Discussion Papers of the
Max Planck Institute for
Research on Collective Goods
2023/12

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September 2023

(This paper replaces discussion paper 2020/26.)

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https://www.coll.mpg.de

Diagnostic Uncertainty and Insurance Coverage in Credence Goods Markets[§]

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Abstract

In markets for credence goods – such as health care or repair services – fraudulent behavior by better informed experts is a common problem. Our model studies how four common features shape experts' provision behavior in credence goods markets: (i) diagnostic uncertainty of experts; (ii) insurance coverage of consumers; (iii) malpractice payments for treatment failure; and (vi) consumer-regarding preferences of experts. Diagnostic imprecision unambiguously leads to less efficient provision. Insurance coverage and malpractice payments have an ambiguous effect on efficient provision. The impact of consumer-regarding preferences on efficiency is positive without insurance but ambiguous in the presence of insurance.

JEL-codes: D82, G22

Keywords: Credence goods, diagnostic uncertainty, insurance coverage, social preferences

This version: 29 September 2023

[§] We thank Matthias Heinz, Marco Schwarz, participants at the 93[rd] Annual Conference of the Western Economic Association, CEAR / MRIC Behavioral Insurance Workshop, 6[th] Workshop in Behavioral and Experimental Health Economics, Annual Meeting of the Austrian Economic Association, and seminar participants at the University of Düsseldorf (DICE), University of Cologne and MPI Bonn for helpful comments. Financial support from the Austrian Science Fund (FWF) through special research area grant SFB F63 and grant numbers P26901 and P27912, and the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany´s Excellence Strategy – EXC 2126/1– 390838866 is gratefully acknowledged.

1. Introduction

The inefficiencies arising from asymmetrically informed market participants have long been explored in economic analysis in order to understand the implications of such asymmetries and to identify potential remedies (Stiegler, 1961, Nelson, 1970, Hurwicz, 1973, Harris and Townsend, 1981). Informational asymmetries are a defining feature of markets for credence goods, in which (expert) sellers can perform a diagnosis, allowing them to acquire superior information about a consumer's needs and the corresponding good or service that suits these needs (Darby and Karni, 1973; Dulleck and Kerschbamer, 2006). Examples of such goods and services abound, ranging from repair services to services provided by medical, legal or financial professionals (Balafoutas and Kerschbamer, 2020). A solid understanding of the way that these markets work, the inefficiencies that are endemic to them (e.g. when sellers provide too much or too little of a given service), and the market and institutional forces that shape these outcomes is crucial for economists and policy-makers seeking to increase efficiency and consumer welfare.

In this paper, we present a model on the provision of credence goods. We build on the seminal model by Dulleck and Kerschbamer (2006) and extend it in four important directions. First, while most of the existing work assumes that experts can identify their consumers' needs perfectly (e.g., Wolinsky, 1993; Dulleck and Kerschbamer, 2006; Dulleck et al., 2011; Hyndman and Ozerturk, 2011; Mimra et al., 2016), in reality this is typically not the case. In almost all relevant markets, diagnosis may fail to identify a consumer's problem perfectly (Schneider, 2012). To allow for this we allow the signal that the expert receives about the consumer's problem to be imperfect.

A second very common assumption in the literature is that consumers bear the full cost of service (Wolinsky, 1993; Dulleck and Kerschbamer, 2006; Fong et al., 2014). In reality, however, the cost of service is often covered by an insurance company. In our model we allow for this by comparing the solution of a model variant without insurance to the solution of a variant where the service costs are covered by an insurance institution.

Third, we allow for malpractice payments for cases where the service fails, which is an important feature of many real-world credence goods markets and which has been discussed as an important factor for cost inflation, in particular in the health care sector (Lyu et al., 2017).

Fourth, while the majority of theoretical papers on credence goods assume that experts are rational profit maximizers, there is evidence both from the lab and the field that (at least some) experts have other-regarding preferences (Liu and Ma, 2013; Brosig-Koch et al., 2016, 2017; Kerschbamer et al., 2017). In our model we allow for this by assuming that experts care not only about their own profit, but also about the consumer's material payoff. Including all of those aspects into a single model allows for a comprehensive analysis of factors that are important for the performance of real-world credence goods markets.

Our model leads to a series of novel results. For the case where the signal that the expert receives about the consumer's problem is precise enough such that efficiency requires to follow it, they can be summarized as follows: First, equal markup prices – that are predicted to yield full efficiency in the simpler framework of Dulleck and Kerschbamer (2006) – only lead to efficient service provision for all expert types if the signal is fully precise. In the presence of diagnostic uncertainty, equal markup prices induce selfish experts to always provide a high-quality service, because following the imprecise signal carries the risk of paying the compensation payment, while always selling high quality does not. Price vectors that carry a higher markup for low-quality service combined with malpractice payments are more robust, and – if well designed – they yield efficient provision for all precision levels and expert types. Second, for given prices, diagnostic imprecision unambiguously leads to less efficient provision: Depending on the prices, the expert is inclined to either always provide the high or always provide the low quality. Third, introducing insurance coverage has an ambiguous effect on efficient service provision. Thus, while insurance is intended to protect consumers, it can also reduce consumer welfare. We characterize the conditions under which this is the case. Fourth, the effect of altruism on efficient provision is positive without insurance coverage, but ambiguous in the presence of insurance. Without insurance, more altruistic experts tend to follow the signal they receive. Without diagnostic uncertainty they do so because following the signal is unambiguously in the interest of the consumer, and with diagnostic uncertainty they do so because the additional benefit of always providing the high-quality service is not enough to justify the additional cost. In the presence of insurance, more altruistic experts tend to always provide the high-quality service, because this strategy provides more benefits to the consumer and the additional cost is covered by the insurance company. In this case less altruistic experts might behave more efficiently than more altruistic ones. We characterize the conditions under which this is the case.

Our paper is related to several strands of previous literature. First, there is a small literature that allows for diagnostic uncertainty in expert markets. Inderst and Ottaviani (2012) allow for imperfect diagnostic abilities in markets for financial advice. They investigate how competition through commissions and hidden kickbacks affects the quality of advice received by customers and the resulting allocation of products. Liu et al. (2020) consider exogenous heterogeneity in experts' diagnostic abilities. They characterize the equilibria that can arise when abilities are unobservable and show that, in some cases, a higher share of high-ability experts can harm efficiency. In Fong et al. (2022) doctors with imperfect diagnostic abilities can refer patients to labs for (further) testing. Kickbacks distort the doctor's incentive to prescribe tests. Patients who are unaware of kickbacks can be hurt by both over-provision and under-provision of lab tests. Baumann and Rasch (2023) study the effect of diagnostic uncertainty in the second opinion model of Wolinsky (1993). The authors consider two main scenarios – imperfect diagnosis for the minor problem, but perfect diagnosis for the major problem; and the opposite constellation. For the former case they find that an improvement in diagnostic precision affects welfare and customer surplus only in a pure-strategy equilibrium in which customers always search for a second opinion when confronted with a major recommendation and experts never defraud customers. For the opposite case in which major problems are correctly diagnosed only with some probability while minor problems are always diagnosed correctly the results are less clear-cut. Compared to our paper, none of these papers embeds the question of how diagnostic uncertainty affects market outcomes in a framework that considers insurance coverage of consumers. In fact, the literature on credence goods markets has, so far, dealt with the effects of diagnostic uncertainty and insurance coverage in completely separate lines of research, thus ignoring how these two prominent factors on credence goods markets might interact with each other. Moreover, none of the above papers derives results that are contingent on the seller's level of pro-sociality towards the consumer.

The literature addressing the effect of insurance coverage on provision behavior in markets for credence goods is much smaller – indeed, we are aware of a single theoretical paper addressing this issue.[1] Sülzle and Wambach (2005) study in a second-opinion model that admits two mixed strategy equilibria whether different proportional degrees of coinsurance on the consumer side can have an impact on the likelihood of fraudulent behavior in the form of overcharging on the seller side (but without considering the provision decision of the seller). They show that the impact of an increase in the coinsurance rate on the equilibrium level of fraud is ambiguous: Either there is less fraud and lower probability of searching for second opinions, or more fraud and more search (depending on the equilibrium considered). Compared to this paper focusing on the overcharging dimension of fraud in a model where diagnosis yields

[1] There are several experimental studies on how insurance coverage affects behavior on credence goods markets – see Lu (2014), Kerschbamer et al. (2016), Huck et al. (2016) and Balafoutas et al. (2017).

a perfect signal and where experts are fully selfish, we investigate the effect of insurance coverage on under- and overprovision in a model where diagnosis might yield an imperfect signal and where the expert might care for the welfare of the consumer.

Related to our model with malpractice payments are the models by Dulleck and Kerschbamer (2009), Bester and Dahm (2018) and Chen et al. (2022). In Dulleck and Kerschbamer's (2009) model experts compete against discounters, where the former can exert costly effort to get precise signals about a consumer's needs, while the latter provide no diagnosis, but only sell services. They find that experts are vulnerable to such competition from discounters and may have incentives to undertreat their customers. Bester and Dahm (2018) add subjective evaluation of consumers regarding the success of a service and show in their theoretical model that first-best outcomes can be achieved by separating diagnosis and treatment. Chen et al. (2022) study the design of efficient liability rules in a setting where the expert needs to be provided with proper incentives both in exerting diagnostic effort and in recommending the appropriate treatment. They show that a well-designed liability rule that imposes a penalty on the expert contingent on whether her misbehavior involves over- or undertreatment can achieve the efficient outcome. Compared to our paper, these contributions do neither discuss the effects of insurance coverage nor of other-regarding preferences.

There is a small theoretical literature on how other-regarding preferences of sellers might influence their provision behavior on credence goods markets. Liu and Ma (2013) consider altruistic physicians who can provide services for patients. If physicians can credibly commit to specific services even before learning the patient's illness, first-best solutions for patients can be achieved. If commitment is impossible, however, even altruistic physicians will provide incorrect services. Kerschbamer et al. (2017) show that other-regarding preferences of sellers can improve or decrease market efficiency depending on the price vector and on the preferences of the seller.[2] None of these studies is linked to diagnostic uncertainty or to insurance coverage, which distinguishes them clearly from our paper that provides a novel and unified framework to study how diagnostic uncertainty, insurance coverage, malpractice payments, and other-regarding preferences of sellers interact on credence goods markets.

The rest of the paper is organized as follows: The next section introduces the model. Section 3 derives the first best solution. Section 4 studies profit-maximizing provision behavior

[2] There is also some experimental work on the impact of other-regarding preferences on the working of credence goods markets. For instance, Hennig-Schmidt and Wiesen (2014) study in a lab experiment whether medical students are more other-regarding than non-medical students, and provide an affirmative answer, similar to findings in Brosig-Koch et al. (2017).

in the absence of insurance and Section 5 explores the impact of introducing insurance coverage. Section 5 concludes.

2. The Model

We consider an economy populated by *ex ante* homogeneous consumers and a single expert. Each consumer (he) has either a major problem $\overline{c}$ requiring a high-quality service (HQS) at cost $\overline{c}$, or a minor problem $\underline{c}$ requiring a low-quality service (LQS) at cost $\underline{c}$, with $\overline{c} > \underline{c}$. For future reference we define $\tilde{c} = \overline{c} - \underline{c}$. The consumer knows that he has an *ex ante* probability h of having the major problem and a probability of $1 - h$ of having the minor one. The consumer derives utility $v > 0$ when his problem is solved through a service provided by the expert, and derives zero utility otherwise. While the HQS solves both problems, the LQS solves only the minor problem. The consumer can observe and verify the kind of service he receives[3], but he only finds out whether the received quality was the needed one when the expert provides LQS for $\overline{c}$ (since in that case his problem remains unsolved).

Ex ante the expert (she) has the same information as the consumer on the severity of the consumer's problem. In contrast to the consumer, the expert is able to acquire additional information by performing a diagnosis. Following large parts of the literature we assume that the diagnosis comes for free and is always performed. We depart from large parts of the literature by assuming that the diagnosis does not yield a perfect but only an imperfect signal. Specifically, we assume that the expert receives a signal $s \in \{\underline{c}, \overline{c}\}$ about the severity of the consumer's problem $\gamma \in \{\underline{c}, \overline{c}\}$ that is correct with probability σ. We call σ the precision level and define it as $\sigma = \Pr(s = \underline{c} | \gamma = \underline{c}) = \Pr(s = \overline{c} | \gamma = \overline{c})$, where $\sigma \in [0.5, 1]$, such that $\sigma = 0.5$ corresponds to a completely uninformative signal and $\sigma = 1$ to a fully precise signal. The consumer knows that the expert observes a signal but does not know which signal she has observed.

In line with Inderst and Ottaviani (2009, 2012) we assume that the expert faces a penalty $t \in (0, v)$ whenever she prescribes the LQS to a consumer having the major problem. This payment is a compensation for service failure from the expert to the consumer. We assume that an external institution (e.g., a court) verifies that the service failed and then enforces the

[3] In the jargon of the literature, this means that verifiability applies. This condition rules out fraud in the (over)charging dimension.

payment of t. This eliminates the possibility of fraudulent behavior of consumers by falsely claiming a failed treatment.

We denote the exogenously given prices for LQS and HQS by $\underline{p}$ and $\overline{p}$, and assume $\underline{p} > \underline{c}$, $\overline{p} > \overline{c}$, and $\underline{p} < \overline{p} \leq v$. For future reference, we define the price difference between LQS and HQS as $\tilde{p} = \overline{p} - \underline{p}$ and the price markups for LQS and HQS as $\underline{\Delta} = \underline{p} - \underline{c}$ and $\overline{\Delta} = \overline{p} - \overline{c}$, respectively. Moreover, we distinguish between three types of price vectors: (i) overtreatment (OT) price vectors, where the markup for HQS exceeds the LQS markup $\left(\overline{\Delta} > \underline{\Delta}\right)$, leading to monetary incentives for the expert to provide HQS; (ii) undertreatment (UT) price vectors, with the LQS markup being higher than the HQS one $\left(\overline{\Delta} < \underline{\Delta}\right)$ and monetary incentives for providing LQS; and (iii) equal markup (EM) price vectors, with $\overline{\Delta} = \underline{\Delta}$.

Following Liu (2011), Inderst and Ottaviani (2012) and Fong et al. (2014) we allow for the possibility that the expert cares positively about the consumer's well-being. To model this motivation, we introduce the parameter $\lambda \in [0,1]$ and assume that the expert maximizes his own material payoff (weighted by one) plus λ times the consumer's surplus. A positive value of λ characterizes a pro-social expert, while $\lambda = 0$ implies that the expert is completely selfish.[4] The expert knows her λ, while the consumer knows only the distribution of this parameter in the population of experts.

With respect to insurance, we first consider a baseline scenario with no insurance (abbreviated NI), which means that the entire price for the service is paid by the consumer. We then compare this baseline scenario with one where an insurance company covers the entire cost of the service (henceforth FI for 'full insurance').

3. First-Best Provision Behavior

Before turning to the actual behavior in the market under consideration we first characterize the welfare maximizing provision policy. To do so we make the following thought experiment: Suppose the consumer is able to observe the diagnosis signal and to implement the service at the same cost as the expert. Which provision strategy would he follow? There are three candidates for the efficient solution of the consumer's problem.

Strategy A: Implement the HQS independently of the outcome of the diagnosis.

[4] For simplicity we do not allow for negative values of λ (spiteful experts). Empirically, spiteful preferences are rare (see Kerschbamer 2015, for instance).

Strategy B: Implement the LQS independently of the outcome of the diagnosis.

Strategy C: Implement the LQS if the signal suggests that the problem is minor and implement the HQS if the signal suggests that the problem is major.

The efficient strategy is the strategy that minimizes generalized costs defined as the direct costs plus the implied utility loss for the case where the service fails. The generalized cost of Strategy A is $\bar{c}$, the generalized cost of Strategy B is $\underline{c} + hv$, and the generalized cost of Strategy C is $(1 - h - \sigma + 2h\sigma)\bar{c} + (h + \sigma - 2h\sigma)\underline{c} + h(1 - \sigma)v$. For the characterization of the efficient provision policy we need to compare those costs. Along the hyperbola

$$\sigma_{AC}^{FB} = \frac{h(v - \tilde{c})}{(1 - 2h)\tilde{c} + hv} \tag{1}$$

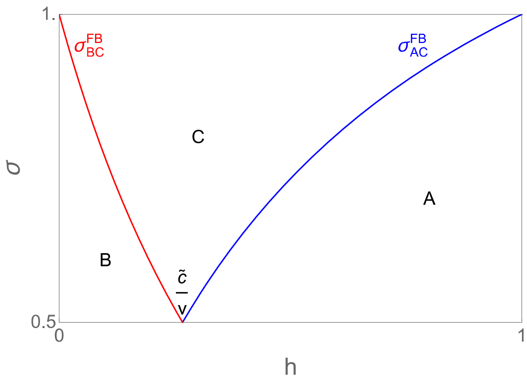
strategies A and C have the same cost, and along the hyperbola

$$\sigma_{BC}^{FB} = \frac{(1 - h)\tilde{c}}{(1 - 2h)\tilde{c} + hv} \tag{2}$$

strategies B and C have the same cost. Using these hyperbolas, we characterize (in Proposition 1) the first-best (FB) provision strategy (see Appendix A for the proof):

Proposition 1 (first-best provision strategy): *The first-best provision strategy is fully characterized in Figure 1. In Area A, efficiency requires to provide the HQS independently of the outcome of the diagnosis (Strategy A); in Area B, efficiency requires to provide the LQS independently of the outcome of the diagnosis (Strategy B); and in Area C, efficiency requires to provide the HQS if the outcome of the diagnosis is* $\bar{c}$ *and the LQS if the outcome is* $\underline{c}$ *(Strategy C).*

Figure 1. *First-best provision strategy*



Note: The functions delineating the areas are those defined in equations (1) and (2).

The intuition for the result illustrated in Figure 1 is simple: Strategy C is optimal if the diagnosis is sufficiently precise and if the likelihood of needing the HQS is neither close to zero nor close to one. If the precision is low, then Strategy A is optimal if the likelihood of needing the HQS is relatively high and Strategy B is optimal if this likelihood is relatively low.

To simplify the exposition, we will from now on focus on the case where the following condition (α) holds:

$$\frac{\tilde{c}}{v} < h \qquad (\alpha)$$

As can be seen in Figure 1, under this condition Strategy A is more efficient than Strategy B.

4 Profit-Maximizing Provision Behavior in the Absence of Insurance (NI)

4.1 Characterization of Provision Behavior in the Absence of Insurance

The profit-maximizing expert has the choice between four pure strategies – strategies A, B and C as defined in the previous section and Strategy D prescribing to provide the HQS when the signal indicates the minor problem and the LQS when the signal indicates the major problem. In Appendix B we show that Strategy D is dominated by one of the other three strategies for any given parameter constellation. The other three strategies are associated with the following utilities for the expert:

Strategy A: $\Pi_A = \overline{p} - \overline{c} + \lambda[v - \overline{p}]$;

Strategy B: $\Pi_B = \underline{p} - \underline{c} - ht + \lambda\left[(1-h)v - \underline{p} + ht\right]$;

Strategy C: $\Pi_C = (1 - h - \sigma + 2h\sigma)(\overline{p} - \overline{c}) + (h + \sigma - 2h\sigma)\left(\underline{p} - \underline{c}\right) - h(1 - \sigma)t + \lambda\left[(1 - h + h\sigma)v - \underline{p}(h + \sigma - 2h\sigma) - \overline{p}(1 - h - \sigma + 2h\sigma) + h(1 - \sigma)t\right]$.

For the characterization of the expert's provision policy we need to compare those payoffs. Along the hyperbola

$$\sigma_{AC}^{NI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{h\big((1-\lambda)\tilde{p} - \tilde{c}\big) + h\lambda(v-t) + ht}{(1-2h)(\tilde{c} - (1-\lambda)\tilde{p}) + h\lambda(v-t) + ht} \qquad (3)$$

strategies A and C yield the same payoff, and along the hyperbola

$$\sigma_{BC}^{NI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{(1-h)(\tilde{c} - (1-\lambda)\tilde{p})}{(1-2h)(\tilde{c} - (1-\lambda)\tilde{p}) + h\lambda(v-t) + ht} \qquad (4)$$

strategies B and C yield the same payoff. With the help of those hyperbolas we can fully characterize the expert's provision strategy for any constellation of the parameters v, h and $\tilde{c}$

satisfying condition (α), any value of the pro-sociality parameter λ, with $\lambda \in [0,1]$, any diagnostic precision $\sigma,$ with $\sigma \in [0.5,1]$, any price vector $(\underline{p}, \overline{p})$, with $\tilde{p} \in [0, v]$, and any transfer t, with $t \geq 0$. This is done in Proposition 2 (see Appendix B for proofs):

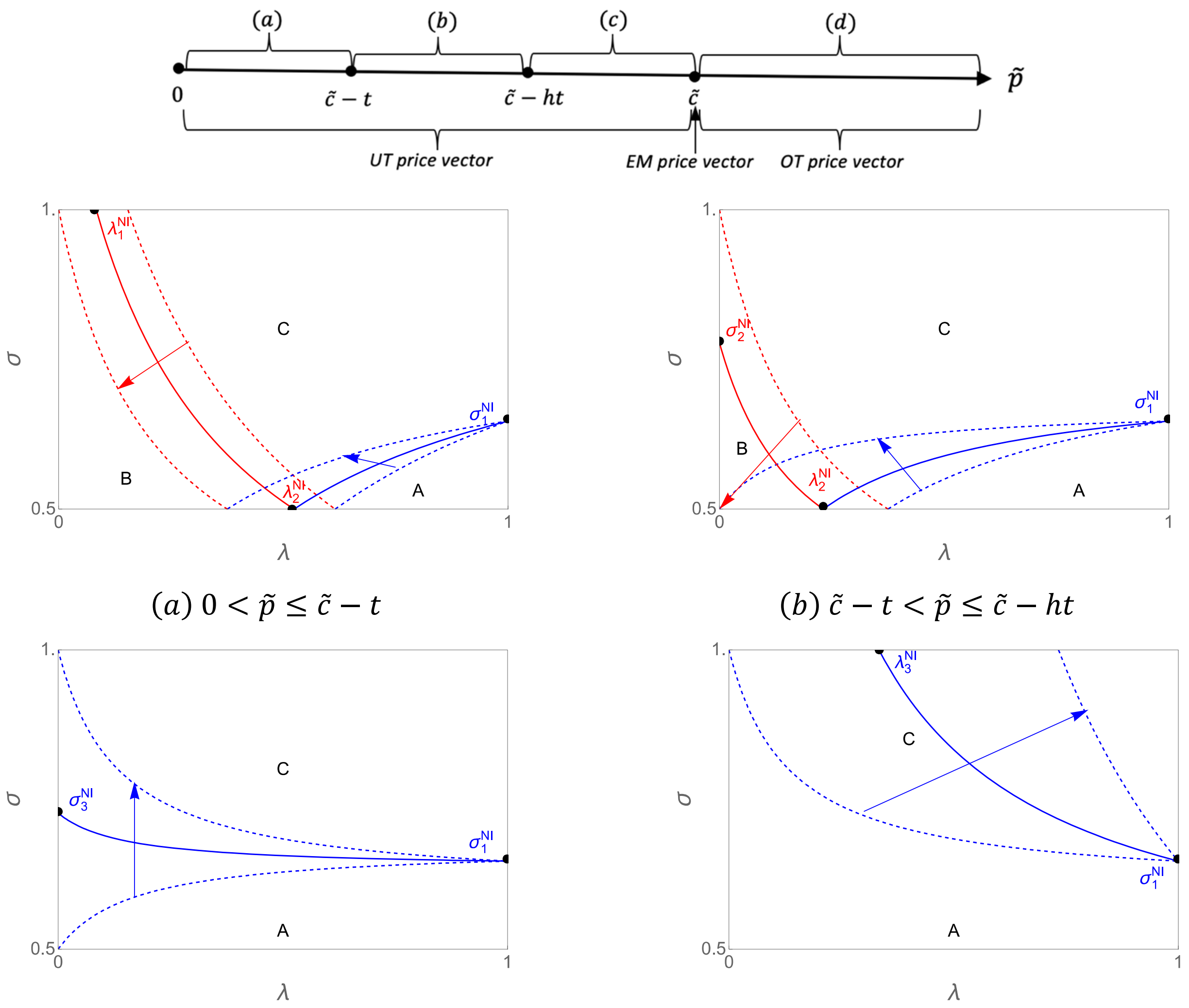
Proposition 2 (provision strategy in the absence of insurance): *For parameter constellations satisfying condition* (α), *the expert's actual provision behaviour in NI (for 'no insurance') is fully characterized in Figure 2. In Area A, the expert provides the HQS independently of the outcome of the diagnosis (Strategy A); in Area B, the expert provides the LQS independently of the outcome of the diagnosis (Strategy B); and in Area C, the expert provides the HQS if the outcome of the diagnosis is $\overline{c}$ and the LQS if the outcome is $\underline{c}$ (Strategy C). The blue curve in each panel is the hyperbola defined in equation (3), and the red curve in panels (a) and (b) is the hyperbola defined in equation (4). Within each panel the solid curves are the curves for interior values of $\tilde{p}$ within the boundaries defining the respective panel. The dashed curves represent the lower and the upper boundary of $\tilde{p}$ in the respective panel. The effect of increasing $\tilde{p}$ from the lower to the upper boundary of the respective panel can be seen by following the corresponding arrow.*

A few comments about Figure 2 are in order. Depending on the magnitude of the transfer t, one of the following four cases is relevant for the constellation under consideration:

- $t = 0$: For this value of *t*, panels (b) and (c) disappear from Figure 2 and the terms λ_1^{NI} and λ_2^{NI} in panel (a) converge to 0 if $\tilde{p}$ converges to $\tilde{c}$. If we increase $\tilde{p}$ gradually starting from $\tilde{p} = 0$, then we are first (for UT price vectors) in panel (a); if $\tilde{p}$ reaches the critical value $\tilde{c}$ (EM price vector) then we are on the boundary between panel (a) and panel (d); and for $\tilde{p} > \tilde{c}$ (OT price vector) we are in the interior of panel (d).
- $t \in (0, \tilde{c})$: For *t* in this range, all panels are relevant: If we increase $\tilde{p}$ gradually starting from $\tilde{p} = 0$, then we are first in panel (a); if $\tilde{p}$ passes the critical value $\tilde{c} - t$ then we reach panel (b); and so on.
- $t \in \left[\tilde{c}, \frac{\tilde{c}}{h}\right)$: For *t* in this range, panel (a) disappears from Figure 2: If we increase $\tilde{p}$ gradually starting from $\tilde{p} = 0$, then we are first in panel (b); if $\tilde{p}$ passes the critical value $\tilde{c} - ht$ then we reach panel (c); and so on.
- $t \geq \frac{\tilde{c}}{h}$: For *t* in this range, panels (a) and (b) disappear from Figure 2: If we increase $\tilde{p}$ gradually starting from $\tilde{p} = 0$, then we are first in panel (c); and if $\tilde{p}$ passes the critical value $\tilde{c}$ then we are in panel (d).

For all values of t, and for each panel that is relevant for the t under consideration, we see the effect of increasing $\tilde{p}$ from the lower to the upper boundary of the respective panel by following the respective arrow.

Figure 2. *Profit-maximizing provision behavior with no insurance (NI)*



$(a)\ 0 < \tilde{p} \leq \tilde{c} - t$ $(b)\ \tilde{c} - t < \tilde{p} \leq \tilde{c} - ht$

$(c)\ \tilde{c} - ht < \tilde{p} < \tilde{c}$ $(d)\ \tilde{c} \leq \tilde{p} \leq v$

Note: The intercept points $\lambda_1^{NI}, \lambda_2^{NI}, \lambda_3^{NI}$ and $\sigma_1^{NI}, \sigma_2^{NI}, \sigma_3^{NI}$ are defined as: $\lambda_1^{NI} = \frac{\tilde{c}-t-\tilde{p}}{v-t-\tilde{p}}$; $\lambda_2^{NI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)-\tilde{p}}$; $\lambda_3^{NI} = 1 - \frac{\tilde{c}}{\tilde{p}}$; $\sigma_1^{NI} = \frac{1}{2} + \frac{h(v-\tilde{c})-(1-h)\tilde{c}}{2[h(v-\tilde{c})+(1-h)\tilde{c}]}$; $\sigma_2^{NI} = \frac{1}{2} + \frac{(1-h)(\tilde{c}-\tilde{p})-h(\tilde{p}-\tilde{c}+t)}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$; $\sigma_3^{NI} = \frac{1}{2} + \frac{h(\tilde{p}-\tilde{c}+t)-(1-h)(\tilde{c}-\tilde{p})}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$.

Within each panel, the diagnostic precision σ of the constellation gives us a horizontal line (not shown in the figure). If we go to the point $\lambda = 1$ on this line, then we see the efficient provision strategy. This is due to the fact that an expert with $\lambda = 1$ is maximizing the sum of the monetary payoffs of the two agents. The efficient solution depends on v, $\tilde{c}$, h, and σ, but not on the prices prevalent on the market or the transfer t – that is, the point σ_1^{NI} is exactly the same in each of the four panels of Figure 2 and within each panel it changes neither in $\tilde{p}$ nor in t.

Under our condition (α), always providing the HQS is more efficient than always providing the LQS. Thus, efficiency requires to follow the signal (Strategy C) if the signal is precise enough ($\sigma > \sigma_1^{NI}$) and to blindly provide HQS (Strategy A) otherwise.[5] For values of the pro-sociality parameter λ in $[0, 1]$ we see which provision strategy the expert of type λ actually chooses. As we can see from the figure, there are constellations where efficiency would require to follow the signal, but egoistic and modestly pro-social experts choose Strategy B (panel (a) for $\sigma > \sigma_1^{NI}$ and panel (b) for $\sigma_2^{NI} > \sigma > \sigma_1^{NI}$) or Strategy A (panel (c) for $\sigma_3^{NI} > \sigma > \sigma_1^{NI}$and panel (d) for $\sigma > \sigma_1^{NI}$). However, there are also constellations where efficiency would require to implement Strategy A, but egoistic and moderately pro-social experts choose Strategy B while modestly pro-social experts choose Strategy C (panel (a) for $\sigma < \sigma_1^{NI}$ and panel (b) for $\sigma < \min(\sigma_2^{NI}, \sigma_1^{NI})$), or where egoistic and scarcely pro-social experts choose Strategy C (panel (b) for $\sigma_2^{NI} < \sigma < \sigma_1^{NI}$ and panel (c) for $\sigma_3^{NI} < \sigma < \sigma_1^{NI}$).

4.2 The impact of prices, transfer, diagnostic uncertainty and altruism on provision behaviour in the absence of insurance

In our discussion in this subsection we will concentrate on constellations where the signal is precise enough such that following the signal (Strategy C) is the efficient provision strategy. In terms of Figure 2 this means that we are restricting attention to precision levels that are above σ_1^{NI}. We call this restriction condition (β):

$$\sigma > \sigma_1^{NI} = \frac{1}{2} + \frac{h(v - \tilde{c}) - (1 - h)\tilde{c}}{2[h(v - \tilde{c}) + (1 - h)\tilde{c}]}. \qquad (\beta)$$

In Section 2 we have defined three types of price vectors: (i) overtreatment (OT) price vectors, where the markup for HQS exceeds the LQS markup; (ii) undertreatment (UT) price vectors, with the LQS markup being higher than the HQS one; and (iii) equal markup (EM) price vectors. In the following discussion we refer to these three types of price vectors:

- **OT:** For perfect precision, selfish and moderately altruistic experts will always decide for Strategy A, as there are direct material incentives for doing so; more altruistic

[5] Referring to the (σ, λ) space, we use the convention that a σ with a letter in the subscript denotes a function (of λ) while a σ with a number in the subscript denotes a point.

experts decide for Strategy C because they care for the customer (who would have to pay the higher cost of always providing HQS). For lower precision levels the tendency of selfish and moderately altruistic experts to decide for Strategy A is even more pronounced as for any $t > 0$ following the imprecise signal carries the risk of paying the compensation payment (in case of failure) while Strategy A is safe in this respect. Within the range of OT price-vectors increasing $\overline{p}$ while keeping $\underline{p}$ constant leads to less efficient provision – as more altruism is required in this case to decide for Strategy C (simply because the material incentive to always provide the HQS is increasing in $\overline{p}$ – for a given $\underline{p}$).

- **EM:** For perfect precision, the selfish expert is indifferent between Strategy A and Strategy C, while more altruistic experts have a strict incentive to choose Strategy C. For lower precision levels selfish and moderately altruistic experts will always decide for Strategy A for any $t > 0$ because following the imprecise signal carries the risk of paying the compensation payment (in case of failure) while Strategy A is safe in this respect.
- **UT:** If the material incentives for always providing the LQS are large (as in panel (a) of Figure 2) selfish and moderately altruistic experts will decide for Strategy B for any precision level simply because they have material incentives for doing so. This incentive is 'muted' when $t > 0$. When t is large enough then the UT price vector induces efficient provision (that is Strategy C) for all expert types and all precision levels – see panel (b) for $\sigma_2^{NI} \leq \sigma_1^{NI}$ and panel (c) for $\sigma_3^{NI} \leq \sigma_1^{NI}$.[6] When t is large and material incentives for always providing the LQS are small then the UT price vector leads to overtreatment for selfish and moderately altruistic experts for imprecise signals – see panel (c) for $\sigma_3^{NI} > \sigma_1^{NI}$. The reason here is the fear of paying the compensation transfer t under Strategy C which is avoided by implementing Strategy A. Within the range of UT price vectors increasing $\overline{p}$ while keeping $\underline{p}$ constant leads first to more efficient provision (in panels (a) and (b) selfish and moderately altruistic experts switch from Strategy B to Strategy C if the high price is increased) but later it leads to less efficient provision (in panel (c) selfish and moderately altruistic experts switch from C to A if $\overline{p}$ is increased while keeping $\underline{p}$ constant). This latter effect is interesting as we are moving in the direction of

[6] Efficient provision for all expert types and precision levels requires that if we draw a horizontal line at σ_1^{NI} then the area above that line is in the interior of area C.

an EM price-vector in this case and since EM is predicted to yield efficient provision under verifiability in a simpler context (see Dulleck and Kerschbamer, 2006, for instance).

The above discussion implies that for $t > 0$ holding the price of the LQS constant and increasing the price for the HQS yields a non-monotonic effect on efficiency of provision: for a low price-difference selfish and moderately altruistic experts decide for Strategy B while more altruistic experts efficiently decide for Strategy C. If starting from here the price of the HQS is increased (keeping the price of the LQS constant) then we get to a more efficient solution as more and more (and at some point, all) expert types decide for Strategy C. However, when we now increase $\overline{p}$ further, then the less altruistic experts decide for Strategy A (while the more altruistic ones still decide for Strategy C). So, in this range (covered by panels (a) and (b)) efficiency decreases in the price of the HQS. While a non-monotonic relationship between $\overline{p}$ and efficiency of provision is also predicted by the standard model (with selfish experts, perfect diagnosis and no transfer in case of failure), the standard model yields full efficiency only for a single point (the EM point) while our model predicts efficiency for a whole range of prices – but not for the EM vector (which is predicted to yield efficient provision only for the perfectly precise signal – but not for an imprecise diagnosis). More generally, our model predicts that EM is not a robust institution. More robust is a UT price vector combined with $t > 0$. The latter combination leads to efficient provision for all types of experts and degrees of diagnostic imprecision. We summarize this discussion as follows:

Corollary 1: *Under conditions α, β and NI (for 'no insurance') the impact of markups on efficient provision is ambiguous. Equal markups only lead to efficient provision if the signal is fully precise or the expert is altruistic enough. An UT price-vector in combination with a well-designed positive transfer yields efficient provision for all precision levels and expert types.*

In general, the *impact of the transfer payment t on efficient provision* is ambiguous: In the presence of an imprecise signal the impact of t on efficiency is positive when combined with a pronounced UT price vector but negative when combined with mild UT, EM or OT: In the case of a pronounced UT price vector a larger t induces selfish and moderately altruistic experts to choose Strategy C instead of Strategy B (panels (a) and (b)), but for mild UT, EM and OT a larger t leads to more overtreatment (because the compensation can be avoided by providing Strategy A instead of Strategy C). We record this as:

Corollary 2: *Under conditions α, β and NI (for 'no insurance') the impact of the compensation payment t on efficient provision is ambiguous: If the signal is imprecise, the impact of an increase in t on efficiency is positive when combined with a pronounced UT price-vector but negative when combined with mild UT, EM or OT.*

Turning to the *impact of diagnostic imprecision on provision behavior* we see that in panels (c) and (d) of Figure 2 a less precise signal induces selfish and moderately altruistic experts to provide Strategy A instead of Strategy C as A avoids the transfer *t* in case of failure while C does not. In panels (a) and (b) it induces selfish and moderately altruistic experts to choose B instead of C. With a more precise signal those experts decide for Strategy C because of the fear to pay the transfer *t* if the treatment fails; if the signal becomes less precise they provide the LQS even if the signal indicates that the problem is serious as they hope that the LQS solves the problem such that they avoid the punishment. Summing up the discussion we conclude:

Corollary 3: *Under conditions α, β and NI (for 'no insurance') the impact of diagnostic imprecision on efficient provision is negative: More diagnostic imprecision unambiguously leads to less efficient provision.*

Turning to the *impact of altruism on provision behavior* we see that more altruism unambiguously leads to more frequent use of Strategy C and therefore to more efficient provision:

Corollary 4: *Under conditions α, β and NI (for 'no insurance') the impact of altruism on efficient provision is positive: More pro-sociality unambiguously leads to more efficient provision.*

Before proceeding, let us shortly discuss how our results compare to related findings in the literature. Most of the literature assumes $t = 0$ (no transfer), $\sigma = 1$ (perfect diagnostic precision) and $\lambda = 0$ (completely selfish experts).[7] For this special case, our figure displays the discontinuity in the expert's provision behavior found in large parts of the literature (see Dulleck and Kerschbamer, 2006): For $\tilde{p} < \tilde{c}$ the expert always provides LQS; for $\tilde{p} > \tilde{c}$ she always provides HQS; and at $\tilde{p} = \tilde{c}$ the expert is indifferent between providing LQS and HQS and is therefore assumed to follow the signal. In Figure 2 we see that this insight extends to the

[7] Previous literature has also considered the case $t = \infty$ – imposed via assuming liability (Dulleck and Kerschbamer, 2006; Dulleck at al. 2011; Chen et al. 2018), which directly rules out undertreatment.

case where the diagnosis produces a noisy signal, but only for the special case where $t = 0$. With $\sigma < 1$ and $t > 0$ the equal markup vector (represented by the dashed curve in panel (d)) gives the egoistic expert a strict incentive to provide the HQS independently of the outcome of the diagnosis. This is quite intuitive: With an equal markup vector the expert earns exactly the same immediate profit from selling the LQS and selling the HQS. However, if she sells the LQS in a world where the signal is noisy, then she runs the risk of getting punished (by having to pay t) while selling the HQS is safe in this regard.

Still staying with the constellation $t = 0$ and $\sigma = 1$, but allowing now for $\lambda > 0$, Figure 2 replicates some of the results in Kerschbamer et al. (2017): If the expert is sufficiently altruistic then she follows the signal even under an UT price vector (panel (a)) or an OT price vector (panel (d)). Our Figure 2 extends the findings from Kerschbamer et al. (2017) by allowing, first, for a compensation for treatment failure ($t > 0$) and, second, for a noisy diagnosis ($\sigma \leq 1$). As we can see in Figure 2, with $\sigma < 1$ the equal markup vector induces experts with a low λ to always provide the HQS. We also see that the range of λ values for which this is the case becomes larger as the signal becomes less informative.

The case where an expert has to pay a transfer $t > 0$ as a compensation for service failure has previously been considered by Dulleck and Kerschbamer (2009) for the special case where $\sigma = 1$ and $\lambda = 0$. The authors show that an expert can be induced to invest in costly diagnosis by a price structure that has $\tilde{p} < \tilde{c}$ and $t > 0$ – but not by constellations that have either $\tilde{p} \geq \tilde{c}$ or $t = 0$. We can see this in panels (b) and (c) of Figure 2 where the point $\sigma = 1$ and $\lambda = 0$ lies in the interior of Area C – which is a necessary condition for an incentive to acquire a costly signal. Our analysis extends that by Dulleck and Kerschbamer (2009) by allowing for arbitrary values of λ in $[0, 1]$ and arbitrary values of σ in $[0.5, 1]$.

5 Profit-Maximizing Provision Behavior in the Presence of Insurance (FI)

5.1 Characterization of provision behavior in the presence of insurance

We next study the effect of introducing full insurance on the expert's provision behavior. Full insurance means that the payment from the consumer to the expert is covered by an insurance company, in exchange for the insurance premium. The latter is paid before the expert-consumer interaction takes place. As a result, the payoff of the consumer is not affected by the price charged by the expert. This changes the expert's payoffs for strategies A, B and C to:

Strategy A: $\Pi_A = \overline{p} - \overline{c} + \lambda v.$

Strategy B: $\Pi_B = \underline{p} - \underline{c} - ht + \lambda[(1-h)v + ht]$.

Strategy C: $\Pi_C = (1 - h - \sigma + 2h\sigma)(\overline{p} - \overline{c}) + (h + \sigma - 2h\sigma)\left(\underline{p} - \underline{c}\right) - h(1 - \sigma)t + \lambda[(1 - h + h\sigma)v + h(1-\sigma)t]$.

Given those payoffs, indifference between strategies A and C is reached along the hyperbola

$$\sigma_{AC}^{FI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{h(\tilde{c}-\tilde{p}) - h\lambda(v-t) - ht}{(1-2h)(\tilde{p}-\tilde{c}) - h\lambda(v-t) - ht} \tag{5}$$

and indifference between strategies B and C is reached along the hyperbola

$$\sigma_{BC}^{FI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{(1-h)(\tilde{p}-\tilde{c})}{(1-2h)(\tilde{p}-\tilde{c}) - h\lambda(v-t) - ht}\,. \tag{6}$$

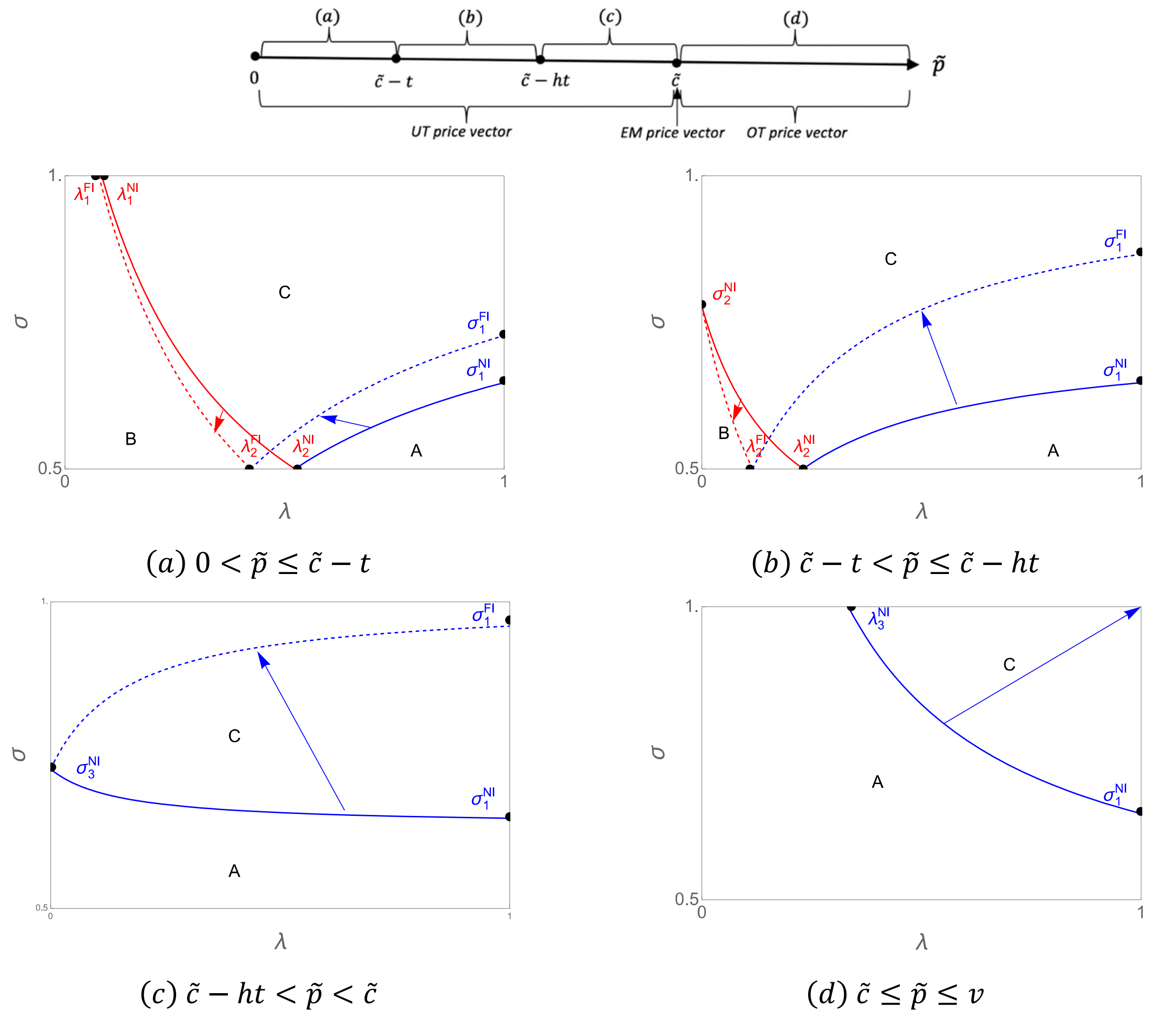
With the help of those hyperbolas we can fully characterize the expert's provision strategy for the full insurance case. This is done in Proposition 3 (see Appendix C for proofs):

Proposition 3 (profit-maximizing provision strategy in the presence of insurance): *For parameter constellations satisfying condition* (α), *the expert's actual provision behavior in FI (for 'full insurance') is characterized in Figure 3. For $\tilde{p} \geq \tilde{c}$ (panel (d) of Figure 3) all experts opt for Strategy A. For $\tilde{p} < \tilde{c}$, panels (a), (b) and (c) of Figure 3 show the effect of introducing full insurance on the expert's provision behavior. The solid red and the solid blue line as well as the areas A, B and C are defined as in Proposition 2 and characterize the provision areas in NI. The dashed blue line in panels (a), (b) and (c) is the hyperbola defined in equation (5), and the dashed red line in panels (a) and (b) is the hyperbola defined in equation (6). Those curves define the provision areas in the FI case.*

The effect of introducing full insurance coverage depends on the expert's type λ and on the prevailing price vector. Selfish experts ($\lambda = 0$) are not affected by the introduction of insurance, since insurance affects only the consumer's payoff and since the consumer's payoff is relevant for the expert's behaviour only if $\lambda > 0$. For pro-social experts ($\lambda > 0$) the incentive to provide the HQS instead of the LQS is increased by introducing insurance, since the consumer does not directly bear the additional cost of the more expensive service. Which implications does this have for the expert's provision policy? The answer to this question depends on the characteristic of the price vector.

Under EM and OT price-vectors (covered by panel (d) of Figure 3) insurance unambiguously leads to less efficient provision: without insurance altruistic experts follow the signal, with insurance they always provide the HQS (Strategy A). This is so because they have direct material incentives for selling the HQS and because consumers also profit from the HQS as the problem is then solved for sure while with Strategy C this is only the case for perfect precision.

Figure 3. *Profit-maximizing provision behavior with no insurance (NI) and full insurance (FI)*



Note: This figure shows the effect of introducing insurance. The solid red and the solid blue line as well as the areas A, B and C are as defined in Proposition 2 and they characterize the provision areas in the NI case. The dashed red and the dashed blue line are the hyperbolas defined in equations (5) and (6) and they define the provision areas in the FI case. The intercept points $\lambda_1^{NI}, \lambda_2^{NI}, \lambda_3^{NI}$ and $\sigma_1^{NI}, \sigma_2^{NI}, \sigma_3^{NI}$ are as defined in the note to Figure 2. The other intercept points are defined as: $\lambda_1^{FI} = \frac{\tilde{c}-t-\tilde{p}}{v-t}$; $\lambda_2^{FI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)}$; $\sigma_1^{FI} = \frac{1}{2} + \frac{h(v-\tilde{c}+\tilde{p})-(1-h)(\tilde{c}-\tilde{p})}{2[h(v-\tilde{c}+\tilde{p})+(1-h)(\tilde{c}-\tilde{p})]}$.

Under UT price vectors – covered by panels (a), (b) and (c) of Figure 3 – there is a clear monetary incentive for the expert to provide the LQS, while the consumer's payoff is still maximized with the HQS. As a consequence, a pro-social expert faces a trade-off. If the material incentive to provide the LQS is rather low – as in panel (c) of the figure – the region in which the expert implements Strategy C unambiguously shrinks in favor of the area in which he implements Strategy A.[8] If the material incentive to provide the LQS is higher – as in panels (a) and (b) of the figure – the effect of introducing insurance on provision behavior depends on the altruism of the expert. More altruistic experts, who would chose Strategy C without insurance, are inclined to implement Strategy A when the signal is imprecise and the customer is insured. The reason is again that the customer profits from always receiving the HQS as the signal is imprecise and the additional cost of the HQS is paid by the insurance. By contrast, moderately altruistic experts who would choose Strategy B under NI when the signal is imprecise might choose Strategy C under the same precision level if the customer is insured. This is due to the fact that for a somewhat altruistic expert the incentive for choosing B is decreased by introducing full insurance since the expert partially internalizes the benefit of the consumer but does not internalize the associated additional cost.[9]

To sum up, introducing full insurance expands Area A (where the HQS is always provided) at the cost of Area C (where the expert follows the signal) independently of the prevailing price vector. If the price vector induces strong material incentives to always provide the LQS (as is the case in panels (a) and (b) of Figure 3), then introducing full insurance in addition expands Area C at the cost of Area B. We summarize this discussion to:

Corollary 5: *Under conditions α and β the impact of introducing insurance on efficient provision is ambiguous: Under OT, EM and mild UT price-vectors insurance unambiguously leads to less efficient provision. Under pronounced UT price-vectors the effect of introducing insurance on provision behavior is negative for more altruistic experts but positive for less altruistic ones.*

[8] More precisely, for all experts with $\lambda > 0$ a higher precision level is needed to choose Strategy C instead of Strategy A, compared to the NI case.

[9] In panels (a) and (b) of Figure 3 the ambiguous effect of introducing insurance is a consequence of the fact that the curve separating areas A and C in the FI case is above and to the left of the corresponding line in the NI case, while the curve separating areas B and C in the FI case is below and to the left of the corresponding line in the NI case. This implies that introducing FI expands the range of λ-types choosing Strategy A for low precision levels as compared to the NI case (where no expert will choose strategy A for precision levels for which choosing C is efficient). At the same time, introducing FI narrows the range of λ-types choosing Strategy B for lower precision levels as compared to the NI case.

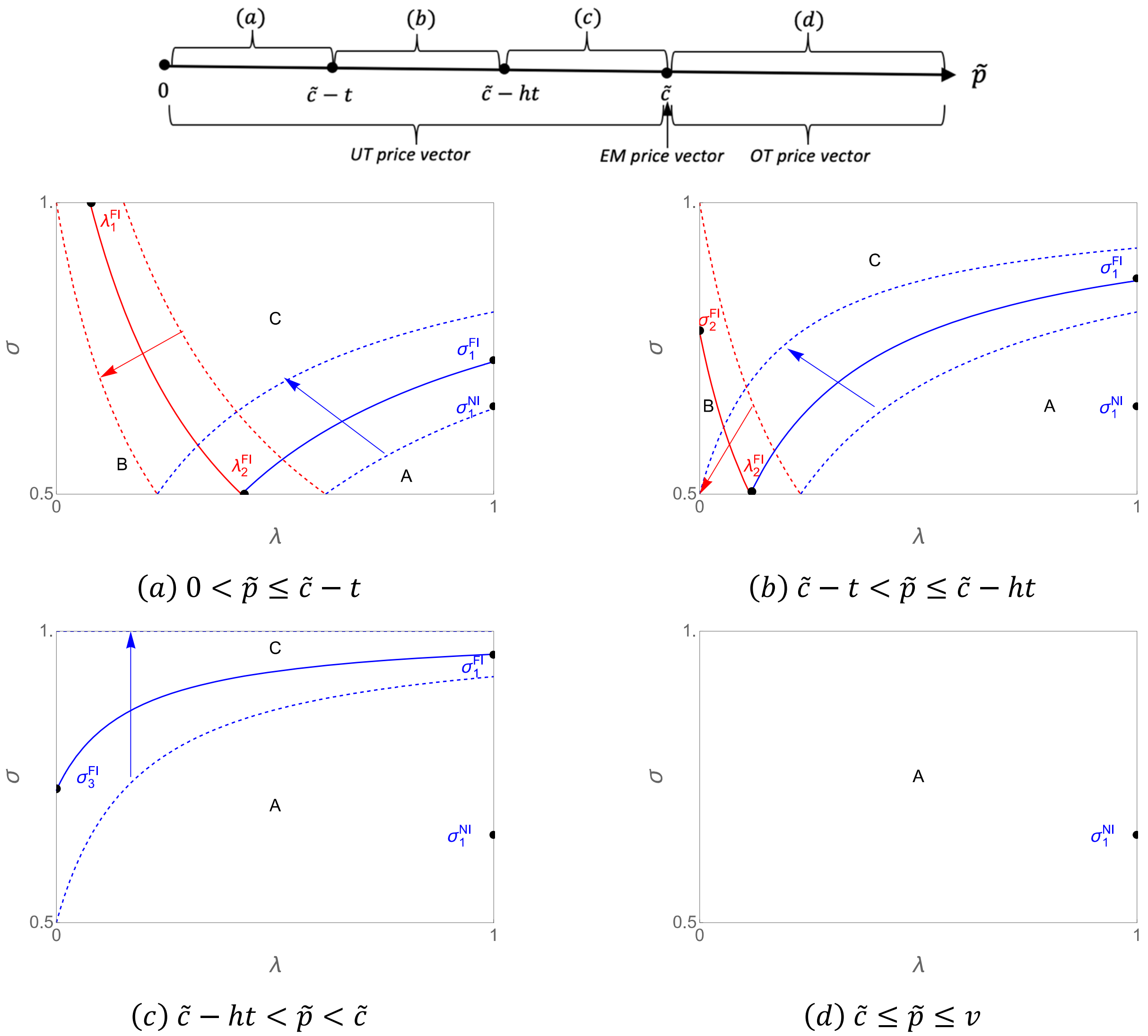
5.2 The impact of prices, transfer, diagnostic uncertainty and altruism on provision behaviour in the presence of insurance

We start again with the *impact of prices on provision behavior.* For $t > 0$ holding the price of the LQS constant and increasing the price for the HQS yields a non-monotonic effect on efficiency of provision. The effect is very similar to the one in the absence of insurance – the main difference being that EM and OT price-vectors induce the expert now to implement Strategy A independently of her pro-sociality and independently of the precision of the signal (see panel (d) of Figure 4). Another difference is that for $t > 0$ efficient provision (that is, Strategy C) for all expert types can only be induced if the signal is sufficiently precise. If the signal is not precise enough then altruistic experts will opt for Strategy A to prevent the customer from harm (see panels (a), (b) and (c) of Figure 4).

As in the no insurance case*, the impact of the compensation transfer on efficiency is ambiguous*: In the presence of an imprecise signal the impact is positive when combined with a pronounced UT price vector, negative when combined with a mild UT, and nonexistent with an EM or an OT price vector: In the case of a pronounced UT price vector a larger t induces selfish and moderately altruistic experts to choose Strategy C instead of Strategy B (panels (a) and (b)), but for mild UT a larger t leads to more overtreatment (panel (c)). For EM and OT (panel (d)) there is no impact as all expert types opt for Strategy A for all values of t.

The *impact of diagnostic imprecision on efficient provision* is negative – as in the setting without insurance: In panel (d) diagnostic imprecision has no impact as Strategy A is implemented for all precision levels and independently of how altruistic the expert is. In panel (c) a less precise signal induces some experts to provide Strategy A instead of Strategy C as A always solves the problem while C does not (thus, A provides greater utility to the customer and also avoids the transfer). In panels (a) and (b) a less precise signal induces selfish and moderately altruistic experts to choose B instead of C and more altruistic experts to choose A instead of C.

Figure 4. *The impact of prices on profit-maximizing provision behaviour in the presence of full insurance (FI)*



Note: This figure shows the effect of increasing $\tilde{p}$ on the expert's provision behavior in the presence of insurance (FI). The (solid and dashed) red and blue lines are the hyperbolas defined in equations (5) and (6) and they characterize the provision areas in the FI case. The point σ_1^{NI} is as defined in the note to Figure 2. The other points are defined as: $\lambda_1^{FI} = \frac{\tilde{c}-t-\tilde{p}}{v-t}$; $\lambda_2^{FI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)}$; ; $\sigma_1^{FI} = \frac{1}{2} + \frac{h(v-\tilde{c}+\tilde{p})-(1-h)(\tilde{c}-\tilde{p})}{2[h(v-\tilde{c}+\tilde{p})+(1-h)(\tilde{c}-\tilde{p})]}$.

More interesting is the *impact of altruism on efficient provision*: While it was unambiguously positive without insurance, with insurance it becomes ambiguous: Under EM and OT (covered by panel (d) of Figure 4) altruism has no impact on provision as all expert types will choose Strategy A under every precision level. For mild UT price-vectors (panel (c) of the figure) the impact of altruism on efficient provision is negative: egoistic and moderately altruistic experts tend to decide for Strategy C (to avoid the punishment in case of failure) while more altruistic experts choose Strategy A if the signal is imprecise (as they care for the welfare of the customer but do not take into account the additional cost of implementing Strategy A instead of Strategy C). For pronounced UT vectors (panels (a) and (b) of the figure) the impact of altruism on efficient provision is ambiguous: If the signal is imprecise, egoistic and moderately altruistic experts decide for Strategy B, more altruistic experts decide for Strategy C and even more altruistic experts decide for Strategy A. That is, here only moderately altruistic experts decide for the efficient provision policy while less and more altruistic experts behave inefficiently.

We summarize this discussion as follows:

Corollary 6: *Under conditions α, β and FI (for 'full insurance') the impact of prices, transfer and diagnostic precision is as in the setting without insurance. However, the impact of altruism is now ambiguous while it was unambiguously positive without insurance.*

4 Concluding Remarks

Our paper has offered a unified theoretical framework that accommodates four important and common features of credence goods markets: (i) Diagnostic uncertainty of experts when trying to identify a consumer's problem, which is a common but hitherto largely neglected feature of credence goods markets (e.g. in health care or repair services); (ii) insurance coverage of consumers, which is frequently in place in credence goods markets, and sometimes even compulsory (as in many countries for health care services); (iii) malpractice payments for cases where the service fails, which is an important feature of many real world credence goods markets and has been discussed as an important factor for cost inflation, in particular in the health care sector; and (iv) consumer-regarding preferences of experts, reflecting the fact that despite their informational advantage many experts do not only care about their own profits, but also consider consumer's welfare. The combination of these factors and their analysis in a unified theoretical framework is a novel contribution to the literature on credence goods markets.

The analysis of our model reveals how service provision in markets for credence goods is affected by these key factors. Diagnostic imprecision unambiguously leads to less efficient provision, while the effects of insurance coverage, price markups and malpractice compensation payments are ambiguous and can increase or reduce consumer welfare, depending on conditions that we characterize in the paper. The effect of pro-sociality by sellers towards consumers on efficient provision is positive without, and ambiguous with insurance coverage for consumers.

Besides advancing the economics literature on credence goods in novel directions, we believe that our findings can serve as a kind of manual for policy-makers who are interested in knowing how service provision, efficiency and consumer welfare in this kind of markets depend on key elements of the environment that policy can influence to varying extents, such as price markups, diagnostic precision, insurance, and malpractice payments. Including all these elements in one unified model makes the analysis complicated, but it is important because – as our analysis reveals – there are several ways in which these elements interact with each other, and knowing how all these moving parts come together can improve the quality of policy decisions and their fit to particular markets and contexts. One aspect of the analysis that is particularly relevant for policy, especially in markets for health care, relates to our findings on insurance. While it is an established fact that insurance coverage can have adverse effects due to moral hazard (e.g., Einav et al., 2013; Einav and Finkelstein, 2018), we have shown that an additional unintended consequence on the supply side is the possibility of a drop in the rate of efficient service provision. We believe that this should be taken into account, along with the derived conditions that give rise to positive and negative welfare effects.

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APPENDIX

Appendix A. Proof of Proposition 1: first-best provision strategy

We start by defining the generalized costs associated with each of the three provision strategies:

- Strategy A: $C_A = \overline{c}$
- Strategy B: $C_B = \underline{c} + hv$
- Strategy C: $C_C = \overline{c}(1 - h - \sigma + 2h\sigma) + \underline{c}(h + \sigma - 2h\sigma) + h(1 - \sigma)v.$

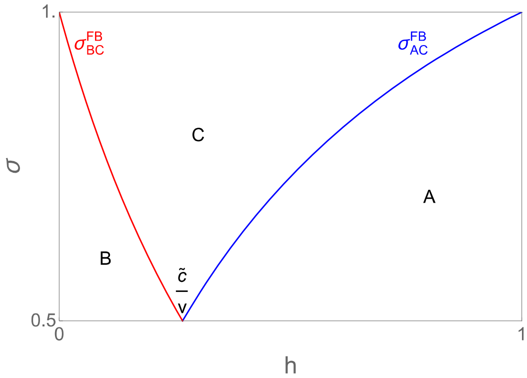
The efficient provision strategy is the one that minimizes generalize costs. Equating C_A and C_C results in the hyperbola σ_{AC}^{FB}, as defined in equation (1) in the body of the paper. For $\sigma < \sigma_{AC}^{FB}$ Strategy A is more efficient than Strategy C and vice versa for $\sigma > \sigma_{AC}^{FB}$. Equations C_B and C_C yield the hyperbola σ_{BC}^{FB} defined in equation (2) in the paper. For $\sigma < \sigma_{BC}^{EXO-FB}$ Strategy B is more efficient than Strategy C and vice versa for $\sigma > \sigma_{BC}^{FB}$. Equating C_A and C_B yields the line $h = \frac{\tilde{c}}{v}$. For $h < \frac{\tilde{c}}{v}$ Strategy B is more efficient than Strategy A and vice versa for $h > \frac{\tilde{c}}{v}$.

Figure 1 depicts the hyperbolas σ_{AC}^{FB} and σ_{BC}^{FB} in the (h, σ) space, for $h \in [0,1]$ and $\sigma \in [0.5,1]$. The intercept of the two hyperbolas is found by equating σ_{AC}^{FB} and σ_{BC}^{FB} and the crossing point corresponds to $h = \frac{\tilde{c}}{v}$ and $\sigma = 0.5$. From our assumption that $\tilde{c} < hv$ (and given that $h \in [0,1]$) it directly follows that $\tilde{c} < v$. Thus, $\frac{\tilde{c}}{v} \in (0,1)$ under any constellation of the parameters $\{\tilde{c}, v\}$.

As a result, the efficient provision strategy has the following properties:

(a) for $\sigma < \sigma_{AC}^{FB} = \frac{h(v-\tilde{c})}{(1-2h)\tilde{c}+hv}$ and $h \in \left[\frac{\tilde{c}}{v}, 1\right]$ efficiency requires to choose Strategy A;
(b) for $\sigma < \sigma_{BC}^{FB} = \frac{(1-h)\tilde{c}}{(1-2h)\tilde{c}+hv}$ and $h \in \left[0, \frac{\tilde{c}}{v}\right)$ efficiency requires to choose Strategy B; and
(c) for $\{\sigma > \sigma_{BC}^{FB} = ((1-h)\tilde{c})/((1-2h)\,\tilde{c} + hv) \wedge \; h \in [0, \tilde{c}/v)\}$ and $\{\sigma > \sigma_{AC}^{FB} = (h(v - \tilde{c}))/((1-2h)\,\tilde{c} + hv) \; \wedge h \in [\tilde{c}/v, 1]\}$ efficiency requires to choose Strategy C.

Figure 1. *First-best provision strategy*



Note: The blue curve is the hyperbola defined in equation (1) in the paper, and the red curve is the hyperbola defined in equation (2) in the paper. In Area A, efficiency requires to implement Strategy A (blindly providing HQS without considering the diagnosis outcome); in Area B, efficiency requires to implement Strategy B (blindly providing LQS without considering the diagnosis outcome); and in Area C, efficiency requires to implement Strategy C (following the signal).

Appendix B. Proof of Proposition 2: profit-maximizing provision strategy in the absence of insurance (NI)

Similarly to proposition 1, the expert has the choice between the three pure strategies outlined in the paper. The fourth pure strategy – Strategy D, where the expert provides a treatment opposite to the signal she receives – is dominated by one of the other three strategies for any given constellation of the parameters $\{\tilde{p}, \tilde{c}, h, v, t\}$. We show this by first ignoring Strategy D and deriving the provision areas for the case where only strategies A, B and C are available. Later we show that in the area where Strategy $X \in \{A, B, C\}$ is preferred to the other two strategies, Strategy X is also preferred to Strategy D.

To characterize the expert's provision policy for the case where only strategies A, B and C are available, we compare the payoffs for the expert associated with each of the three strategies. By equating the payoffs associated with strategies A and C (as specified in the paper) we get the boundary condition $\sigma_{AC}^{NI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{h\left((1-\lambda)\tilde{p}-\tilde{c}\right)+h\lambda(v-t)+ht}{(1-2h)(\tilde{c}-(1-\lambda)\tilde{p})+h\lambda(v-t)+ht}$ or $\lambda_{AC}^{NI} = f(\sigma, h, \tilde{p}, \tilde{c}, v, t) = \frac{(h+\sigma-2h\sigma)(\tilde{p}-\tilde{c})+h(1-\sigma)t}{(h+\sigma-2h\sigma)\tilde{p}-h(1-\sigma)(v-t)}$. By equating the payoffs associated with strategies B and C (as specified in the paper) we get the boundary condition $\sigma_{BC}^{NI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{(1-h)(\tilde{c}-(1-\lambda)\tilde{p})}{(1-2h)(\tilde{c}-(1-\lambda)\tilde{p})+h\lambda(v-t)+ht}$ or $\lambda_{BC}^{NI} = f(\sigma, h, \tilde{p}, \tilde{c}, v, t) = \frac{(1-h-\sigma+2h\sigma)(\tilde{p}-\tilde{c})+h\sigma t}{(1-h-\sigma+2h\sigma)\tilde{p}-h\sigma\,(v-t)}$.

Functions σ_{AC}^{NI} and σ_{BC}^{NI} are hyperbolas. To define the areas in the (λ, σ) space in which each of the three strategies is optimal for the expert, we first derive the vertices of the two hyperbolas. The vertex of hyperbola σ_{AC}^{NI} is $V\lambda_{AC}^{NI} = \frac{h(1-h)(v(\tilde{p}-\tilde{c})+\tilde{c}t)}{\left((2h-1)\tilde{p}-h\llbracket(v-t)\right)\rrbracket^2}$, while the vertex of hyperbola σ_{BC}^{NI} is $V\lambda_{BC}^{NI} = \frac{-h(1-h)(v(\tilde{p}-\tilde{c})+\tilde{c}t)}{\left((2h-1)\tilde{p}-h\llbracket(v-t)\right)\rrbracket^2}$.

From these expressions, it is easy to see that the two hyperbolas are geometrically similar and mirroring each other. Furthermore, the respective hyperbola does not exist when the associated vertex is 0. The latter is true iff $\tilde{p} = \frac{\tilde{c}(v-t)}{v}$. Consequently, when $\tilde{p} = \frac{\tilde{c}(v-t)}{v}$, the vertex $V\lambda_{AC}^{NI}$ changes from positive to negative (i.e., the curve changes from concave to convex), while the vertex $V\lambda_{BC}^{NI}$ changes vice versa (i.e., the curve changes from convex to concave).

Next, let us derive the boundary values of functions $\lambda_{AC}^{NI}, \sigma_{AC}^{NI}, \lambda_{BC}^{NI}$ and σ_{BC}^{NI}.

- $\lambda_{BC}^{NI}(\sigma = 1) = \lambda_1^{NI} = \frac{\tilde{c}-t-\tilde{p}}{v-t-\tilde{p}}$ is the λ-value of the function λ_{BC}^{NI} when $\sigma = 1$.
- $\lambda_{BC}^{NI}(\sigma = 0.5) = \lambda_{AC}^{NI}(\sigma = 0.5) = \lambda_2^{NI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)-\tilde{p}}$ is the λ-value of the function λ_{BC}^{NI} or function λ_{AC}^{NI} when $\sigma = 0.5$.
- $\lambda_{AC}^{NI}(\sigma = 1) = \lambda_3^{NI} = 1 - \frac{\tilde{c}}{\tilde{p}}$ is the λ-value of the function λ_{AC}^{NI} when $\sigma = 1$.
- $\sigma_{AC}^{NI}(\lambda = 1) = \sigma_1^{NI} = \frac{1}{2} + \frac{h(v-\tilde{c})-(1-h)\tilde{c}}{2[h(v-\tilde{c})+(1-h)\tilde{c}]}$ is the σ-value of the function σ_{AC}^{NI} when $\lambda = 1$.
- $\sigma_{BC}^{NI}(\lambda = 0) = \sigma_2^{NI} = \frac{1}{2} + \frac{(1-h)(\tilde{c}-\tilde{p})-h(\tilde{p}-\tilde{c}+t)}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$ is the σ-value of the function σ_{BC}^{NI} when $\lambda = 0$.
- $\sigma_{AC}^{NI}(\lambda = 0) = \sigma_3^{EXO-NI} = \frac{1}{2} + \frac{h(\tilde{p}-\tilde{c}+t)-(1-h)(\tilde{c}-\tilde{p})}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$ is the σ-value of the function σ_{AC}^{NI} when $\lambda =$ 0.
- $\sigma_{BC}^{NI}(\lambda = 1) = \sigma_4^{NI} = \frac{1}{2} + \frac{(1-h)\tilde{c}-h(v-\tilde{c})}{2[h(v-\tilde{c})+(1-h)\tilde{c}]}$ is the σ-value of the function σ_{BC}^{NI} when $\lambda = 1$.

Next, let us analyze one-by-one the locations of those boundary values on the λ-axis and the σ-axis.

1. $\lambda_1^{NI} = \frac{\tilde{c}-t-\tilde{p}}{v-t-\tilde{p}}$:
   i. $\lambda_1^{NI} < 0$ iff $\tilde{c} - t < \tilde{p} < v - t$.
   ii. $\lambda_1^{NI} \in [0,1]$ iff $\tilde{p} < \tilde{c} - t$.
   iii. $\lambda_1^{NI} > 1$ iff $\tilde{p} > v - t$.
2. $\lambda_2^{NI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)-\tilde{p}}$:
   i. $\lambda_2^{NI} < 0$ iff $\tilde{c} - ht < \tilde{p} < hv$.
   ii. $\lambda_2^{NI} \in [0,1]$ iff $\tilde{p} < \tilde{c} - ht$.
   iii. $\lambda_2^{NI} > 1$ iff $\tilde{p} > hv$.
3. $\lambda_3^{NI} = 1 - \frac{\tilde{c}}{\tilde{p}}$:
   i. $\lambda_3^{NI} < 0$ iff $\tilde{p} < \tilde{c}$.
   ii. $\lambda_3^{NI} \in [0,1]$ if $\tilde{c} \leq \tilde{p} \leq \tilde{p} + \tilde{c}$.
   iii. $\lambda_3^{NI} > 1$ iff $\tilde{p} > \tilde{p} + \tilde{c}$.
4. $\sigma_1^{NI} = \frac{1}{2} + \frac{h(v-\tilde{c})-(1-h)\tilde{c}}{2[h(v-\tilde{c})+(1-h)\tilde{c}]}$: given our assumption $\tilde{c} < hv$ we immediately get $\sigma_1^{NI} \in [0.5,1]$.
5. $\sigma_2^{NI} = \frac{1}{2} + \frac{(1-h)(\tilde{c}-\tilde{p})-h(\tilde{p}-\tilde{c}+t)}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$:
   i. $\sigma_2^{NI} < 0.5$ if $\tilde{c} - ht < \tilde{p} \leq \tilde{c}$.
   ii. $\sigma_2^{NI} \in [0.5,1]$ iff $\tilde{c} - t < \tilde{p} < \tilde{c} - ht$.
   iii. $\sigma_2^{NI} > 1$ if $\tilde{p} > \tilde{c}$.
6. $\sigma_3^{NI} = \frac{1}{2} + \frac{h(\tilde{p}-\tilde{c}+t)-(1-h)(\tilde{c}-\tilde{p})}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$:
   i. $\sigma_3^{NI} < 0.5$ if $\tilde{c} - t < \tilde{p} < \tilde{c} - ht$.
   ii. $\sigma_3^{NI} \in [0.5,1]$ iff $\tilde{c} - ht < \tilde{p} < \tilde{c}$.
   iii. $\sigma_3^{NI} > 1$ $\tilde{p} \geq \tilde{c}$.
7. $\sigma_4^{NI} = \frac{1}{2} + \frac{(1-h)\tilde{c}-h(v-\tilde{c})}{2[h(v-\tilde{c})+(1-h)\tilde{c}]}$: given our assumption $\tilde{c} < hv$ we immediately get $\sigma_4^{NI} < 0.5$.

Let us now consider each panel of Figure 2 in detail, accounting for the underlying condition $\tilde{c} < hv$, as well as for the additional condition $\tilde{c} > t$. We derive typical locations of the curves λ_{AC}^{NI} and λ_{BC}^{NI} when $\tilde{p}$ falls in the specific interval, as well as upper and lower boundaries of the respective functions.

a. ***Panel (a)*** corresponds to the case where $0 < \tilde{p} < \tilde{c} - t$. Following the geometrical properties of hyperbolas λ_{AC}^{NI} and λ_{BC}^{NI}, function λ_{AC}^{NI} is concave and function λ_{BC}^{NI} is convex, since $\tilde{p} < \frac{\tilde{c}(v-t)}{v}$. Both functions intersect at λ_2^{NI}. The price difference restriction immediately yields $\lambda_1^{NI} \in [0,1]$; since $\tilde{p} < \tilde{c} - t < \tilde{c} - ht$, $\lambda_2^{NI} \in [0,1]$; furthermore, $\sigma_1^{NI} \in [0.5,1]$ and $\sigma_4^{NI} < 0.5$. The upper and lower boundaries of the λ_{AC}^{NI} and λ_{BC}^{NI} functions are determined by the location of the intercepts λ_1^{NI}, λ_2^{NI} and σ_1^{NI} at the upper and the lower limit of $\tilde{p}$, thus at $\tilde{p} = 0$ and at $\tilde{p} = \tilde{c} - t$: σ_1^{NI} is independent of $\tilde{p}$, therefore, it remains constant at any $\tilde{p}$; $\lambda_1^{NI}(\tilde{p} = 0) = \frac{\tilde{c}-t}{v-t}$ and $\lambda_1^{NI}(\tilde{p} = \tilde{c} - t) = 0$; $\lambda_2^{NI}(\tilde{p} = 0) = \frac{\tilde{c}-ht}{h(v-t)}$ and $\lambda_2^{NI}(\tilde{p} = \tilde{c} - t) = \frac{(1-h)t}{h(v-t)-\tilde{c}+t}$, therefore $\lambda_2^{NI}(\tilde{p} = 0) > \lambda_2^{NI}(\tilde{p} = \tilde{c} - t)$ always under the assumption $t < \tilde{c} < hv$ and both λ_1^{NI} and λ_2^{NI} decrease as $\tilde{p}$ increases from 0 to $\tilde{c} - t$.

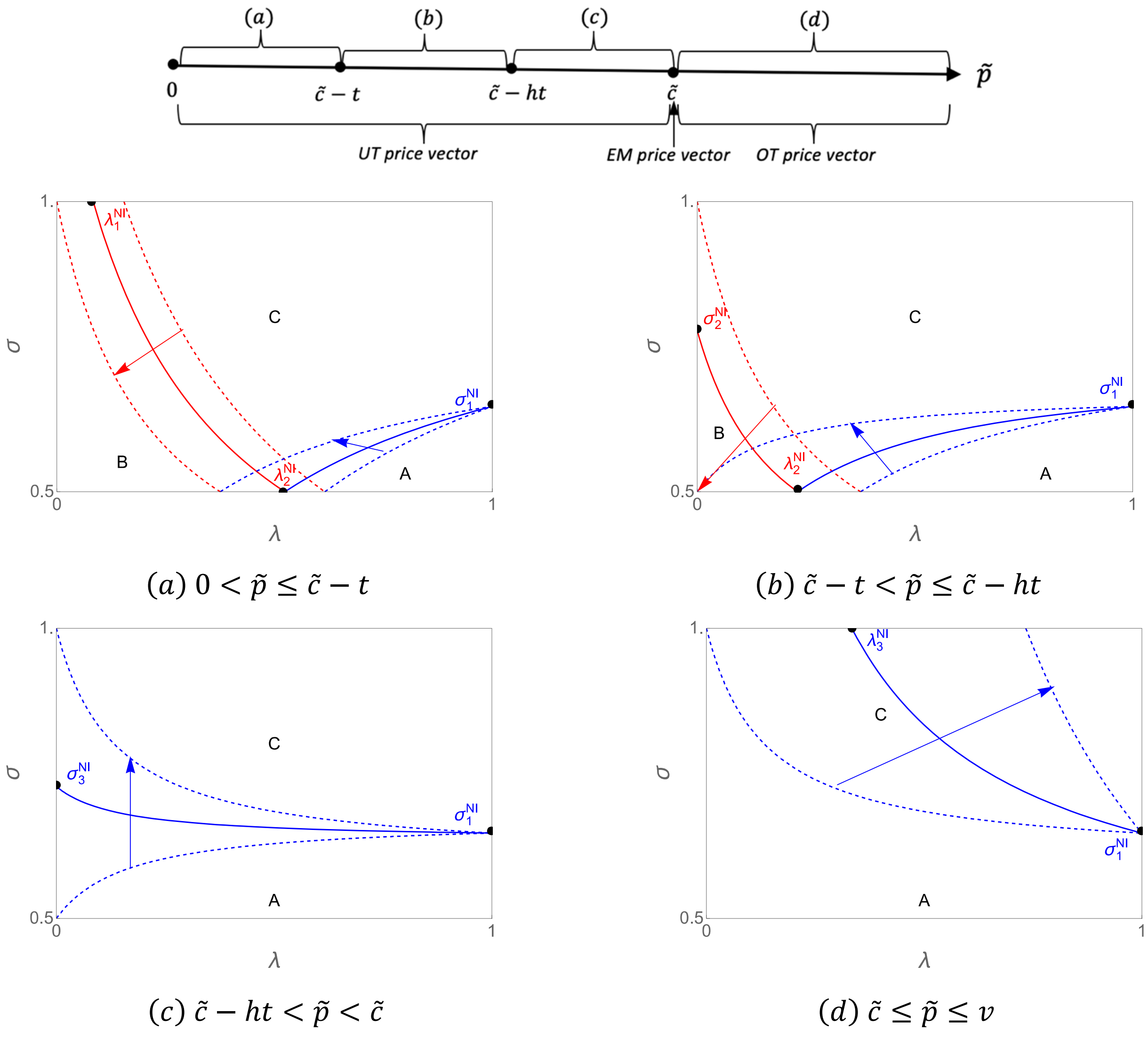
b. ***Panel (b)*** corresponds to the case where $\tilde{c} - t < \tilde{p} < \tilde{c} - ht$. As in panel (a), function λ_{AC}^{NI} is concave and function λ_{BC}^{NI} is convex. Since $\tilde{p} < \tilde{c} - ht$, $\lambda_2^{NI} \in [0,1]$; furthermore, $\sigma_1^{NI} \in [0.5,1]$ and $\sigma_4^{NI} < 0.5$. Given the price difference restriction $\tilde{p} > \tilde{c} - t$, $\lambda_1^{NI} < 0$ and $\sigma_2^{NI} \in [0.5,1]$. Hence, the major difference between panel (b) and panel (a) is caused by a change in the curvature of the function λ_{BC}^{NI} as a result of the increase in $\tilde{p}$. Consequently, the intercept λ_1^{NI} moves outside of the range $\lambda \in [0,1]$ and the curve intersects the σ-axis in σ_2^{NI}. The upper and lower limit of the two functions are as follows: σ_2^{NI} $(\tilde{p} = \tilde{c} - t) = 1, \sigma_2^{NI}$ $(\tilde{p} = \tilde{c} - ht) = 0.5$; $\lambda_2^{NI}(\tilde{p} = \tilde{c} - t) = \frac{(1-h)t}{h(v-t)-\tilde{c}+t}$ and $\lambda_2^{NI}(\tilde{p} = \tilde{c} - ht) = 0$. Therefore, both σ_2^{NI} and λ_2^{NI} decrease as $\tilde{p}$ moves from the lower limit to the upper limit. As in the previous sub-case σ_1^{NI} remains constant.

c. ***Panel (c)*** corresponds to the case where $\tilde{c} - ht < \tilde{p} < \tilde{c}$. In this range of $\tilde{p}$, the shape of functions λ_{AC}^{NI} and λ_{BC}^{NI} changes at $\tilde{p} = \frac{\tilde{c}(v-t)}{v}$. As long as $\tilde{p} < \frac{\tilde{c}(v-t)}{v}$, λ_{AC}^{NI} is concave and λ_{BC}^{NI} is convex. At $\tilde{p} = \frac{\tilde{c}(v-t)}{v}$, both functions are straight lines. At $\tilde{p} > \frac{\tilde{c}(v-t)}{v}$, λ_{BC}^{NI} is concave and λ_{AC}^{NI} is convex. However, since $\tilde{p} > \tilde{c} - ht$, $\lambda_2^{NI} < 0$ and the λ_{BC}^{NI} curve does not appear in the $\lambda \in [0,1]$ interval. Since $\tilde{c} - ht < \tilde{p} < \tilde{c}$, $\sigma_3^{NI} \in [0.5,1]$; $\sigma_1^{NI} \in [0.5,1]$ always. When $\tilde{p}$ is at its lower limit, $\sigma_3^{NI}(\tilde{p} = \tilde{c} - ht) = 0.5$. When $\tilde{p}$ is at its upper limit, $\sigma_3^{NI}(\tilde{p} = \tilde{c}) = 1$. Therefore, σ_3^{NI} increases as $\tilde{p}$ increases from the lower to the upper limit, while σ_1^{NI} remains constant.

d. ***Panel (d)*** corresponds to the case where $\tilde{p} > \tilde{c}$. In this range of $\tilde{p}$, λ_{AC}^{NI} remains convex and λ_{BC}^{NI} remains concave. However, since $\lambda_2^{NI} < 0$ for $\tilde{p} > \tilde{c}$, the λ_{BC}^{NI} curve remains outside the $\lambda \in [0,1]$ range. Since $\tilde{p} > \tilde{c}, \lambda_1^{NI} \in [0,1]$; $\sigma_1^{NI} \in [0.5,1]$ always. At the lower limit of $\tilde{p}$ $(\tilde{p} = \tilde{c})$, $\lambda_3^{NI}(\tilde{p} = \tilde{c}) = 0$, and λ_3^{NI} increases as $\tilde{p}$ increases. As in the previous sub-case σ_1^{NI} remains constant.

We complete the proof by showing that Strategy D, where the expert provides a treatment opposite to the signal she receives, is dominated by one of the other three strategies for any given parameter constellation. Strategy D is associated with the following utility for the expert: $\Pi_D = (h + \sigma - 2h\sigma)\overline{\Delta} + (1 - h - \sigma + 2h\sigma)\underline{\Delta} - h\sigma t + \lambda\left[(1 - h\sigma)v - \underline{p}(1 - h - \sigma + 2h\sigma) - \overline{p}(h + \sigma - 2h\sigma) + h\sigma t\right]$. First consider panel (a) of Figure 2. In this panel Strategy A is strictly preferred over the other two strategies for constellations satisfying $\lambda > \lambda_2^{NI}$ and $\sigma < \sigma_{AC}^{NI}$. We now show that for all $\lambda > \lambda_2^{NI}$ we have $\Pi_A > \Pi_D$. To see this note that $\Pi_A - \Pi_D = (1 - h - \sigma + 2h\sigma)(\tilde{p} - \tilde{c}) + (1 - \lambda)\tilde{p} + \lambda h\sigma(v - t) + h\sigma t$, which is zero at ($\lambda = \lambda_2^{NI}$ and $\sigma = 0.5$) and strictly increasing in λ and σ. Next note that Strategy B is strictly preferred over the other two strategies for constellations satisfying $\lambda < \lambda_2^{NI}$ and $\sigma < \sigma_{BC}^{NI}$. For $\lambda < \lambda_2^{NI}$ we have $\Pi_B > \Pi_D$ since $\Pi_B - \Pi_D = (h + \sigma - 2h\sigma)(\tilde{c} - \tilde{p}) + \lambda(\sigma - 2h\sigma - h)\tilde{p} + h(1 - \sigma)(\lambda(t - v) - t)$ is zero at ($\lambda = \lambda_2^{NI}$ and $\sigma = 0.5$) and strictly decreasing in λ and strictly increasing in σ. Finally note that $\Pi_C - \Pi_D = (1 - \sigma)\big((\tilde{p} - \tilde{c})(1 - 2h) - \lambda(1 - 2h)\tilde{p} - \lambda h(v - t) - ht\big)$ is zero at ($\lambda = \lambda_2^{NI}$ and $\sigma = 0.5$) and strictly increasing in λ and σ. Thus, in panel (a) of Figure 2 Strategy D is dominated by at least one of the other three strategies for any parameter constellation. The proof for panels (b), (c) and (d) is similar and available upon request.

Figure 2. *Profit-maximizing provision behavior with no insurance (NI)*



Note: The blue curve is each panel is the hyperbola defined in equation (3) in the paper, and the red curve in panels (a) and (b) is the hyperbola defined in equation (4) in the paper. The intercept points $\lambda_1^{NI}, \lambda_2^{NI}, \lambda_3^{NI}$ and $\sigma_1^{NI}, \sigma_2^{NI}, \sigma_3^{NI}$ are defined as: $\lambda_1^{NI} = \frac{\tilde{c}-t-\tilde{p}}{v-t-\tilde{p}}$; $\lambda_2^{NI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)-\tilde{p}}$; $\lambda_3^{NI} = 1 - \frac{\tilde{c}}{\tilde{p}}$; $\sigma_1^{NI} = \frac{1}{2} + \frac{h(v-\tilde{c})-(1-h)\tilde{c}}{2[h(v-\tilde{c})+(1-h)\tilde{c}]}$; $\sigma_2^{NI} = \frac{1}{2} + \frac{(1-h)(\tilde{c}-\tilde{p})-h(\tilde{p}-\tilde{c}+t)}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$; $\sigma_3^{NI} = \frac{1}{2} + \frac{h(\tilde{p}-\tilde{c}+t)-(1-h)(\tilde{c}-\tilde{p})}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$.

Appendix C. Proof of Proposition 3: profit-maximizing provision strategy in the presence of full insurance (FI)

To analyze expert's provision behavior in the presence of full insurance, we proceed in a similar way as in Appendix B (NI case). That is, we first ignore Strategy D and derive the provision areas for the case where only strategies A, B and C are available. Later we show that in area X ∈ {A, B, C}, Strategy X strictly dominates Strategy D.[10]

The boundary between strategies A and C (as specified in equation (5) in the paper) is now defined by $\sigma_{AC}^{FI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{h(\tilde{c}-\tilde{p})-h\lambda(v-t)-ht}{(1-2h)(\tilde{p}-\tilde{c})-h\lambda(v-t)-ht}$ or $\lambda_{AC}^{FI} = f(\sigma, h, \tilde{p}, \tilde{c}, v, t) = \frac{(h+\sigma-2h\sigma)(\tilde{p}-\tilde{c})+h(1-\sigma)t}{h(1-\sigma)(t-v)}$. The boundary between strategies B and C (as specified in equation (6) in the paper) is defined by $\sigma_{BC}^{FI} = f(\lambda, h, \tilde{p}, \tilde{c}, v, t) = \frac{(1-h)(\tilde{p}-\tilde{c})}{(1-2h)(\tilde{p}-\tilde{c})-h\lambda(v-t)-ht}$ or $\lambda_{BC}^{FI} = f(\sigma, h, \tilde{p}, \tilde{c}, v, t) = \frac{(1-h-\sigma+2h\sigma)(\tilde{p}-\tilde{c})+h\sigma t}{h\sigma\,(t-v)}$.

Next, we derive the vertices of the hyperbolas σ_{AC}^{NI} and σ_{BC}^{NI} to define the areas in the (λ, σ) space in which each of the three strategies is optimal for the expert. The vertex of hyperbola σ_{AC}^{FI} is $V\lambda_{AC}^{FI} = \frac{(1-h)(\tilde{p}-\tilde{c})}{h(v-t)}$, while the vertex of hyperbola σ_{BC}^{FI} is $V\lambda_{BC}^{FI} = \frac{-(1-h)(\tilde{p}-\tilde{c})}{h(v-t)}$.

As in the NI case, the two hyperbolas are geometrically similar and mirroring each other. Furthermore, the respective hyperbola does not exist when the associated vertex is 0. The latter is true iff $\tilde{p} = \tilde{c}$. Consequently, when $\tilde{p} = \tilde{c}$, the vertex $V\lambda_{AC}^{FI}$ changes from positive to negative (i.e. the curve changes from concave to convex), while the vertex $V\lambda_{BC}^{FI}$ changes vice versa (i.e. the curve changes from convex to concave).

Next, let us derive the boundary values of the functions $\lambda_{AC}^{FI}, \sigma_{AC}^{FI}, \lambda_{BC}^{FI}$ and σ_{BC}^{FI}.

- $\lambda_{BC}^{FI}(\sigma = 1) = \lambda_1^{FI} = \frac{\tilde{c}-t-\tilde{p}}{v-t}$ is the λ-value of the function λ_{BC}^{FI} when $\sigma = 1$.
- $\lambda_{BC}^{FI}(\sigma = 0.5) = \lambda_{AC}^{FI}(\sigma = 0.5) = \lambda_2^{FI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)}$ is the λ-value of the function λ_{BC}^{FI} or function λ_{AC}^{FI} when $\sigma = 0.5$.
- $\lambda_{AC}^{FI}(\sigma = 1) = \infty$ is the λ-value of the function λ_{AC}^{FI} when $\sigma = 1$.
- $\sigma_{AC}^{FI}(\lambda = 1) = \sigma_1^{FI} = \frac{1}{2} + \frac{h(\tilde{c}-\tilde{p}-v)-(1-h)(\tilde{p}-\tilde{c})}{2[(1-h)(\tilde{p}-\tilde{c})+h(\tilde{c}-\tilde{p}-v)]}$ is the σ-value of the function σ_{AC}^{FI} when $\lambda = 1$.
- $\sigma_{BC}^{FI}(\lambda = 0) = \sigma_2^{FI} = \sigma_2^{NI} = \frac{1}{2} + \frac{(1-h)(\tilde{c}-\tilde{p})-h(\tilde{p}-\tilde{c}+t)}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$ is the σ-value of the function σ_{BC}^{FI} when $\lambda = 0$.
- $\sigma_{AC}^{FI}(\lambda = 0) = \sigma_3^{FI} = \sigma_3^{NI} = \frac{1}{2} + \frac{h(\tilde{p}-\tilde{c}+t)-(1-h)(\tilde{c}-\tilde{p})}{2[h(\tilde{p}-\tilde{c}+t)+(1-h)(\tilde{c}-\tilde{p})]}$ is the σ-value of the function σ_{AC}^{FI} when $\lambda = 0$.
- $\sigma_{BC}^{FI}(\lambda = 1) = \sigma_4^{FI} = \frac{1}{2} + \frac{(1-h)(\tilde{p}-\tilde{c})-h(\tilde{c}-\tilde{p}-v)}{2[(1-h)(\tilde{p}-\tilde{c})+h(\tilde{c}-\tilde{p}-v)]}$ is the σ-value of the function σ_{BC}^{FI} when $\lambda = 1$.

Next, let us analyze one-by-one the locations of the just derived boundary values on the λ-axis and the σ-axis.

1. $\lambda_1^{FI} = \frac{\tilde{c}-t-\tilde{p}}{v-t}$:
   i. $\lambda_1^{FI} < 0$ iff $\tilde{p} > \tilde{c} - t$.
   ii. $\lambda_1^{FI} \in [0,1]$ iff $\tilde{p} < \tilde{c} - t$.

[10] This latter proof is similar to that in Appendix B and is available from the authors upon request.

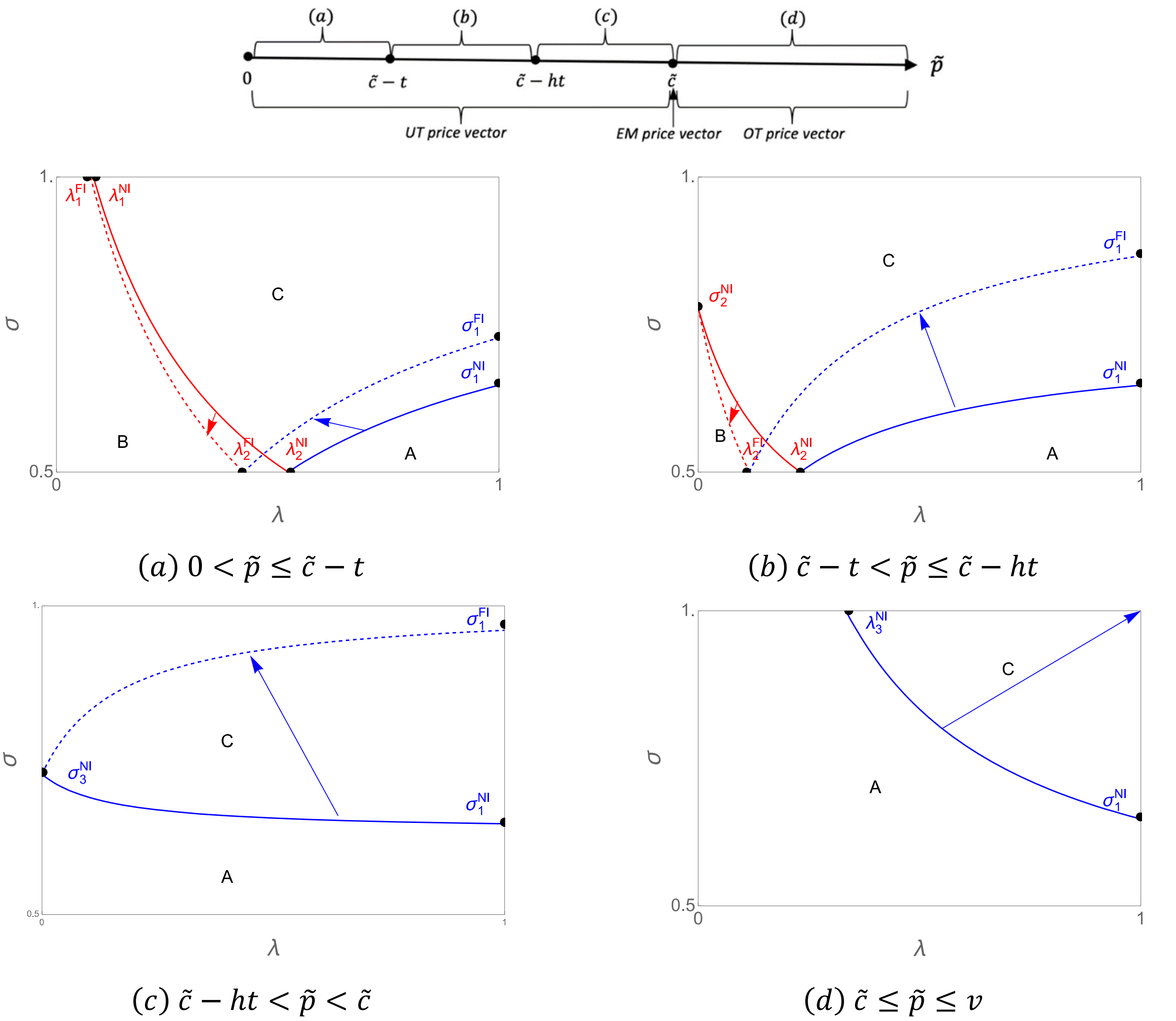
iii. $\lambda_1^{FI} > 1$ never as long as $\tilde{c} < v$.

2. $\lambda_2^{FI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)}$:
   i. $\lambda_2^{FI} < 0$ iff $\tilde{p} > \tilde{c} - ht$.
   ii. $\lambda_2^{FI} \in [0,1]$ iff $\tilde{p} < \tilde{c} - ht$.
   iii. $\lambda_2^{FI} > 1$ never as long as $\tilde{c} < hv$.
3. $\sigma_1^{FI} = \frac{1}{2} + \frac{h(\tilde{c}-\tilde{p}-v)-(1-h)(\tilde{p}-\tilde{c})}{2[(1-h)(\tilde{p}-\tilde{c})+h(\tilde{c}-\tilde{p}-v)]}$:
   i. $\sigma_1^{FI} < 0.5$ never, given our assumption $\tilde{c} < hv$.
   ii. $\sigma_1^{FI} \in [0.5,1]$ iff $\tilde{p} < \tilde{c}$.
   iii. $\sigma_1^{FI} > 1$ iff $\tilde{p} \geq \tilde{c}$.
4. σ_2^{FI} is identical to σ_2^{NI} and conditions are defined in Appendix B.
5. σ_3^{FI} is identical to σ_3^{NI} and conditions are defined in Appendix B.
6. $\sigma_4^{FI} = \frac{1}{2} + \frac{(1-h)(\tilde{p}-\tilde{c})-h(\tilde{c}-\tilde{p}-v)}{2[(1-h)(\tilde{p}-\tilde{c})+h(\tilde{c}-\tilde{p}-v)]}$: given our assumption $\tilde{c} < v$ we immediately get $\sigma_4^{FI} > 1$.

Next, let us consider each sub-case of Figure 3, accounting for the underlying condition $\tilde{c} < hv$, as well as for the additional condition $\tilde{c} > t$. We derive typical locations of the curves λ_{AC}^{FI} and λ_{BC}^{FI} when $\tilde{p}$ falls in the specific interval and compare these with the λ_{AC}^{NI} and the λ_{BC}^{NI} curve.

a. ***Panel (a)*** corresponds to the case where $0 < \tilde{p} < \tilde{c} - t$. In this case λ_{AC}^{FI} is concave and λ_{BC}^{FI} is convex, since $\tilde{p} < \tilde{c}$. Both function intersect at λ_2^{FI}. The price difference restriction immediately yields that $\lambda_1^{FI} \in [0,1]$ and $\lambda_2^{FI} \in [0,1]$ since $\tilde{p} < \tilde{c} - t < \tilde{c} - ht$; $\sigma_1^{FI} \in [0.5,1]$. Compared to the NI case, Area C shifts to the left with $\lambda_1^{FI} < \lambda_1^{NI}$, $\lambda_2^{FI} < \lambda_2^{NI}$, and $\sigma_1^{FI} > \sigma_1^{NI}$. The dynamics of the intercept points $\lambda_1^{FI}, \lambda_2^{FI}, \sigma_1^{FI}$ as $\tilde{p}$ increases from 0 to $\tilde{c} - t$ is similar to the respective intercepts of the NI case, namely λ_1^{FI} and λ_2^{FI} decrease and σ_1^{FI} increases as $\tilde{p}$ increases.
b. ***Panel (b)*** corresponds to the case where $\tilde{c} - t < \tilde{p} < \tilde{c} - ht$. Under this price difference restriction λ_{AC}^{FI} remains concave and λ_{BC}^{FI} is convex, since $\tilde{p} < \tilde{c}$. Since $\tilde{p} < \tilde{c} - ht, \lambda_2^{NI} \in [0,1]$ and $\sigma_1^{NI} \in [0.5,1]$. Given the price difference restriction $\tilde{p} > \tilde{c} - t$, $\lambda_1^{FI} < 0$ and $\sigma_2^{FI} \in [0.5,1]$. Compared to the location of the NI functions, $\lambda_2^{FI} < \lambda_2^{NI}$ and $\sigma_1^{FI} > \sigma_1^{NI}$, while $\sigma_2^{FI} = \sigma_2^{NI}$. As $\tilde{p}$ moves from the lower limit to the upper limit, λ_2^{FI} decreases, σ_1^{FI} increases and σ_2^{FI} decreases.
c. ***Panel (c)*** corresponds to the case where $\tilde{c} - ht < \tilde{p} < \tilde{c}$. In this range of $\tilde{p}$, λ_{AC}^{FI} remains concave and λ_{BC}^{FI} remains convex, since $\tilde{p} < \tilde{c}$. Since $\tilde{p} > \tilde{c} - ht, \lambda_2^{FI} < 0$ and the λ_{BC}^{FI} curve does not appear in the $(\lambda \in [0,1], \sigma \in [0.5,1])$ range, same as λ_{BC}^{NI}. Since $\tilde{c} - ht < \tilde{p} < \tilde{c}$, $\sigma_1^{FI} \in [0.5,1]$; $\sigma_3^{FI} \in [0.5,1]$ always. As compared to the NI case, Area C shrinks upward, since $\sigma_1^{FI} > \sigma_1^{NI}$ and $\sigma_3^{FI} = \sigma_3^{NI}$. As a consequence, the range of $\{\lambda, \sigma\}$ parameter constellations under which Strategy C is optimal is much smaller in FI, as compared to NI.
d. ***Panel (d)*** corresponds to the case where $\tilde{p} \geq \tilde{c}$. In this range of $\tilde{p}$, λ_{AC}^{FI} turns convex and λ_{BC}^{FI} turns concave. Since $\tilde{p} \geq \tilde{c}$, $\sigma_1^{FI} > 1$ and $\sigma_3^{FI} > 1$, which brings the λ_{AC}^{FI} curve outside the $(\lambda \in [0,1], \sigma \in [0.5,1])$ range, while λ_{AC}^{NI} remains in the range of interest. As a result, when $\tilde{p} \geq \tilde{c}$ there exists no $\{\lambda, \sigma\}$ parameter constellation under which Strategy C is optimal when there is full insurance.

Figure 3. *Profit-maximizing provision behavior with no insurance (NI) and full insurance (FI)*



Note: This figure shows the effect of introducing insurance. The solid red and the solid blue line, as well as the areas A, B and C, are as defined in Proposition 2 and they characterize the optimal provision areas in the NI case. The dashed red and the dashed blue line are the hyperbolas defined in equations (5) and (6) and they define the optimal provision areas in the FI case. The intercept points $\lambda_1^{NI}, \lambda_2^{NI}, \lambda_3^{NI}$ and $\sigma_1^{NI}, \sigma_2^{NI}, \sigma_3^{NI}$ are as defined in the note to Figure 2. The intercept points $\lambda_1^{FI}, \lambda_2^{FI}$ and σ_1^{FI} are defined as: $\lambda_1^{FI} = \frac{\tilde{c}-t-\tilde{p}}{v-t}$; $\lambda_2^{FI} = \frac{\tilde{c}-ht-\tilde{p}}{h(v-t)}$; ; $\sigma_1^{FI} = \frac{1}{2} + \frac{h(v-\tilde{c}+\tilde{p})-(1-h)(\tilde{c}-\tilde{p})}{2[h(v-\tilde{c}+\tilde{p})+(1-h)(\tilde{c}-\tilde{p})]}$.