When do experts cheat and whom do they target?

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A credence good is a product or service whose usefulness or necessity is better known to the seller than to the buyer. This information asymmetry often persists even after the credence good is consumed. I propose two new theories of expert cheating, suggesting that identifiable heterogeneities among customers can cause expert sellers to defraud their customers. According to these theories, cheating arises as a substitute for price discrimination, and experts cheat selectively. For instance, experts target high-valuation and high-cost customers. Finally, selective cheating may damage the communication of useful information from customers to experts and result in inferior services.

1. Introduction

In this article I examine markets for credence goods, that is, a product or service whose usefulness or necessity to the buyer is better known to the seller than to the buyer. This information asymmetry often persists even after the credence good is consumed. Providers of credence services are here termed “experts,” as this reflects their special skills in diagnosing and solving customers’ problems. Examples of experts in the context of this article include physicians, dentists, lawyers, car mechanics, home improvement contractors, real estate agents, etc. Of concern in the market for credence goods is that experts may take advantage of their informational advantage over their customers. Due to customers’ ignorance about the required service, the expert may be tempted to exaggerate the severity of a customer’s problem and recommend an expensive but unnecessary treatment. This incentive is exacerbated by the customer’s inability to verify ex post whether the recommended treatment actually has been provided or whether some simpler procedure was given instead.

Most theoretical studies on markets for expert services are built on two-by-two models in which a customer’s problem (1) may be either of two possible levels of severity and (2) will require one of two possible treatments to fix. Examples of analyses based on such two-by-two models of expert services include the contributions of Pitchik and Schotter (1987, 1993), Wolinsky

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This article is from a chapter of my Ph.D. dissertation at Boston University. I am indebted to Ching-to Albert Ma for his advice throughout the writing of the dissertation. Much of the article was written during my service at The Hong Kong University of Science and Technology. Constructive comments and suggestions from two anonymous referees and the Editor have substantially improved the quality of the article. I also wish to thank Eric Chou, Leemore Dafny, Hsueh-Ling Huynh, John Leahy, Dilip Mookherjee, Robert Rosenthal, Jay Surti, Balázs Szentes, John Wooders, and participants in various seminars for helpful comments and discussion. The usual disclaimer applies.
(1993), Taylor (1995), Emons (1997, 2001) and Alger and Salanie (2003).\textsuperscript{1,2} Except in Pitchik and Schotter’s studies, where prices are exogenously given, only two possible equilibrium outcomes have been identified in these two-by-two models: either the expert fixes a customer’s problem at a flat rate regardless of the severity of the problem, or whenever the expert posts a price list with different prices for different services, the expert always honestly reports each customer’s problem.\textsuperscript{3}

In reality, experts do set different prices for different treatments, and certainly when they do so, they are not always honest. Contrary to the findings from two-by-two models, real-life experts cheat selectively. Anecdotal evidence shows that women are more likely to be cheated by car mechanics, and the elderly and the young are the preferred targets of dishonest firms offering tour packages. Similarly, small business owners constitute the largest groups of cyber fraud and phone-switching victims. In addition, some con artists even choose to target the religious, rich, or sick.\textsuperscript{4}

In an article in \textit{Money} (June 1996, p. 174), Allen Wood of California’s Bureau of Consumer Affairs gives customers this advice: “Dishonest mechanics don’t rip off every customer, only the ones they think are easy to fool.”\textsuperscript{5} In other words, experts can not only identify customers’ problems but also other individual characteristics—and on the basis of these characteristics they decide whom to defraud.

The theoretical prediction that experts do not cheat in two-by-two models whenever they optimally charge different prices for different treatments has been attributed by different authors to different causes. According to Wolinsky (1993), experts’ behaviors are disciplined by either customers’ search for second opinions or experts’ concerns for reputation. Emons (2001, pp. 378–379) attributes honest reporting by the expert to the cost involved in cheating. He argues that in a setting without cheating costs, “overtreatment is always profitable.”

Although Pitchik and Schotter’s (1987, 1993) fixed-price models provide the more realistic prediction that experts misreport some, but not all, minor problems as serious, this result relies on the assumption that treatment prices are exogenously given at certain levels. To date there is no flexible-price model that explains under which situations the market will endogenously give rise to the price levels these authors consider.

In this article, I not only point out the limitation of two-by-two models in capturing the pattern of expert cheating, but also provide richer alternative models that shed new light on the economics behind expert cheating. In a two-by-two model, apart from the severities of their problems, customers are homogeneous in the following sense: All customers suffer to the same extent if they have the same problem, and the expert’s costs for providing a particular procedure is constant across different customers. In reality, however, customers are heterogeneous in various dimensions independently of the problems they may have, and often the differences among them are identifiable to the expert. For example, how much a patient worries about specific medical symptoms, as well as the patient’s occupation and insurance coverage, help a physician determine the patient’s willingness to pay for a treatment. Also, on the cost side of the equation, the

\textsuperscript{1} The frameworks of Taylor (1995) and Emons (1997, 2001) are slightly different from the others. In their models, a customer either has a problem or does not have a problem. Those who do not have a problem need no treatment after diagnosis, whereas those who have a problem do need treatment. Their no-problem and problem states respectively correspond to the “minor” and “serious problems” in other models. Thus, these models are also two-by-two.

\textsuperscript{2} Wolinsky (1993) provides an informal discussion on extending the model to one with arbitrarily many problems.

\textsuperscript{3} A list containing a bait-and-switch price may be offered in equilibrium as well; the expert may post two different prices but it is common knowledge between the expert and the customer that one of the prices is meaningless because it will never be charged.


profitability of performing a given procedure may vary substantially due to patient complications (observable to physicians).

Accordingly, I modify the two-by-two model to introduce identifiable heterogeneities among customers. My results are threefold. First, experts cheat customers on the basis of identifiable customer characteristics, specifically those customers who have higher valuations for treatments and those whose problems are more costly to fix. Second, experts use cheating to replace price discrimination. Since the differences in customers' valuations and costs of repair can be recognized only by the expert during the diagnosis, when the expert constructs a price list for her services, she sometimes is unable or finds it suboptimal to indirectly price discriminate between customers by offering multiple price lists. Thus, although the expert offers the same price list to different customers up front, she discriminates against high-valuation and high-cost customers by exaggerating the severity of their problems. Third, due to fear of being targeted for cheating, customers sometimes hold back information about their problem that could possibly help the expert in providing a corrective service. As a result of this lack of communication, customers receive inferior service. To demonstrate how this form of efficiency loss may arise, I have extended the information asymmetry in expert markets from one-sided to two-sided.

My article is organized in the following manner. In Section 2 I provide a comparative literature review. In Section 3 I illustrate a basic two-by-two model in which searches for second opinions and reputation concerns are both absent, and I discuss the limitations of two-by-two models. To build new theories of expert cheating, in Section 4 I modify the basic model in two ways to introduce identifiable customer heterogeneities. In Section 5, I extend the basic model to allow customers to possess some private information that can help the expert provide a more accurate diagnosis and thus a higher-quality treatment. Finally, I provide conclusions in Section 6. The proofs to all propositions are in Appendix A.

2. Comparison with related literature

The notion of credence goods was introduced by Darby and Karni (1973). Pitchik and Schotter (1987, 1993) later conducted a more formal theoretical investigation of fraudulent behavior in expert markets. Although they find that the expert sometimes cheats and sometimes does not, this interesting result is derived in a fixed-price environment.

In the context of the physician/patient relationship, Dranove (1988) endogenizes the pricing decisions in expert markets. In an otherwise very general model, he focuses his analysis on the case that consumers observe the expert's recommendation strategy both in and out of equilibrium, and this differentiates his work from the current article and others cited here. In his analyses, he derives a very rich set of testable implications on how demand inducement relates to the treatment price and other exogenous variables.

In a competitive setting, Wolinsky (1993) demonstrates how cheating can be eliminated when customers search for second opinions or when experts have reputation concerns. Considering both competitive and monopolistic settings, Emons (1997, 2001) assumes that treatments are verifiable and thus cheating becomes costly. Then he studies how the price mechanism can discipline experts to practice honestly. In his models, it requires cheating costs to prevent cheating because he also assumes that once customers have visited an expert, regardless of the market structure and the price the expert charges, customers cannot refuse any recommended service.

In the basic model of the current article, I show that this no-cheating result extends to a framework in which customers do not have the option to search for second opinions, experts have no concerns for reputations, and cheating is costless. In my two-by-two model, since these disciplinary forces on experts' behavior are absent, one naturally expects cheating to arise. The results show, however, that whenever the expert optimally sets a price list with two prices, she...

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6 When analyzing the case in which customers have different valuations for treatments, I assume that the expert does not price discriminate. In Fong (2004), I derive formally under which conditions the expert will endogenously choose to set one price list for all customers.

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always honestly charges customers according to the price list. The robustness of this rather
degenerate no-cheating result suggests there is inherent difficulty in using a two-by-two model to
explain expert cheating.

My basic model is used primarily to motivate the need for a better understanding of how
expert cheating arises. The first main novelty of this article is its development of new theories
of expert cheating that can capture, in a flexible-priced environment, the observation that experts
charge different prices for different treatments and sometimes overcharge their customers. To
this end, I find that identifiable customer heterogeneities play a crucial role in explaining expert
cheating. These new theories also help us understand how experts select victims for cheating.
Moreover, these extensions provide the new insight that cheating sometimes arises as a substitute
for price discrimination. Another novelty of the article is its study of how the way in which experts
pick victims may hinder communication of useful information from customers to experts.

Other important studies of expert markets that are also related to my article include those
by Biglaiser (1993), Taylor (1995), and Pesendorfer and Wolinsky (2003). Biglaiser shows that
the presence of long-lived experts who have the ability to identify sellers’ qualities can act
as middlemen to reduce buyers’ distrust of sellers’ qualities. Elimination of such information
asymmetry will speed up transactions and enhance welfare.

Taylor studies the relationship between owners of durable goods and experts who provide
diagnosis and treatment for durable goods. In his model, when experts provide treatments at
the same price regardless of customers’ problems, customers do not have incentive to properly
maintain the durable good. Then he demonstrates how _ex post_ pricing and long-term contracts,
such as extended service plans, may eliminate such a moral hazard problem and thus induce
customers to take better care of their durable goods.

In a competitive setting, Pesendorfer and Wolinsky study experts’ disincentives to exert effort
to provide an accurate diagnosis. The authors find that customers’ search for second opinions will
motivate experts to implement such effort, and they show that a social planner can enhance welfare
by limiting price competition.

3. Basic model: a price-setting expert monopolist who will not cheat

There is a continuum of customers with measure one. Each has a problem about which it
is common knowledge that it may be either serious (_s_), with probability _a_, or minor (_m_), with
probability _1_ - _a_. If problem _i_ ∈ {_m_, _s_} is left untreated, a customer (henceforth he) bears a
loss of _e_ _i_, with _e_ _m_ < _e_ _s_. An expert monopolist (henceforth she) provides costless diagnosis and
costly treatment services at costs _r_ _m_ and _r_ _s_ for customers’ problems _m_ and _s_. Both treatments are
efficient to provide, i.e., _0_ < _r_ _m_ < _e_ _m_ and _0_ < _r_ _s_ < _e_ _s_, but treatments for different problems are
not substitutable.

The existence of customers’ problems is verifiable; however, customers do not know which
 treatment has been provided as long as the problem is repaired: when the problem is actually
but the expert has recommended treatment _j_, _j_ ≠ _i_, she does not have to incur any additional cost
besides _r_ _i_ in faking treatment _j_. In this sense, cheating is costless.

At the beginning of the game, the expert announces two prices, _p_ _m_ and _p_ _s_, that she charges
for the minor and the serious treatments. After observing these prices, customers decide whether
to visit the expert. When a customer arrives at the expert’s office, what I term the _recommendation subgame_ defined by (_p_ _m_, _p_ _s_) begins. The expert first observes the customer’s problem and
recommends a (minor)_8_ treatment at the price _p_ _m_, recommends a (serious) treatment at the price
_p_ _s_, or refuses to provide any treatment. If the customer accepts the expert’s offer, the expert must
repair the problem at the quoted price.

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7 For easier comparison with the earlier literature, I do not specify a price for diagnosis. This can be easily
incorporated, and it can be shown that the expert always provides free diagnosis in equilibrium in the benchmark model.
8 Notice that this part of the recommendation is just cheat talk. The customer may only infer the actual problem
he has from the recommended price.
9 Here I assume that the expert does not commit to treating customers’ problems at either of the announced prices.
A pure strategy of the expert in a recommendation subgame specifies whether she refuses to provide a treatment, charges $p_m$, or charges $p_s$, conditioned on the problem being $i$, for $i \in \{m, s\}$. A mixed strategy assigns probabilities of taking these actions, respectively denoted by $\rho_i$, $\beta_i$, and $1 - \rho_i - \beta_i$, conditioned on the problem being $i$, for $i \in \{m, s\}$. A pure strategy of the customer in the recommendation subgame specifies whether he accepts or rejects a recommended treatment at the price $p_i$, for $p_i \in \{p_m, p_s\}$. A mixed strategy assigns probabilities of accepting $(\gamma_i)$ and rejecting $(1 - \gamma_i)$ a treatment at the price $p_i$, for $p_i \in \{p_m, p_s\}$.

It will soon become clear that the expert will not mix over prices she posts, but both the expert and the customer may mix in many recommendation subgames. Therefore, when we look at the whole game, without loss of generality we focus on mixed strategies of the expert which each specify a price list $\{p_m, p_s\} \in \mathbb{R}_+^2$ and, for the recommendation subgame following the posting of every price list $\{p_m, p_s\} \in \mathbb{R}_+^2$, the probabilities $\{\rho_i, \beta_i, 1 - \rho_i - \beta_i\}$, for $i \in \{m, s\}$.

A mixed strategy of the customer specifies $\{\gamma_i, 1 - \gamma_i\}$ for $p_i \in \{p_m, p_s\}$ for the recommendation subgame following the posting of every price list $\{p_m, p_s\} \in \mathbb{R}_+^2$.

Throughout this article, to rule out trivial cases I restrict my attention to situations in which the following conditions are satisfied:

$$\alpha \ell_s + (1 - \alpha)\ell_m < r_s. \quad (R)$$

Without this restriction, the expert will set a single price for both problems at the customers’ ex ante expected loss (i.e., $p_m = p_s = \alpha \ell_s + (1 - \alpha)\ell_m$). I call this a one-price-fixes-all offer. Since this price is higher than both $r_m$ and $r_s$, it is profitable for the expert to repair both problems at this price. Knowing that the problem is always fixed, all customers are willing to visit the expert and the expert captures all the surplus. The assumption that both treatments are efficient to provide and (R) together imply $0 < r_m < \ell_m < r_s < \ell_s$.

The following proposition states the main result in the basic model.

**Proposition 1 (no-cheating result).** There always exists a unique subgame-perfect Nash equilibrium outcome not involving weakly dominated strategies. The expert charges different prices for different treatments in equilibrium if and only if condition (R) holds. In this equilibrium, the expert sets $p_m = \ell_m$, $p_s = \ell_s$. In the recommendation subgame, she always truthfully reveals the nature of the problem ($\beta_m = 0$, $\beta_s = 1$) and never refuses to provide treatment ($p_m = \rho_s = 0$). The customer accepts a treatment at price $p_m$ with probability $\gamma_m = 1$, and at price $p_s$ with probability $\gamma_s = (\ell_m - r_m)/(\ell_s - r_m)$.

In the proof of Proposition 1, I show that in a recommendation subgame with $\{p_m, p_s\} \in (r_m, \ell_m) \times (r_s, \ell_s)$, there is a unique equilibrium in which both players play totally mixed strategies. The equilibrium strategy profile in each subgame is characterized by these probabilities:

$$\gamma_m = 1, \quad \gamma_s = \frac{p_m - r_m}{p_s - r_m}, \quad (1)$$

$$\rho_m = \rho_s = 0, \quad \beta_m = \frac{\alpha(\ell_s - p_s)}{(1 - \alpha)(p_s - \ell_m)}, \quad \beta_s = 1. \quad (2)$$

Because $\beta_m \in (0, 1)$, cheating does arise in these subgames, very much as in Pitchik and Schotter (1987).

In the whole game, however, these subgames are never reached. The expected profit of the expert and customers in the recommendation subgame is

\[ p_m \text{ and } p_s. \]

This assumption is natural if we understand the model as a simplified exposition of the following more realistic setting. There are many problems (> 2) but the expert is capable of treating only two of them, $m$ and $s$. Therefore, the expert can always refuse to provide an unprofitable treatment by claiming that she is unable to treat it, even if she actually can. In this richer setting, $\alpha$ should be understood as the conditional probability of the problem being $s$, given that it is either $m$ or $s$.

Notice that only in this section do I explicitly model the possibility that the expert sets a price list such that she may refuse treatment during the recommendation subgame. It will be clear that $\rho_m$ and $\rho_s$ must be zero in any equilibrium.

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expert and the expected cost of each customer derived from equations (1) and (2) are

\[ \Pi(p_m, p_s) = \alpha(p_s - r_s)\gamma_s + (1 - \alpha)(p_m - r_m) \]
\[ = \alpha(p_s - r_s) \frac{p_m - r_m}{p_s - r_m} + (1 - \alpha)(p_m - r_m), \tag{3} \]

\[ C(p_m, p_s) = [\alpha + (1 - \alpha)\beta_m]p_s + (1 - \alpha)(1 - \beta_m)p_m \]
\[ = p_m + [\alpha + (1 - \alpha)\beta_m](p_s - p_m) \]
\[ = p_m + \frac{\alpha(\ell_s - \ell_m)(p_s - p_m)}{(p_s - \ell_m)}. \tag{4} \]

By equation (3), the expected profit of the expert increases in both \( p_m \) and \( p_s \), and it is therefore maximized at \( p_m = \ell_m \) and \( p_s = \ell_s \). According to (2), \( \beta_m \) goes to zero when \( p_s \) goes to \( \ell_s \). That explains why there is no cheating in equilibrium.

Here I provide some more intuition for the no-cheating result. The second term in (3) is the expert’s profit conditioned on the customer’s problem being minor. In that realization, the expert does not have a strict incentive to cheat, so she always earns \((p_m - r_m)\). Changing \( p_s \) will not affect the profit in this realization. Now consider the realization that the customer’s problem is serious. Since the expert prefers earning the difference \((p_s - r_s)\) to making a loss, she always recommends a serious treatment; however, such treatment is accepted only with probability \((p_m - r_m)/(p_s - r_m)\). This is reflected in the first term of (3). One can interpret \((p_s - r_s)/(p_s - r_m)\) as the demand. Since \( r_s > r_m \), raising \( p_s \) leads to a drop in demand less than the increase in incremental margin in this realization, and it does not affect the profit in the realization of a minor problem. As a result, the overall profit increases in \( p_s \).

When the expert charges the profit-maximizing price \( p_s = \ell_s \), any positive probability of cheating does not constitute an equilibrium because if customers believe that the expert cheats with any probability, they will strictly prefer not to accept the treatment, given such a high price for the serious treatment. On the other hand, the expert indeed has no incentive to cheat because customers accept the serious treatment with a low enough probability.

Note that although the expert’s private information is fully revealed in equilibrium, the outcome is inefficient. In fact, what supports the no-cheating equilibrium is exactly some form of efficiency loss. Efficiency requires that all customers’ problems be repaired. But because the price of the serious treatment is higher than that of the minor treatment, customers must reject a recommended serious treatment with some probability in order to eliminate the expert’s incentive to misreport a minor problem as serious. This leads to an underproduction of serious treatments. A fraction \( \alpha \) of the customers have the serious problem and each of them rejects the serious treatment with probability \( (\ell_s - \ell_m)/(\ell_s - r_m) \). Because every rejection forgoes a potential efficiency gain of \((\ell_s - r_s)\), the total efficiency loss is

\[ \frac{\alpha(\ell_s - r_s)(\ell_s - \ell_m)}{\ell_s - r_m}. \]

In Emons’ (2001) monopolist model, no-cheating implies efficiency. This is because in his model, customers cannot refuse any recommended treatment; thus, underproduction of treatments is not an issue. My finding is in sharp contrast to his.

Recall that there is no cheating in equilibrium only because the price of the serious treatment is as high as the loss from the serious problem. One may expect that when there is competition or when customers must incur a cost to visit an expert, the expert must lower prices to attract customers to visit her. Once \( p_s \) is set below \( \ell_s \), cheating will arise. When there are multiple experts, it is natural to consider that customers search for second opinions. Wolinsky (1993) has already shown that in this situation, severe enough price competition will induce experts to commit to honesty by specializing in treating the minor problem. So, cheating still may not arise.

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11 When recommended a serious treatment, the customer is indifferent between accepting it at \( p_s \) or rejecting it. In the latter case, his expected loss is still \( p_s \).
What if customers choose experts on the basis of the prices they charge, but once they have visited one expert they do not seek second opinions? A simple extension of my setup answers this question. Let us modify the basic model by introducing many identical experts. Each expert offers a price list \( \{ p_m, p_s \} \) to attract customers. Upon observing these prices, each customer chooses one expert to visit. After the expert has made a recommendation, the customer decides whether to accept the treatment or leave the problem unsolved. The assumptions on parameters in the basic model are retained. In this setting, experts compete to minimize customers’ expected losses as was specified in equation (4), subject to the constraint that they make nonnegative profit. So the equilibrium prices solve

\[
\min_{\{ p_m, p_s \}} C(p_m, p_s) = p_m + \frac{\alpha(p_s - p_m)(\ell_s - \ell_m)}{(p_s - \ell_s)},
\]

subject to

\[
\alpha(p_s - r_s) \frac{p_m - r_m}{p_s - r_m} + (1 - \alpha)(p_m - r_m) \geq 0.
\]

It is easy to verify that the solution is \( (p_m, p_s) = (r_m, \ell_s) \). Plugging these prices into equations (1) and (2), we have

\[
\gamma_m = 1, \quad \gamma_s = 0, \quad \rho_m = \rho_s = 0, \quad \beta_m = 0, \quad \beta_s = 1.
\]

So, introducing competition into this model does not lead to cheating, even if customers do not search for second opinions.

One may also expect that if the expert monopolist is regulated, \( p_s \) may be set lower than \( \ell_s \). Again, since the expert’s profit increases in \( p_s \) and customers’ cost decreases in \( p_s \), fixing \( p_s \) at \( \ell_s \) indeed improves the welfare of all players. So if the regulator’s objective is to maximize any weighted average of customers’ surplus and the expert’s profit, we should not see cheating arise.

To further verify the robustness of Proposition 1, I extend the basic model to one with three possible levels of severity in customers’ problems (see Appendix B). By doing so, I obtain a qualitatively similar result to Proposition 1, which states that whenever the expert posts three prices for three different problems in equilibrium, the equilibrium price of each problem equals how much a customer suffers from that problem, and the expert always honestly charges according to the price list.

4. When the expert cheats, she cheats selectively

- The no-cheating result in the previous section suggests that the expert’s superior information about customers’ needs for services is inadequate alone to account for the well-documented observations that sellers in credence-good markets cheat, and they cheat selectively. Some other characteristics of these markets must also be responsible for the existence of cheating. In this section I incorporate two elements of real-life expert markets into the basic model: (1) customers’ loss from the same problem may differ and (2) some customers’ problems are more costly to treat, where such differences are often observable to the expert. Each situation I consider involves a specific modification of the basic model, and in both situations, for certain ranges of parameter values, the expert cheats in equilibrium and cheats only one type of customer.

   - Customers suffer to different extents from the same problem. My first variation from the basic model is to relax the assumption that customers suffer equally from the same problem. For example, a crack on the muffler of a car will not bother much a car owner with bad hearing. But if the owner is a hi-fi enthusiast and has installed an expensive car stereo, he will suffer much more.

     The expert serves a market in which customers suffer to different extents from the same problem. From the expert’s point of view, it would be ideal if she could price discriminate between
customers of different valuations. In that case, she would offer a menu of different price lists and let customers who value her services differently self-select. Nevertheless, in many situations, experts are constrained or find it optimal to put up one single price list for different types of customers. One possibility is that customers’ valuations are very diverse and it becomes hard to offer a price list for every type of customer. Given that the expert offers different customers the same price list, she discriminates against them in another way: she is less honest to customers who suffer more from the serious problem. Below, I formalize this idea.

Model modification. Consider a model that is similar to the basic model in every respect except in what follows. There are two types \( \{T \in \{H, L\}\} \) of customers. A fraction \( \theta \) of them are of type \( H \) and suffer a loss \( \ell^H \) from the serious problem. The remaining fraction \( (1 - \theta) \) are of type \( L \) and suffer a loss \( \ell^L \) from the same problem, where \( \ell^L < \ell^H \). Both types suffer equally \( \ell^m \) from the minor problem. Customers’ types are observable to the expert. I assume that the ex ante expected losses of both types satisfy restriction (R): 

\[
\alpha \ell^L_s + (1 - \alpha) \ell^m < \alpha \ell^H_s + (1 - \alpha) \ell^m < \ell^s.
\]

For ease of exposition, I assume that the expert does not price discriminate.\(^\text{13}\) Also, hereafter I do not explicitly model the possibility that the expert refuses to provide any treatment. As we have seen from the previous section, in equilibrium the expert will never post a price list such that in some recommendation subgames she would rather refuse to provide any treatment.

Equilibrium. The expert’s mixed strategy specifies a price list \( \{p_m, p_s\} \in \mathbb{R}^2 \) and, for every possible price list, the probabilities of charging \( p_s \) and \( p_m \) conditional on each diagnostic outcome for each type of customer: \((\beta^T, 1 - \beta^T)\), for \( i \in \{m, s\}, T \in \{L, H\}\). A mixed strategy for a type- \( T \) customer specifies, for every possible price list, the probabilities of accepting and rejecting each recommended treatment: \((\gamma^T, 1 - \gamma^T)\), for \( i \in \{m, s\}, T \in \{L, H\}\). After setting the prices, the expert faces two possible recommendation subgames: one with type- \( H \) and the other with type- \( L \) customers. I can adapt the logic in the proof of Proposition 1 to argue that the profit-maximizing prices \( p_m \) and \( p_s \) must belong to the ranges \([r_m, \ell^m]\) and \([r_s, \ell^H]\) respectively. So there is no loss of generality in assuming that the expert chooses prices from these ranges.

According to the analysis in the basic model, by setting \( p_s \) at \( \ell^H_s \), a type- \( H \) customer’s loss from the serious problem, the expert earns the highest possible profit from type- \( H \) customers. She is also totally honest with these customers. Nevertheless, since \( p_s > \ell^L_s \), type- \( L \) customers never accept the serious treatment, and the expert earns no profit from type- \( L \) customers who have a serious problem. The larger the fraction of type- \( L \) customers, the larger this loss of profit.

When the fraction of type- \( L \) customers is significant, it is more profitable to lower \( p_s \) to \( \ell^L_s \) to induce some type- \( L \) customers to accept the serious treatment. From the insight we draw from equation (2), once \( p_s \) is set below \( \ell^H_s \), the expert will cheat type- \( H \) customers with a positive probability, i.e., \( \beta^H_m > 0 \).

\[\text{Proposition 2. Let } \theta \in [0, 1] \text{ denote the fraction of type-} \ H \text{ customers. Cheating arises if and only if } \theta < \left( (\ell^L_s - r_s)/(\ell^H_s - r_s) \right) \left( (\ell^H_m - r_m)/(\ell^L_m - r_m) \right).\]

When the expert cheats, she cheats only type- \( H \) customers.

I have considered heterogeneity in \( \ell_s \) but not in \( \ell_m \). Heterogeneity in \( \ell_m \) does not induce selective cheating, and incorporating both forms of heterogeneities only complicates the analysis without introducing additional insights for the following reason: Imagine that customers differ only in the loss due to a minor problem (i.e., \( \ell_m \in \{\ell^L_m, \ell^H_m\} \), where \( \ell^L_m < \ell^H_m \)). In this case, there is no loss of generality in focusing on \( \{p_m, p_s\} \in [r_m, \ell^H_m] \times [r_s, \ell^L] \). When \( p_m > \ell^L_m \), a type- \( L \)

\(^\text{12}\) After Proposition 2, I discuss why heterogeneity in customers’ losses from the minor problem is unimportant for the issue that I am interested in here.

\(^\text{13}\) For a more general treatment that endogenizes the pricing mechanism and demonstrates under what conditions the expert will optimally choose to post only one price list and cheat customers, see Fong (2004).
customer will not accept a treatment at price $p_m$ because when a treatment is recommended at this price, he will infer from $p_m < r_s$ that it is a minor problem. This customer will not accept a serious treatment either, for the following reason. If he accepted with a positive probability, then the expert would always misreport a minor problem as serious, knowing that a minor treatment would never be accepted. This implies that it is not worthwhile for the customer to accept the serious treatment, which is a contradiction.

Knowing that no service will ever be provided when $p_m > \ell^H_m$, no type-L customers will visit the expert when such a $p_m$ is charged. Therefore, the expert’s tradeoff is between setting $p_m = \ell^H_m$, which attracts visits by both types of customers, and setting $p_m = \ell^H_s$, which generates the most profit from type-H customers but drives away all type-L customers. In either case, the optimal price of the serious treatment is still $p_s = \ell^s$, and there is no cheating. If both forms of heterogeneities are considered, then there will be many more possible cases to consider, but, qualitatively, Proposition 2 is unaffected.

☐ Some customers’ problems are more costly to treat. Providing the same treatment to different customers may not be equal in cost to the expert. Some customers are just more demanding and harder to serve. Others may have slight complications in their problems that cost the expert extra time and effort in fixing them.

Suppose that at the same time a customer is diagnosed to have a minor problem, the expert also notices that the problem is relatively more costly to fix compared to the minor problem suffered by other customers. Due to the higher repair cost, there is little profit in providing a minor treatment. As a result, coercing the customer into receiving a serious treatment, which is also more expensive, becomes relatively more attractive. In this subsection I study how such an incentive to discriminate against customers with costly problems may induce fraud in equilibrium.

Model modification. Consider a model that is similar to the basic model in every respect except in what follows. There are two types of customers. A fraction $\theta$ of them are of type $H$ and the rest are of type $L$. It costs $r_m^T$ to treat the minor problem suffered by a type-$T$ customer, where $T \in \{H, L\}$ and $0 < r_m^L < r_m^H < \ell_m$. It costs the same ($r_s$) to repair everyone’s serious problem. Customers know the distribution of types but not their own. Unlike in the previous subsection, I do not impose a restriction on the number of price lists the expert can offer. The expert learns each customer’s type during the meeting with the customer. On the basis of the diagnosis and the customer’s type, the expert determines which treatment to recommend.

Equilibrium. Since customers do not know whether their own costs of repair are high or low, the expert cannot induce self-selection by offering different price lists. Therefore, a mixed strategy for the expert specifies a price list $\{p_m, p_s\} \in \mathbb{R}^2$ and, for every possible price list, the probabilities of charging $p_s$ and $p_m$ conditional on each diagnostic outcome for each type of customer: $(\beta^T_1, 1 - \beta^T_1)$, for $i \in \{m, s\}$, $T \in \{L, H\}$. A mixed strategy for a customer specifies, for every possible price list, the probabilities of accepting and rejecting each recommended treatment: $(\gamma_i, 1 - \gamma_i)$, for $i \in \{m, s\}$.

As in the previous model, I adapt the logic in the proof of Proposition 1 to argue that there is no loss of generality in focusing on $\{p_m, p_s\} \in [r_m^L, \ell_m] \times [r_s, \ell_s]$. Now, I explain why the expert has a stronger incentive to cheat a type-$H$ customer than to cheat a type-$L$ customer. Misreporting a type-$T$ customer’s minor problem as serious is more profitable if and only if $(p_m - r_m^T)/(p_s - r_m^T) < \gamma_s$. Note that $(p_m - r_m^H)/(p_s - r_m^H) < (p_m - r_m^L)/(p_s - r_m^L)$. In other words, if the expert finds it profitable to cheat a type-$L$ customer, then she must also find it profitable to cheat a type-$H$ customer. Conversely, if the expert finds it unprofitable to cheat a type-$H$ customer, then she also must find it unprofitable to cheat a type-$L$ customer.

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14 More precisely, when a problem is diagnosed to be minor, the expert is comparing the profits between reporting honestly $(p_m - r_m)$ and exaggerating the problem $\gamma_s (p_s - r_m)$. Given the same $\gamma_s$, when $r_m$ drops, $(p_m - r_m)$ drops more than $\gamma_s (p_s - r_m)$ does. Therefore, misreporting becomes relatively more attractive.

15 In the previous model, customers know their own types, but in this model they do not. Therefore, all customers play the same strategy here.
Suppose the expert announces $p_s = \ell_s$. Subsequently, in the recommendation subgame, she must be honest to all customers in order to induce some of them to accept the serious treatment. In turn, to maintain the expert’s incentive to report her diagnoses truthfully to all customers, customers will accept a serious treatment with a probability as low as $\gamma_s = (p_m - r_m^H)/(p_s - r_m^H)$.

However, if the expert lowers $p_s$ from $\ell_s$ to $\hat{p}_s = \alpha \ell_s + (1 - \alpha)\theta \ell_m:[\alpha + (1 - \alpha)\theta]$, the acceptance rate of the serious treatment $\gamma_s$ will jump up to $(p_m - r_m^L)/(p_s - r_m^L)$ for the following reason. At this higher acceptance rate, $(p_m - r_m^L)/(p_s - r_m^L)$, the expert’s best reply is to cheat all type-H customers but remain honest with all type-L customers. In other words, a customer’s minor problem is misreported as serious with probability $fJ_m = e^{oJ_m + (1 - e)fJ_m} = e$. On the other hand, since the treatment price $p_s$ is lowered to $\hat{p}_s$, customers still have enough incentive to accept a serious treatment even though the expert is now cheating with some probability. That explains why $\gamma_s = (p_m - r_m^L)/(p_s - r_m^L)$ and $(fJ_m, fJ_m) = (0, 1)$ are best replies to each other when $p_s = \hat{p}_s$.

Accordingly, if $\theta$ is relatively small and $r_m^H$ is significantly larger than $r_m^L$, then $p_s$ is only slightly lower than $\ell_s$ but $(p_m - r_m^L)/(p_s - r_m^L)$ is much larger than $(p_m - r_m^H)/(p_s - r_m^H)$. In other words, lowering $p_s$ by a small amount can induce many more customers to accept the serious treatment, which can be profitable. Once $p_s$ is set lower than $\ell_s$, some customers will be cheated.

**Proposition 3.** Suppose a fraction $\theta$ of customers cost the expert $r_m^L$ to repair their minor problem and the rest cost $r_m^H$, where $r_m^H < r_m^L$. There exists some $\hat{\theta} > 0$ such that cheating must arise when $\theta \in (0, \hat{\theta})$. Furthermore, when $r_m^H$ is close enough to $r_m^L$, the expert cheats with a positive probability regardless of $\theta$. When the expert cheats, she cheats only type-H customers.

Similar to the previous model, in this model I have considered heterogeneity in $r_m$, but not in $r_s$. The expert has an incentive to cheat only when the problem is minor. Therefore, heterogeneity in $r_s$ among customers does not give rise to differential incentives to cheat. Suppose it cost different amounts, $r_m^L$ and $r_m^H$, to fix the serious problem. It could be shown that if $a\ell_s + (1 - a)\ell_m < r_s^L < r_s^H$, then what is described in Proposition 1 would still be the unique equilibrium.

### 5. Obfuscation by customers: an example

In existing theoretical models of expert markets, including those in the previous sections, customers make no contribution to the process of diagnosis. They only decide whether to accept or reject a recommendation. In reality, however, customers can often do more than that. Many customers have some ideas about their problems before they consult an expert, and the information they possess often helps the expert make a more accurate diagnosis and/or provide more successful treatment. In this section I extend the model to capture these elements by allowing imperfection in the expert’s diagnosis and possession of information by customers that can be used to correct this imperfection. I also introduce a visit cost. Now that customers have to incur a cost to visit the expert, the expert must lower the price of the minor treatment to give customers some surplus of her service. Otherwise, no customer will visit her. It is clear that a customer would benefit from sharing his information with the expert if the expert used the information only to provide a better service. Unfortunately, after the expert has acquired the information, her incentive to cheat the customer increases, knowing that now the customer values her treatment more. When the expert becomes dishonest, the probability that a customer enjoys the surplus from a minor treatment decreases. As a result, customers in the extended framework may find it optimal to withhold their private information and let the expert provide inferior service in order to avoid being picked as victims for cheating.

Here I use an example to illustrate why customers sometimes prefer not to help the expert help them. When customers are looking for rental apartments through realty companies, it is very common for them to be asked: “Would you tell us your budget so that we can more efficiently

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16 Wolinsky (1993) also studies imperfection in experts’ diagnosis. However, he does not model customers’ possession of useful information.

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show you apartments most suitable for you?” If the realty agent were merely going to use this information to help the customer find the most suitable apartment, then her awareness of his budget would save his time. Unfortunately, if the agent knows that the customer is willing to pay $2,000 for a one-bedroom apartment and there happen to be some nice one-bedroom apartments available for $1,000–1,500, it is likely that a strategic agent would not let the customer know about these options but reserve them for those with tighter budgets. So a customer may want to underestimate his budget so as not be excluded from good deals.

□ Model. Unlike in Section 3, here there are two similar but different versions of serious problems, $s_1$ and $s_2$. Customers with either serious problem suffer the same loss $\ell_i$ if the problem is left untreated. There are two treatments for these serious problems, $T_1$ and $T_2$. Treatment $T_i$ fixes problem $s_i$ completely but recovers only $\ell_i - \varepsilon$ of the loss caused by problem $s_j$, $i, j = 1, 2, i \neq j$. The loss $\varepsilon$ due to the provision of inappropriate serious treatment is not verifiable. The costs of providing treatments $T_1$ and $T_2$ are both $r_s$. Besides, there is a visit cost at level $t$ for each customer trip to the expert.

The expert can always perfectly diagnose the problem if it is minor. If the problem is $s_i$, $i = 1, 2$, however, then there is a probability $\delta \in (0, 1/2)$ that the expert believes it to be $s_j$, $j \neq i$.\(^{17}\) Since $\delta < .5$, when the expert has diagnosed a problem to be $s_j$, she believes that it is more likely to be $s_i$. A fraction $\theta$ of the customers receive a private signal. (In other words, the customers notice symptoms of a problem.) This signal is uninformative to the customer. Once it is communicated to the expert, however, it makes the expert’s diagnosis ability perfect (i.e., $\delta$ becomes zero).

After a customer has arrived at the expert’s office, the expert first solicits the signal from the customer, who, if he has received a signal, must decide whether to disclose it. Afterward, the diagnosis is performed regardless of whether the customer has given the expert a signal. Next, the expert makes a recommendation. At this point, the customer does not have a second chance to reveal the signal.\(^{18}\) Conditional on the recommendation made, the customer decides whether to accept the treatment, and if a recommendation is accepted, the expert fixes the problem at the price charged, as in previous models. Since the loss $\varepsilon$ is not verifiable, it is impossible for the expert to promise provision of follow-up service when that part of the loss is not recovered.\(^{19}\) In other words, customers must bear the consequence of the expert’s mistake if the customers choose not to reveal the signal to the expert. I also assume that although it is equally costly to provide $T_1$ or $T_2$, if the problem is more likely to be $s_i$ than $s_j$, the expert always provides treatment $T_i$. Finally, I restrict the expert to set the same price list for all customers. In particular, she cannot set different prices for the serious problem and then state that if a customer reveals his signal, then he pays a higher price for the serious treatment.\(^{20}\)

□ Equilibrium. If the expert does not learn the signal from the customer and the problem is found out to be serious, then with probability $\delta$ a loss of $\varepsilon$ cannot be recovered. In this case,

\(^{17}\) The way I model diagnostic errors is similar to Wolinsky (1993) in the sense that we both assume the expert does not make mistakes when the problem is minor. The difference is that in his model there is only one type of serious problem, and a diagnostic error occurs when an expert concludes that a problem is minor while it is actually serious.

\(^{18}\) This restriction will become a natural consequence if I further detail the model as follows. There are two diagnostic tests but only one of them is perfect. Both tests are equally costly at $c > 0$. Without the signal from the customer, the expert can only pick a test at random, so the diagnosis is subject to error. The signal lets the expert know which test is the perfect one. The expert will never perform the test for a second time even if the customer reveals the signal after the first diagnosis is performed, because doing so is costly to the expert and the loss $\varepsilon$ is not verifiable. It can also be shown that the presence of diagnostic cost will not affect equilibrium prices.

\(^{19}\) Even if that loss were verifiable, the expert might not make such a promise. For instance, if $(1 + \delta)r_s \geq \ell_s$, the expected cost of fully fixing a serious problem exceeds the loss due to a serious problem. Such a promise makes provision of serious treatment unprofitable.

\(^{20}\) If customers do not know whether they have the signal that will be useful for the expert’s diagnosis until she asks them for it, that may be a more reasonable assumption in many situations; then price discrimination will be impossible, as customers are ex ante identical in this case. In that case, such an assumption will be unnecessary.
the expected benefit to the customer in having a known serious problem treated is \( \ell_s - \delta \epsilon \). If the customer reveals the signal instead, then the benefit to the customer increases to \( \ell_s \).

If the expert expects that customers never disclose the signal, then, according to Proposition 1, the expert’s optimal pricing strategy prescribes \( p_s = \ell_s - \delta \epsilon \). If the expert instead expects customers to reveal the signal, then the environment becomes the first model in Section 4: a fraction \( \theta \) of customers receiving the signal value a serious problem’s being treated at \( \ell_s \), and the rest value it at \( \ell_s - \delta \epsilon \). Applying Proposition 2, we immediately obtain that when \( \theta \in [0, (\ell_s - \delta \epsilon - r_s)/(\ell_s - r_s)](\ell_s - r_m)/(\ell_s - \delta \epsilon - r_m)] \), the expert always sets \( p_s = \ell_s - \delta \epsilon \). In this section I focus on the case when \( \theta \) falls in this range. So, regardless of the expert’s expectation of the customers’ disclosure policy, she finds it optimal to set \( p_s = \ell_s - \delta \epsilon \).

Now I address the following question: Knowing that disclosing the signal to the expert potentially helps repair the serious problem more successfully, does the customer always find it desirable to share the signal with the expert? I shall provide a surprising answer.

**Proposition 4.** Let \( \theta \in [0, 1] \) be the fraction of customers who possess the signal. If \( \theta < \[(\ell_s - \delta \epsilon - r_s)/(\ell_s - r_s)](\ell_s - r_m)/(\ell_s - \delta \epsilon - r_m)\] \), then the expert sets \( p_s = \ell_s - \delta \epsilon \), and every customer who possesses the signal conceals it from the expert in equilibrium.

The positive visit cost plays a crucial role in establishing Proposition 4. Since visiting the expert is costly, the expert must set \( p_m < \ell_m \) to attract customers’ visits. If the expert successfully solicits the signal from a customer, the gain to the customer from having a serious problem treated is increased. As a result, the expert will cheat with a positive probability. If she does not obtain the signal, she will not cheat. That the customer is indifferent between accepting and not accepting a serious treatment in equilibrium suggests that he can benefit only when a minor treatment is recommended, where the gain is \( \ell_m - p_m > 0 \). Disclosing the signal decreases the probability that a minor treatment is recommended and thus reduces the expected gain the customer can obtain from the expert’s services.\(^{21}\) That explains why the customer finds it better to withhold the signal from the expert.

The analysis in this section is intended to initiate research on communication from customers to experts. Obviously, I study only one specific type of private information that customers may possess. Some other information that customers may or may not want to share with the expert includes the previous diagnosis, if they have seen another expert, their own knowledge level, etc. Regardless of its limitation, the analysis in this section has made us aware that asymmetric information in expert markets is two-sided instead of one-sided; and experts’ incentives to cheat may impair both directions of communication between an expert and a customer.

### 6. Conclusion

In this article I have shown that it is generally difficult to use a two-by-two model of expert markets to explain how experts cheat their customers. My theories of expert cheating suggest that, apart from experts’ superior information about customers’ needs, other heterogeneities among customers that experts can identify can explain why real-life experts not only cheat, but also cheat selectively. Two candidates proposed are heterogeneity among customers to the extent that each customer suffers from a problem, and heterogeneity in the amount it costs an expert to treat a customer’s problem.

I have also taken the first step to studying asymmetric information in expert markets as a two-sided rather than a one-sided issue. On the basis of this extended model, it is shown that an expert’s incentive to cheat selectively not only may inhibit effective communication of the expert’s information to customers, but also may discourage customers from sharing useful information with her.

\(^{21}\) Here the expected gain to customers refers to the gain in the recommendation subgame. The expert will set \( p_m \) high enough such that the gain in the recommendation subgame equals the visit cost. Customers, then, do not have any surplus from consulting the expert in equilibrium.

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I fully recognize that customers’ search for second opinions and experts’ concerns for reputation and other market forces are important in disciplining experts’ behavior. I have chosen to motivate my research in a one-shot monopolist setting just because it is most suitable to demonstrate how the no-cheating result from a two-by-two model readily extends even when the market environment favors cheating. To maintain a coherent line of reasoning, all the modifications in the latter part of the article have been built on the same market structure.

It is important for future research to verify whether selective cheating remains a natural equilibrium outcome when experts compete and customers search for second opinions. There are good reasons to believe that this is the case. First, at any given prices of treatment, the expert can afford to cheat with a higher probability on those customers with higher valuations while maintaining their incentives to accept treatments instead of searching for another expert. Second, given a certain probability of customers accepting the serious treatment instead of visiting another expert, there is less profit in honestly reporting minor problems to more costly customers; thus the expert has a stronger incentive to misreport the problems of costly customers.

The findings in this article lay the foundation for further research on other possible causes of expert cheating. One of them is customer heterogeneity in knowledge. This is motivated by the anecdotal evidence that car mechanics and computer salesmen often target ignorant customers. Suppose that among customers, some can self-diagnose their problems but just need the expert’s treatment services. Unlike the case when all customers are ignorant, the only way to attract expert customers who already know that they have a serious problem is to lower the price of the serious treatment. Once the price of the serious treatment is lowered, then ignorant customers will become targets for cheating. Finally, in the analysis of strategic communication from customers to the expert, I have considered only one type of private information customers may possess. Future research can address a more in-depth study of this issue.

Appendix A

Proofs of Propositions 1–4 follow.

Proof of Proposition 1. Step 1. In any recommendation subgame that follows the expert posting a price list containing some price \( p \notin [r_m, \ell_m] \cup [r_s, \ell_s] \), no profit will be generated by a treatment at that price.

It is straightforward that any recommendation at \( p > \ell_s \) will be rejected, and any recommendation at \( p < r_m \) leads to zero profit or a loss. For some profit to be generated by a treatment at \( p \in (r_m, \ell_m) \), it must be that it is accepted sometimes. If so, since \( r_s > p \), the expert will recommend a treatment at \( p \) only if the problem is minor. This contradicts the notion that customers sometimes accept the treatment.

Step 2. In any subgame following \( \{p_m, p_s\} \in (r_m, \ell_m) \times (r_s, \ell_s) \), the equilibrium strategy profile is characterized by the probabilities

\[
\gamma_m = 1, \quad \gamma_s = \frac{p_m - \ell_m}{p_s - \ell_m},
\]

\[
\rho_m = \rho_s = 0, \quad \beta_m = \frac{\alpha(\ell_s - p_s)}{(1 - \alpha)(p_s - \ell_m)}, \quad \beta_s = 1.
\]

The expected profit is

\[
\Pi(p_m, p_s) = \alpha(p_s - r_s) \frac{p_m - \ell_m}{p_s - \ell_m} + (1 - \alpha)(p_m - r_m).
\]

Since \( p_m < \ell_m \), it is the customer’s best reply to set \( \gamma_m = 1 \), which in turn implies \( \rho_m = 0 \). Also since \( p_m < r_s \), it is the expert’s best reply to set \( \beta_s = 1 \). Since \( r_s < p_s \), any strategy specifying \( \beta_s < 1 \) is weakly dominated. So, \( \beta_s = 1 \), \( \rho_s = 0 \). Note the following best replies: if \( \gamma_s = 1 \), then \( \beta_m = 1 \) because \( p_m < p_s \); if \( \beta_m = 1 \), then \( \gamma_s = 0 \) because \( \alpha(\ell_s + (1 - \alpha)\ell_s < r_s) < p_s \); if \( \gamma_s = 0 \), then \( \beta_m = 0 \) because \( r_m < p_m \); and if \( \beta_m = 0 \), then \( \gamma_s = 1 \) because \( p_s < \ell_s \). So there is no pure-strategy equilibrium in the subgame and \( \beta_m, \gamma_s \in (0, 1) \).

It requires \( (p_m - r_m) = \gamma_s(p_s - r_s) \) for the expert to mix between charging \( p_m \) and \( p_s \) when the problem is minor; this establishes (A1). Similarly, for the customer to mix between accepting and rejecting a treatment at \( p_s \), it requires

22 For empirical evidence supporting the notion that market forces do provide incentives for experts to take actions favorable to customers, see Hubbard (1998).
\[(\alpha \xi + (1 - \alpha)\beta m[m]/(\alpha + (1 - \alpha)\beta m) = p_s . \]
By manipulating this equality, the \(\beta m\) in (A2) can be derived. The strategies
characterized by (A1) and (A2) give rise to (A3).

Step 3. In any equilibrium, \(\{p_m, p_s\} \in [r_m, \ell_m] \times [r_s, \ell_s]\).

(i) Rule out \(\{p_m, p_s\} \in [r_m, \ell_m]^2\). Since \(\max\{p_s, p_m\} < r_s\), the maximum possible profit from such a price list
is \((1 - \alpha)\max\{p_s, p_m\} - r_m\), which is less than the profit from charging \(\{p_m, p_s\}\) arbitrarily close to but less than
\(\ell_m, \ell_s\), according to (A3).

(ii) Rule out \(\{p_m, p_s\} \in [r_s, \ell_s]^2\). Suppose max\{\(\gamma_m\), \(\gamma_s\)\} > 0. Then the expert sets \(p_m = p_s = 0\) and either \(\alpha m \geq \beta m, \beta m > 0\) or \(\beta m \geq \beta m, \beta m > 0\). If \(\beta m \geq \beta m, \beta m > 0\), then \(\beta m(\ell_m + (1 - \alpha)\beta m[m]/(\alpha \beta m + (1 - \alpha)\beta m) \leq \alpha \ell_s + (1 - \alpha)\ell_s < r_s \leq p_m\), and the customer’s best reply is \(\gamma_m = 0\), which contradicts \(\beta m > 0\). Similar logic out
\(\beta m \geq \beta m, \beta m > 0\). So, \(\{p_m, p_s\} \in [r_s, \ell_s]^2\) leads to zero profit.

(iii) Rule out \(p_s \in [r_m, \ell_m] \cap \{r_s, \ell_s\}, p_s \notin [r_m, \ell_m] \cup [r_s, \ell_s]\). This can be ruled out because profits in such
subgames are the same as those with \(p_m = p_s \in [r_m, \ell_m] \cup [r_s, \ell_s]\).

(iv) Rule out \(p_m = r_m\). If \(p_m = r_m\), the customer must set \(\gamma_s = 0\), otherwise the expert would always cheat, which
contradicts \(\gamma_s > 0\).

(v) Rule out \(p_s = r_s\). Customers must set \(\gamma_s \leq (p_m - r_m)/(p_s - r_m)\), otherwise the expert’s best reply would
be \(\beta m = 1\), which contradicts \(\gamma_s > 0\). Therefore, the expert earns \(\Pi(p_m, r_s) = (1 - \alpha)(p_m - r_m)\), which is less than what
she would have earned by setting \(p_s = r_s \in (r_s, \ell_s]\), according to (A3).

Step 4. Equations (A1)–(A3) hold when \(p_m = \ell_m\) and \(p_s = \ell_s\), and the claim of the proposition is true.

In (A3), \(\Pi\) increases in both \(p_m\) and \(p_s\). If at \(p_s = \ell_s\) customers played \(\gamma_s < (p_m - r_m)/(p_s - r_m)\), then there would be
a discrete drop in profit at \(p_s = \ell_s\). In response, the expert would choose the maximum price \(p_s\) in the open set \((r_s, \ell_s]\),
and there would be no solution. For the same reason, we can rule out \(\gamma_s < 1\) at \(p_m = \ell_m\). Therefore (A1), (A2), and (A3)
hold at \(p_m = \ell_m\) and \(p_s = \ell_s\), and also at \(\{p_m, p_s\} = \{\ell_m, \ell_s\}\), profit is maximized. It is obvious that \(\beta m = p_s = 0\) and \(\beta s = 1\). To support a \(\gamma_s > 0\), it must also hold that \(\beta m = 0\). \(\Box\).

Proof of Proposition 2. I adapt the arguments in the proof of Proposition 1 to reason that the profit-maximizing \(\{p_m, p_s\}\)
must fall on the ranges \([r_m, \ell_m] \times (r_s, \ell_s]^2\).

If the expert sets \(p_s \leq \ell_s\), then according to (1), \(\gamma_s = 1\), \(\gamma_s = (p_m - r_m)/(p_s - r_m), T \in \{L, H\}\). Therefore, the expert’s total expected profit has the same expression as (3).

\[\Pi_1(p_m, p_s) = \alpha p_m - r_m - r_m, (p_s - r_s) + (1 - \alpha)(p_m - r_m), \quad \{p_m, p_s\} \in [r_m, \ell_m] \times [r_s, \ell_s].\]

If the expert sets \(p_s > \ell_s\), then type-L customers never accept a treatment at \(p_s\), i.e., \(\gamma_s = 1, \gamma_s = 0\), while type-H
customers still play \(\gamma_s = 1, \gamma_s = (p_m - r_m)/(p_s - r_m)\). In this case, the total expected profit of the expert is

\[\Pi_1(p_m, p_s) = \alpha (p_m - r_m) + (1 - \alpha)(p_m - r_m), \quad \{p_m, p_s\} \in [r_m, \ell_m] \times (\ell_s, \ell_s].\]

So, \(\Pi_1\) increases in both \(p_m\) and \(p_s\) for \(\{p_m, p_s\} \in [r_m, \ell_m] \times (r_s, \ell_s]^H\), except that it drops discretely when \(p_s\) goes
from below to above \(\ell_s^H\), as type-L customers stop accepting the treatment at \(p_s\).

Therefore, the only candidate equilibrium price lists are \([\ell_m, \ell_s]^L\) and \([\ell_m, \ell_s]^H\), and the expert posts \(\{p_m, p_s\} = \{\ell_m, \ell_s^L\}\) if and only if \(\Pi_1(\ell_m, \ell_s^L) > \Pi_1(\ell_m, \ell_s^H), i.e.\), \(\theta < (\ell_s^L - r_s)/(\ell_s^H - r_s)\). When \(\{p_m, p_s\} = \{\ell_m, \ell_s^L\}\), according to (A2), \(\beta m = \alpha (\ell_s^L - \ell_m)/(1 - \alpha)(\ell_s^L - \ell_s^L) = 0\) and \(\beta m = 0\). The expert cheats only type-H customers.

Then we look at the cases when \(\theta \geq (\ell_s^L - r_s)/(\ell_s^H - r_s)/(\ell_s^H - \ell_s^L)/r_s^H)\). The expert sets \(p_m = \ell_m, p_s = \ell_s^H\). It is obvious that \(\beta m = \beta m = 0, i.e.\), she is totally truthful. \(\Box\).

Proof of Proposition 3. Again, I adapt arguments from the proof of Proposition 1 to reason that the profit-maximizing
\(\{p_m, p_s\}\) must fall in \([r_m, \ell_m] \times [r_s, \ell_s]\). It is straightforward that for all these price lists, \(\gamma_s = 1, \beta s^L = \beta s^H = 1\).

Notice that the best reply of the expert specifies that

\[\beta m^L(\gamma_s) = \begin{cases} 0 & \text{if } \gamma s < (p_m - r_m^L)/(p_s - r_s^L), \\ \{0, 1\} & \text{if } \gamma s = (p_m - r_m^L)/(p_s - r_s^L), \\ 1 & \text{if } \gamma s > (p_m - r_m^L)/(p_s - r_s^L), \end{cases}, T \in \{H, L\}.

So the probability a customer’s minor problem is reported as serious, \(\beta m(\gamma s) = (1 - \theta)\beta m^L(\gamma s) + \theta \beta m^H(\gamma s)\), is a step-function
\(\gamma s\) stepping up at \(\gamma s = (p_m - r_m^L)/(p_s - r_s^L)\) from zero to \(\theta\), and then at \(\gamma s = (p_m - r_m^L)/(p_s - r_s^L)\) from \(\theta\) to one.

\(^{23}\) Here, both \(\ell_s^L\) and \(\ell_s^H\) do not appear in \(\Pi_1\), for the same reason that \(\ell_s\) does not appear in \(\Pi\) in the benchmark
model.

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Adapting step 2 of the proof of Proposition 1, in equilibrium of the recommendation subgame, \( Y_s \in (0, 1) \). To support this, it requires that \( P_s = \frac{1}{\xi} \) if \( P_s = \xi \).

Define \( P_m = \frac{1}{\xi} \) if \( P_s = \xi \).

Adapting the arguments used in the proof of Proposition 1 to rule out \( Y_m < 1 \) and \( Y_s < \frac{1}{\xi} \) when \( P_m = \xi \) or \( P_s = \xi \), it can be shown that for the purpose of deriving the equilibrium outcome of the whole game, there is no loss of generality in assuming that \( Y_s = \frac{1}{\xi} \) when \( P_s = \xi \) and \( Y_s = \frac{1}{\xi} \) when \( P_s = \xi \).

Notice that the expert has a strict preference to cheat only when \( P_s \in (\xi, f_s] \) and she cheats only type-\( H \) customers. With these and \( Y_m = 1 \), we can derive the expected profit as
check the robustness of Proposition 1. Let these possible problems be denoted by problems 1, 2, and 3. If a customer has problem \( i \in \{1, 2, 3\} \), which happens with probability \( \alpha_i (\alpha_1 + \alpha_2 + \alpha_3 = 1) \), then he suffers a loss of \( \ell_i \), where \( \ell_1 < \ell_2 < \ell_3 \). We retain the assumption that all treatments are efficient to provide, i.e., \( \ell_i < \ell_i, i \in \{1, 2, 3\} \).

Let \( K \) denote a subset of possible problems, so \( K \) may be \{1\}, \{2\}, \{3\}, \{1, 2\}, \{2, 3\}, \{1, 3\} or \{1, 2, 3\}. Let \( \ell_K \) denote the expected loss a customer suffers conditioned on \( i \in K \), and \( p_K \) denote the treatment price the expert posts for the whole subset of problems \( K \). Moreover, let \( \beta^K \) denote the probability that the expert charges \( p_K \) given that the problem is diagnosed to be \( i \), and \( y_K \) denote the probability that the customer accepts a recommended treatment at the price \( p_K \). Throughout this Appendix, I retain the assumption that in equilibrium of any recommendation subgame, no agents play weakly dominated strategies. As in Sections 4 and 5, for ease of exposition I rule out the possibility that the expert sets a price list such that she sometimes refuses to provide any treatment.

Recall that when there are two possible levels of severity, regardless of the parameter values, there is only one single equilibrium outcome that does not involve weakly dominated strategy. This uniqueness result does not carry over to this more general setting. Throughout this Appendix, I impose the following equilibrium-selection criterion to rule out constraints on the expert’s profit maximization caused by arbitrary off-equilibrium beliefs:

**Assumption B1.** If there exists more than one equilibrium in a subgame that follows the announcement of a set of price(s), then the one that generates the highest profit to the expert will be selected.

Also, when I state that “the expert posts \( n \) prices,” it means the expert sets \( n \) prices and all \( n \) prices are charged by her and accepted by customers with positive probabilities in the recommendation subgame. If a price on the posted price list will never be used, then both the expert and customers can infer that, and the expert can simply drop that price without affecting the equilibrium behaviors in the recommendation subgame. Equilibria with redundant prices are not considered here. Now I state the main claim of this appendix.

**Proposition B1.** Under Assumption B1, if in equilibrium the expert posts three different prices, these prices must be \( p_1 = \ell_1, p_2 = \ell_2 \), and \( p_3 = \ell_3 \), and she is totally honest in the recommendation subgame, i.e., \( \beta_1^1 = \beta_2^2 = \beta_3^3 = 1 \).

**Proof.** Consider an arbitrary equilibrium in which the expert posts three different prices and call these prices \( p_1, p_2, \) and \( p_3 \), where \( p_1 < p_2 < p_3 \). For all three prices to be meaningful, it must be that \( y_1 > 0 \) and \( \beta_1^i + \beta_2^i + \beta_3^i > 0 \) for \( i = 1, 2, 3 \). To provide the expert an incentive to sometimes charge \( p_1 \), we must have that for some \( r \in \{r_1, r_2, r_3\} \), \( y_1(p_1 - r) \geq y_j(p_1 - r) \) for all \( j \neq i \). In other words, if \( p_j > p_1 \), then \( y_1 > y_j \) is required. So for every price to be charged with a positive probability, it must be that \( y_1 > y_2 > y_3 > 0 \). If \( y_1, y_2, y_3 \), for some \( y_1 < 1 \), constitute an equilibrium strategy of customers, so do \((1, y_2/y_1, y_3/y_1)\), but the latter generate more profit. Assumption B1 implies that

(i) \( y_1 = 1 \).

Notice we do not restrict that \( r_1 < r_2 < r_3 \). Rank and rename the repair costs so that \( r_a < r_b < r_c \), where \( a, b, c \in \{1, 2, 3\} \).\(^{24}\) For \( p_3 \) to be charged with a positive probability, it requires

(ii) \( \beta_3^1 > 0 \).

Suppose \( \beta_3^1 = 0 \). Then \( y_1(p_1 - r_a) \geq y_3(p_3 - r_a) \) for either \( i = 1 \) or 2, and this would in turn imply that \( y_1(p_1 - r_j) > y_j(p_j - r_j) \) for \( i = 1 \) or 2, \( j = a, b, c \), which would mean \( \beta_3^2 = \beta_3^3 = 0 \) and render \( p_3 \) redundant. By symmetry, for \( p_1 \) to be charged with a positive probability, it must hold that

(iii) \( \beta_1^3 > 0 \).

Now show that (iv) \( \beta_2^2 > 0 \). Suppose \( \beta_2^2 = 0 \). Then either \( \beta_2^2 > 0 \) or \( \beta_2^3 > 0 \) must hold for \( p_2 \) to be meaningful. First suppose \( \beta_2^1 > 0 \). To support \( \beta_2^1, \beta_1^2 > 0 \), it would require that \( (p_1 - r_a) = y_2(p_2 - r_a) \), which would in turn imply \( (p_1 - r_a) < y_2(p_2 - r_a), i = a, b, c \), and thus \( \beta_1^2 = \beta_2^3 = 0 \). If \( \beta_1^2 = \beta_2^2 = 0 \), then customers would infer that the problem is \( i \) whenever either \( p_1 \) or \( p_2 \) is charged. To support \( y_1, y_2 > 0 \), it would require \( p_1 < p_2 \leq \ell_a \). In the spirit of Assumption B1, \( y_3 = (p_1 - r_a)/(p_3 - r_a) \), which is the highest possible level compatible with \( \beta_2^2 \neq 0 \). The profit of the expert is

\[
\Pi = \begin{cases} 
\alpha_a(p_1 - r_a) + \alpha_b(p_1 - r_a)(p_3 - r_c) & \text{if } p_3 \leq r_b, \\
\alpha_a(p_1 - r_a) + \alpha_b + \alpha_c(p_1 - r_a)(p_3 - r_c) & \text{if } p_3 > r_b.
\end{cases}
\]

In either case, the expert always prefers to increase \( p_1 \) for any \( p_1 < p_2 \leq \ell_a \). So it cannot hold in equilibrium that \( p_1 < p_2 \).

\(^{24}\) For ease of exposition, I do not consider the nongeneric cases that the repair costs of different problems are exactly equal. The arguments in the proof easily extend to these cases. It can also be shown that when treatment costs of different problems are identical, the expert usually finds it more profitable to lump problems together and set fewer than three prices. For example, if \( r_1 = r_2 = r_3 \), it is optimal to charge \( p_{123} = \ell_{123} \); if \( r_1 = r_2 < r_3 \), it is optimal to charge \( p_{12} = \ell_{12} \) and \( p_3 = \ell_3 \), etc.

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Now, suppose $\beta_i^2 > 0$ for $i = 1, 2$. For $\beta_i^2 > 0$, it requires $\gamma_2(p_2 - r_c) = \gamma_3(p_3 - r_c)$, which implies $\gamma_2(p_2 - r_1) > \gamma_3(p_3 - r_1), i = 1, 2$, and thus $\beta_1^3 = \beta_2^3 = 0$. In turn, $\beta_i^3 = \beta_i^2 = 0$ implies that customers infer that the problem is $c$ when either $p_2$ or $p_3$ is charged. For $\gamma_2, \gamma_3 < 1$, it requires $p_2 = p_3 = \ell_c$, which contradicts that $p_2 < p_3$. By now, (iv) is established.

(ii)–(iv) together imply that
\[
\begin{align*}
(p_1 - r_a) &\geq \max\{\gamma_2(p_2 - r_a), \gamma_3(p_3 - r_a)\}, \\
\gamma_2(p_2 - r_b) &\geq \max\{(p_1 - r_b), \gamma_3(p_3 - r_b)\}, \\
\gamma_3(p_3 - r_c) &\geq \max\{(p_1 - r_c), \gamma_2(p_2 - r_c)\}.
\end{align*}
\]

(B1)

In the spirit of Assumption B1, we choose the highest possible $\gamma_2$ and $\gamma_3$ satisfying (B1):
\[
\begin{align*}
\gamma_2 &= \min\left\{\frac{p_1 - r_a}{p_2 - r_a}, \frac{\gamma_3(p_3 - r_c)}{p_2 - r_c}\right\}, \\
\gamma_3 &= \min\left\{\frac{p_1 - r_a}{p_3 - r_a}, \frac{\gamma_2(p_2 - r_b)}{p_3 - r_b}\right\}.
\end{align*}
\]

(B2)

Plugging $\gamma_3$ into $\gamma_2$ gives
\[
\gamma_2 = \min\left\{\frac{p_1 - r_a}{p_2 - r_a}, \frac{p_1 - r_a}{p_3 - r_a}, \frac{p_1 - r_a}{p_2 - r_b} \gamma_3(p_2 - r_b) \frac{\gamma_3(p_3 - r_c)}{p_2 - r_c}\right\} = \frac{p_1 - r_a}{p_2 - r_a}.
\]

The second equality holds because
\[
\frac{p_2 - r_b}{p_3 - r_b} > \frac{p_2 - r_c}{p_3 - r_c}
\]
and thus
\[
\gamma_2(p_2 - r_b) \frac{p_3 - r_c}{p_2 - r_c} > \gamma_2.
\]

The third equality is due to
\[
\frac{p_1 - r_a}{p_3 - r_c} \frac{p_3 - r_c}{p_2 - r_c} > \frac{p_1 - r_a}{p_3 - r_a} = \frac{p_1 - r_a}{p_2 - r_a}.
\]

Plugging $\gamma_2 = (p_1 - r_a)/(p_2 - r_a)$ back into $\gamma_3$ in (B2), noticing that
\[
\frac{p_1 - r_a}{p_2 - r_a} \frac{p_2 - r_b}{p_3 - r_a} > \frac{p_1 - r_a}{p_2 - r_a} \frac{p_2 - r_a}{p_3 - r_a} = \frac{p_1 - r_a}{p_3 - r_a},
\]
we have
\[
\gamma_3 = \frac{p_1 - r_a}{p_2 - r_a} \frac{p_2 - r_b}{p_3 - r_a}.
\]

In response to $\gamma_2$ and $\gamma_3$, the expert sets $\beta_1^1 = \beta_2^1 = \beta_3^1 = 0$. Moreover, the expected profit is
\[
\alpha_1(p_1 - r_a) + \alpha_2 \frac{p_1 - r_a}{p_2 - r_a} (p_2 - r_b) + \alpha_3 \frac{p_1 - r_a}{p_2 - r_a} \frac{p_2 - r_b}{p_3 - r_a} (p_3 - r_c).
\]

(B3)

The profit increases in all prices. Since $\beta_1^1 = \beta_2^1 = 0$, (B3) holds for $p_1 \in [r_a, \ell_a]$ and it is optimal to set $p_1 = \ell_a$. Since $\beta_3^1 = 0$, (B3) holds for $p_2 \in [r_b, \max\{\ell_a, \ell_b\}]$ and the expert charges $p_2 = \max\{\ell_a, \ell_b\}$. Since $p_2 < p_1$, it must be $p_2 = \ell_b > \ell_a = p_1$. Since $\beta_3^1 = 0$, (B3) holds for $p_3 \in [\ell_c, \max\{\ell_b, \ell_c\}]$. Again, since $p_3 > p_2$, it must be $p_3 = \ell_c > \ell_b = p_2$. Since $\ell_a < \ell_b < \ell_c$ and $\ell_1 < \ell_2 < \ell_3$, it must be $a = 1, b = 2$, and $c = 3$, and $p_1 = \ell_1, p_2 = \ell_2$, and $p_3 = \ell_3$. To induce customers to accept some treatments, the expert must be fully honest. Q.E.D.

References


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