When Do Experts Cheat And Whom Do They Target?*

Yuk-fai Fong†

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Abstract

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. The author proposes 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.

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†Management and Strategy Department, Kellogg School of Management, Northwestern University, Leverone Hall, 6th Floor, 2001 Sheridan Road, Evanston, IL 60208-2001; email: y-fong@kellogg.northwestern.edu.
1 Introduction

In this paper I examine markets for credence goods. A credence good 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 paper 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 (1993), Taylor (1995), Emons (1997, 2001) and Alger and Salanié (2003).\footnote{Except in Pitchik and Schotter’s studies where prices are exogenously given, only two possible equilibrium outcomes have been studied in these two-by-two models: the expert either offers to fix a customer’s problem at a flat rate regardless of the severity of the problem or whenever the expert offers 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 ripped
off 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 men even choose to target the religious, rich or sick.4

In an article in *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.”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, p. 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 implicit assumption that treatment prices are exogenously given at certain levels. To date there is no flexible-price model that explains under what situations the market will endogenously give rise to the price levels these authors consider.

In this paper, 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 which shed new light on the economics behind expert cheating. In a two-by-two model, apart from the severities of their problems, customers are very *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 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 three-fold. 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 only be recognized by the expert during the diagnosis, when the expert constructs a price list for her services, the expert 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 regarding 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. In order 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 paper is organized in the following manner. In the next section I provide a comparative literature review. Next, I illustrate a basic two-by-two model where search for second opinions and reputation concerns are absent, and discuss limitations of two-by-two models. To build new theories of expert cheating, I then modify the basic model in two ways to introduce identifiable customer heterogeneities. I subsequently 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.

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 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 that differentiates his work from the current paper 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 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 paper, 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 of 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 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.

While the basic model is used primarily to motivate the need of a better understanding of how expert cheating arises, the first main novelty of this paper is the 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.

Besides, these extensions provide the new insight that cheating sometimes arises as a substitute for price discrimination. Another novelty of the paper is its study of how the way experts pick victims may hinder communication of useful information from customers to experts.

Other important studies of expert markets which are also related to my paper include those by Biglaiser (1993), Taylor (1995), and Pesendorfer and Wolinsky (2003). Biglaiser (1993) 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 (1995) studies the relationship between owners of durable goods and experts who provide diagnosis and treatment for durable goods. In his model, when customers are given a one-price-fixes-all deal, they 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 (2003) study experts' disincentive to
exert effort to provide an accurate diagnosis. They 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 are a continuum of customers with measure 1. Each has a problem of which it is
common knowledge that it may be either serious \((s)\), with probability \(\alpha\), or minor \((m)\), with
probability \(1 - \alpha\). If problem \(i \in \{m, s\}\) is left untreated, a customer (henceforth he) bears a
loss of \(l_i\), with \(l_m < l_s\). An expert monopolist (henceforth she) provides costless diagnosis and
costly treatment services for customers’ problems. Treatments for different problems are not
substitutable. Name the treatment for problem \(i\) as treatment \(i\) and let \(r_i\) denote its cost.

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
\(i\) but the expert has recommended treatment \(j, j \neq i\), she just needs to repair at cost \(r_i\), but
does not have to incur any additional cost in faking treatment \(j\). In this sense, cheating is
costless.

At the beginning of the game, the expert announces two prices, \(p_m\) and \(p_s\), for the minor
and serious treatment. If 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) 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.

A pure strategy of the expert in a recommendation subgame specifies whether she refuses
to provide a treatment, charges \(p_s\), or charges \(p_m\), 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, conditioned on the expert charging 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, but both the expert and the customer may mix in many recommendation subgames. Therefore, when we look at the whole game, we focus on mixed strategies of the expert which each specify a price list \( \{p_m, p_s\} \in \mathbb{R}_+^2 \) and, for every recommendation subgame following every price list, \( \{\rho_i(p_m, p_s), \beta_i(p_m, p_s), 1 - \rho_i - \beta_i : i = m, s\} \). A mixed strategy of the customer specifies \( \{\gamma_i, 1 - \gamma_i : p_i = p_m, p_s\} \), for every recommendation subgame following every price list.

Throughout this paper, I restrict my attention to situations in which the following conditions are satisfied:

\[
0 < r_m < l_m, \quad 0 < r_s < l_s, \\
\alpha l_s + (1 - \alpha) l_m < r_s.
\]

(R)

The first line of (R) states that the expert has effective technologies to treat both problems, and the second line rules out uninteresting cases. Without the second restriction, the expert will set a single price for both problems at the customers’ \textit{ex ante} expected loss (i.e., \( p_m = p_s = \alpha l_s + (1 - \alpha) l_m \)). I call this a \textit{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. One immediate implication of (R) is \( 0 < r_m < l_m < r_s < l_s \).

Now, I state the main result in the basic model:

\textit{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 \(p_m = l_m, \ p_s = l_s\). 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 \((\rho_m = \rho_s = 0)\). Customers accept a treatment offered at price \(p_m\) with probability \(\gamma_m = 1\), and a treatment offered at price \(p_s\) with probability \(\gamma_s = (l_m - r_m) / (l_s - r_m)\).

**Proof.** See Appendix A.

In the proof of Proposition 1, I show that in a recommendation subgame with \(p_m \in (r_m, l_m)\) and \(p_s \in (r_s, l_s)\), there is a unique equilibrium in which both players play totally mixed strategies. The equilibrium strategy profile in each subgame is characterized by the probabilities of mixing over pure strategies:

\[
\gamma_m = 1, \quad \gamma_s = \frac{p_m - r_m}{p_s - r_m}; \\
\rho_m = \rho_s = 0, \quad \beta_m = \frac{\alpha (l_s - p_s)}{(1 - \alpha) (p_s - l_m)}, \quad \beta_s = 1. \tag{2}
\]

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 the expected cost of each customer derived from equations (1) and (2) are\(^\text{11}\)

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

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

By equation (3), the expected profit of the expert increases in both \(p_m\) and \(p_s\), and is therefore maximized at \(p_m = l_m\) and \(p_s = l_s\). According to equation (2), \(\beta_m\) goes to zero when \(p_s\) goes to \(l_s\). That explains why there is no cheating in equilibrium.
Here I provide some more intuition of the no-cheating result. The second term in equation (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 wants to earn the difference \((p_s - r_s)\) instead of 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 equation (3). One can understand \((p_s - r_s)\) as the incremental margin and \((p_m - r_m) / (p_s - r_m)\) 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 \(p_s = l_s\), 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 there is 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 are repaired. But, because the price of serious treatment is higher than that of minor treatment, customers must reject a 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 treatment. A fraction \(\alpha\) of the customers has the serious problem and each of them rejects the serious treatment with probability \((l_s - l_m) / (l_s - r_m)\). Because every rejection forgoes a potential efficiency gain of \((l_s - r_s)\), the total efficiency loss is
In Emons’s (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.

What supports the no-cheating result in this section is the high price of serious treatment \( p_s = l_s \). One may expect that when there is competition or when customers must incur a cost to visit an expert, the expert must lower the prices to attract the customer’s first visit. Once \( p_s \) is set below \( l_s \), cheating arises. 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.

Yet, 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 or reject the treatment. When a treatment is rejected, a customer’s problem remains 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 non-negative profit. So the equilibrium prices solve

\[
\min_{(p_m, p_s)} C(p_m, p_s) = p_m + \frac{\alpha (p_s - p_m) (l_s - l_m)}{l_s - r_m}
\]

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 \( (p_m, p_s) = (r_m, l_s) \). Plugging these prices into equations
(1) and (2), we have

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

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 \( l_s \). Again, since the expert’s profit increases in \( p_s \) and customers’ cost decreases in \( p_s \), fixing \( p_s \) at \( l_s \) 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 to 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 charges 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 regarding customers’ needs for services alone is inadequate 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 customers.

### 4.1 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. However, if he is a Hi-fi enthusiast and has installed an expensive car stereo, he will suffer much more.

Given that the expert serves customers who suffer to different extents from the same problem, it might be ideal for she to 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 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 \(l^H_s\) from the serious problem. The remaining fraction \((1 - \theta)\) are of type \(L\) and suffer a loss \(l^L_s\) from the same problem, where \(l^L_s < l^H_s\). Both types suffer equally \((l_m)\) from the minor problem. Customers’ types are observable to the expert. None of \(l^L_s\) and \(l^H_s\) is too large so that the ex ante expected losses of both types satisfy restriction (R):

\[
\alpha l^L_s + (1 - \alpha) l_m < \alpha l^H_s + (1 - \alpha) l_m < r_s.
\]

For simplicity of exposition, I assume in the main text that the expert does not price discriminate. The endogenization of the pricing mechanism is postponed to Appendix C. 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 any equilibrium, the expert will not post a price list such that in the recommendation subgame she would rather refuse to provide any treatment.

**Equilibrium.** The expert’s mixed strategy specifies a price list \( \{p_m, p_s\} \), and for every possible price list, a recommendation policy for each type of customer characterized by the probabilities \( \beta^T_m, \beta^T_s, T \in \{L, H\} \). A mixed strategy of a type-\( T \) customer specifies \( \gamma^T_m, \gamma^T_s, T \in \{L, H\} \), for every possible price list. 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 steps 1 and 2 in the proof of Proposition 1 to argue that the profit-maximizing prices \( p_m \) and \( p_s \) must belong to the ranges \([r_m, l_m]\) and \([r_s, l_s^H]\) respectively.

According to the analysis in the basic model, by setting \( p_s \) at \( l_s^H \), 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 \( p_s > l_s^L \), type-\( L \) customers never accept the serious treatment, and the expert earns no profit from type-\( L \) customers having a serious problem. The larger the fraction of type-\( L \) customers, the larger is this loss of profit.

When the fraction of type-\( L \) customers is significant, it is more profitable to lower \( p_s \) to \( p_s = l_s^L \) 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 \( l_s^H \), the expert will cheat the type-\( H \) customers with a positive probability, i.e. \( \beta^H_m > 0 \).

**Proposition 2.** Let \( \theta \in [0, 1] \) denote the fraction of type-\( H \) customers. Cheating arises if and only if \( \theta < \frac{l_s^L - r_s}{l_s^H - r_s} \frac{l_s^H - r_m}{l_s^L - r_m} \). When the expert cheats, she only cheats type-\( H \) customers.

*Proof.* See Appendix A.

I have only considered heterogeneity in \( l_s \) but not in \( l_m \). Heterogeneity in \( l_m \) 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., $l_m \in \{l_m^L, l_m^H\}$, where $l_m^L < l_m^H$). In this case, there is no loss of generality in focusing on $\{p_m, p_s\} \in [r_m, l_m^H] \times [r_s, l_s]$. When $p_m > l_m^L$, a type-$L$ customer will not accept a treatment at $p_m$ 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 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 $p_m > l_m^L$, no type-$L$ customers will visit the expert when such a $p_m$ is charged. Therefore, the expert’s trade-off is between setting $p_m = l_m^L$, which attracts visits of both types of customers, and setting $p_m = l_m^H$, 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 $p_s = l_s$, 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.

In Appendix C, I show how expert cheating may still arise in a framework in which the expert is free to offer a menu of price lists and let customers of different types self select between these price lists. Selective cheating occurs when the expert only observes customers’ types imperfectly and the probability of identifying a customer’s type is relatively low. In this case, when the expert cheats, she targets those type-$H$ customers whose type she identifies during diagnosis. Again, cheating arises in a selective manner.

### 4.2 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 com-
lications 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 treat compared to the minor problem suffered by other customers. Due to the higher repair cost, there is little profit in recommending 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 treatment suffered by a type-\( T \) customer, where \( T \in \{H, L\} \) and \( 0 < r_m^L < r_m^H < l_m \). It costs the same \( (r_s) \) to repair everyone’s serious problem. Customer know the distribution of types but not their own. Unlike in the previous subsection, I do not impose the 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 a 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 how, the expert cannot induce self-selection by offering different price lists. Therefore, a mixed strategy of the expert’s specifies a price list \( \{p_m, p_s\} \), and for every possible price list, a recommendation policy for each type of customers characterized by \( \beta_m^T, \beta_s^T \), \( T \in \{L, H\} \). A mixed strategy of a customer specifies \( \gamma_m, \gamma_s \) for every possible price list.

First, I explain why the expert has a stronger incentive to cheat a type-\( H \) customer than to cheat a type-\( L \) customer. As in the previous model, I adapt steps 1 and 2 in the proof of Proposition 1 to argue that there is no loss of generality in focusing on \( \{p_m p_s\} \in [r_m^L, l_m] \times [r_s, l_s] \). 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.

Suppose the expert announces \(p_s = l_s\). 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 \(l_s\) to \(\hat{p}_s = [\alpha l_s + (1 - \alpha) \theta l_m] / [\alpha + (1 - \alpha) \theta]\), 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. Although at the acceptance rate \((p_m - r_m^L) / (p_s - r_m^L)\) the expert’s best reply is to cheat all type-H customers, she remains honest to all type-L customers (i.e., \(\beta_m = \theta \beta_m^H + (1 - \theta) \beta_m^L = \theta\)). Since the treatment price \(p_s\) is lowered to \(\hat{p}_s\), customers still have enough incentive to accept a serious treatment even the expert is now cheating with some probability. That explains why \(\gamma_s = (p_m - r_m^L) / (p_s - r_m^L)\) and \((\beta_m^L, \beta_m^H) = (0, 1)\) are best replies to each other.

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 \(l_s\) 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 \(l_s\), some customers will be cheated.

**Proposition 3.** Suppose a fraction \(\theta\) of customers cost the expert \(r_m^H\) to repair their minor problem and the rest cost \(r_m^L\), where \(r_m^L < r_m^H\). 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 \(l_m\), the expert cheats with a positive probability regardless of \(\theta\). When the expert cheats, she only cheats type-H
customers.

Proof. See Appendix A.

Similar to the previous model, in this model I have only 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, \( r_s^L \) and \( r_s^H \), to fix the serious problem. It could be shown that if \( \alpha l_s + (1 - \alpha) l_m < r_s^L < r_s^H \), then what 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 often have some ideas about their problems before they consult an expert, and the information they possess often helps the expert make more accurate diagnosis and/or provide more successful treatments. 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 which 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 would only use the information to provide 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, in the extended framework customers 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 that they are asked a question similar to this: “Would you tell us your budget so that we can more efficiently show you apartments most suitable for you?” If the agent’s only use of this information was to help him find the right apartment, her awareness of the customer’s budget would avoid her from showing him apartments he would never consider and thus save his time. Unfortunately, if the agent knows that the customer is willing to pay $2,000 for a one-bedroom apartment and there happens to be some nice $1,000-1,500 one-bedroom apartments available, it is likely that she would not let the customer know about these options but reserve them for those with tighter budgets. So a customer may want to understate his budget in order not be excluded from good deals.

5.1 Model

Unlike in Sections 3, here there are two similar but different serious problems, $s_1$ and $s_2$ and customers with either serious problem suffer the same loss $l_s$ if the problem is left untreated. There are two treatments for these serious problems, $\tau_1$ and $\tau_2$. Treatment $\tau_i$ fixes problem $s_i$ completely but recovers only $l_s - \varepsilon$ 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 $\tau_1$ and $\tau_2$ are both $r_s$. Besides, there is a visit cost at the level $t$ for each customer’s 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 $\delta \in (0, \frac{1}{2})$ that the expert believes it to be $s_j$, $j \neq i$. Since $\delta < 0.5$, when the expert has diagnosed a problem to be $s_i$, she believes that it is more likely to be $s_i$. A fraction $\theta$ of customers receive a useful signal. (They may receive as many irrelevant signals as possible.) If a useful signal is communicated to the expert, it makes
the expert’s diagnosis ability perfect (i.e., $\delta$ becomes 0). Customers do not know which signal is useful and whether they have that signal until the expert solicits it from them.\footnote{The expert cannot convince the customer a signal he provides is useful unless it is indeed useful. This is to rule out the possibility that the expert randomly asks the customer something irrelevant and then, regardless of the answer, lies to him that his answer helps the diagnosis.} The expert cannot convince the customer a signal he provides is useful unless it is indeed useful. This is to rule out the possibility that the expert randomly asks the customer something irrelevant and then, regardless of the answer, lies to him that his answer helps the diagnosis.\footnote{After a customer has arrived at the expert’s office, the expert first solicits the signal from the customer. Then the customer decides whether to disclose the signal to the expert, if he has received one. Afterward, the diagnosis is performed regardless of whether the customer has provided a signal. Next, the expert makes a recommendation. At this point, the customer does not have a second chance to reveal the signal. Conditioned 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 loss is not recovered.} In other words, customers must bear the consequence of the expert’s mistake if they choose not to reveal the signal to the expert. I also assume that, while it is equally costly to provide $\tau_1$ or $\tau_2$, if the problem is more likely to be $s_i$ than $s_j$, the expert always provides treatment $\tau_i$.

5.2 Equilibrium

If the expert does not learn the customer’s signal and the problem is found out to be serious, then with probability $\delta$ a loss of $\varepsilon$ cannot be recovered. In this case, the expected benefit of a necessary serious treatment to the customer is $l_s - \delta \varepsilon$. If the customer reveals the signal instead, then the benefit increases to $l_s$.

If the expert expects that customers never disclose the signal, then, according to Proposition 1, the expert’s optimal pricing strategy prescribes $p_s = l_s - \delta \varepsilon$. If the expert expects customers to reveal the signal instead, 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 $l_s$, and the rest value it at $l_s - \delta \varepsilon$. Applying Proposition 2, we immediately obtain that, when $\theta \in \left[0, \frac{l_s - \delta \varepsilon - r_s}{l_s - r_s}, \frac{l_s - r_m}{l_s - \delta \varepsilon - r_m}\right]$, the expert always set $p_s = l_s - \delta \varepsilon$. 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 $p_s = l_s - \delta \varepsilon$.

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 provide a surprising answer to this question subsequently.

**Proposition 4.** Let $\theta \in [0, 1]$ be the fraction of customers who possess the signal. If $\theta < \frac{l_s - \delta \varepsilon - r_s}{l_s - r_s}, \frac{l_s - r_m}{l_s - \delta \varepsilon - r_m}$, then the expert sets $p_s = l_s - \delta \varepsilon$, and every customer who possesses the signal conceals the signal from the expert in equilibrium.

**Proof.** See Appendix A.

The positive visit cost plays a crucial role in establishing Proposition 4. Since visiting the expert is costly, the expert must set $p_m < l_m$ 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 feels indifferent between accepting and rejecting a serious treatment in equilibrium suggests that he can only benefit when a minor treatment is recommended, where the gain is $l_m - p_m > 0$. Disclosing the signal decreases the probability that a minor treatment is recommended and thus reduces the expected gain of the customer.\(^{21}\) That explains why the customer chooses 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 only study 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 include 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 paper, 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 identifiable heterogeneities among customers 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 study 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.

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 paper 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 it is the case. First, at any given prices of treatments, 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 paper 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 they just need the expert’s treatment services. Unlike when all customers are ignorant, the only way to attract expert customers who 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 only considered one type of private information customers may possess. Future research can address a more in-depth study of this issue.

**Appendix A: Proofs of Main Results**

*Proof of Proposition 1.*

**Step 1.** Any recommendation to treat the problem at $p \notin [r_m, l_m] \cup [r_s, l_s]$ yields non-positive profit.

It is straightforward that (i) any recommendation at $p > l_s$ will be rejected, and (ii) any recommendation at $p < l_m$ will be accepted. Based on (ii), we can also establish that (iii) any recommendation at $p < r_m$ leads to a loss to the expert. Suppose a treatment at $p \in (l_m, r_s)$
is recommended. Since \( p < r_s \), customers must infer that the problem is minor. Because \( l_m < p \), (iv) customers will not accept any treatment at \( p \in (l_m, r_s) \). The claim of step 1 follows immediately (i), (iii) and (iv).

**Step 2.** In any subgame following \( \{p_m, p_s\} \in (r_m, l_m) \times (r_s, l_s) \), the equilibrium strategy profile is characterized by the following probabilities, and gives rise to the following expected profit:

\[
\begin{align*}
\gamma_m &= 1, \gamma_s = \frac{p_m - r_m}{p_s - r_m}; \\
\rho_m &= \rho_s = 0, \beta_m = -\frac{\alpha(l_s - p_s)}{(1 - \alpha)(p_s - l_m)}, \beta_s = 1.
\end{align*}
\]

(A1) \hspace{1cm} (A2)

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

(A3)

By (ii), \( \gamma_m = 1 \), which implies \( \rho_m = 0 \). Since \( p_m < r_s \), any strategy specifying \( \beta_s < 1 \) or \( \rho_s > 0 \) is (weakly) dominated by another which specifies \( \beta_s = 1 \) and \( \rho_s = 0 \). Notice 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 \( \alpha l_s + (1 - \alpha) l_s < r_s \); if \( \gamma_s = 0 \), then \( \beta_m = 0 \) because \( r_m < p_m \); and if \( \beta_m = 0 \), then \( \gamma_s = 1 \) because \( p_s < l_s \). So, there is no pure strategy equilibrium in the subgame and \( \beta_m, \gamma_s \in (0, 1) \).

It requires \( p_m - r_m = \gamma_s (p_s - r_m) \) for the expert to mix between charging \( p_m \) and \( p_s \) when the problem is minor. So, (A1) is established. Similarly, it requires \( \frac{\alpha l_s + (1 - \alpha) \beta_m l_m}{\alpha + (1 - \alpha) \beta_m} = p_s \), for the customer to mix between accepting and rejecting a treatment at \( p_s \). Manipulating the equality give \( \beta_m = \frac{\alpha l_s - p_s}{(1 - \alpha)(p_s - l_m)} \) in (A2). The strategies characterized by (A1) and (A2) give rise to (A3).

**Step 3.** In any equilibrium, \( p_m \in (r_m, l_m), p_s \in (r_s, l_s) \).

(v) Rule out \( \{p_m, p_s\} \in [r_m, l_m]^2 \). Since \( \max \{p_s, p_m\} < r_s \), the maximum possible profit from such 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 \( \{l_m, l_s\} \), according to (A3). (vi) Rule out \( \{p_m, p_s\} \in [r_s, l_s]^2 \). Suppose \( \max \{\gamma_m, \gamma_s\} > 0 \). Then \( \rho_m = \rho_s = 0 \) and either “\( \beta_m \geq \beta_s \) and \( \beta_m > 0 \)” or “\( \beta_s \geq \beta_m \) and \( \beta_s > 0 \)”. Suppose “\( \beta_m \geq \beta_s \) and \( \beta_m > 0 \)”. Then \( \frac{\alpha \beta_m l_s + (1 - \alpha) \beta_m l_m}{\alpha \beta_s + (1 - \alpha) \beta_s} \leq \alpha l_s + (1 - \alpha) l_m < r_s \leq p_m \), and the customer’s best reply is \( \gamma_m = 0 \), which contradicts
\( \beta_m > 0 \). Similar logic rules out \( \beta_s \geq \beta_m \) and \( \beta_s > 0 \). So, \( \{p_m, p_s\} \in [r_s, l_s]^2 \) leads to zero profit. (\textit{vii}) Rule out \( p_i \in [r_m, l_m] \cup [r_s, l_s], p_j \notin [r_m, l_m] \cup [r_s, l_s], i \neq j \). This is because profits in such subgames are the same as those with \( p_m = p_s = p_i \in [r_m, l_m] \cup [r_s, l_s] \).

(\textit{viii}) Rule out \( p_m = r_m \). In this case, the customer must set \( \gamma_s = 0 \) or otherwise the expert would always cheat, which contradicts \( \gamma_s > 0 \). (\textit{ix}) Rule out \( p_s = r_s \). Customers must set \( \gamma_s \leq (p_m - r_m) / (p_s - r_m) \) or 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 \( p_s \in (r_s, l_s) \), according to (A3).

**Step 4.** Equations (A1) to (A3) hold when \( p_m = l_m \) and \( p_s = l_s \), and the claim of the proposition is valid.

Notice that (A3) increases in both prices for \( \{p_m, p_s\} \in (r_m, l_m) \times (r_s, l_s) \). In subgames with \( p_m = l_m \) or \( p_s = l_s \), equilibria with \( \gamma_m < 1 \) and \( \gamma_s < (p_m - r_m) / (p_s - r_m) \) are also supported. However, it cannot happen in an equilibrium of the whole game. Suppose it did. Then, at \( p_m = l_m \) and \( p_s = l_s \), there would be a discrete drop in profit. In response, the expert would set \( p_m \) and \( p_s \) as close as possible to \( l_m \) and \( l_s \) in the open set \( \{p_m, p_s\} \in (r_m, l_m) \times (r_s, l_s) \) and there would be no solution. Therefore, in equilibrium, \( \gamma_m = 1 \) and \( \gamma_s = (p_m - r_m) / (p_s - r_m) \), and thus (A3) holds, when \( p_m = l_m \) and \( p_s = l_s \). This implies that the profit is maximized at \( p_m = l_m, p_s = l_s \). It is obvious that \( p_m = p_s = 0 \) and \( \beta_s = 1 \). To support a \( \gamma_s > 0 \), it must also hold that \( \beta_m = 0 \). \textit{Q.E.D.}

**Proof of Proposition 2.** Recall that the expert’s strategy specifies a price list \( \{p_m, p_s\} \), and for every possible price list, a recommendation policy for each type of customers characterized by \( \beta_m^T, \beta_s^T, T \in \{L, H\} \). A strategy of a type-\( T \) customer specifies a pair \( (\gamma_m^T, \gamma_s^T) \) for every possible price list, \( T \in \{L, H\} \). I adopt the arguments in the proof of Proposition 1 to reason that the profit maximizing prices must fall on the ranges \( p_m \in (r_m, l_m], p_s \in (r_s, l_s^H] \).

If the expert sets \( p_s \leq l_s^T \), then according to (1), \( \gamma_m^T = 1, \gamma_s^T = (p_m - r_m) / (p_s - r_m), T \in \{L, H\} \). In other words, customers of both types play the same strategy in the recommendation
subgame. Therefore, the expert’s total expected profit has the same expression as (3).\footnote{23}

$$
\Pi_1 (p_m, p_s) = \alpha \frac{p_m - r_m}{p_s - r_m} (p_s - r_s) + (1 - \alpha) (p_m - r_m), \quad p_m \in [r_m, l_m], p_s \in [r_s, l_s^L].
$$

If the expert sets $p_s > l_s^L$, then type-$L$ customers never accept a treatment at $p_s$. That is $\gamma_m^L = 1, \gamma_s^L = 0$. But type-$H$ customers play $\gamma_m^H = 1, \gamma_s^H = (p_m - r_m) / (p_s - r_m)$. In this case, the total expected profit of the expert is

$$
\Pi_1 (p_m, p_s) = \alpha \frac{p_m - r_m}{p_s - r_m} (p_s - r_s) + (1 - \alpha) (p_m - r_m), \quad p_m \in [r_m, l_m], p_s \in [l_s^L, l_s^H].
$$

Like in the basic model, the expected profit increases in $p_m$ for $p_m \in [r_m, l_m]$. It also increases in $p_s$ for $p_s \in [r_s, l_s^L]$ and for $p_s \in (l_s^L, l_s^H]$ except that it drops discretely when $p_s$ just goes from below to above $l_s^L$. This is because type-$L$ customers stop accepting the treatment at $p_s$.

Therefore, the expert’s problem boils down to the choice between two pricing strategies:

(i) $p_m = l_m, p_s = l_s^L$ and (ii) $p_m = l_m, p_s = l_s^H$. The expert sets $p_m = l_m, p_s = l_s^L$ if and only if $\Pi_1 (l_m, l_s^L) > \Pi_1 (l_m, l_s^H)$, i.e.,

$$
\theta < \frac{l_s^L - r_s}{l_s^L - r_m}.
$$

When $p_s = l_s^L$, cheating arises if and only if she meets type-$H$ customers who having a minor problem. Plugging $p_m = l_m, p_s = l_s^L$, and $l_s = l_s^H$ into (A2), we obtain that $\beta_m^H = \frac{\alpha (l_s^H - l_s^L)}{(1-\alpha)(l_s^L - l_m)} > 0$. It is easy to verify that $\beta_m^L = 0$. So, the expert only cheats type-$H$ customers.

Then we look at the cases when $\theta \geq \frac{l_s^L - r_s}{l_s^L - r_m}$. The expert sets $p_m = l_m, p_s = l_s^H$. It is obvious that $\beta_m^L = \beta_m^H = 0$, i.e., she is totally truthful. \textit{Q.E.D.}

\textit{Proof of Proposition 3.} The expert’s strategy specifies a price list $\{p_m, p_s\}$, and for every price list, the probabilities $\beta_m^T, \beta_s^T, T \in \{L, H\}$. The customer’s strategy specifies $\gamma_m, \gamma_s$ for every price list. Again, I adapt arguments in the proof of Proposition 1 to reason that the profit maximizing price list must fall in $\{p_m, p_s\} \in [r_m^L, l_m] \times [r_s, l_s]$. It is straightforward that for all these price lists, $\gamma_m = 1, \beta_m^L = \beta_m^H = 1.$
The probability that a customer gets cheated is \( \gamma \) discretely when \( \gamma \) has strict preference to cheat only when \( \gamma \) is a step-function of \( \gamma \) at customers. With these and \( m = 3 \), the best reply of the expert specifies that

\[
\beta^T_m(\gamma_s) = \begin{cases} 
0 & \text{if } \gamma_s < (p_m - r^T_m)/(p_s - r^T_m), \\
[0, 1] & \text{if } \gamma_s = (p_m - r^T_m)/(p_s - r^T_m), \quad T \in \{H, L\}, \\
1 & \text{if } \gamma_s > (p_m - r^T_m)/(p_s - r^T_m).
\end{cases}
\]

The probability that a customer gets cheated is \( \beta_m(\gamma_s) \equiv (1 - \theta) \beta^L_m(\gamma_s) + \theta \beta^H_m(\gamma_s) \), which is a step-function of \( \gamma_s \) stepping up at \( \gamma_s = (p_m - r^H_m)/(p_s - r^H_m) \) from 0 to \( \theta \), and then at \( \gamma_s = (p_m - r^L_m)/(p_s - r^L_m) \) from \( \theta \) to 1. Adapting step 2 of the proof of Proposition 1, in equilibrium \( \gamma_s \in (0, 1) \). To support this, it must hold that \( p_s = \frac{\alpha(1 - \alpha) \beta^L_m}{\alpha(1 - \alpha) \beta^H_m} \), i.e.,

\[
\beta_m = \frac{\alpha(l_s - p_s)}{(1 - \alpha)(p_s - l_m)}.
\]

Therefore, the equilibrium \( \gamma_s \) solves

\[
\beta_m(\gamma_s) = \frac{\alpha(l_s - p_s)}{(1 - \alpha)(p_s - l_m)}. \quad \text{(A4)}
\]

Define \( \hat{p}_s \equiv \frac{\alpha(1 - \alpha) \beta^H_m}{\alpha(1 - \alpha) \beta^L_m} \). Then \( \beta_m > \theta \) if and only if \( p_s < \hat{p}_s \). Plugging this into the inverse of (A4), in equilibrium,

\[
\gamma_s = \begin{cases} 
(p_m - r^H_m)/(p_s - r^H_m) & \text{if } p \in (\hat{p}_s, l_s) \\
[(p_m - r^H_m)/(p_s - r^H_m), (p_m - r^L_m)/(p_s - r^L_m)] & \text{if } p = \hat{p}_s \\
(p_m - r^L_m)/(p_s - r^L_m) & \text{if } p \in [r_s, \hat{p}_s)
\end{cases}
\]

For the purpose of deriving the equilibrium outcome of the whole game, there is no loss of generality in assuming that \( \gamma_s = (p_m - r^L_m)/(p_s - r^L_m) \) when \( p = \hat{p}_s \). Notice that the expert has strict preference to cheat only when \( \gamma_s = (p_m - r^L_m)/(p_s - r^L_m) \) and she cheats only type-\( H \) customers. With these and \( \gamma_m = 1 \), we can derive the profit as

\[
\Pi_3 = \begin{cases} 
\alpha (p_s - r_s) \frac{p_m - r^H_m}{p_s - r^H_m} + (1 - \alpha) \left[ (1 - \theta) (p_m - r^L_m) + \theta (p_m - r^H_m) \right] & \text{if } p_s \in (\hat{p}_s, l_s], \\
\alpha (p_s - r_s) \frac{p_m - r^H_m}{p_s - r^H_m} + (1 - \alpha) \left[ (1 - \theta) (p_m - r^L_m) + \theta \frac{(p_m - r^H_m)(p_m - r^L_m)}{p_s - r^L_m} \right] & \text{if } p_s \in [r_s, \hat{p}_s].
\end{cases}
\]

Since \( \Pi_3 \) increases in both \( p_m \) and \( p_s \) for all \( \{p_m, p_s\} \in [r_m, l_m] \times [r_s, l_s] \) except it drops discretely when \( p_s \) goes from below \( \hat{p}_s \) to above \( \hat{p}_s \). Therefore, the only candidate equilibrium
prices are \( \{l_m, \hat{p}_s\} \) and \( \{l_m, l_s\} \). The expert chooses \( \{l_m, \hat{p}_s\} \) if and only if \( \Delta \equiv \Pi_3 (l_m, l_s) - \Pi_3 (l_m, \hat{p}_s) < 0 \).

\[
\Delta = \alpha (l_s - r_s) \frac{l_m - r^H_m}{l_s - r^H_m} - \alpha (\hat{p}_s - r_s) \frac{l_m - r^H_m}{\hat{p}_s - r^H_m} + (1 - \alpha) \theta \left[ (l_m - r^H_m) - \frac{(\hat{p}_s - r^H)(l_m - r^H_m)}{\hat{p}_s - r^H_m} \right].
\]

Since \( \lim_{\theta \to 0} \hat{p}_s = l_s \), we have

\[
\lim_{\theta \to 0} \Delta = \alpha (l_s - r_s) \left[ \frac{l_m - r^H_m}{l_s - r^H_m} - \frac{l_m - r^H_m}{\hat{p}_s - r^H_m} \right] < 0.
\]

By continuity, there exists some \( \hat{\theta} > 0 \) such that \( \Pi_3 (l_m, l_s) < \Pi_3 (l_m, \hat{p}_s) \) for all \( \theta \in (0, \hat{\theta}) \).

Finally,

\[
\lim_{r^H_m \to l_m} \Delta = - [(1 - \alpha) \theta (\hat{p}_s - r^H_m) + \alpha (\hat{p}_s - r_s)] \frac{l_m - r^H_m}{\hat{p}_s - r^H_m} < 0.
\]

This completes the proof. \( Q.E.D. \)

Proof of Proposition 4. Recall that when \( \theta \in \left[ 0, \frac{l_s - \delta \varepsilon - r_s}{l_s - r_s}, \frac{l_s - \delta \varepsilon - r_m}{l_s - \delta \varepsilon - l_m} \right) \), the expert sets \( p_s = l_s - \delta \varepsilon \) regardless of customers’ disclosure policy. Given a positive visit cost, the expert must set \( p_m < l_m \) to attract customers.

If a customer withholds the signal, then the expert will be totally truthful to him, and the expected cost to the customer is

\[
C = \alpha (p_s + \delta \varepsilon) + (1 - \alpha) p_m + t
\]

\[
= \alpha l_s + (1 - \alpha) p_m + t.
\]

If the customer discloses the signal instead, then the value of getting a serious problem fixed increases from \( l_s - \delta \varepsilon \) to \( l_s \) which exceeds \( p_s \). According to (A2), the expert would play a completely mixed strategy with \( \beta_m = \alpha \delta \varepsilon / (1 - \alpha) (l_s - \delta \varepsilon - l_m) > 0 \). The total expected cost to the customer becomes

\[
\tilde{C} = [\alpha + (1 - \alpha) \beta_m] p_s + (1 - \alpha) (1 - \beta_m) p_m + t
\]

\[
= \alpha l_s + (1 - \alpha) \beta_m l_m + (1 - \alpha) (1 - \beta_m) p_m + t
\]

\[
= \alpha l_s + (1 - \alpha) p_m + t + (1 - \alpha) (l_m - p_m) \beta_m > C
\]
where the second equality is based on \( \frac{\alpha l + (1 - \alpha) \beta m}{\alpha + (1 - \alpha) \beta} = p_s \). Therefore, customers strictly prefer concealing the signal from the expert. (Working backward, we can show that \( p_m = l_s - t/(1 - \alpha) \)). Q.E.D.

**Appendix B: Extension to Allow Three Levels of Severity**

In this appendix, I extend the basic model to allow for three possible levels of severity in customers’ problems in order to check the robustness of Proposition 1. Let these problems customers may suffer from be denoted by 1, 2 and 3. If a customer has the 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 \( l_i \) where \( l_1 < l_2 < l_3 \). And we retain the assumption that all treatments are efficient to provide, i.e., \( r_i < l_i, i \in \{1, 2, 3\} \).

Let \( K \) denote a subset of these possible problems and \( l_K \) the expected loss a customer suffers conditioned on the problem belonging to the subset \( K \). So \( K \) may be \( \{1\}, \{2\}, \{3\}, \{1, 2\}, \{2, 3\}, \{1, 3\} \) or \( \{1, 2, 3\} \). Throughout this appendix, I retain the assumption that in equilibrium of any recommendation subgame, no agents play weakly dominated strategies. The rest of this appendix is devoted to analyzing under what situations a result qualitatively similar to Proposition 1 will hold. Like in Sections 4 and 5, I rule out the possibility that the expert sets a price list such that sometimes refuses to provide any treatment. We would get exactly the same results if we allowed such possibility.

Recall that when there are two possible levels of severity, regardless of the parameter values, there is only one single equilibrium outcome which does not involve weakly dominated strategy. This uniqueness result does not carry over to this more general setting.

To illustrate this point, let us consider a special case with parameters satisfying \( r_1 < r_2 < l_{12} \) and \( r_3 > l_{23} > l_{123} \). With these parameter restrictions, let us study a subgame in which the expert sets only two prices, one for both treatments 1 and 2, \( p_{12} \in (l_1, l_{12}) \) and the other for treatment 3, \( p_3 \in (r_3, l_3) \). Let \( \beta_i^K \) denote the probability that the expert charges \( p_K \).
given that the problem is diagnosed to be \( i \), and \( \gamma_K \) denote the probability that the customer accepts a recommended treatment at the price \( p_K \). Define \( \hat{\beta}_2^3 = \frac{\alpha_1 l_1 + \alpha_2 l_2}{\alpha_2 (l_2 - p_{12})} \). It can be verified that as long as \( p_3 \geq \frac{\alpha_2 \hat{\beta}_2^3 l_2 + \alpha_3 l_3}{\alpha_2 \hat{\beta}_2^3 + \alpha_3} \), the strategy profile characterized by the following probabilities constitutes an equilibrium in the subgame: \( \beta_{12}^1 = 1, \beta_{12}^2 \in (1 - \hat{\beta}_2^3, 1), \beta_2^3 = \frac{\alpha_3 l_3 - p_3}{\alpha_2 p_3 - l_2}, \beta_3^3 = 1, \gamma_{12} = 1, \gamma_3 = \frac{(p_{12} - r_2)}{(p_3 - r_2)} \); the values of \( \gamma_3 \) and \( \beta_2^3 \) ensure that both the expert and the customer find it incentive compatible to play a totally mixed strategy.

There exists, however, another equilibrium characterized by \( \beta_{12}^1 = 1, \beta_2^3 = \beta_3^3 = 1, \gamma_{12} = \gamma_3 = 0 \). The customer’s rejecting all treatments is optimal given the expert’s recommendation strategy and because \( p_{12} > l_1 \) and \( p_3 > l_{23} \), and the expert’s recommendation policy is also optimal given that any recommendation will be rejected. Unlike in the basic model, this inefficient equilibrium cannot be ruled out by elimination of weakly dominated strategies. If the expert believes that the latter equilibrium will be selected if she sets such price list \{\( p_{12}, p_3 \)\} \( \in (l_1, l_{12}) \times (r_3, l_3) \), then she is “forced” to set another price list even if this price list generates less profit than the first of the two equilibria just discussed does. Throughout this appendix, I impose the following equilibrium selection criteria to rule out such constraints on the expert’s profit maximization supported by arbitrary off-equilibrium beliefs.

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

Also, when I state that “the expert announces \( n \) prices”, it means the expert sets \( n \) prices and all \( n \) prices are charged by the expert and accepted by customers with positive probabilities. If a price on the 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. I consider such redundant price as meaningless. Here is the main claim of this appendix.

Proposition B1. Under Assumption E, if in equilibrium the expert sets three prices, these prices
must be \( p_1 = t_1, \ p_2 = t_2 \) and \( p_3 = l_3 \), and we have \( \beta_1^3 = \beta_2^3 = \beta_3^3 = 1 \). In other words, the expert honestly reports every diagnosed problem and all her private information is revealed.

**Proof.** Consider an arbitrary equilibrium in which the expert sets 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 in equilibrium \( \gamma_i > 0 \) and \( \beta_1^3 + \beta_2^3 + \beta_3^3 > 0 \) for \( i = 1, 2, 3 \). To give the expert an incentive to sometimes charge \( p_i \), it requires \( \gamma_i(p_i - r) \geq \gamma_j(p_j - r) \), for all \( j \neq i \) for some \( r \in \{r_1, r_2, r_3\} \). In other words, if \( p_j > p_i \), then \( \gamma_i > \gamma_j \) is require. So for each price to be charged with a positive probability, it requires that \( \gamma_1 > \gamma_2 > \gamma_3 > 0 \). If \( (\gamma_1, \gamma_2, \gamma_3) \) constitute an equilibrium strategy of customers, so do \( (1, \gamma_2/\gamma_1, \gamma_3/\gamma_1) \). Assumption E implies that \( (i) \gamma_1 = 1 \).

Notice we do NOT restrict that \( r_1 < r_2 < r_3 \). Rank and rename the repair costs so \( r_a < r_b < r_c \), where \( a, b, c \in \{1, 2, 3\} \).\(^{26}\) For \( p_3 \) to be recommended with a positive probability, it requires \( (ii) \beta_3^3 > 0 \). Suppose \( \beta_3^3 = 0 \). Then \( \gamma_i(p_i - r_c) \geq \gamma_3(p_3 - r_c) \) for \( i = 1 \) or \( 2 \), and this in turn implies that \( \gamma_i(p_i - r_j) > \gamma_3(p_3 - r_j) \) for \( i = 1 \) or \( 2 \), \( j = a, b \), which means \( \beta_3^3 = \beta_3^2 = 0 \), which is a contradiction. By symmetry, for \( p_1 \) to be charged with a positive probability, it must hold that \( (iii) \beta_1^3 > 0 \).

Now, show that \( (iv) \beta_b^2 > 0 \). Suppose \( \beta_b^2 = 0 \). Then either \( \beta_b^2 > 0 \) or \( \beta_c^2 > 0 \) must hold. First suppose \( \beta_c^2 > 0 \). To support \( \beta_a^3, \beta_a^1 > 0 \), it must be that \( (p_1 - r_a) = \gamma_2(p_2 - r_a) \), which implies \( (p_1 - r_i) < \gamma_2(p_2 - r_i), i = b, c \), and thus \( \beta_b^1 = \beta_c^1 = 0 \), and \( \beta_b^1 = \beta_b^2 = 0 \) in turn implies that \( p_3 \leq r_b \) or \( \beta_b^3 = 1 \). In either case, customers infer that the problem is \( a \) whenever either \( p_1 \) or \( p_2 \) is charged. To support \( \gamma_1, \gamma_2 > 0 \), it requires \( p_1 < p_2 \leq l_a \). In the spirit of Assumption E, \( \gamma_3 = (p_1 - r_a) / (p_3 - r_a) \) which is the highest possible level compatible with \( \beta_a^1 \neq 0 \). The profit of the expert is

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

In either case, the expert always prefers to increase \( p_1 \) for any \( p_1 < p_2 \leq l_a \). So it is not an
equilibrium as long as \( p_1 < p_2 \).

Now, suppose \( \beta_c^2 > 0 \). For \( \beta_c^2, \beta_c^3 > 0 \), it requires \( \gamma_2 (p_2 - r_c) = \gamma_3 (p_3 - r_c) \), which implies \( \gamma_2 (p_2 - r_i) > \gamma_3 (p_3 - r_i) \) and thus \( \beta_c^3 = \beta_c^2 = 0 \). In turn, \( \beta_a^1 = \beta_a^2 = 0 \) implies \( p_1 \leq r_a \) or \( \beta_a^1 = 1 \). In either case, customers infer that the problem is \( c \) when either \( p_2 \) or \( p_3 \) is charged. For \( \gamma_2, \gamma_3 < 1 \), it requires \( p_2 = p_3 = l_c \) which contradicts that three prices are different. Now, (iv) is established.

(ii)-(iv) together imply that

\[
(p_1 - r_a) \geq \max \{ \gamma_2 (p_2 - r_a), \gamma_3 (p_3 - r_a) \},
\]

\[
\gamma_2 (p_2 - r_b) \geq \max \{ (p_1 - r_b), \gamma_3 (p_3 - r_b) \},
\]

\[
\gamma_3 (p_3 - r_c) \geq \max \{ (p_1 - r_c), \gamma_2 (p_2 - r_c) \}.
\]

As long as \( \gamma_2 \) and \( \gamma_3 \) satisfy (5), i.e., \( \gamma_2 \leq \min \left\{ \frac{p_1 - r_a}{p_2 - r_a}, \frac{\gamma_2 (p_3 - r_a)}{p_2 - r_c} \right\} \) and \( \gamma_3 \leq \min \left\{ \frac{p_1 - r_a}{p_3 - r_a}, \frac{\gamma_2 (p_2 - r_b)}{p_3 - r_b} \right\}, \)

the expert has the same incentives and the acceptance rates can be supported in equilibrium. In the spirit of Assumption E, we choose the highest possible \( \gamma_2 \) and \( \gamma_3 \) satisfying (5). Therefore,

\[
\gamma_2 = \min \left\{ \frac{p_2 - r_a}{p_3 - r_a}, \frac{\gamma_2 (p_2 - r_c)}{p_2 - r_c} \right\}, \quad \gamma_3 = \min \left\{ \frac{p_1 - r_a}{p_3 - r_a}, \frac{\gamma_2 (p_2 - r_b)}{p_3 - r_b} \right\}
\]

Plugging \( \gamma_3 \) into \( \gamma_2 \), we have

\[
\gamma_2 = \min \left\{ \frac{p_1 - r_a}{p_2 - r_a}, \frac{p_1 - r_a (p_3 - r_c)}{p_2 - r_c}, \frac{\gamma_2 (p_2 - r_b)}{p_3 - r_b} \right\}
\]

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

The second equality is due to \( \frac{p_2 - r_b}{p_3 - r_b} > \frac{p_2 - r_c}{p_2 - r_c} \) and thus \( \frac{\gamma_2 (p_2 - r_b)}{p_3 - r_b} > \gamma_2 \). The third equality is due to \( \frac{p_1 - r_a (p_3 - r_c)}{p_2 - r_c} \) and \( \frac{p_1 - r_a (p_3 - r_c)}{p_2 - r_c} = \frac{p_1 - r_a}{p_2 - r_a} \). Plugging \( \gamma_2 = (p_1 - r_a)/(p_2 - r_a) \) back into \( \gamma_3 \), noticing that \( \frac{p_1 - r_a (p_2 - r_b)}{p_2 - r_c} < \frac{p_1 - r_a (p_2 - r_a)}{p_3 - r_a} = \frac{p_1 - r_a}{p_3 - r_a} \), we have

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

Given these values of \( \gamma_2 \) and \( \gamma_3 \), the expected profit is

\[
\alpha_1 (p_1 - r_a) + \alpha_2 \frac{p_1 - r_a}{p_2 - r_a} (p_2 - r_b) + \alpha_3 \frac{p_1 - r_a}{p_2 - r_a} (p_2 - r_b) (p_3 - r_c) \]. (B2)
The profit increases in all prices. Since $\beta_1^b = \beta_2^c = 0$, (B2) holds for $p_1 \in [r_a, l_a]$ and it is optimal to set $p_1 = l_a$. Since $\beta_2^c = 0$, (B2) holds for $p_2 \in [r_b, \max \{l_a, l_b\}]$ and the expert charges $p_2 = \max \{l_a, l_b\}$. Since $p_2 > p_1$, it must be $p_2 = l_b > l_a$. Since $\beta_3^a = 0$, (B2) holds for $p_3 \in [r_c, \max \{l_b, l_c\}]$. So, $p_3 = l_c > l_b$. Since $l_a < l_b < l_c$, $a = 1$, $b = 2$ and $c = 3$. In order to induce customers to mix, the expert must be fully honest. Q.E.D.

Appendix C: Endogenization of Uniform Pricing

In Subsection 4.1, I model that the expert is restricted to offer the same price list for both types of customers who suffer to different extents from the serious problem. With this assumption, I showed that when the fraction of high-valuation customers is relative small, then the expert will target these customers for cheating. Here, I show how selective cheating may still arise in a framework where the expert is free to offer a menu of price lists to induce customers of different types to self select. It will be shown that selective cheating happens when the expert only identifies customers’ types with a relatively low probability (Proposition C1).

Further Modification of Model in Subsection 4.1. Here, the main difference from Subsection 4.1 is that the expert does not always identify a customer’s type and she is not restricted to offer the same price list to different types of customers. Same as before, there are two types ($T \in \{H, L\}$) of customers. A fraction $\theta$ of type-$H$ suffer a loss $l_s^H$ if they have the serious problem, and the remaining fraction $(1 - \theta)$ of type-$L$ suffer a loss $l_s^L$ if they have the same problem, where $l_s^L < l_s^H$. Both types suffer equally ($l_m$) from the minor problem. Unlike in Subsection 4.1, here the expert sets a menu of price lists which consists of $p \equiv \{p_m, p_s\}$ and $\hat{p} \equiv \{\hat{p}_m, \hat{p}_s\}$ for customers to select from. Adopting arguments used in the proof of Proposition 1, we can restrict our attention to $p, \hat{p} \in [r_m, l_m] \times [r_s, l_s^H]$ without loss of generality. It may be that $p \neq \hat{p}$ in case of separation of types or $p = \hat{p}$ in case of pooling. During the diagnosis for a type-$H$ customer, the expert identifies his type with probability $\delta \in (0, 1)$. If
the customer is type-$L$, the expert does not receive any information about his type. Because of
that, when the expert does not identify a customer’s type, absent any additional information,
she updates and assigns a probability $\frac{\theta(1-\delta)}{1-\theta\delta}$ that this customer is type-$H$. Finally, I retain
the assumption $\alpha l_s^L + (1-\alpha) l_m < \alpha l_s^H + (1-\alpha) l_m < r_s$.

Equilibrium. Due to the further complication of the model, it is necessary to introduce
additional notations to facilitate the analysis. Consider the recommendation subgame following
a customer’s choosing $p$. Let $\beta_m$ ($\beta_s$) denote the probability that the expert charges $p_s$ when
she finds out the problem to be $m$ ($s$), given that she does not observe the customer’s type. Let $\beta_m^H$ ($\beta_s^H$) be the probability that the expert charges $p_s$ when she finds out the problem to be $m$ ($s$), given that she learns that the customer is type-$H$. Also let $\gamma_i^T$, $T \in \{L, H\}$, $i \in \{m, s\}$, be the probability that a type-$T$ customer accepted the treatment $i$ in the subgame following the
customer’s choosing the price list $p$. Similarly, we define $(\hat{\beta}_m, \hat{\beta}_s)$ and $(\hat{\gamma}_m^L, \hat{\gamma}_s^L, \hat{\gamma}_m^H, \hat{\gamma}_s^H)$ as the corresponding probabilities in the subgame following a customer’s choosing $\hat{p}$.

The rest of this appendix is devoted to establish this result:

Proposition C1. There exist $\tilde{\theta} > 0$ and $\tilde{\delta} > 0$ such that if $\theta < \tilde{\theta}$ and $\delta < \tilde{\delta}$, then in equilibrium,
the expert charges $p = \hat{p} = \{l_m, l_s^L\}$ and cheats all those type-$H$ customers whose type is
identified by her during diagnosis, but is honest to all other customers.

I first construct some basic results and label them as lemmas. At the end, I use some
of these lemmas to I construct a short proof for the above stated proposition. Based on the
analysis in the basic model, we know that in any equilibrium,

$$\gamma_m^L = \gamma_m^H = \gamma_s^L = \gamma_s^H = 1 \quad \text{and} \quad \beta_s = \beta_s^H = \hat{\beta}_s = \hat{\beta}_s^H = 1. \quad (C1)$$

Lemma C1. Define $\delta' \in (0, 1)$ by $\frac{\alpha l_s^L + (1-\alpha) \delta' l_m}{\alpha + (1-\alpha) \delta'} = l_s^L$. If $\delta \leq \delta'$, then for all $\beta_m$, $\beta_m^H \in [0, 1]$,

$$\frac{\alpha l_s^L + (1-\alpha) \delta' \beta_m l_m}{\alpha + (1-\alpha) \delta' \beta_m} > \frac{\alpha l_s^L + (1-\alpha) \beta_m l_m}{\alpha + (1-\alpha) \beta_m}. \quad (C1')$$
Proof. Since \( \frac{\alpha l^H_s + (1 - \alpha) \delta l_m}{\alpha + (1 - \alpha) \delta} \) decreases in \( \delta \), if \( \delta \leq \delta' \), then

\[
\frac{\alpha l^H_s + (1 - \alpha) \delta l_m}{\alpha + (1 - \alpha) \delta} \geq l^L_s. \tag{C2}
\]

The second inequality immediately follows (C2) and the last inequality holds because the expressions on both sides of the inequality are weight averages of \( l^L_s \) and \( l_m \) and the one on the right has a smaller weight on \( l^L_s \):

\[
\frac{\alpha + (1 - \alpha) \delta}{\alpha + (1 - \alpha) \delta m (1 - \alpha)} = \frac{\alpha}{\alpha + (1 - \alpha) \beta_m} > 0.
\]

Q.E.D.
The inequality expressed in Lemma C1 is illustrated in Figure 1. Let \( \beta_m = \beta \) and \( \beta_m = \bar{\beta} \) respectively solve

\[
\frac{\alpha l_s^L + (1 - \alpha) \beta_m l_m}{\alpha + (1 - \alpha) \beta_m} = p_s, \quad \text{and} \quad \frac{\alpha l_s^H + (1 - \alpha) [\delta \beta_m^H + (1 - \delta) \beta_m] l_m}{\alpha + (1 - \alpha) [\delta \beta_m^H + (1 - \delta) \beta_m]} = p_s.
\]

(C3)

(C4)

In other words, if the expert’s recommendation strategy specifies \( \beta_m = \beta \), then type-L customers are indifferent between rejecting and accepting a serious treatment at \( p_s \), and if \( \beta_m = \bar{\beta} \), then type-H customers are indifferent between rejecting and accepting a serious treatment at \( p_s \). Lemma C1 and the fact that both fractions decrease in \( \beta_m \) together imply that \( \beta < \bar{\beta} \) for all \( p_s \in [r_s, l_s^L] \). For a graphical illustration of this relationship, please again refer to Figure 1.

Some manipulation on (C3) and (C4) will give

\[
\beta = \frac{\alpha (l_s^L - p_s)}{(1 - \alpha) (p_s - l_m)}, \quad \bar{\beta} = \frac{\alpha (l_s^H - p_s) - (1 - \alpha) \delta \beta_m^H (p_s - l_m)}{(1 - \alpha) (1 - \delta) (p_s - l_m)}.
\]

Consider a recommendation subgame following a customer’s choosing \( p \in [r_m, l_m] \times [r_s, l_s^L] \).

**Lemma C2.** Suppose that \( \delta \leq \delta' \). Consider the recommendation subgame following a customer’s choosing any price list \( p \in [r_m, l_m] \times [r_s, l_s^L] \). Also suppose it is common knowledge that the expert believes with probability \( \theta' \in (0, 1) \) this customer is type-H. (i) The strategy profile described by (C1) and

\[
\beta_m = \frac{\alpha (l_s^L - p_s)}{(1 - \alpha) (p_s - l_m)}, \quad \beta_m^H = 1, \quad \gamma_s^L = \frac{p_m - r_m}{p_s - r_m} \frac{1 - \theta' \delta}{1 - \theta' (1 - \delta)}, \quad \gamma_s^H = 1
\]

constitutes an unique equilibrium in the subgame if \( \frac{p_m - r_m}{p_s - r_m} > \frac{\theta' \delta}{1 - \theta' \delta} \).

(ii) The strategy profile described by (C1) and

\[
\beta_m = \frac{\alpha (l_s^H - p_s) - (1 - \alpha) \delta (p_s - l_m)}{(1 - \alpha) (1 - \delta) (p_s - l_m)}, \quad \beta_m^H = 1, \quad \gamma_s^L = 0, \quad \gamma_s^H = \frac{p_m - r_m}{p_s - r_m} \frac{1 - \theta' \delta}{\theta' (1 - \delta)}
\]

constitutes an unique equilibrium in the subgame if \( \frac{p_m - r_m}{p_s - r_m} < \frac{\theta' \delta}{1 - \theta' \delta} \).

(iii) Any one of the following strategy profiles described by (C1) and

\[
\beta_m \in \left( \frac{\alpha (l_s^L - p_s)}{(1 - \alpha) (p_s - l_m)}, \frac{\alpha (l_s^H - p_s) - (1 - \alpha) \delta (p_s - l_m)}{(1 - \alpha) (1 - \delta) (p_s - l_m)} \right), \quad \beta_m^H = 1, \quad \gamma_s^L = 0, \quad \gamma_s^H = 1,
\]

\( \beta \).
or those in (i) and (ii) constitutes an equilibrium in the subgame if \( \frac{p_m - r_m}{p_s - r_m} = \frac{\theta'(1-\delta)}{1-\theta' \delta} \).

Proof. (a) First I show that for any \( p \) containing \( p_s \in [r_s, l^L_s] \), it holds that \( \beta_m \in \{\beta, \bar{\beta}\} \). Suppose \( \beta_m < \beta(p_s) \), then customers’ best responses are \( \gamma^L_s = \gamma^H_s = 1 \). Similarly, if \( \beta_m > \bar{\beta}(p_s) \), then \( \gamma^L_s = \gamma^H_s = 0 \). Either case cannot be an equilibrium.

(b) Construct an equilibrium in which \( \beta_m = \beta \). Customers’ best response to \( \beta_m = \beta \) is \( \gamma^H_s = 1, \gamma^L_s \in [0, 1] \). To support \( \beta_m = \beta \in (0, 1) \), it requires the expert to be indifferent between charging \( p_m \) and \( p_s \) when she does not identify a customer’s type, i.e., \( \frac{\theta'(1-\delta)}{1-\theta' \delta} = \frac{p_m - r_m}{p_s - r_m} \). This is possible only if \( \frac{p_m - r_m}{p_s - r_m} \geq \frac{\theta'(1-\delta)}{1-\theta' \delta} \), and the inequality must be strict when \( \gamma^L_s > 0 \). Rewriting the equality gives \( \gamma^L_s = \frac{(p_m - r_m)(1-\theta') - \theta'(1-\delta)}{1-\theta' \delta} \). Besides, \( \gamma^H_s = 1 \) implies \( \beta^H_m = 1 \).

So, we have the strategy profile as stated in (i).

(c) Construct an equilibrium in which \( \beta_m = \bar{\beta} \). Customers’ best response to \( \beta_m = \bar{\beta} \) is \( \gamma^H_s \in [0, 1], \gamma^L_s = 0 \). To support \( \beta_m = \bar{\beta} \in (0, 1) \), it requires \( \frac{\theta'(1-\delta)}{1-\theta' \delta} = \frac{p_m - r_m}{p_s - r_m} \). This is possible only if \( \frac{p_m - r_m}{p_s - r_m} \leq \frac{\theta'(1-\delta)}{1-\theta' \delta} \), and the inequality must be strict when \( \gamma^H_s < 1 \). Rewriting the equality gives \( \gamma^H_s = \frac{p_m - r_m}{p_s - r_m} \frac{1-\theta'}{\theta'(1-\delta)} \). Besides, \( \gamma^H_s > \frac{p_m - r_m}{p_s - r_m} \) implies \( \beta^H_m = 1 \). Plugging \( \beta^H_m = 1 \) into \( \bar{\beta} \) gives the \( \beta_m \) as stated in (ii).

(d) Now construct an equilibrium in which \( \beta_m \in (\beta, \bar{\beta}) \). Customers’ best response to it is \( \gamma^L_s = 0, \gamma^H_s = 1 \). This cannot be supported as an equilibrium if \( \frac{p_m - r_m}{p_s - r_m} \neq \frac{\theta'(1-\delta)}{1-\theta' \delta} \) as if that was the case, then \( \beta_m = 0 \) or \( \beta_m = 1 \), a contradiction in either case. Now, focus on \( \frac{p_m - r_m}{p_s - r_m} = \frac{\theta'(1-\delta)}{1-\theta' \delta} \). Also, \( \gamma^H_s = 1 \) implies \( \beta^H_m = 1 \). So, we have the strategy profile as stated in (i).

(a)-(d) together imply that when \( \frac{p_m - r_m}{p_s - r_m} > \frac{\theta'(1-\delta)}{1-\theta' \delta} \), only the strategy profile in (i) constitutes an equilibrium, when \( \frac{p_m - r_m}{p_s - r_m} < \frac{\theta'(1-\delta)}{1-\theta' \delta} \), only the strategy profile in (ii) constitutes an equilibrium, and when \( \frac{p_m - r_m}{p_s - r_m} = \frac{\theta'(1-\delta)}{1-\theta' \delta} \), only the strategy profiles in (i), (ii) and (iii) can constitute an equilibrium. Q.E.D.

Based on the equilibrium strategy profiles described in Lemma C2, we can further establish this result.
Lemma C3. Suppose \( \delta \leq \delta' \) and \( \theta \leq \frac{l_m - r_m}{l_s - r_m} \). Define \( \bar{r} \equiv \alpha r_s + (1 - \alpha) r_m \). If the expert chooses to offer only one price list \( \{p_m, p_s\} \in [r_m, l_m] \times [r_s, l_s^L] \), then the profit is maximized at \( \{p_m, p_s\} = \{l_m, l_s^L\} \) and the corresponding profit is

\[
\theta \delta \left( l_s^L - \bar{r} \right) + (1 - \theta \delta) \left[ \alpha \left( l_s^L - r_s \right) \frac{l_m - r_m}{l_s^L - r_m} + (1 - \alpha) (l_m - r_m) \right].
\]  
(C5)

Proof. If the expert charges on price, then \( \theta' = \theta \). Based on the strategy profiles described in Lemma C2, we can recover that the expert’s expected profit given different prices she chooses satisfying \( \{p_m, p_s\} \in [r_m, l_m] \times [r_s, l_s^L] \) as follows. If \( \frac{p_m - r_m}{p_s - r_m} < \frac{\theta(1-\delta)}{1-\delta'} \), then

\[
\Pi = \theta \delta \left[ \frac{p_m - r_m}{p_s - r_m} \frac{1 - \theta \delta}{\theta(1 - \delta)} (p_s - \bar{r}) \right] + (1 - \theta \delta) \left[ \alpha (p_s - r_s) \frac{p_m - r_m}{p_s - r_m} + (1 - \alpha) (p_m - r_m) \right].
\]

If \( \frac{p_m - r_m}{p_s - r_m} = \frac{\theta(1-\delta)}{1-\delta'} \), then

\[
\Pi = \theta \delta \left[ \frac{p_m - r_m}{p_s - r_m} \frac{1 - \theta \delta}{\theta(1 - \delta)} (p_s - \bar{r}) \right] + (1 - \theta \delta) \left[ \alpha (p_s - r_s) \frac{p_m - r_m}{p_s - r_m} + (1 - \alpha) (p_m - r_m) \right].
\]

If \( \frac{p_m - r_m}{p_s - r_m} > \frac{\theta(1-\delta)}{1-\delta'} \), then

\[
\Pi = \theta \delta (p_s - \bar{r}) + (1 - \theta \delta) \left[ \alpha (p_s - r_s) \frac{p_m - r_m}{p_s - r_m} + (1 - \alpha) (p_m - r_m) \right].
\]  
(C6)

The profit increases everywhere in \( p_m \) and \( p_s \) when \( \frac{p_m - r_m}{p_s - r_m} < \frac{\theta(1-\delta)}{1-\delta'} \) or \( \frac{p_m - r_m}{p_s - r_m} > \frac{\theta(1-\delta)}{1-\delta'} \), and there is a discrete upward jump in profit when increase in \( p_m \) leads to switch of inequality. Also \( \frac{l_m - r_m}{l_s^L - l_m} > \frac{\theta(1-\delta)}{1-\delta'} \) because of the assumption that \( \theta \leq \frac{l_m - r_m}{l_s^L - r_m} \). So the profit is maximized at \( \{p_m, p_s\} = \{l_m, l_s^L\} \). Plugging this into (C6) gives the profit as stated in (C5). Q.E.D.

Potentially, some menus of price lists may induce all type-L customers to reject the serious treatment. Next, I show under what situations such menus are always suboptimal.

Lemma C4. For all \( \delta \in (0, \delta'] \), there exist \( \tilde{\theta} \in (0, 1) \), independent of \( \delta \), such that for all \( \theta \leq \min \left\{ \tilde{\theta}, \frac{l_m - r_m}{l_s^L - r_m} \right\} \), any profit-maximizing price list(s) must induce some type-L customers to accept the serious treatment.
Proof. Even if every other treatment recommendation will be accepted, as long as all type-L customers reject a serious treatment, the expected profit the expert earns may not exceed \( \theta (l^H_s - [\alpha r_s + (1 - \alpha) r_m]) + (1 - \theta) (1 - \alpha) (l_m - r_m) \). As \( \theta \to 0 \), such maximum tends to \((1 - \alpha) (l_m - r_m) \). On the other hand, the profit that she earns by offering just one price list \( \{p_m, p_s\} = \{l_m, l_s\} \) tends to

\[
\alpha (l^L_s - r_s) \frac{l_m - r_m}{l^L_s - r_m} + (1 - \alpha) (l_m - r_m) > (1 - \alpha) (l_m - r_m).
\]

Therefore, for every \( \delta \in (0, \delta') \), there exist a \( \tilde{\theta} (\delta) > 0 \) such that for all \( \theta < \tilde{\theta} (\delta) \), it is suboptimal to induce all type-L customers to reject the serious treatment. Since the inequality in display remains straight for all \( \delta \), there exists \( \tilde{\theta} = \inf_{\delta \in [0, \delta]} \tilde{\theta} (\delta) \) which is independent of the actual value of \( \delta \) such that whenever \( \theta \leq \tilde{\theta} \), it is suboptimal to set prices which induces all type-L customers to reject the serious treatment. Q.E.D.

Then, I proceed to analyze under what situations full- or semi-separation of types will not happen in equilibrium even the expert is free to offer a menu of price lists.

Lemma C5. For all \( \theta \in (0, \min \left\{ \tilde{\theta}, \frac{l_m - r_m}{l^L_s - r_m} \right\} \) \), there exist \( \tilde{\delta} > 0 \), independent of \( \theta \), such that if \( \delta \leq \min \left\{ \tilde{\delta}, \delta' \right\} \), then separation does not occur in equilibrium.

Proof. Suppose the price list \( \hat{p} \) attracts some or all type-H customers and the remaining customers chose \( p \). According to Lemma C4, when \( \theta \leq \min \left\{ \tilde{\theta}, \frac{l_m - r_m}{l^L_s - r_m} \right\} \), in any equilibrium, type-L customers sometimes accept the serious treatment. This requires \( p_s \leq l^L_s \). Next, for all \( \theta \leq \min \left\{ \tilde{\theta}, \frac{l_m - r_m}{l^L_s - r_m} \right\} \), for separation to occur in equilibrium, it requires that \( p_m \geq \hat{p}_m \) for some \( \hat{p}_m > r_m \). If \( p_m = r_m \), then the expert earns no profit from those who choose \( p \) and the total profit is no more than \( \left[ \min \left\{ \tilde{\theta}, \frac{l_m - r_m}{l^L_s - r_m} \right\} \right] \left[ \alpha (l_s - r_s) \frac{\hat{p}_m - r_m}{p_s - r_m} + (1 - \alpha) (\hat{p}_m - r_m) \right] \) which is in turn less than \( \tilde{\theta} (l^H_s - \tilde{\theta}) + (1 - \tilde{\theta}) (1 - \alpha) (l_m - r_m) \). Again according to Lemma C4, the latter is less than the profit from offering one price list \( \{p_m, p_s\} = \{l_m, l_s\} \). So, \( p_m \) must be strictly larger than \( r_m \). These together implies that we can focus on \( p \in [\hat{p}_m, l_m] \times [r_s, l^L_s] \).

Now suppose (full- or semi-) separation happened so that \( \theta' < \theta \). When \( \theta' (1 - \delta) \geq \frac{p_m - r_m}{p_s - r_m} \),
Proof of Proposition 6. From lemmas C4 and C5, we know that if \( \delta \leq \min\{\delta', \tilde{\delta}\} \) and \( \theta \leq \min\{\tilde{\theta}, \frac{l_m - r_m}{l_s - r_m}\} \), then in equilibrium, the expert offers only one price list and type-L customers accept the serious treatment with a positive probability. These together with Lemma C3 imply
that the equilibrium prices must be $p = \hat{p} = \{l_m, l_s^L\}$, and according to Lemma C2 (i), the equilibrium strategy of the expert in the recommendation subgame is

$$\beta_m = 0, \beta_H^m = 1, \beta_s = \hat{\beta}_s = 1.$$ 

In other words, the expert is honest to all the customers whom she cannot identify their type. However, she misreports as serious the minor problems of all those customers who are identified as type-$H$ during diagnosis. We just need to define $\tilde{\theta} \equiv \min \{\delta', \tilde{\delta}\}$ and $\hat{\delta} \equiv \min \{\tilde{\delta}, \frac{l_m - r_m}{l_s^L - r_m}\}$ to complete the proof.  \textit{Q.E.D.}
References


Notes

1The frameworks of Taylor (1995) and Emons (1997, 2001) are slightly different from 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 need treatment. Their no-problem and problem states respectively correspond to the minor and serious problems in other models. Thus, these models also are two-by-two.

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

3A bait-and-switch variance to a flat-rate can 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 will never be charged.


6When analyzing the case customers have different valuations for treatments, I assume in the main text that the expert does not price discriminate. Only in Appendix C I derive formally conditions under which the expert endogenously chooses to set one price list for all customers.
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.

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.

Here I assume that the expert does not commit to treating customers’ problems at either of the announced prices $p_m$ and $p_s$. This assumption is very 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 only capable of treating 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 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.

When recommended a serious treatment, the customer feels indifferent between accepting it at $p_s$ or rejecting it. In the latter case, his expected loss is still $p_s$.

After Proposition 2, I discuss why heterogeneity in customers’ losses from the minor problem is unimportant for the issue in which I am interested here.

More precisely, when a problem is diagnosed to be minor, the expert is comparing between the profits from 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.

In the previous model, customers know their own type, but in this model they do not.
Therefore, all customers play the same strategy here, unlike in the previous model.

15Wolinsky (1993) also studies imperfection in experts’ diagnosis. However, he does not model customers’ possessions of useful information.

16The way I model diagnostic errors is similar to the way Wolinsky (1993) does, in a sense that we both assume that 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.

17For example, a computer technician may pin down what has caused a PC to go out of order and locate the damaged hardware part(s) or system file(s) by asking the owner if he has some bad habit of operating a PC or if he observed some specific abnormality with the unit before its breakdown. Such information is useful because it helps speed up the repair service and avoids mistakes like unnecessary formatting of the hard disk which usually contains valuable data to the owner. An inexpert user may have a lot of information about his PC, but usually cannot judge whether any part his information is relevant.

18If this was allowed, then communication of useful information would break down just because of such incentive, and the issue would become trivial.

19This 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 right one. The expert will never perform the test for the 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.
Even if that loss was verifiable, the expert might not make such a promise. For instance, if \((1 + \delta) r_s \geq l_s\), the expected cost of fully fixing a serious problem exceeds the loss due to a serious problem. Such promise makes provision of serious treatment unprofitable.

Here the expected gain to customers refers to the gain in the recommendation subgame. The expert will set a \(p_m\) 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.

For empirical evidence supporting that market forces do provide incentives for experts to take actions favorable to customers, see Hubbard (1998).

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

Arguments will be similar to those used in the proof of Proposition 1 to rule out \(\gamma_m < 1\) and \(\gamma_s < (p_m - r_m)/(p_s - r_m)\) when \(p_m = l_m\) or \(p_s = l_s\).

The notations \(p_{12}\) and \(p_3\) may mislead readers to think that I restrict the expert to charge \(p_{12}\) when the problem is either 1 or 2 and \(p_3\) when the problem is 3. In fact, the expert is free to charge any of these two prices conditioned on any diagnostic result. It just turns out that in the equilibrium of the subgame that I construct, the expert always charges \(p_{12}\) when the problem is either 1 or 2 and \(p_3\) when the problem is 3. So, the notations are chosen on the basis of my ex post knowledge of the expert’s equilibrium behavior.

For the 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 set less than three prices. For example, if \(r_1 = r_2 = r_3\), it is optimal to charge \(p_{123} = l_{123}\); if \(r_1 = r_2 < r_3\), it is optimal to charge \(p_{12} = l_{12}\) and \(p_3 = l_3\), etc.
In general, the expert may infer customers’ types on the basis of their choice of price pairs, and in that case, updating will be done differently, but still according to Bayes’ rule. For example, if the expert infers that among customers choosing price pair $p$, a fraction $\theta' \neq \theta$ of them are of type $H$. In that case, when the expert does not observe the customer’s type, she will assign a probability $\frac{\theta'(1-\delta)}{1-\theta'\delta}$ of the customer’s being type-$H$. 