medically necessary and appropriate? We address these questions with our model, and our empirical analysis attempts to answer them.

The study setting for the empirical study is the state of Maine's PBC system for its publicly funded substance abuse treatment services. Examining the clinicians' referral practice using a logistic regression, we find that PBC causes the providers to increase referrals. Next, we test the distributions of clients with different drug abuse severities among different treatment programs before and after the introduction of PBC. Under PBC clients with high severity of drug abuse are more likely treated in more intensive programs; conversely, clients with low severity of drug abuse are more likely treated in less intensive programs. This is consistent with the hypothesis that PBC results in better match between client groups and providers. This result remains robust in various sensitivity analyses. We then examine dumping of clients by following the treatment history of a client after he is referred. Dumping is not found to be worsen by PBC.

The rest of the paper is organized as follows. The next two sections describe the study setting and present a theoretical model of matching and referral, respectively. The data, empirical implementations and findings are next presented. Finally, some conclusions are drawn and future work is discussed.

Study setting: Maine's performance-based contracting in substance abuse treatment

In Maine, state contracts account for about 40% of private substance abuse treatment providers' revenues. In the 1980s, the state's allocations to providers were based on historical funding levels, with yearly changes being spread evenly across providers according to changes in state and federal appropriations. In October 1989, the Maine addiction treatment system (MATS) was launched. MATS collects standardized information on providers and admission and discharge data on their performances; any provider receiving federal and state funds must comply [30]. Information is collected when a client is admitted (or readmitted) into and leaves a program; if a client fails to complete a course of treatment, the information reported to MATS is based on the last treatment contact.

On 1 July 1992, the state of Maine introduced PBC as a practical incentive system. PBC has also been promoted by the Institute of Medicine [31]. Under PBC 'allocation of resources for the contract year may be affected by provider performance in the previous year' [17]. PBC uses a *subset* of MATS information to evaluate provider performances under three categories: efficiency, effectiveness, and special populations. Efficiency specifies units of treatment delivered in the contract year. Effectiveness measures changes in client addiction status and social functioning between admission and discharge. PBC uses more than ten effectiveness measures: drug use frequency, employment and employability, criminal involvement, reduction in problems with family or employers, etc. Special populations deals with service delivery to target populations (women, adolescents, the elderly, and poly drug and IV drug users).

There are many types of substance abuse treatment programs in Maine. These 'modalities' include residential rehabilitation, non-residential rehabilitation, halfway house, extended shelter, evaluation, outpatient, extended care, and others. Table 1 presents definitions of these treatment modalities (source: Maine Addiction Treatment System Instruction Manual, Office of Substance Abuse, 1995). PBC defines different numbers of indicators and performance standards for different modalities [30]. A treatment program is said to 'meet overall standard' if it meets minimum performance standards in each of the efficiency, effectiveness and special populations categories.

Although PBC seeks to raise efficiency, its unintended incentives to providers may lead to perverse effects. Providers may achieve a better treatment performance simply by admitting only less severely ill clients – a selection strategy. Clients with severe substance abuse problems may be dumped. Shen (Selection incentives in a performance-based contracting system, unpublished manuscript, Boston University, 1998) assessed this provider strategy by simulating the degree of selection in outpatient programs under PBC. It was estimated that on average 11% of the uninsured indigent clients were rejected by the outpatient treatment programs. Shen concluded that PBC caused adverse selections. However, Shen only examined selection of patient severity

Table 1. Services (Modality) definitions

Residential rehabilitation. Provides recovery through a 'therapeutic community' model which emphasizes personal growth through family and group support and interaction. Therapy focuses on attitudes, skills, and habits, conductive to facilitating the recipient's transition back to the family and community.
Non-residential rehabilitation. A component which provides an intensive and structured program of substance abuse evaluation, diagnosis and treatment services in a setting which does not include an overnight stay.
Halfway house. A community-based, peer-oriented residential program that provides treatment and supportive services in a chemical free environment for persons involved in a recovery process. Programs are varied in character each designed to relate to the target group served, taking into consideration the needs of the individual. The Halfway House shall address the cultural, social, and vocational needs of the clients it serves. In any instance, the program will provide transitional assistance in bridging the gap between substance abuse and society.
Extended shelter. A component which provides a structured therapeutic environment for clients who have completed a detoxification program, and who need a social support system in order to provide continuity of treatment of substance abuse problem, and/or to enable the client to develop an appropriate supportive environment in order to maintain sobriety and to develop linkages with community services.
Evaluation. Systematic clinical process intended to determine the status of a clients' substance use/abuse. To then access his/her need for treatment is indicated to outline the modality of treatment. The term 'diagnosis' refers to medical diagnosis, and 'evaluation' to educational, social, psychological, etc., evaluations performed by licenses/recognized individuals within the profession.
Extended care. A component which provides a long-term supportive environment for final-stage substance abusers. The extended care component requires sustained abstinence and provides minimal treatment and ongoing living experience within the facility/program or re-entry into the treatment system. The term of residency is usually in excess of 180 days.
Outpatient. A component which may provide assessment, evaluation, diagnosis, treatment, and aftercare services in a non-residential setting. These services may also be provided to the families of substance abusers and other concerned persons, whether or not the abuser is receiving treatment.

in outpatient programs; she did not tract patients' treatment careers. In fact, some of the indigent clients were referred to and treated in more intensive treatment programs, such as residential rehabilitation. These clients have been matched with more suitable programs, and should not be considered as being dumped from the system. In this paper, we propose a matching model and track patients' treatment processes. As a result, we are able to offer a broader perspective on selection than Shen.

Commons *et al.* [30] asked whether PBC had improved quality of care in Maine by aggregating treatment outcome indicators used by PBC at the provider level. It was found that PBC effectiveness measures improved after PBC was implemented. They acknowledged, however, that PBC might encourage providers simply to *report* a better outcome. This is called provider 'gaming' by Lu [32], who re-examined the performance impact of PBC with client-level data. A structural evaluation model was employed to include more than one outcome measure. The key variable in Lu [32] was a relapse measure constructed from MATS data. Relapse was not included in Maine's PBC as a performance standard, and therefore a measure not subject to gaming. Including the relapse measure and all PBC outcome measures in the structural evaluation model, Lu [32] was unable to find evidence to support the hypothesis that PBC improved treatment outcomes. This suggests that gaming may exist after PBC was implemented. Our paper is a continuing effort to investigate the impacts of PBC. We study referral patterns and the distribution of client illness severity among programs, which are not included in PBC performance assessments, and hence not subject to gaming.

A model of matching and referral

We now present a model of referral of patients by providers. We describe consumers preferences, the treatment, and then the referral process. Next, we consider two incentive regimes: the first is a fixed-price payment mechanism while the second allows payment to be made contingent on treatment outcomes; these correspond to the two regimes before and after PBC.

To make our analysis tractable, we employ a model of product differentiation in the Hotelling class. There is a continuum of consumers, each demanding one unit of health care service from one of two providers. A consumer is characterized by a parameter, t, which follows the uniform distribution on $[0, 1]$. Providers 1 and 2 are located at $t = 0$ and 1, respectively. Although each consumer may benefit from treatment from either one of the two providers, the magnitude of the benefit depends on the parameter t, which captures the mismatch between a consumer and providers. Equivalently, each consumer may respond differently according to providers' practice styles. Precisely, let $U_j(t)$ be the utility of a patient with parameter t if he receives treatment from provider j, $t \in [0, 1]$, and $j = 1, 2$. Then

$$U_1(t) = V - t, \qquad U_2(t) = V - (1 - t)$$

where V is sufficiently big so that the patient will want to obtain some treatment. If a patient is untreated, his utility is zero.

A consumer only knows that his characteristic parameter t comes from the uniform distribution, not its actual value. After the patient meets with a provider, the provider finds out the patient's parameter t. This becomes the provider's private information. In other words, upon an initial meeting with a patient, the provider knows how well the patient will respond to his treatment; the patient and the social planner do not.

A provider who has assessed the patient's characteristic may decide to provide treatment, or refer the patient to another provider. For simplicity, we assume that the patient is passive, and follows the provider's advice. The providers' marginal costs of service for a patient are constant (independent of t) and identical; let this cost be c.

We now describe the incentive systems under which the providers operate; then we define their preferences. We consider two incentive mechanisms. The first is a fixed-price mechanism: a provider is paid a fixed amount, say a, when treatment is given to a patient. This corresponds to the original regime in the Maine substance abuse treatment system. Under the fixed-price mechanism, the per-patient profit for a provider is $a - c$.

The second is a performance-based mechanism. This corresponds to the Maine PBC system. Here, the outcome of the treatment is assumed to be verifiable information; for simplicity, we assume that the actual utility level of a patient is used to determine the payment. Recall that when provider j treats a patient with parameter t, the patient's utility is $U_j(t)$. We assume a linear payment scheme, so provider j's payment is $\alpha + \beta U_j(t)$, and his profit for treating a patient with parameter t is $\pi_j(t) = \alpha + \beta U_j(t) - c$. (We assume that the providers are reimbursed based on treatment performance on each individual client. In practice, however, the most common form of PBC payment is usually based on overall performance of the treatment population. An earlier version of the paper contained an analysis of PBC that was based on the average utility of the treatment population.)

Providers are altruistic, their preferences being convex combinations of profits and patients' utilities. Under the fixed-price contracting regime, utilities for Providers 1 and 2 from treating a patient with parameter t are, respectively,

$$\begin{aligned} &\gamma(V - t) + (1 - \gamma)(a - c), \\ &\gamma(V - 1 + t) + (1 - \gamma)(a - c) \end{aligned} \qquad (1)$$

where γ, $0 < \gamma < 1$, is the weight on patient utility. Under the performance-based mechanism, the corresponding utilities are

$$\begin{aligned} &\gamma(V - t) + (1 - \gamma)[\alpha + \beta(V - t) - c], \\ &\gamma(V - 1 + t) + (1 - \gamma)[\alpha + \beta(V - 1 + t) - c] \end{aligned} \qquad (2)$$

A referral is defined as a transfer of a patient from one provider to another. When a patient seeks treatment from a provider, say Provider 1, his parameter t will be revealed. Now Provider 1 has the options of treating the patient and referring the patient to Provider 2. If Provider 1 decides to treat the patient, his utility is given by the expressions above. If Provider 1 decides to refer the patient to Provider 2, then Provider 1's profit from the patient will be zero, and his utility from this referral will be given by γ multiplied by whatever utility level the patient obtains eventually.

The strategic game consists of three stages. In the first stage, without knowing his parameter t, each patient seeks treatment from one of the providers. The patient's parameter t is now revealed to the provider. In the second stage, a provider who is matched with a patient decides whether to treat the patient or to refer this patient to the other provider. In the third stage, the parameter of any patient that has been referred in the previous stage is now revealed to the new provider. This provider then decides whether to supply treatment or not; if the provider does not, the patient will remain untreated. The strategic interaction between the providers stems from their altruistic preferences. Provider 1's referral decision depends on what Provider 2 will do to the patient. For example, if Provider 2's strategy calls for him to refuse treatment to a patient, Provider 1 may want to treat that patient himself – even though Provider 1 would have found it optimal to refer if Provider 2 were willing to treat upon such a referral.

For each incentive regime, we derive the subgame-perfect equilibria. First, let us consider the fixed-price payment regime. We begin with the equilibrium strategies when a provider meets with a referred patient. Suppose that Provider 2 has referred to Provider 1 a patient with parameter t. If Provider 1 treats this patient, Provider 1's utility is $\gamma(V-t)+(1-\gamma)(a-c)$; if he does not, then his utility is zero. If there is $\hat{t}_1$ in $[0,1]$ satisfying $\gamma(V-\hat{t}_1)+(1-\gamma)(a-c)=0$ or

$$\hat{t}_1 = V + \frac{1-\gamma}{\gamma}(a-c) \tag{3}$$

then Provider 1 will treat the referred patient if the parameter is smaller than $\hat{t}_1$. Similarly, if Provider 1 refers to Provider 2 a patient with parameter t, then Provider 2 will treat the patient if $\gamma(V-1+t)+(1-\gamma)(a-c)\geqslant 0$. If there exists $\hat{t}_2$ in $[0,1]$ satisfying $\gamma(V-1+\hat{t}_2)+(1-\gamma)(a-c)=0$ or

$$\hat{t}_2 = 1 - V - \frac{1-\gamma}{\gamma}(a-c) \tag{4}$$

Provider 2 will treat the referred patient if the parameter is larger than $\hat{t}_2$.

Now consider stage 2, and suppose that a patient with parameter t is matched with Provider 1. If Provider 1 treats the patient, his utility is $\gamma(V-t)+(1-\gamma)(a-c)$. If he refers the patient to Provider 2 and the patient is treated, Provider 1's utility is $\gamma(V-1+t)$, otherwise it is 0. At stage 1, because they receive no information about their treatment proclivity parameter t, consumers will randomly select one of the two providers for services.

Because of symmetry, social efficiency requires that Provider 1 treats all patients with parameters t between 0 and 0.5, while Provider 2 treats the rest. In the fixed-price incentive regime, the first best is implementable. Simply set $a=c$, then in equilibrium each provider will attempt to maximize each patient's utility: Provider 1 will refer a patient with parameter $t>0.5$ and vice versa for Provider 2. The case of $a=c$ seems unrealistic, however. We have not included fixed costs in the model, and strict marginal cost pricing may be infeasible in the presence of fixed costs. Whenever $a>c$, a provider will tend to refer patients at a rate lower than socially optimal.

From the equilibrium strategy in stage 3, we know that for $a>c$ Provider 2 will treat all referred patients with $t>0.5$. Clearly, Provider 1 will treat all patients with $t<0.5$. For $t>0.5$, Provider 1 will refer a patient to Provider 2 if and only if $\gamma(V-t)+(1-\gamma)(a-c)<\gamma(V-1+t)$, or

$$t > \frac{1}{2} + \frac{1-\gamma}{2\gamma}(a-c) > 0.5.$$

Let us assume that the middle term of the above expression is less than 1; otherwise Provider 1 will not refer any patients. Similarly, Provider 2 will refer to Provider 1 a patient whose value of t satisfies

$$t < \frac{1}{2} - \frac{1-\gamma}{2\gamma}(a-c) < 0.5.$$

Some patients with parameters in the interval

$$\left[\frac{1}{2} - \frac{(a-c)(1-\gamma)}{2\gamma},\ \frac{1}{2} + \frac{(a-c)(1-\gamma)}{2\gamma}\right] \equiv [t^-, t^+]$$

will be mismatched compared to the first best. Those patients with t between 0.5 and t^+ and matched with Provider 1 will not be referred to and treated by Provider 2; those with t between t^- and 0.5 and matched with Provider 2 will not be referred to and treated by Provider 1. Clearly, the length of the mismatch interval is decreasing in γ, and increasing in $a-c$. Figure 1 illustrates the mismatch interval.

Proposition 1. For $a>c$ in the fixed-price incentive regime, a provider refers patients to another provider at a rate lower than the first best,

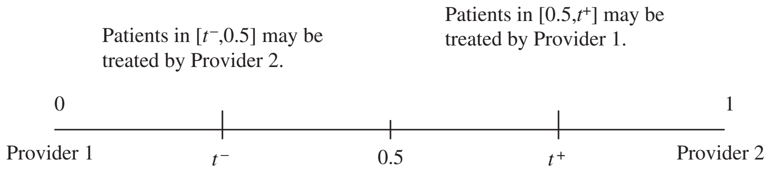

Figure 1. Patient mismatch

resulting in mismatching. The degree of mismatching increases with the price-cost margin, $a - c$, but decreases with the degree of provider altruism, γ.

Proposition 1 summarizes the incentives of providers who possess superior patient information, but who are not completely altruistic. Because a provider makes a profit equal to $a - c$ for treating a patient, and he values a patient's utility and his profit with respective weights γ and $1 - \gamma$, he will supply treatment to some patients even when they will be better off treated by the other provider. The mismatch occurs because of imperfect agency, and the limitation of the payment mechanism that is not based on performance. As we show next, incentives for mismatch between providers and patients can be reduced by performance-based contracting.

In a performance-based incentive mechanism, a provider is paid according to the outcome of the treatment he supplies to patients. From (2), we can, respectively, rewrite Providers 1 and 2's utilities from treating a patient with parameter t as

$$[\gamma + (1-\gamma)\beta](V - t) + (1-\gamma)[\alpha - c],$$
$$[\gamma + (1-\gamma)\beta](V - 1 + t) + (1-\gamma)[\alpha - c]$$

Comparing these with the corresponding expressions in (1), we observe that the performance-based mechanism effectively raises the degree of altruism. If β is set at 0, then this regime is reduced to the fixed-price mechanism. Moreover, if we define $\gamma + (1-\gamma)\beta$ to be δ, then the results for the fixed-price mechanism can be adapted. In this case, the utility functions in (1) become

$$\delta(V - t) + (1-\gamma)(\alpha - c),$$
$$\delta(V - 1 + t) + (1-\gamma)(\alpha - c)$$

where $\delta > \gamma$ since $\beta > 0$. Because we know from Proposition 1 that mismatch between patients and providers decreases with respect to the degree of altruism, we conclude that performance-based mechanism may reduce mismatch compared to fixed-price mechanism. That PBC tends to increase referral rates is our main theoretical result and we state it as Proposition 2.

Proposition 2. Suppose that $a = \alpha$ so that the provider is paid the same amount per treated patient in the fixed-price and performance-based regimes. Then for $\beta > 0$ the degree of mismatch in the performance-based regime is smaller than in the fixed-price regime, and the referral rate will be higher.

We now discuss a number of simplifying assumptions and the robustness of the model. First, in practice, the referral process may be more complicated, and may lead to patient dumping. If providers' payments and patients' benefits from treatment are sufficiently low, dumping may happen in equilibrium. Consider first the fixed-price incentive regime. When a and V are sufficiently low, then in equilibrium a patient with a value of t close to 0.5 will be referred by one provider, but subsequently rejected by the other. A referral is successful only if a patient is located close to one provider but has been matched initially to the other provider. A similar equilibrium dumping outcome may also obtain under PBC (when α is small). However, as we have said, PBC raises providers' degrees of altruism, and a provider has less tendency to dump a patient (when $a = \alpha$, as in the hypothesis of Proposition 2). That is, a patient who is rejected by two providers (dumped) under the fixed-price regime may be successfully referred by one provider to another under PBC. Proposition 2 remains valid when some patients may be rejected by all providers under the fixed-price regime.

For simplicity, we have used a two-stage process (an initial match and a referral) to model patient–provider interactions. In practice, an episode of treatment may involve multiple referrals and providers. Very often the provider receives some payment even when a patient is referred to another provider, and the patient receives some benefit before referral. We bypass the complexity of a dynamic referral process in order to highlight the incentive effect of PBC. We do not believe complex referral processes will change the basic incentives. Referring a patient to another provider means giving up some potential revenue (all or part of the payment a or α). PBC encourages more referrals by tying provider's reward to patient benefits or outcomes. Then referral becomes a less costly option for a provider: keeping a patient may generate a less desirable outcome, which is discouraged by PBC.

The providers in the model are assumed to be identical. In practice, providers differ in their treatment intensities and costs. The model can be modified to consider these differences. First, we can let patients have treatment benefits that differ across providers. If a type t patient obtains utility $V_1 - t_1$ from Provider 1, and $V_2 - 1 + t$ from Provider 2, where $V_1 \neq V_2$, referral under the first best will be asymmetric. We will make use of asymmetry in our empirical test later. If $V_2 > V_1$, PBC will encourage more referrals from Provider 1 to Provider 2. By comparing the severity levels of patients of providers with different treatment intensities before and after PBC, we test whether referrals lead to better matches.

Second, our assumption that providers have identical costs is for convenience and ease of exposition. Asymmetric treatment costs among providers will not change the results at all if we interpret the payment to the providers as margins over costs. More generally, however, the providers' costs may depend on patients' characteristics; in our model, the providers' costs may be functions of t. Without imposing more structure on these functions, it is unclear how the equilibrium referral rates under each regime will be affected. But in any case the effect of PBC – that providers' degrees of altruism have been increased – remains the same. We expect Proposition 2 to be correct under more general cost structures.

We have assumed that patients incur no switching cost when they are referred. Including it will not change the qualitative results; the precise referral rates (values of t^- and t^+ and the corresponding values under PBC) will adjust continuously according to the switching cost since provider preferences exhibit altruism. Proposition 2 is also valid when the total reimbursement to providers remains the same after PBC (the case of constant global budget). Under a constant global budget, the post-PBC fixed unit payment α must be less than its pre-PBC counterpart a, given that a portion of the post-PBC payment is reserved for rewarding superior performance ($\beta > 0$). From Proposition 1, we know that the degree of mismatch decreases with decreasing unit fixed payment. In other words, the referral rate increases with a lower fixed per-patient payment. Therefore, under neutral-budget where $\beta > 0$ and $\alpha < a$, the degree of mismatch in performance-based regime is smaller than in the fixed-price regime, and the referral rate will be higher.

Data, empirical approach, and results

Data and sample selection

The MATS data contain information on clients treated in Maine's publicly funded substance abuse programs between 1 October 1989 and 30 December 1995. Each client is given a unique identification number and can be tracked throughout his treatment history in MATS. Our sample in this study includes primary clients discharged after 1 July 1990 and before 1 July 1995, who are not from detoxification, emergency shelter, driver education and evaluation program (DEEP), and demonstration projects. Some important cases with mix information, such as concurrent psychiatric problems and legal involvement at admission, are not reported on the detoxification and emergency shelter clients. All DEEP providers were mandated to report client information only beginning in 1992. Similarly, the demonstration projects, including case management, psyched group, group demonstration project, and relapse prevention, are relatively new programs that started only after PBC was introduced. Our sample consists of 18 972 clients. Each of these clients may have one or more episodes in the sample period. For the empirical analysis of referral, we use the first episodes of these clients. For matching, we use the first and second (if any) episodes. For the analysis of dumping, we use our entire sample to construct the dumping indicator, but use only the first episodes for the regressions.

Our empirical strategy relies on comparisons before and after the implementation of PBC. A control group does not exist. This is of course a common feature of studies employing data from natural experiments. In fact, it is practically impossible to design a controlled experiment with the population size as big as the state of Maine. We, however, argue that the implementation of PBC in Maine's substance abuse treatment system is orthogonal to other variables that can affect substance abuse treatment, such as general health status of the population, drug prices, labor market conditions in the health sector, provider market structure, etc. We make this claim based on the following observations. First, patient flow in Maine's publicly funded substance abuse treatment system has been steady over our sample period, and migration and mobility in Maine has been minimal. Second, the population of providers in Maine's contract system has been relatively stable over the years. The official purpose of Maine's implementation of PBC is to help providers with their performances, not to eliminate treatment programs [32]. Third, the economic environment in Maine, including factors such as inflation, unemployment rate, and crime rate, has been stable over the sample period. Finally, included in our regression models are clients' insurance sources; we have also controlled for possible exogenous shocks by including admission quarters in some of our sensitivity analysis. As we will see, our results are robust. The likelihood is small that the introduction of PBC is significantly correlated with unobserved shocks that affect substance abuse treatment in Maine.

Descriptive results

Client characteristics. Table 2 presents sample client characteristics. MATS provides two measures of a client's drug use severity at time of admission. The first measure is self-reported frequency of primary drug use. The reported information falls into one of ten categories: no use in the past 3 months, no use in the past month, once per month, 2–3 days per month, once per week, 2–3 days per week, 4–6 days per week, once daily, 2–3 times daily, and more than 3 times daily. The second measure is counselor-assessed severity level of the client's primary substance abuse problem. There are five assessment categories: casual/experimental, lifestyle-involved, lifestyle-dependent, dysfunctional, or undetermined. Additional admission case mix measures in MATS include whether a client has psychiatric problem or legal involvement. Besides the usual demographic characteristics such as age, sex, marital status, and education, MATS has payment source information: Medicaid, the state government, out-of-pocket, private insurance companies, and others.

Provider characteristics. Treatment programs differentiate in modalities (see Table 1) and geographic locations. MATS lists whether a treatment program is in a rural area, defined as an area with population under five thousand. Table 2 reports percentages of the entire sample according to treatment modalities and programs located in rural areas.

Comparisons before and after PBC. We segregate our sample according to whether the client is discharged before or after the introduction of PBC on 1 July 1992. Client and provider characteristics of the pre-PBC (7777 clients) and post-PBC subsamples (11 195 clients) are presented in Table 2. We have tested the difference of the means of each variable in pre-PBC and post-PBC subsamples. The chi-square test statistics and significance levels are reported in Table 2. A significant result of the chi-square test indicates that the mean of a variable in the pre-PBC group is systematically different from the post-PBC group. Fisher's exact tests for all pair comparisons give consistent results. The comparison results suggest that percentages of clients who drink at least 2–3 days/week are higher in the post-PBC sample. The percentages of clients in all four counselor-assessed severity categories increase in the post-PBC group. This indicates that severity of illness is better documented in post-PBC period. Percentages of clients with psychiatric problem and legal involvement at admission increase in the post-PBC group. There are higher percentage of Medicaid clients and lower percentage of privately insured clients in the post-PBC group. Percentages of female clients and clients under age of 20 increase in the post-PBC group, while percentages of married clients and clients with high school education drop. On the provider side, in the post-PBC sample, percentages of clients treated in residential rehabilitation, halfway house, and outpatient programs increase. Percentages of clients treated in evaluation and extended care programs decrease. Percentage of clients treated in rural programs increases.

Table 2. Sample descriptive statistics

Variables	Overall	Pre-PBC	Post-PBC	Pre. vs Post
Client characteristics				
Admission drug use frequency				
0/past 3 month	0.19	0.24	0.16	160.44***
0/past 1 month	0.24	0.22	0.26	38.74***
once/month	0.06	0.06	0.07	10.40***
2–3/month	0.07	0.07	0.07	0.87
once/week	0.06	0.06	0.06	6.52**
2–3/week	0.11	0.10	0.12	28.63***
4–6/week	0.06	0.05	0.06	3.05*
once/day	0.08	0.10	0.07	51.47***
2–3/day	0.04	0.04	0.05	10.55***
4 or more/day	0.08	0.07	0.09	24.07***
Severity at admission				
Casual/experimental	0.07	0.07	0.08	7.55***
Lifestyle-involved	0.18	0.16	0.19	19.57***
Lifestyle-dependent	0.32	0.29	0.33	33.82***
Dysfunctional	0.19	0.18	0.19	9.59***
Undetermined	0.24	0.30	0.20	217.61***
Psychiatric problem	0.12	0.09	0.14	108.97***
Legal involvement	0.57	0.54	0.60	59.66***
Female	0.28	0.25	0.30	64.21***
Marital status				
Married	0.21	0.23	0.21	10.05***
Divorced/widowed/separated	0.31	0.32	0.30	6.59***
Age				
20 or younger	0.16	0.13	0.19	100.61***
40 or older	0.19	0.19	0.19	0.16
Education				
College	0.04	0.04	0.04	1.21
High school	0.55	0.57	0.54	16.91***
Payment source				
Medicaid	0.20	0.18	0.22	49.79***
State	0.25	0.25	0.25	0.22
Out-of-pocket	0.26	0.26	0.26	0.08
Private insurance	0.16	0.17	0.16	10.08***
Provider characteristics				
Treatment modality				
Residential	0.04	0.04	0.05	11.56***
Non-residential	0.03	0.03	0.03	0.00
Halfway House	0.03	0.03	0.04	11.91***
Extended shelter	0.00	0.00	0.00	2.38
Evaluation	0.10	0.12	0.09	26.75***
Extended care	0.00	0.01	0.00	3.39*
Outpatient	0.79	0.77	0.80	16.71***
Rural (population < 5000)	0.17	0.17	0.18	6.13**

Notes: * significance $\leqslant 0.10$, ** significance $\leqslant 0.05$, *** significance $\leqslant 0.01$.
Chi-square statistics are reported under the column of 'Pre. vs Post'.

Empirical approach and results

In this section, we test whether PBC has led to more referrals and better client–provider match, the two main theoretical predictions. We also examine whether PBC has led to more dumping.

Has PBC increased referral? We use the first episodes of clients in our sample and measure clinician referral using information in the MATS discharge forms. A dummy variable, REFERRAL, is constructed to indicate whether a deliberate action was made to refer the client to another substance abuse service at time of discharge. Deliberate action is defined as the event that during a treatment episode the clinician has transported the client, written letters, made telephone calls to set up appointments, or taken similar action to see that the client actually is seen by the referred program. A simple suggestion to a client to go somewhere for help is *not* considered a referral for the purpose of MATS. Naturally, we use a logistic regression to test the clinicians' referral practice

$$\Pr(\text{REFERRAL} = 1) = \frac{\exp(\beta_i X_i)}{1 + \exp(\beta_i X_i)} \quad \text{for individual } i \tag{5}$$

The explanatory variables (X) include PBC, a dummy variable indicating whether PBC has been introduced at time of discharge. A dummy variable indicating whether treatment is complete at time of discharge is included. Also included as explanatory variables are client characteristics such as age, sex, marital status, education level, client case mix measures (including drug use frequency, counselor-assessed severity, psychiatric problem, and legal involvement at time of admission), and insurance source. Information of the explanatory variables are from clients' first episodes. We also include provider characteristics – type of treatment modality and location of the treatment program. In all regressions, the outpatient modality is used as baseline; therefore, the outpatient dummy is omitted.

The parameter estimation results of Model (5) are presented in Table 3 (SAS version 8.01 was used for all analysis). The PBC dummy, after controlling for client and provider characteristics, is significantly positive. This result supports Proposition 2: the introduction of PBC leads to a higher referral rate. It should be noted that our referral variable does not capture all referrals. In Maine, a clinician is required to report all treatment episodes, regardless of how long the treatment lasts. However, in practice, a clinician may sometimes spot a mismatch upon a client's first visit. He may choose to refer the client right away and not report this short episode to MATS. We do not have information to account for this kind of referrals. The actual increase in referral rate under PBC may have been higher than what our regression results indicate.

Table 3. Estimation analysis of referral

Variable	Estimate	T-value
Intercept	−3.51	−22.94**
PBC	0.10	2.20*
Completed treatment	0.59	11.61**
Residential	2.77	30.71**
Nonresidential	1.92	20.12**
Halfway House	1.82	17.79**
Extended shelter	3.35	10.28**
Evaluation	1.42	20.22**
Extended care	1.33	5.25**
Rural (population < 5000)	−0.18	−2.78**
0/past 1 month	0.17	2.10*
once/month	0.03	0.24
2–3/month	0.34	3.18**
once/week	0.46	4.14**
2–3/week	0.56	6.24**
4–6/week	0.83	7.90**
Once/day	0.86	9.19**
2–3/day	0.84	7.41**
4 or more/day	0.78	8.16**
Lifestyle-involved	0.41	3.54**
Lifestyle-dependent	0.50	4.40**
Dysfunctional	0.51	4.30**
Undetermined	0.23	2.05*
Psychiatric problem	0.33	4.92**
Legal involvement	0.05	0.91
Female	0.09	1.59
Married	0.14	2.00*
Divorced/widowed/separated	0.07	1.14
20 or younger	0.36	4.97**
40 or older	0.08	1.25
College	−0.03	−0.28
High school	−0.11	−2.10*
Medicaid	0.00	0.05
State	−0.03	−0.39
Out-of-pocket	−0.20	−2.32*
Private insurance	0.28	3.12**
−2 log likelihood	−16534.41	

Note: * significance ⩽0.05, ** significance ⩽0.01.

The variable on treatment completion at discharge is significantly positive. This positive correlation can be partly explained using our theoretical model: clinician may choose to provide some treatment before making a referral. Results on other variables suggest that high admission drug use frequency, high counselor-assessed severity, and having psychiatric problem at admission also contribute to a higher referral rate. Compared with outpatient program, all other treatment modalities are significantly related to a higher referral rate. This is reasonable given that outpatient program is usually the final stage of substance abuse treatment. Referral rates among extended shelter and residential rehabilitation programs are among the highest. Clients who are privately insured have a higher referral rate, while those who pay their own expenses or rely on the state government have a lower referral rate. Utilization review and control implemented by private insurance companies are usually strict. This may enhance a clinician's incentive to refer a client with high risk. In its contract with a provider, the state government of Maine specifies that a minimum percentage of allocated funding must be spent on treating clients without any payment sources. The providers therefore have a larger incentive to retain state-paid clients to meet such quota. The incentive on retaining the self-paid clients is less clear, but is most likely related to the provider's concern on attracting this group of clients.

Has PBC improved matching? Our theoretical model predicts that increased referrals under PBC will lead to better patient–provider matching. In our empirical model, a patient's type is measured by the admission counselor-assessed severity. Of the two available severity measures, admission drug use frequency is used by Maine's PBC to construct reduction of use, a performance measure. The counselor-assessed severity measure is not used by PBC and therefore not subject to potential provider gaming. A provider's type is measured by the treatment modality. We define a 'high severity client' as someone with admission counselor-assessed severity level of 'lifestyle-dependent' or 'dysfunctional'.

As discussed earlier, a referral may occur upon the first visit and the initial episode may not be documented in MATS. The distribution effect of this kind of referral is therefore noted in the client's first treatment episode recorded in MATS. On the other hand, if a referral happens after some treatment has taken place and been documented, the matching effect of this referral is reflected by the client's second treatment episode in MATS. We therefore test whether PBC improves matching by examining the distribution of highly severe clients in two different samples. First, we use the first treatment episodes of the 18972 clients in our sample. We examine the probability of a client having a high illness severity (i.e. the distribution of clients) by the following logit specification:

$$\Pr(\text{a high severity client}) = \frac{\exp(\beta_i X_i)}{1+\exp(\beta_i X_i)} \quad \text{for individual } i \tag{6}$$

Besides variables included in Model (5) except treatment completion, we include interaction terms of the PBC dummy and the treatment modality dummies. The regression results of Model (6) are reported in Table 4 under 'First Episodes'. When outpatient program is used as the baseline, the residential and non-residential rehabilitation modality dummies are significantly positive; so are the interaction terms of PBC with these modality dummies. This has the following interpretations. First, high severity clients are more likely treated in intensive programs such as residential and nonresidential rehabilitation than in outpatient programs. Second, PBC enhances their possibilities of being treated in these intensive programs. The evaluation modality and the interaction term of PBC and evaluation modality are found to be significantly negative. The introduction of PBC has further reduced the possibility of clients with high severity being treated in evaluation programs. No significant result on other interaction terms has been found.

Second, we follow all clients in our sample after their first discharge. A subsample of 9756 clients have a second treatment episode. A client's type is measured by his admission severity assessment in the first treatment episode. However, a provider's type is measured by the treatment modality of the client's second treatment program. The regression results of Model (6) on the subsample are reported in Table 4 under 'Second Episodes'. Again, we find that PBC enhances the possibility of high severity clients being treated in inpatient programs such as residential rehabilitation and halfway house. We also find that PBC reduces the likelihood of clients with high severity being directed to evaluation

Table 4. Estimation analysis of matching

Variable	First episodes		Second episodes	
	Estimate	T-value	Estimate	T-value
Intercept	0.11	1.67*	0.76	5.71***
PBC	0.22	6.08***	−0.05	−0.68
Residential	0.81	5.81***	0.60	3.87***
Non-residential	0.70	4.45***	−0.12	−0.49
Halfway House	0.99	6.47***	0.75	2.78***
Extended shelter	−1.11	−2.67***	−0.23	−1.36
Evaluation	−1.01	−11.24***	−1.13	−4.87***
Extended care	0.09	0.22	0.92	1.47
PBC*Residential	1.31	5.81***	1.14	4.55***
PBC*Non-residential	0.76	3.30***	−0.09	−0.30
PBC*Halfway house	13.64	0.13	2.90	2.78***
PBC*Extended shelter	3.79	3.42***	3.02	6.73***
PBC*Evaluation	−0.44	−3.52***	−0.78	−2.29**
PBC*Extended care	13.82	0.05	12.56	0.05
Rural (population < 5000)	−0.00	−0.06	−0.21	−2.38**
0/past 1 month	−0.31	−6.56***	0.11	1.18
Once/month	−0.74	−10.03***	−0.38	−2.44**
2–3/month	−0.84	−11.65***	−0.51	−3.52***
Once/week	−0.87	−11.34***	−0.46	−2.73***
2–3/week	−0.16	−2.78***	0.30	2.44**
4–6/week	0.41	5.45***	0.78	4.86***
Once/day	0.13	2.05**	0.24	1.78*
2–3/day	1.17	12.10***	1.18	6.01***
4 or more/day	1.84	18.84***	1.39	8.42***
Psychiatric problem	0.44	8.27***	0.34	3.26***
Legal involvement	−0.29	−7.78***	−0.29	−3.87***
Female	−0.03	−0.73	−0.07	−0.81
Married	0.17	3.68***	0.27	2.74***
Divorced/widowed/separated	0.21	4.75***	0.25	2.99***
20 or younger	−0.5	−9.04***	−0.39	−3.56***
40 or older	0.17	3.81***	0.04	0.43
College	−0.23	−2.64***	0.07	0.34
High school	−0.05	−1.37	−0.07	−0.94
Medicaid	0.12	2.34**	0.00	0.04
State	−0.23	−4.78***	−0.23	−2.31**
Out-of-pocket	−0.28	−5.16***	−0.42	−3.77***
Private insurance	0.17	2.89***	0.17	1.27
−2 log likelihood	26298.58		6609.07	

Note: *significance ⩽0.10, ** significance ⩽0.05, *** significance ⩽0.01.

programs after their initial treatment. In Maine's system, other than the differentiation of treatment intensity across residential and halfway house, outpatient, and evaluation programs, comparisons among other treatment modalities are not straightforward. For example, treatment offered by extended care and extended shelter programs are not well defined, with some programs serving as a gateway into the actual substance abuse treatment system. In sensitivity analyses, we repeated the estimations using a subsample in which extended care and extended shelter episodes are excluded. The results on the impact of PBC on client distribution remain unchanged. We also grouped treatment modalities into 'intensive' and 'less intensive' programs, and included in the regressions only the PBC and 'intensive' interaction dummy. We could not find any stratification in the data to reduce the missing values in the counselor-assessed severity measure. We have, however, tried using admission drug use frequency to measure client types instead. The results on client distribution across programs are robust under all these different specifications. In sum, PBC has improved matching in both first and second treatment episodes.

Has PBC increased dumping? Dumping has a negative impact on risk selection. In our model, dumping refers to situations in which a client is sequentially referred from one provider to the next without being treated. We construct a dumping indicator in the following way. We track every client who has been referred at discharge. If a client does not have a second treatment episode within 90 days after the initial referral, he is considered dumped. A follow-up window of 90 days is used to account for right-censoring. Otherwise we examine what happens at the end of his second treatment episode. If he is referred again and does not have a third treatment episode within 90 days, he is also considered dumped. Otherwise we continue to examine his third treatment episode, etc. We track up to the fourth episode – if a client has been referred four times, and has failed to have another treatment within 90 days after the fourth referral, he is again regarded dumped. We estimate the probability of dumping using the following logistic equation:

$$\Pr(\text{a client dumped}) = \frac{\exp(\beta_i X_i)}{1+\exp(\beta_i X_i)} \quad \text{for individual } i \tag{7}$$

We include in X the same variables in Model (6) (the information of the explanatory variables is from clients' first episodes). The estimation results of Model (7) are reported in Table 5. The PBC dummy is positive but insignificant. This suggests that PBC does not significantly lead to more dumping in Maine's system. This result is robust when we change the definition of dumping from tracking till after the fourth referral to only after the third, the second, or the first. Compared to outpatient program, all other treatment modalities are associated with higher rates of dumping. The state-paid or self-paid clients are least likely dumped. The results on case mix measures are consistent with the pattern of risk selection. Clients with high admission drug use frequency, high counselor-assessed severity, and psychiatric problem at admission are more likely dumped. Finally, clients initially treated in a rural program are more likely dumped.

Table 5. Estimation analysis of dumping

Variable	Estimate	T-value
Intercept	−3.74	−19.28***
PBC	0.09	1.46
Residential	0.8	7.06***
Non-residential	0.93	6.81***
Halfway House	0.82	5.58***
Extended shelter	0.95	2.42**
Evaluation	1.38	17.00***
Extended care	0.73	2.24**
Rural (population < 5000)	0.21	2.68***
0/past 1 month	−0.01	−0.09
Once/month	−0.19	−1.22
2–3/month	−0.03	−0.22
Once/week	0.18	1.26
2–3/week	0.09	0.80
4–6/week	0.43	3.30***
Once/day	0.53	4.52***
2–3/day	0.51	3.63***
4 or more/day	0.31	2.58***
Lifestyle-involved	0.55	3.53***
Lifestyle-dependent	0.62	4.15***
Dysfunctional	0.78	5.03***
Undetermined	0.44	2.98***
Psychiatric problem	0.63	8.13***
Legal involvement	0.01	0.16
Female	0.04	0.57
Married	0.07	0.74
Divorced/widowed/separated	0.06	0.77
20 or younger	0.62	6.94***
40 or older	0.01	0.15
College	−0.17	−1.08
High school	−0.21	−3.12***
Medicaid	−0.08	−0.72
State	−0.18	−1.82*
Out-of-pocket	−0.25	−2.37**
Private insurance	−0.08	−0.70
−2 log likelihood	9701.29	

Note: * significance ⩽0.10, ** significance ⩽0.05, *** significance ⩽0.01.

Conclusion

We have presented a model of patient–provider matching, and compared the incentive properties of fixed-price and performance-based contracts.

We show generally that PBC gives better incentives for providers, resulting in less mismatch. Using a data set from the Maine substance abuse treatment system, we have tested the model empirically; the evidence broadly supports our theory. Specifically, PBC has significantly increased referral rates among providers. Also, clients with highly severe drug use problems are more likely treated in more intensive programs under PBC; those with less severe problems, in less intensive modalities. PBC leads to a redistribution of clients among providers and a better match between patient and provider types, a positive risk selection effect.

Our data set does not allow us to assess welfare issues because resource and cost information is unavailable. Our analysis does appear to lead to encouraging views on the risk selection benefits of PBC. A better match between clients and treatment programs is a necessary step in improving health care delivery efficiency. In practice, incentive contracts may or may not work as they are intended, and it is important to assess empirically their performances. Incentives in a system as complicated as substance abuse treatments in the state of Maine are bound to be multifaceted. Our effort to study referral should be regarded as a contribution to piece together various consequences of PBC.

Our matching model concentrates on the referral process; it does not study the choice of treatments when a provider may have a variety of options. Whereas this limitation of our model may not be too restrictive for substance abuse treatments, it may be more critical for medical or surgical problems. Extending our model to consider choices of treatment by a provider may be fruitful. It also may be interesting to apply our model to other data sets of health services.

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