Technology improvements in monitoring – do policyholders benefit?

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Abstract

New technologies like wearable devices and telematics improve insurers' ability to monitor policyholders' prevention behavior. In this paper, we analyze whether policyholders benefit from technologies that enhance monitoring accuracy. Under imperfect monitoring, a mixed-strategy equilibrium arises under which policyholders randomize over the use of prevention. An equilibrium where policyholders always engage in prevention is not feasible. Policyholders only benefit from improved monitoring accuracy if such an improvement raises the probability of engaging in prevention. We provide a criterion for this to be the case. Hence, monitoring policyholders more accurately may reduce social welfare even in the absence of privacy costs. If insurers give advice which reduces the cost of prevention, the effects on the policyholders' prevention efforts and welfare are also ambiguous. Our results may thus help explain why demand for insurance contracts with sophisticated monitoring technologies is still low to date.

Keywords: insurance · moral hazard · monitoring · risk classification · Internet of Things

JEL-Classification: D8 · G22 · G52 · I12 · O33

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1 Introduction

To tackle moral hazard in insurance markets, insurers may cover losses only partially or observe the effort taken by the policyholders to prevent losses. In his seminal paper, Shavell (1979) shows that partial coverage is generally desirable if the insurer has no or only imperfect information about the policyholder's prevention efforts. If only the occurrence but not the size of loss depends on the policyholder's effort, a deductible is the optimal policy (Holmström, 1979). In many real-world markets, however, policyholders show a clear preference for low or zero deductibles (Sydnor, 2010). When deductibles are low or even zero, their incentive effect on prevention is small and insurers may resort to monitoring the policyholders' prevention effort directly.

The technological progress over the past years has significantly extended insurers' possibilities to monitor prevention efforts. The Internet of Things (IoT) allows to collect large amounts of behavioral data for risk assessment. In car insurance, telematics sensors can monitor the policyholder's driving style. In health and life insurance, wearable devices can collect information about physical activity. In addition, insurers can give advice on prevention issues to reduce the cost of prevention. For example, insurers can use a health app not only to track the policyholders' activity but also to recommend fitness classes in their neighborhood making health prevention more pleasant and thus less costly. New technologies hence might have the potential to improve risk assessment and to promote the prevention of risks (The Geneva Association, 2021). However, insurers have to apply complex algorithms to evaluate the monitoring data. In particular, the use of machine learning and artificial intelligence may turn the insurers' risk assessment into a black box. Typically, insurers do not even evaluate the monitoring data themselves but only receive aggregated data from a service provider (Eling and Kraft, 2020) which may amplify the lack of transparency. Moreover, terms and conditions on how observed prevention efforts enter premium calculations are often imprecise and intransparent.[1] If insurers and policyholders do not know the mechanism underlying the monitoring technology, the use of new technologies can increase the monitoring accuracy but monitoring remains imperfect.

In this paper, we analyze whether policyholders benefit from technologies that enhance monitoring accuracy. We consider a setting in which policyholders may exert prevention efforts and insurers use a monitoring technology which provides a binary signal about whether a policyholder exerted effort or not. In a competitive market, insurers offer full insurance contracts with a premium depending on the signal of the monitoring technology. Both insurers and policyholders do not know the mechanism underlying the monitoring technology. They

[1] For example, a clause according to which health-conscious behavior of the policyholder is relevant to the premium has been declared invalid in a recent court ruling in Germany because it did not specify further criteria for health-conscious behavior (LG München I, 2021).

only know that exerting effort increases the likelihood to obtain one of the two signals whereas not exerting effort increases the likelihood of the other signal.

In this setting, a mixed-strategy equilibrium arises under which policyholders randomize over the use of prevention. An equilibrium where policyholders always engage in prevention is not feasible. In contrast, perfect monitoring can incentivize the policyholders to always engage in prevention. Improving the monitoring technology to get closer to perfect monitoring, however, has ambiguous effects. We provide a criterion to determine whether policyholders engage in prevention more or less often as the monitoring technology gets more accurate. More accurate monitoring only has a positive welfare effect if the policyholders engage in prevention more often as the technology improves. A sufficient condition for a positive effect is that the signal suggesting that the policyholder exerted effort makes the insurer at least as confident about the policyholder's behavior as the signal suggesting that the policyholder did not exert effort does. If insurers give advice on prevention issues, the effects of cost reductions are also ambiguous. The criterion to determine whether policyholders engage in prevention more or less often as the cost of prevention decreases is the same as the one to determine the effect of technology improvements. Reducing the cost of prevention also only has a positive welfare effect if it induces the policyholders to engage in prevention more often.

At first glance, premium discounts for risk-reducing behavior are a promising avenue to promote healthy habits or considerate driving. However, we find that policyholders do not necessarily benefit from more accurate monitoring technologies. Our model stacks the deck in favor of greater accuracy because technology improvements are costless and consumers do not attach intrinsic value to their privacy. Even then social welfare can be higher when monitoring is less accurate. Our results may thus help explain why demand for insurance contracts with sophisticated monitoring technologies is still low to date.

This paper contributes to the literature on moral hazard by discussing imperfect monitoring as a means to reduce moral hazard. Arrow (1963) describes moral hazard as a deterrent effect of insurance on prevention efforts and names coinsurance as a countermeasure. On the other hand, Ehrlich and Becker (1972) show that insurance and prevention can be complements if insurers observe prevention efforts and the insurance premium is negatively related to the level of effort. Shavell (1979) shows that imperfect monitoring combined with coinsurance is valuable. Harris and Raviv (1978, 1979) as well as Holmström (1979) find optimal risk-sharing arrangements in a general principal-agent model. In the insurance context, their optimal sharing arrangements contain a considerable coinsurance rate. Following Harris and Raviv (1979), insurers even refuse to pay the indemnity if the monitoring signal suggests insufficient prevention effort. In practice, health insurance contracts which do not cover medical expenditures if the policyholder fails to fulfill a step count goal or car insurance contracts which only cover accidents if the driver perfectly adheres to speed limits are hard to sell. If insurers follow the policyholders' preference for small or zero deductibles, they likely deviate from the optimal contract meaning that they fully indemnify losses regardless of the monitoring signal. To the best of our knowledge, the literature has not discussed so far what happens if insurers only create incentives for prevention through premium discrimination based on the monitoring signal. We fill this gap by studying the market outcome with full insurance contracts whose premium depends on an imperfect monitoring signal.

We also add to the literature on risk classification by discussing the behavioral and welfare implications of classification based on imperfectly monitored prevention efforts. The early risk classification literature studies immutable characteristics like age, race, or gender, which are imperfectly correlated with risk classes (Hoy, 1982; Crocker and Snow, 1986). Hoy (1989) takes into account that policyholders may engage in prevention and that insurers may or may not observe the prevention effort. However, he only analyzes the welfare implications of screening mechanisms matching policyholders to their exogenous prevention technologies and does not discuss the use of screening mechanisms that capture the policyholder's prevention effort.[2] The IoT changes the nature of the data that insurers can use to classify risks because it improves their ability to monitor prevention behavior. So far, only few contributions explicitly discuss the use of behavioral information in insurance pricing. Bond and Crocker (1991) as well as Polborn (2008) analyze risk classification based on consumption choices of goods positively correlated with risk, like cigarettes or particular types of cars. They consider heterogeneous policyholders who belong to different risk classes because they have different tastes for the correlative good. Our setting differs from their work because we consider a priori homogeneous policyholders who only make different prevention choices in equilibrium because it is optimal for them to randomize their prevention effort. Filipova-Neumann and Welzel (2010) investigate adverse selection effects with telematics sensors in car insurance which reveal behavioral patterns that result from insufficient skills or deadlocked habits. We complement their work by investigating moral hazard issues. At first glance, we take a more optimistic view on the use of behavioral information in insurance pricing because we assume that appropriate incentives may induce policyholders to change their behavior. However, we show that complex pricing algorithms may discourage the policyholders from purchasing a monitoring contract. Even if the policyholders purchase a monitoring contract, they do not always engage in prevention. Our findings therefore reveal potentially unforeseen challenges when risks shall be classified based on behavior.

The paper proceeds as follows. The next section sets up the formal model. Section 3 studies the market equilibrium for the extreme cases of perfect and uninformative monitoring. Section 4 derives the market equilibrium with imperfect monitoring. Section 5 analyzes how the policyholders adapt their behavior if monitoring gets more accurate and discusses whether the policyholders benefit from more accurate monitoring. Section 6 performs the same analysis when insurers give advice on prevention issues which reduces the cost of prevention. The final section concludes.

[2] Hoy (1989) defines a prevention technology as a functional relationship between a policyholder's level of effort and the probability of loss.

2 The model

The policyholders are risk-averse expected utility maximizers with an increasing and concave utility function $u(\cdot)$ and initial wealth w. They face a binary loss risk of size l. The probability of loss depends on a policyholder's prevention action $A \in \{E, N\}$. If the policyholder exerts effort, $A = E$, a loss occurs with probability π^E. If she does not exert effort, $A = N$, a loss occurs with probability π^N, with $\pi^E < \pi^N$. The disutility of exerting effort is $c > 0$.[3]

Insurers use a monitoring device to assess the policyholder's prevention efforts, which is free of charge.[4] The insurer cannot observe the prevention action directly but receives a monitoring signal $s \in \{e, n\}$. We denote the conditional probability that the insurer receives the signal s given that the policyholder has chosen the action A by p_{sA}. In particular, if we consider monitoring as a classification task to determine whether a policyholder exerts effort, p_{eE} is the sensitivity and p_{nN} is the specificity of the monitoring technology. Both the insurer and the policyholder do not know the mechanism underlying the monitoring technology but the conditional probabilities p_{sA} characterizing the accuracy of the monitoring technology are common knowledge. The signal is informative in the sense that exerting effort increases the likelihood to obtain the signal e:

$$p_{eE} > p_{eN}.^{5} \tag{1}$$

The monitoring signal is observable for both the insurer and the policyholder and contractible in the sense that the insurance premium may depend on the signal.[6]

Throughout the paper, we use the following notation: The conditional probability that the policyholder has chosen the action A given that the insurer receives the signal s is p_{As}. In contrast to the conditional probability p_{sA} which is intrinsic to the monitoring technology, p_{As} also depends on the probability that the insured exerts effort. The probability that the insured exerts (does not exert) effort is q_E ($q_N = 1 - q_E$) and the probability that the insurer receives the signal e (n) is q_e ($q_n = 1 - q_e$). The table in Appendix A.1 provides an overview of our notation.

In a competitive market, full insurance is offered at the fair premium conditional on the information available. The fair full insurance premium with the monitoring signal $s \in \{e, n\}$

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[3] Considering a binary effort and a separable utility cost of effort is in line with many applications of monitoring devices. For example, when a policyholder decides whether she goes on a walk to improve her health prospects or whether she pays extra attention to speed limits to reduce her accident risk, she makes a binary decision and the risk-reducing action causes some disutility but no monetary cost.

[4] For example, the policyholder can install a health or telematics app on her smartphone at negligible cost which enables the insurer to track the policyholder's physical activity or driving behavior.

[5] This assumption is equivalent to assuming that not exerting effort rather generates the signal n, i.e. $p_{nN} > p_{nE}$, since $p_{nA} = 1 - p_{eA}$ for $A \in \{E, N\}$.

[6] In car insurance, for example, a smartphone app may collect data about the policyholder's driving style and inform the policyholder whether she has been classified as a safe driver. If the policyholder is classified as a safe driver, the insurer receives the monitoring signal e and grants a premium discount.

is

$$P(s) = p_{Es}\ \pi^E l + p_{Ns}\ \pi^N l. \tag{2}$$

The fair premium based on the monitoring signal is a weighted average of the expected loss with and without prevention efforts. If the insurer receives the signal s, the policyholder has exerted effort with probability p_{Es} in which case the expected loss equals $\pi^E l$. With probability p_{Ns} the policyholder has not exerted effort and the expected loss equals $\pi^N l$. The signal e suggests that the policyholder has exerted effort and therefore results in a premium discount compared to the signal n, i.e. $P(e) < P(n)$.[7] The premium schedule $(P(e), P(n))$ is public knowledge.

Knowing the premium schedule $(P(e), P(n))$, the policyholder chooses the prevention action $A \in \{E, N\}$ which maximizes her expected utility

$$EU(A) = p_{eA}\ u(w - P(e)) + p_{nA}\ u(w - P(n)) - c(A), \tag{3}$$

with $c(E) = c$ and $c(N) = 0$. Hence, she exerts effort (is indifferent whether to exert effort, exerts no effort) if $EU(E) > (=, <)\ EU(N)$.

Figure 1 depicts the sequence of play. In the first stage, the insurer offers insurance with a premium schedule $(P(e), P(n))$ and the policyholder signs her most preferred contract which maximizes her expected utility. The policyholder then decides whether to exert effort by maximizing her expected utility given the contract she has signed. The insurer collects and evaluates data about the policyholder's behavior resulting in a monitoring signal $s \in \{e, n\}$. Depending on the signal s, the policyholder pays one of the two premiums from the premium schedule. In the final two stages, nature determines whether the policyholder suffers a loss and the insurer indemnifies the loss if it occurs.

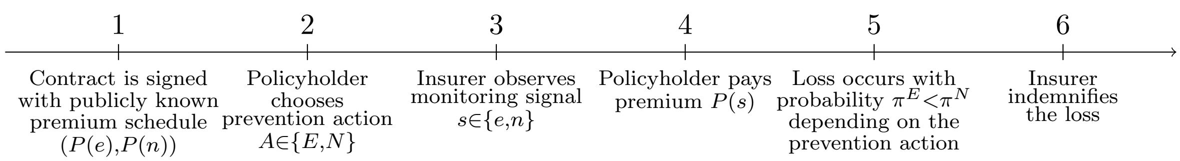

Figure 1: Sequence of play

3 Perfect and uninformative monitoring

We first investigate the two extreme cases of perfect and uninformative monitoring. Monitoring is perfect if the monitoring technology classifies all policyholders correctly which means that both the sensitivity and the specificity are equal to 100%, i.e. $p_{eE} = p_{nN} = 1$. Building

[7] See Appendix A.2.1 for a formal proof.

upon (1), monitoring is perfect if

$$1 = p_{eE} > p_{eN} = 0.$$

With perfect monitoring, the fair premiums are $P(e) = \pi^E l$ and $P(n) = \pi^N l$ and the policyholder exerts effort (is indifferent whether to exert effort, exerts no effort) if $u\left(w - \pi^E l\right) - u\left(w - \pi^N l\right) > (=, <)\ c$.[8] The policyholder exerts effort if and only if the utility benefit from the certain premium discount exceeds the utility cost of exerting effort. Hence, if the effect of exerting effort on the probability of loss is sufficiently large, perfect monitoring has the capability to provide full coverage and to incentivize prevention at the same time.

The other extreme is uninformative monitoring. Monitoring is uninformative if the prevention effort and the signal are independent of each other. Building upon (1), monitoring is uninformative if

$$p_{eE} = p_{eN},$$

i.e. if exerting effort does not affect the likelihood to obtain the signal e. If prevention effort and monitoring signal are independent, $P(e) = q_E\ \pi^E l + q_N\ \pi^N l = P(n)$.[9] Hence, there is no benefit in exerting effort. Since effort is costly, the policyholder never exerts effort and the fair premiums equal $P(e) = P(n) = \pi^N l$. Consequently, uninformative monitoring does not have the capability to provide full coverage and to incentivize prevention at the same time.

The results for the two extreme cases of perfect and uninformative monitoring reflect the classical moral hazard problem that insurance eliminates incentives for prevention if insurers do not observe prevention efforts. If insurers use monitoring devices like wearables or telematics sensors with a transparent pricing algorithm, perfect monitoring might be possible. In car insurance, for example, the insurer might offer a 10 percent premium discount for full compliance with speed limits and use a telematics sensor to capture driving speed. Similarly, health or life insurance contracts might guarantee a \$10 premium discount if the policyholder's wearable device counts 10,000 steps per day. In real-world monitoring contracts, however, pricing algorithms are typically not that straightforward. Insurers use the monitoring device to collect vast amounts of data and feed this data into a complex and intransparent algorithm which decides whether the policyholder gets "a premium discount" for "safe driving" or "health-conscious behavior". Such algorithms act as a black box which veils the relation between the policyholder's prevention effort and the premium discount. Hence, monitoring is typically imperfect in real-world contracts. In the following section, we analyze how such imperfection affects the market equilibrium and the policyholders' behavior.

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[8] The fair premiums can easily be calculated by applying Bayes' theorem in (2), see Appendix A.2.2.

[9] See Appendix A.2.2 for a formal derivation of the fair premiums.

4 Market equilibrium with imperfect monitoring

Monitoring is imperfect if

$$1 > p_{eE} > p_{eN} > 0.$$

Exerting effort increases the likelihood of the signal e but there is no one-to-one correspondence between signals and prevention efforts. With imperfect monitoring, the policyholder exerts effort (is indifferent whether to exert effort, exerts no effort) if

$$[p_{eE} - p_{eN}] \times [u(w - P(e)) - u(w - P(n))] > (=, <)\ c.$$

Compared with perfect monitoring the cost of exerting effort remains unchanged while its benefit decreases. On the one hand, exerting effort does no more result in a premium discount with certainty since an imperfect monitoring technology may misclassify the policyholder. On the other hand, the premium discount is smaller with imperfect monitoring because the insurer anticipates that some of the policyholders with the monitoring signal suggesting that the policyholder exerts effort have actually not exerted effort and vice versa. One might expect that if the effect of prevention on the probability of loss is sufficiently large, imperfect monitoring still incentivizes the policyholders to exert effort just as perfect monitoring does. This is not the case, however. Instead, the following proposition describes the market equilibrium with imperfect monitoring.

Proposition 1. *In the Perfect Bayesian Nash Equilibrium, the policyholders either follow the pure strategy "never exert effort" or a mixed strategy in which they randomize their prevention action.*

Proof. In the Perfect Bayesian Nash Equilibrium (PBNE),

a) the policyholder's prevention strategy at stage 2 is optimal given the insurance contract that she has signed at stage 1,

b) the insurer's beliefs, on which she bases her premium calculations according to (2), is consistent with the policyholder's prevention strategy,

c) the contract which the policyholder signs at stage 1 maximizes her expected utility among the offered contracts.

We first identify all equilibrium candidates fulfilling a) and b) by specifying the associated prevention strategy for the policyholder. For each prevention strategy, the pricing formula (2) yields a zero-profit contract which the insurer may offer at stage 1.[10] Among these contracts, the policyholder chooses the one which maximizes her expected utility according

[10] More precisely, the zero-profit premiums can be derived from the prevention strategy by applying Bayes' theorem in (2). For details, see Appendix A.2.2.

to c). Possible strategies for the policyholder are the pure strategies “always exert effort” and “never exert effort” as well as mixed strategies in which she randomizes her prevention action.

1) Pure strategy “always exert effort”: If the policyholder always exerts effort, the fair premiums are $P(e) = P(n) = \pi^E l$ because the insurer anticipates that the policyholder has exerted effort regardless of the monitoring signal. With a flat premium schedule, however, there is no incentive to exert effort. $EU(E) = u\left(w - \pi^E l\right) - c < u\left(w - \pi^E l\right) = EU(N)$ implies that the policyholder does not exert effort. Hence, the pure strategy “always exert effort” can never arise in equilibrium.

2) Pure strategy “never exert effort”: If the insurer assumes that the policyholder never exerts effort, the fair premiums are $P(e) = P(n) = \pi^N l$. There is no benefit in exerting effort and the policyholder indeed chooses not to exert effort since $EU(E) = u\left(w - \pi^N l\right) - c < u\left(w - \pi^N l\right) = EU(N)$. Hence, the insurer's beliefs are consistent with the policyholder's prevention strategy which implies that “never exert effort” is a candidate for equilibrium.

3) Mixed strategy: In an informationally consistent mixed strategy equilibrium, a policyholder facing the premium schedule $(P(e), P(n))$ must be indifferent between the two prevention actions. Indifference holds if $EU(E) = EU(N)$, which is equivalent to

$$[p_{eE} - p_{eN}] \times [u(w - P(e)) - u(w - P(n))] - c = 0. \tag{4}$$

Plugging in (2) and using Bayes' theorem, (4) characterizes all possible mixed strategies $(q_E, q_N) = (q_E, 1 - q_E) \in [0,1]^2$ for the policyholder. However, (4) does not necessarily have a solution $q_E \in [0,1]$.[11] Hence, a mixed strategy in which the policyholder randomizes her effort level might or might not exist.

If (4) does not have a solution $q_E \in [0,1]$, the only equilibrium candidate fulfilling a) and b) is the one with the premium schedule $(P(e), P(n)) = \left(\pi^N l,\ \pi^N l\right)$ and the pure strategy “never exert effort”. Therefore, the contract $\left(\pi^N l,\ \pi^N l\right)$ is the only one offered at stage 1 and hence also fulfills c). In conclusion, the policyholders follow the pure strategy “never exert effort” in the PBNE.

If (4) has at least one solution $q_E \in [0,1]$, we have identified several equilibrium candidates. With the pure strategy “never exert effort”, the fair insurance premiums are $P(e) = P(n) = \pi^N l$. With a mixed strategy, there is a positive probability that the policyholder exerts effort implying $P(s) < \pi^N l,\ s \in \{e, n\}$. Plugging this inequality into (3) with $A = N$ implies that every mixed strategy yields higher expected utility than the pure strategy “never exert

[11] In particular, (4) does not have a solution if $c > [p_{eE} - p_{eN}] \times \left[u\left(w - \pi^E l\right) - u\left(w - \pi^N l\right)\right]$ since $\pi^E l < P(e) < P(n) < p^N l$. Therefore, a mixed strategy does not exist if prevention is very costly, if the monitoring signal is too inaccurate, or if the policyholders benefit only little from a premium discount.

effort". Moreover, if (4) has several solutions $q_E \in [0,1]$, the largest q_E yields the highest expected utility:

$$\frac{dEU\left(A\right)}{dq_E} = -p_{eA}\ u'\left(w - P\left(e\right)\right)\frac{\partial P\left(e\right)}{\partial q_E} - p_{nA}\ u'\left(w - P\left(n\right)\right)\frac{\partial P\left(n\right)}{\partial q_E}.$$

The calculations in Appendix A.2.3 show that $\frac{\partial P(e)}{\partial q_E} < 0$ and $\frac{\partial P(n)}{\partial q_E} < 0$ which implies $\frac{dEU(A)}{dq_E} > 0$. Intuitively, if the policyholder exerts effort more often, losses occur less often and insurance gets cheaper which increases the policyholder's expected utility. Hence, the largest $q_E \in [0,1]$ which solves (4) payoff dominates all other equilibrium candidates and characterizes the policyholder's mixed strategy in the PBNE according to c). □

Proposition 1 implies that under imperfect monitoring an equilibrium where policyholders always engage in prevention is not feasible. In equilibrium, either insurers do not use the monitoring signal for premium discrimination and policyholders do not exert effort or insurers discriminate premiums based on the monitoring signal and policyholders randomize over the use of prevention. Although improved risk assessment and the promotion of prevention constitute a promising avenue for the use of IoT devices like wearables or telematics sensors in insurance pricing, monitoring contracts are not much in demand by now. The public debate names privacy concerns and disproportionate monitoring costs as potential reasons. Proposition 1 suggests that if policyholders and insurers are not able to retrace how the policyholder's behavior enters premium calculations, the monitoring signal will not be used for premium discrimination in equilibrium. This finding may help explain why monitoring contracts might not be in demand even if monitoring does not cause any costs and policyholders have no privacy concerns sharing behavioral data with their insurer.

5 Technology improvements

Comparing the results for the two extreme cases of perfect and uninformative monitoring discussed in section 3 yields the following insights: Improving the monitoring technology from an uninformative to a perfect one induces the policyholder to exert effort, decreases the fair insurance premiums, and increases the policyholder's expected utility.[12] These results suggest that a more accurate monitoring technology is beneficial because it helps to prevent losses, reduce the cost of insurance, and eventually increase the policyholder's welfare. Does this also hold for imperfect monitoring technologies? Does more accurate but still imperfect monitoring induce more policyholders to exert effort? Do technology improvements have a positive welfare effect? To answer these questions, we conduct several comparative statics analyses which investigate the mixed strategy equilibrium in Proposition 1.

[12] To be precise, these statements hold if $u\left(w - \pi^E l\right) - u\left(w - \pi^N l\right) > c$, i.e. if the effect of exerting effort on the probability of loss is sufficiently large such that perfect monitoring incentivizes prevention.

The accuracy of a monitoring technology is captured by the sensitivity p_{eE} as well as the specificity p_{nN}. An increase in the sensitivity or specificity means that the probability that the insurer classifies a policyholder correctly increases. We therefore define technology improvements as increases in the sensitivity or specificity of the monitoring technology.

Proposition 2. *Improving the monitoring technology by increasing its sensitivity or specificity*
... increases (decreases) the probability that the policyholders exert effort,
... decreases (increases) the fair insurance premiums, and
... increases (decreases) the policyholders' expected utility
if

$$\frac{u'\left(w-P\left(e\right)\right)}{u'\left(w-P\left(n\right)\right)} < (>) \ \frac{p_{En}\ p_{Nn}}{p_{Ee}\ p_{Ne}}.$$

Proof. See Appendix A.3.1. □

Corollary 1. *Improving the monitoring technology by increasing its sensitivity or specificity*
... increases the probability that the policyholders exert effort,
... decreases the fair insurance premiums, and
... increases the policyholders' expected utility
if

$$\left|p_{Nn} - p_{En}\right| \leq \left|p_{Ee} - p_{Ne}\right|.$$

Proof. See Appendix A.3.2. □

Proposition 2 reveals that the effect of technology improvements on the policyholders' behavior, the fair insurance premiums and the policyholders' welfare are inextricably linked with each other. Either technology improvements induce the policyholders to exert effort more often, the insurance premiums decrease and the policyholders' welfare increases or technology improvements induce the policyholders to exert effort less often, the insurance premiums increase and the policyholders' welfare decreases. Technology improvements have a direct effect on the fair premiums and the policyholders' expected utility because the insurer classifies more policyholders correctly. They also have an indirect effect because the policyholders adapt their behavior in equilibrium. The direct effect of more correct classifications decreases the premium for the signal suggesting effort and increases the premium for the signal suggesting no effort. The indirect effect of adaptions in behavior decreases both premiums if the policyholders exert effort more often and it increases both premiums if they exert effort less often. Proposition 2 shows that the indirect effect prevails: The fair insurance premiums decrease if and only if the policyholders exert effort more often after a technology improvement. Concerning the welfare effect of technology improvements, the direct effect of more correct classifications is positive if the policyholder exerts effort whereas it is negative if she does not exert effort. The indirect effect again depends on whether the policyholders exert effort more or less often as the technology improves. Again the indirect effect prevails and the policyholders' expected utility increases if and only if they exert effort more often after a technology improvement.

In general, technology improvements do not necessarily induce the policyholders to exert effort more often, and hence, they do not necessarily have a positive welfare effect. Corollary 1 provides a sufficient condition for a positive effect of technology improvements. It can be interpreted as the signal e being at least as meaningful as the signal n: If $|p_{Nn} - p_{En}| = 0$, the monitoring signal n does not help the insurer to decide whether the policyholder should get a premium discount: There is a 50:50 chance that the policyholder has exerted effort or not. On the other hand, if $|p_{Nn} - p_{En}| = 1$, the monitoring signal n lets the insurer know for sure whether the policyholder has exerted effort. The same holds for $|p_{Ee} - p_{Ne}|$ and the signal e. Consequently, the inequality which yields a positive effect is fulfilled if $s = e$ makes the insurer as least as confident about whether the policyholder has exerted effort as $s = n$ does, i.e. if the signal e is at least as meaningful as the signal n.

Intuitively, if the accuracy of the monitoring technology increases, ceteris paribus, exerting effort becomes more attractive because more policyholders are classified correctly and the difference between the two premiums increases. Hence, the policyholders would unanimously exert effort if the insurers did not adapt their beliefs about the policyholders' behavior. As shown in Proposition 1, however, "always exert effort" can never be the equilibrium strategy. Instead, the policyholders adapt their behavior (and the insurers adapt their beliefs) such that indifference is reestablished. If the policyholders exert effort more often, both premiums decrease. Due to decreasing marginal utility, the effect of a given premium decrease is stronger when the policyholders are less wealthy, i.e. with $P(n)$. Moreover, changes in behavior have a stronger effect on $P(n)$ than on $P(e)$ if the signal e is more meaningful than the signal n: q_E is like a prior for the insurer's beliefs about the policyholder's prevention effort before she receives the monitoring signal. If there is only little meaning in the signal, the insurer's beliefs are close to this prior. Hence, a change in the prior has a strong effect on the premium. On the other hand, if the signal is very meaningful, the prior is not so important. The insurer cares little about the fraction of the population exerting effort but she heavily relies on the monitoring signal when she determines the fair premiums. Hence, a change in the prior only has a weak effect on the premium with a meaningful signal. Consequently, as q_E increases, the premium based on the less meaningful signal decreases more than the premium based on the more meaningful signal. Thus, indifference is reestablished by increasing q_E if the signal e is more meaningful than the signal n because $P(n)$ decreases more than $P(e)$ in this case.

6 Advice on prevention issues

IoT devices do not only allow insurers to collect information about the policyholder's behavior but insurers may also advise the policyholder how to prevent losses. For example, a wearable device may be connected with a health app which informs the policyholder about fitness classes in her neighborhood. Such advice can reduce the cost of prevention for the policyholder:

Joining the fitness class in your neighborhood is probably much more fun than going for a run on your own. Many IoT devices also try to motivate prevention efforts with gamification. For example, contests on specific prevention goals can help to increase prevention efforts if the policyholder tries to get to the top of the leaderboard. New technologies have the potential to move the role of insurers from pure risk takers to holistic risk advisors. If the insurer's advice reduces the cost of prevention, does the policyholder engage in prevention more often? Does the policyholder benefit if the cost of prevention decreases? A comparative statics analysis of the mixed strategy equilibrium answers these questions.

Proposition 3. *Reducing the cost of prevention*
... increases (decreases) the probability that the policyholders exert effort,
... decreases (increases) the fair insurance premiums, and
... increases (decreases) the policyholders' expected utility
if

$$\frac{u'\left(w-P\left(e\right)\right)}{u'\left(w-P\left(n\right)\right)} < (>) \; \frac{p_{En}\; p_{Nn}}{p_{Ee}\; p_{Ne}}.$$

Proof. See Appendix A.3.3. □

Corollary 2. *Reducing the cost of prevention*
... increases the probability that the policyholders exert effort,
... decreases the fair insurance premiums, and
... increases the policyholders' expected utility
if

$$\left|p_{Nn}-p_{En}\right| \leq \left|p_{Ee}-p_{Ne}\right|.$$

Proof. Analogously to the proof of Corollary 1. □

Similar to Proposition 2, the effect of cost reductions on the policyholder's behavior and welfare cannot be signed unambiguously in general. Although reduced costs of prevention make prevention efforts more attractive in the first place, the effect on the equilibrium strategy depends on how changes in behavior affect the policyholder's expected utility. In the mixed strategy equilibrium, the policyholder's behavior (and the insurer's beliefs) must be adapted such that the policyholder remains indifferent whether to exert effort. The fair premiums do not depend directly on the cost of prevention. Hence, they decrease if and only if the policyholders exert effort more often as the cost of prevention decreases. Concerning the policyholder's expected utility, there is both a direct and an indirect effect. Again, the indirect effect resulting from adapted behavior prevails. If the policyholder exerts effort more often, insurance gets cheaper and the policyholder's welfare increases. If the policyholder exerts effort less often, however, insurance gets more expensive and the policyholder's welfare decreases. A sufficient condition for a positive effect on the policyholder's behavior and welfare is again that the signal e is at least as meaningful as the signal n.

7 Conclusion

This paper investigates whether policyholders benefit from technology improvements in monitoring. Under imperfect monitoring, a mixed-strategy equilibrium arises under which policyholders randomize over the use of prevention. An equilibrium where policyholders always engage in prevention is not feasible. Technology improvements only have a positive welfare effect if they induce the policyholders to engage in prevention more often which is not necessarily the case. Similarly, advice on prevention issues which reduces the cost of prevention does not necessarily have a positive effect on the policyholders' behavior and welfare.

Contracts monitoring prevention efforts are promising at first glance. They have the potential to reduce losses, e.g. by promoting healthy behaviors or considerate driving, but still to provide full insurance coverage. Our results suggest, however, that the incentives provided by monitoring contracts do not always create the desired effects. If insurer and policyholder do not know the mechanism underlying the monitoring technology, monitoring does not incentivize the policyholders to always exert effort. The monitoring signal might not even be used for premium discrimination in equilibrium which can be an explanation why monitoring contracts are not much in demand by now.

Complex pricing algorithms and imprecise terms and conditions blur the relation between the actual prevention effort and the insurers' risk assessment. However, insurers can only promote risk-reducing behavior if the policyholders know how their behavior affects the insurance premium. Therefore, insurers should keep their pricing algorithms as simple as possible and communicate transparently how premiums are linked to observed behavior in order to make sure that contracts monitoring prevention efforts indeed induce the policyholders to prevent losses.

A Appendix

A.1 Notation

For the sake of readability, we use the following notation throughout the paper:

Symbol	Definition	Interpretation
π^A		Probability of loss with action $A \in \{E, N\}$
p_{sA}	$\mathbb{P}(s \mid A)$	Conditional probability that the insurer receives the signal $s \in \{e, n\}$ given that the policyholder has chosen action $A \in \{E, N\}$ p_{eE}: sensitivity, p_{nN}: specificity
Δp	$p_{eE} - p_{eN}$	Effect of effort on the probability of the signal suggesting effort
p_{As}	$\mathbb{P}(A \mid s)$	Conditional probability that the policyholder has chosen action $A \in \{E, N\}$ given that the insurer receives the signal $s \in \{e, n\}$
q_A	$\mathbb{P}(A)$	(Unconditional) probability that the policyholder chooses action $A \in \{E, N\}$
q_s	$\mathbb{P}(s)$	(Unconditional) probability that the insurer receives the signal $s \in \{e, n\}$
$P(s)$		Premium when the insurer receives the signal $s \in \{e, n\}$
u_s	$u(w - P(s))$	Utility when the insurer receives the signal $s \in \{e, n\}$
Δu	$u_e - u_n$	Utility difference between the two signals

A.2 Fair premiums

A.2.1 Proof of $P(e) < P(n)$

Using the notation introduced in Appendix A.1, we apply Bayes' theorem to rewrite

$$\begin{aligned} p_{Ee} &= \frac{p_{eE}\ q_E}{p_{eE}\ q_E + p_{eN}\ q_N} = \left(1 + \frac{p_{eN}\ q_N}{p_{eE}\ q_E}\right)^{-1}, \\ p_{En} &= \frac{p_{nE}\ q_E}{p_{nE}\ q_E + p_{nN}\ q_N} = \left(1 + \frac{p_{nN}\ q_N}{p_{nE}\ q_E}\right)^{-1}. \end{aligned}$$

According to (1), $p_{eN} < p_{eE}$ and $p_{nN} > p_{nE}$ which implies

$$\frac{p_{eN}\ q_N}{p_{eE}\ q_E} < \frac{p_{nN}\ q_N}{p_{nE}\ q_E}, \text{ and hence, } p_{Ee} > p_{En}.$$

Therefore,

$$P(n) - P(e) = (p_{Ee} - p_{En})\left(\pi^N l - \pi^E l\right) > 0.$$

A.2.2 Bayes' rule

Applying Bayes' rule yields

$$\begin{aligned}
P(e) &= p_{Ee}\ \pi^E l + p_{Ne}\ \pi^N l \\
&= \frac{p_{eE}\ q_E}{q_e}\ \pi^E l + \frac{p_{eN}\ q_N}{q_e}\ \pi^N l \\
&= \frac{p_{eE}\ q_E}{p_{eE}\ q_E + (1-p_{nN})\ q_N}\ \pi^E l + \frac{(1-p_{nN})\ q_N}{p_{eE}\ q_E + (1-p_{nN})\ q_N}\ \pi^N l,
\end{aligned}$$

$$\begin{aligned}
P(n) &= p_{En}\pi^E l + p_{Nn}\pi^N l \\
&= \frac{p_{nE}\ q_E}{q_n}\ \pi^E l + \frac{p_{nN}\ q_N}{q_n}\ \pi^N l \\
&= \frac{(1-p_{eE})\ q_E}{(1-p_{eE})\ q_E + p_{nN}\ q_N}\ \pi^E l + \frac{p_{nN}\ q_N}{(1-p_{eE})\ q_E + p_{nN}\ q_N}\ \pi^N l.
\end{aligned}$$

Hence, the fair premiums are a function of the monitoring accuracy measured by the sensitivity p_{eE} and specificity p_{nN}, the insured's prevention behavior captured by the probability that she exerts effort q_E and the distribution of the loss risk characterized by the parameters π^E, π^N, and l.

Inserting $p_{eE} = p_{nN} = 1$ yields $P(e) = \pi^E l$ and $P(n) = \pi^N l$ when monitoring is perfect. If monitoring is uninformative, $p_{eE} = p_{eN} = q_e$ and $p_{nE} = p_{nN} = q_n$ since the monitoring signal and the effort level are independent of each other. Hence, $P(e) = q_E\ \pi^E l + q_N\ \pi^N l = P(n)$.

A.2.3 Partial derivatives with respect to q_E

If the insured exert effort more often, ceteris paribus, insurance becomes cheaper because losses occur less often. Formally, differentiating the fair pricing formulas in Appendix A.2.2 with $q_N = 1 - q_E$ yields

$$\begin{aligned}
\frac{\partial P(e)}{\partial q_E} &= \frac{p_{eE}\ q_e - p_{eE}\ q_E\,[p_{eE} - p_{eN}]}{(q_e)^2}\ \pi^E l + \frac{-p_{eN}\ q_e - p_{eN}\ q_N\,[p_{eE} - p_{eN}]}{(q_e)^2}\ \pi^N l \\
&= \frac{1}{(q_e)^2}\ p_{eE}\,[q_e - p_{Ee}\ q_e + q_E\ p_{eN}]\,\pi^E l + \frac{1}{(q_e)^2}\ p_{eN}\,[-q_e - q_N\ p_{eE} + p_{Ne}\ q_e]\,\pi^N l \\
&= \frac{1}{(q_e)^2}\ p_{eE}\,[p_{eN}\ q_N + q_E\ p_{eN}]\,\pi^E l + \frac{1}{(q_e)^2}\ p_{eN}\,[-p_{eE}\ q_E - q_N\ p_{eE}]\,\pi^N l \\
&= -\frac{1}{(q_e)^2}\ p_{eE}\ p_{eN}\left(\pi^N l - \pi^E l\right)
\end{aligned}$$

$$< \quad 0,$$

where we used $p_{sA}\ q_A = p_{As}\ q_s$ several times. Analogously,

$$\frac{\partial P\,(n)}{\partial q_E} = -\frac{1}{(q_n)^2}\ p_{nE}\ p_{nN}\left(\pi^N l - \pi^E l\right) < 0.$$

A.2.4 Partial derivatives with respect to p_{eE} and p_{nN}

If the insurer classifies more insured correctly, ceteris paribus, the premium with the prevention discount decreases and the premium without the discount increases, i.e. premium discrimination becomes stronger. Formally, differentiating the fair pricing formulas in Appendix A.2.2 yields

$$\begin{aligned}
\frac{\partial P\,(e)}{\partial p_{eE}} &= \frac{q_E\ q_e - p_{eE}\ q_E\ q_E}{(q_e)^2}\ \pi^E l + \frac{0 - p_{eN}\ q_N\ q_E}{(q_e)^2}\ \pi^N l \\
&= \frac{q_E\ q_e(1 - p_{Ee})}{(q_e)^2}\ \pi^E l + \frac{-p_{Ne}\ q_e\ q_E}{(q_e)^2}\ \pi^N l \\
&= -\frac{q_E\ p_{Ne}}{q_e}\left(\pi^N l - \pi^E l\right)\ <\ 0,
\end{aligned}$$

where we used $p_{sA}\ q_A = p_{As}\ q_s$. Analogously, one obtains

$$\frac{\partial P\,(e)}{\partial p_{nN}} = -\frac{q_N\ p_{Ee}}{q_e}\left(\pi^N l - \pi^E l\right)\ <\ 0,$$

$$\frac{\partial P\,(n)}{\partial p_{eE}} = \frac{q_E\ p_{Nn}}{q_n}\left(\pi^N l - \pi^E l\right)\ >\ 0,$$

$$\frac{\partial P\,(n)}{\partial p_{nN}} = \frac{q_N\ p_{En}}{q_n}\left(\pi^N l - \pi^E l\right)\ >\ 0.$$

A.3 Mathematical proofs

A.3.1 Proof of Proposition 2

Since (4) defines the insured's mixed strategy in the PBNE, applying the implicit function theorem to (4) reveals how the insured adapt their behavior if the monitoring technology gets more accurate:

$$\frac{dq_E}{dp_{eE}} = -\frac{\partial(4)/\partial p_{eE}}{\partial(4)/\partial q_E} \quad \text{and} \quad \frac{dq_E}{dp_{nN}} = -\frac{\partial(4)/\partial p_{nN}}{\partial(4)/\partial q_E}.$$

We compute the numerators as follows:

$$\frac{\partial(4)}{\partial p_{eE}} = \Delta u + \Delta p\left[-u'_e\ \frac{\partial P\,(e)}{\partial p_{eE}} + u'_n\ \frac{\partial P\,(n)}{\partial p_{eE}}\right] > 0,$$

$$\frac{\partial(4)}{\partial p_{nN}} \quad = \quad \Delta u + \Delta p \left[-u_e' \frac{\partial P(e)}{\partial p_{nN}} + u_n' \frac{\partial P(n)}{\partial p_{nN}} \right] > 0,$$

where the signs of the partial derivatives of the fair premiums with respect to p_{eE} and p_{nN} follow from the calculations in Appendix A.2.4. For the denominators,

$$\begin{aligned} \frac{\partial(4)}{\partial q_E} &= \Delta p \left[-u_e' \frac{\partial P(e)}{\partial q_E} + u_n' \frac{\partial P(n)}{\partial q_E} \right] \\ &= \Delta p \left(\pi^N l - \pi^E l \right) \left[u_e' \frac{p_{eE}\, p_{eN}}{(q_e)^2} - u_n' \frac{p_{nE}\, p_{nN}}{(q_n)^2} \right], \end{aligned}$$

where we refer to the calculations in Appendix A.2.3 for the partial derivatives of the fair premiums with respect to q_E. Since $\Delta p \left(\pi^N l - \pi^E l \right) > 0$, the bracketed term determines the sign of the denominators. It follows that

$$\frac{\partial(4)}{\partial q_E} > (=, <)\ 0 \iff \frac{u_e'}{u_n'} > (=, <) \frac{p_{nE}\, p_{nN}\, (q_e)^2}{p_{eE}\, p_{eN}\, (q_n)^2} = \frac{p_{En}\, p_{Nn}}{p_{Ee}\, p_{Ne}}. \tag{5}$$

In conclusion,

$$\frac{dq_E}{dp_{eE}} > (<)\ 0 \text{ and } \frac{dq_E}{dp_{nN}} > (<)\ 0 \iff \frac{u_e'}{u_n'} < (>) \frac{p_{En}\, p_{Nn}}{p_{Ee}\, p_{Ne}},$$

which is the first statement of Proposition 2. On the left-hand side, $\frac{u_e'}{u_n'} < 1$ due to decreasing marginal utility. On the right-hand side, $\frac{p_{En}}{p_{Ee}} < 1$ whereas $\frac{p_{Nn}}{p_{Ne}} > 1$.[13] Hence, the effect of technology improvements on the insured's behavior cannot be signed unambiguously in general.

For the effect of technology improvements on the fair premiums, the following calculations focus on the effect on the discounted premium $P(e)$ when the sensitivity p_{eE} increases. The effect on the discounted premium $P(e)$ when the specificity p_{nN} increases as well as the effect on the non-discounted premium $P(n)$ when the sensitivity p_{eE} or the specificity p_{nN} increases is determined analogously. The chain rule yields

$$\begin{aligned} \frac{dP(e)}{dp_{eE}} &= \frac{\partial P(e)}{\partial p_{eE}} + \frac{\partial P(e)}{\partial q_E} \frac{dq_E}{dp_{eE}} \\ &= \frac{\partial P(e)}{\partial p_{eE}} + \frac{\partial P(e)}{\partial q_E} \left(- \frac{\Delta u + \Delta p \left[-u_e' \frac{\partial P(e)}{\partial p_{eE}} + u_n' \frac{\partial P(n)}{\partial p_{eE}} \right]}{\Delta p \left[-u_e' \frac{\partial P(e)}{\partial q_E} + u_n' \frac{\partial P(n)}{\partial q_E} \right]} \right). \end{aligned}$$

[13] See Appendix A.2.1 for a proof.

The denominator of the expression in parentheses is equal to $\frac{\partial(4)}{\partial q_E}$ and according to the previous calculations it is positive if and only if $\frac{u_e'}{u_n'} > \frac{p_{En}\ p_{Nn}}{p_{Ee}\ p_{Ne}}$. In this case, $\frac{dP(e)}{dp_{eE}} > (=,<)\ 0$ if

$$\Delta p\ u_n'\ \frac{\partial P(e)}{\partial p_{eE}}\ \frac{\partial P(n)}{\partial q_E} > (=,<)\ \Delta u\ \frac{\partial P(e)}{\partial q_E} + \Delta p\ u_n'\ \frac{\partial P(n)}{\partial p_{eE}}\ \frac{\partial P(e)}{\partial q_E}.$$

From the calculations in Appendix A.2.4 and A.2.3, it follows that the left-hand side of this expression is positive whereas the right-hand side is negative. In conclusion, $\frac{dP(e)}{dp_{eE}} > 0$ if $\frac{u_e'}{u_n'} > \frac{p_{En}\ p_{Nn}}{p_{Ee}\ p_{Ne}}$. A negative denominator switches all inequalities which yields the "decreases" part of the second claim in Proposition 2.

Finally, to determine the effect of technology improvements on the insured's expected utility, it suffices to consider the effect on either $EU(E)$ or $EU(N)$ since $EU(E) = EU(N)$ in a mixed strategy equilibrium. When the sensitivity increases,

$$\frac{dEU(N)}{dp_{eE}} = -\left[p_{nN}\ u_n'\ \frac{dP(n)}{dp_{eE}} + p_{eN}\ u_e'\ \frac{dP(e)}{dp_{eE}}\right] > (=,<)\ 0$$

$$\text{if} \quad \frac{dP(n)}{dp_{eE}} < (=,>)\ 0 \quad \text{and} \quad \frac{dP(e)}{dp_{eE}} < (=,>)\ 0.$$

Similarly, increasing the specificity yields

$$\frac{dEU(E)}{dp_{nN}} = -\left[p_{nE}\ u_n'\ \frac{dP(n)}{dp_{nN}} + p_{eE}\ u_e'\ \frac{dP(e)}{dp_{nN}}\right] > (=,<)\ 0$$

$$\text{if} \quad \frac{dP(n)}{dp_{nN}} < (=,>)\ 0 \quad \text{and} \quad \frac{dP(e)}{dp_{nN}} < (=,>)\ 0.$$

In conclusion, technology improvements increase (decrease) the insured's expected utility if they decrease (increase) the fair premiums which holds if $\frac{u_e'}{u_n'} < (>)\ \frac{p_{En}\ p_{Nn}}{p_{Ee}\ p_{Ne}}$.

A.3.2 Proof of Corollary 1

We rewrite the condition in Proposition 2 as

$$\frac{u_e'}{u_n'} < (>) \frac{h(p_{Nn})}{h(p_{Ee})},$$

with $h(x) = x(1-x)$. For $x_1, x_2 \in [0,1]$, $h(x_1) \geq h(x_2)$ if and only if $|x_1 - 0.5| \leq |x_2 - 0.5|$. Since

$$|p_{Nn} - 0.5| = 0.5\,|p_{Nn} - p_{En}| \ \text{ and } \ |p_{Ee} - 0.5| = 0.5\,|p_{Ee} - p_{Ne}|,$$

it follows that

$$\frac{h(p_{Nn})}{h(p_{Ee})} \geq 1 \iff |p_{Nn} - p_{En}| \leq |p_{Ee} - p_{Ne}|.$$

Since $\frac{u_e'}{u_n'} < 1$ due to decreasing marginal utility, this proves Corollary 1.

A.3.3 Proof of Proposition 3

To determine how the insured adapt their behavior as the cost of prevention decreases, we apply the implicit function theorem to (4) which yields

$$\frac{dq_E}{dc} = -\frac{\partial(4)/\partial c}{\partial(4)/\partial q_E}.$$

The first claim of Proposition 3 follows with $\frac{\partial(4)}{\partial c} = -1 < 0$ together with (5).

Concerning the effect on the fair premiums, changing the cost of prevention does not have a direct effect but only an indirect effect as the insured adapt their behavior. Hence, the second claim of Proposition 3 follows from

$$\frac{dP\left(s\right)}{dc} = \frac{\partial P\left(s\right)}{\partial c} + \frac{\partial P\left(s\right)}{\partial q_E}\ \frac{dq_E}{dc} = \frac{\partial P\left(s\right)}{\partial q_E}\ \frac{dq_E}{dc},\ \ s \in \left\{e,\ n\right\},$$

together with Appendix A.2.3.

Finally, to determine the effect of cost reductions on the insured's welfare, it suffices again to consider the effect on either $EU\left(E\right)$ or $EU\left(N\right)$ since $EU\left(E\right) = EU\left(N\right)$ in a mixed strategy equilibrium. The third claim of Proposition 3 follows from

$$\frac{dEU\left(N\right)}{dc} = -\left[p_{nN}\ u_n'\ \frac{dP\left(n\right)}{dc} + p_{eN}\ u_e'\ \frac{dP\left(e\right)}{dc}\right] > (=, <)\ 0$$

$$\text{if} \quad \frac{dP\left(n\right)}{dc} < (=, >)\ 0 \quad \text{and} \quad \frac{dP\left(e\right)}{dc} < (=, >)\ 0.$$

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