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Opening up the black box: Technological transparency and prevention

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Abstract

We discuss the behavioral and welfare implications of uncovering determinants of successful prevention. Based on a novel reinterpretation of prevention, we introduce the concept of technological transparency (TT)—the extent to which scientific knowledge allows agents to predict the success of their effort conditional on observable risk determinants. When risk determinants are observable ex ante, TT refines the information partition and induces more efficient prevention but does not necessarily improve welfare when the risk is insurable. At the same time, TT may harm welfare if information is incompletely disclosed. When risk determinants are only observable ex post, TT may increase effort by triggering future regret. Our framework facilitates a deeper understanding of the connection between knowledge and the efficient choice of preventive effort. Our findings inform the cost-benefit analysis of advancing knowledge about risk processes, as well as the effective disclosure of such knowledge to the public.

KEYWORDS

prevention, regret, technological transparency, value of information

JEL CLASSIFICATION

D61; D80; D90; H00

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1 | INTRODUCTION

“Success = talent + luck. Great success = a little more talent + a lot of luck”

Daniel Kahneman, *Thinking, Fast and Slow*

Most life outcomes depend inevitably on both our own actions and factors beyond our control. Disentangling the roles of luck and effort, however, is often not trivial. In any situation where the efficacy of effort is interpreted in terms of the probability of some event, the exogenous determinants of that event are completely hidden. A prominent example of such is self-protection (also referred to as loss prevention, see Courbage, Rey, & Treich, 2013; Ehrlich & Becker, 1972), which is a costly effort to reduce the likelihood of a loss event. For instance, while healthy diet and regular physical exercise help reduce the probability of developing diabetes, the successful prevention of diabetes is shown to also depend on exogenous factors including one's genetic makeup (Frayling, 2007). However, which exact genes are involved in this process, as well as the complex mechanism of this gene–lifestyle interaction, are still far from being perfectly understood (L. Qi, Hu, & Hu, 2008).

As in the example mentioned above, any self-protection technology has an inherent possibility of failing. While an agent knows by how much a larger effort is more likely to succeed, she does not know the *risk determinants*, that is, factors that determine the actual success of her effort. Without knowledge about the risk determinants, any self-protection technology resembles a black box as the mechanism of its success is invisible to the agent. How can we shed light into this black box and what happens if we do?

We propose the concept of *technological transparency* (TT), which describes the extent to which scientific knowledge allows agents to predict the success of prevention conditional on observable risk determinants. The more risk determinants are uncovered by scientific research, the better we are able to explain and predict the success of any effort. In its extreme form, full TT reveals all risk determinants so that an agent can perfectly predict whether or not an effort will succeed as soon as she observes those risk determinants. An improvement of TT refers to the process of uncovering previously unknown risk determinants so that the success of effort can be predicted with higher precision.

One simple example of TT can be seen from the history of blood transfusion. It is common knowledge today that the success of blood transfusion is predominately determined by people's blood type. For simplicity, assume blood type is the only determinant of successful blood transfusion. Before different blood types were discovered in 1901 (Landsteiner, 1900), blood transfusion had been seen as a highly risky activity that occasionally succeeded but often failed.¹ Discovering blood types and understanding their role in determining successful blood transfusion is an example of obtaining full TT. Through revealing the mechanism of successful blood transfusion, full TT transformed blood transfusion from a highly unreliable treatment method to one whose success can be perfectly predicted conditional on knowing the blood types of the donor and the recipient.

Consider another example where the effort can take multiple values, say an investment to reinforce a house to prevent it from being destroyed by a hurricane. The more investment is made, the more likely the house will be successfully protected, but the actual success still depends on the intensity of the hurricane. Without TT, all we know is how the loss probability

¹The first successful blood transfusion documented in human history was performed in 1667, according to <https://www.heart-valve-surgery.com/heart-surgery-blog/2009/01/03/first-blood-transfusion/>.

changes with the amount of the investment—the conventional way prevention is described. In this example, TT would be obtained by first identifying a measurable parameter characterizing the actual intensity of a hurricane, and then specifying the relationship between this parameter and the minimum investment to keep the house safe.

The aim of this article is twofold. First, we establish a framework that allows us to formally define TT in the context of prevention. Next, we apply this framework to analyze how TT affects agents' behavior and welfare. While TT describes our ability to predict the success of effort conditional on the observation of risk determinants, TT alone does not specify when the risk determinants are observed. Risk determinants can be observed either before or after the effort is made. For the former, we speak of *ex ante* observable risk determinants, such as when blood types can be tested before a blood transfusion is performed, or when a genetic test can be undertaken before one's lifestyle is chosen. For the latter, risk determinants can only be observed *ex post*, such as when the actual intensity of a hurricane or an earthquake can only be measured after its occurrence. The implication of TT depends crucially on when the risk determinants can be observed.

When combined with *ex ante* observable risk determinants, improving TT leads to a Pareto improvement of welfare through enabling better-informed decision making. However, this welfare effect becomes very different when the agent can not only invest to prevent the risk, but also insure the risk via the (private) insurance market. For an insurable risk, TT has an ambiguous effect on welfare. This is because as TT unravels the risk, it also unravels the insurance market for that risk and hence introduces a negative distributional consequence on social welfare. As a result, the overall welfare effect of TT involves a tradeoff between more efficient prevention and an exaggeration of social disparity. Moreover, when TT is improved by the discovery of some, but not all previously unknown risk determinants, the welfare improvement may be additionally undermined if information regarding the newly uncovered risk determinants is incompletely disclosed, that is, the agent learns her risk type but not how her risk type affects the marginal productivity of her effort. Such incomplete disclosure of information is not uncommon in reality: in the preventive healthcare for complex diseases where risks depend on both genetic and lifestyle factors, studies on the gene–lifestyle interaction are sparse compared to those studying either genes or lifestyle in isolation (L. Qi et al., 2008). As personal genetic testing services become increasingly affordable, people often pay to have their genetic risk factors tested. However, such tests rarely offer any information on how the revealed genetic risk types interact with the effectiveness of prevention. We formally show that incomplete information disclosure may lead to a harmful “illusion of knowledge” by leading to less efficient effort.

When combined with *ex post* observable risk determinants, TT no longer creates *ex ante* informational benefit for decision making. However, even in this case, TT still reveals the optimal effort in hindsight. Hence, as soon as the agent observes the risk determinants *ex post*, she realizes what she “should have done” in the past, although at this point it would be already too late to change her effort. We argue that this hindsight effect induced by TT can alter the agent's choice by triggering counterfactual thinking and regret, that is, disutility from realizing having made a sub-optimal decision (Bell, 1982; Loomes & Sugden, 1982). We show that anticipating future regret raises a regret-averse agent's preventive effort. The more regret-averse the agent is, the more strongly TT affects her effort. This result also shows that even when TT is not yet available, there exists a positive effect on effort from anticipating future acquisition of TT.

Technically, we model full TT with the help of a novel interpretation of self-protection that reveals the latent states of the decision problem from its conventional, reduced-form definition.

Specifically, each state in our model corresponds to a unique deterministic function of effort that fully specifies when the loss occurs and does not occur. Building on the state-dependent model of self-protection, full TT is defined as the mapping from each combined realization of the risk determinants to a particular state. In other words, full TT transforms the observation of the risk determinants to the identification of the true state. On the other hand, an improvement of TT induced by the discovery of some, but not all risk determinants maps from each realization of the newly discovered risk determinants to a particular set of states. Combined with the observation of risk determinants, improving TT leads to a refinement of the underlying information partition (Aumann, 1976) and allows the determination of a more efficient effort.

Based on this framework, we first analyze the consequence of improving TT when risk determinants are *ex ante* observable. We then look at the situation with *ex post* observable risk determinants. Finally, we also extend our framework to include improvements of TT through the discovery of endogenous risk determinants, that is, those whose values the agent must choose herself, such as one's alcohol or cigarette consumption. The existence of endogenous risk determinants introduces inter-technological complementarity and substitutability, which we show to be a crucial determinant for the impact of TT. We also reveal a fundamental link between the degree of inter-technological complementarity and the dimension of the underlying state space.

Our framework provides a fresh look at risk mitigation technologies that facilitates a deeper understanding of the connection between knowledge about risk determinants and the efficient choice of preventive effort. Our findings suggest that while more efficient and adequate risk mitigation effort may be enabled by advancing the knowledge about previously hidden risk determinants, to fully exploit the value of such knowledge and in extreme cases, prevent such knowledge from harming welfare, it is crucial for the interaction between the preventive effort and the newly discovered risk determinants to be revealed to the decision-maker in addition to the risk determinants themselves. In case of insurable risks, the positive welfare effect of TT is no longer guaranteed unless an additional wealth redistribution is imposed. Our results shed light on the effective communication of scientific discoveries about risk determinants to the public. Finally, while we concentrate on risk mitigation decisions, the concept of TT has in fact a much broader range of application. Just as in self-protection, any effort that affects the outcome by altering the probability of *some* event(s) is subject to TT, where our modeling framework may also be applied.

The rest of this article is structured as follows. Section 2 defines TT based on a new way of modeling self-protection. Section 3 analyzes the consequences of TT when risk determinants are *ex ante* observable. Section 4 examines *ex post* observable risk determinants and the indirect behavioral impact of TT through anticipated future regret. Section 5 extends the framework to include endogenous risk determinants. Section 6 concludes and discusses the implications of our results. All proofs appear in the appendix.

2 | SELF-PROTECTION AND TECHNOLOGICAL TRANSPARENCY

Consider an agent with an initial endowment $w > 0$ who faces a potential loss L , $L \in (0, w)$ being a positive constant. First, let us recap the conventional definition of self-protection that is commonly adopted by prior literature.

Definition 1 (Self-protection: a reduced-form model). Self-protection is a costly effort that reduces the loss probability. Let x denote the cost of utilizing a self-protection technology. The loss probability $p(x)$ is decreasing in x .

An inherent property of self-protection is that any effort may either succeed or fail.² While prior self-protection analyses assume $p(x)$ to be decreasing and convex in x with almost no exception, they are silent on when and why the effort will succeed or fail. We aim to discuss exactly the determinants of success while preserving properties of $p(x)$ commonly adopted by prior studies. To do so, we introduce a new definition of self-protection by recovering the latent states of the decision problem from its conventional interpretation.

Definition 2 (Self-protection: a state-dependent model). Consider a probability space $(\Omega, \mathcal{F}, \mu)$, where Ω is the state space, \mathcal{F} is the σ -algebra and μ is the probability measure. Let x denote the cost of utilizing a self-protection technology. The loss $l(\omega, x)$ is a random variable with the support $\{0, L\}$. $l(\omega, x)$ is nonincreasing in x for all $\omega \in \Omega$.

Definition 3. A reduced-form self-protection model is said to *represent* a state-dependent self-protection model if $p(x) = \mu(\{\omega \in \Omega | l(\omega, x) = L\})$ for all x .

The state-dependent model highlights the fact that in each state of the world, no risk should exist and the effort has to be the sole determinant of the occurrence of the loss. Furthermore, the loss size is nonincreasing in effort, that is, as long as some effort suffices (fails) to prevent the loss, then in the same state, any higher (lower) effort will also suffice (fail) to prevent the loss. In fact, the state-dependent model implies the existence of a random variable that characterizes the states in terms of their desirability.

Corollary 1. *For every state-dependent self-protection model, there exists a threshold effort: a random variable $t: \Omega \rightarrow \mathbb{R}$ satisfying $l(\omega, x) = L \cdot \mathbb{I}\{x < t(\omega)\}$, where $\mathbb{I}\{\cdot\}$ is the indicator function. Furthermore, $t(\omega)$ follows a mixed type distribution whose survival function coincides with $p(\cdot)$ in the reduced-form model representing the state-dependent model. Equivalently, the cumulative distribution function $F(\cdot)$ of the threshold effort satisfies:*

1. $F(t) = 0$, if $t < 0$
2. $F(t) = 1 - p(t)$, if $t \geq 0$.

The threshold effort is the lowest effort such that the loss does not occur. It is a manifestation of the state variable ω as a behaviorally relevant concept: the better the state, the lower the threshold effort. More effort reduces the probability of the loss event by exceeding more potential realizations of the threshold effort and, as a result, pushing more states into the no loss event.

When interpreting self-protection as a reduction of the loss probability as in Definition 1, the states are hidden and the state space is merely partitioned into two events: “loss” and “no loss.”

²We assume $p(x)$ to be strictly between 0 and 1. However, all conclusions in this paper remain unaffected if $p(x) = 1$ or $p(x) = 0$ are allowed for some effort levels.

Definition 2, on the other hand, distinguishes between the states, which is a necessary step towards disentangling the roles of nature and effort in determining the occurrence of the loss.

Definition 3 connects every state-dependent model with a reduced-form model. Specifically, when describing the same prevention technology, the loss probability in the reduced-form model coincides with the collective probability of all states where the loss occurs despite the effort—that is, states whose threshold efforts exceed the effort.

It is worth pointing out that while the state-dependent model reveals the existence of the states, it still describes the states as purely abstract concepts. Therefore, the state-dependent model offers a new way of looking at self-protection, but does not in itself contain more information than the reduced-form model. Our next step is to turn the abstract states concrete and interpretable.

Suppose $\tilde{y}_1, \tilde{y}_2, \dots, \tilde{y}_N$ are random variables whose realizations y_1, y_2, \dots, y_N can be observed.³ Let Y_1, Y_2, \dots, Y_N denote their ranges. We now introduce the definition of TT:

Definition 4. In a state-dependent self-protection model,

1. having *full TT* means knowing the function $\lambda: \prod_{i=1}^n Y_i \rightarrow \Omega$;
2. compared to the situation where no risk determinant is understood, having an *improvement of TT* induced by \tilde{y}_i means knowing the function $\lambda_i: Y_i \rightarrow \mathcal{F}$ such that $\lambda_i(y) = \{\omega \in \Omega \mid \lambda^{-1}(\omega) \cdot \hat{e}_i = y\}$, where \hat{e}_i stands for the column unit vector whose i th row equals 1.

TT refers to the extent to which one can predict the success of prevention *conditional on* the observation of risk determinants. Full TT requires the identification of a set of risk determinants that collectively lead to a perfect prediction of the state, together with the mapping between each realization of the risk determinants to a particular state. In other words, it assigns tangible interpretations to the otherwise abstract states.

In case there is more than one risk determinant, knowing a subset of them usually does not allow a perfect prediction of the state. An improvement of TT is induced by the discovery of previously unknown risk determinants so that the quality of the prediction can be improved. Note that TT per se does not imply the observation of risk determinants: it merely describes which risk determinants there are and what we are able to do after observing them.

Generally speaking, risk determinants may be either causal or correlational. Causal risk determinants are those that determine the states through a particular causal mechanism, such as blood types determining the success of blood transfusion. Correlational risk determinants are those that statistically correlate with the state variable, but do not in themselves cause the states, such as an individual's chronological age, which correlates with the occurrence rate of many diseases.⁴ Identifying all causal risk determinants is sufficient, but often not necessary for full TT. Knowing correlational risk determinants may also lead to full TT if the risk determinants jointly enable a perfect prediction of the state. The latter is becoming increasingly convenient thanks to advancements in Big Data and predictive analytics. In reality, scientific advancement is usually a gradual process, and the identification of correlational risk determinants often serves as a first step towards forming hypotheses about, and eventually finding

³We use a tilde sign to indicate a random variable, whereas the same variable without tilde stands for its realization.

⁴Our definition of risk determinant is in line with the use of the term in the insurance industry, which often relies on correlation instead of causation.

causal risk determinants. Therefore, TT often brings us closer to understanding the causation of risks and the mechanism of prevention.

The following example (simplified for an expositional purpose only) demonstrates the concepts of full TT, the state, and the threshold effort.

Example 1. An agent wants to reinforce her house to prevent it from being destroyed by a hurricane. By conducting experiments and simulations, researchers show that the success of the reinforcement effort depends solely on a measurable parameter characterizing the intensity of the hurricane. Each value of the parameter requires a minimum effort such that the house is kept safe.

In Example 1, full TT is obtained through identifying the (only) risk determinant and the mapping from its range to the state space. A higher reinforcement effort is more likely to succeed by exceeding the threshold efforts of more potential intensities of the hurricane. The following example illustrates the improvement of TT.

Example 2. The development of disease A depends on both the quality of one's lifestyle x and one's genetics. People start by realizing only the benefit of x expressed by the probability of developing A: $p(x)$. One day, scientific research shows that gene \tilde{y}_1 correlates with the onset of A. However, taken together, x and \tilde{y}_1 still do not completely explain the onset of A. Five years later, research further uncovers gene \tilde{y}_2 as another risk determinant. When taking x , \tilde{y}_1 and \tilde{y}_2 into account, the occurrence of disease A can now be perfectly predicted.

For simplicity, let us assume that both genes have two potential variants: $Y_1 = \{\alpha_1, \alpha_2\}$ and $Y_2 = \{\beta_1, \beta_2\}$. Then, full TT would reveal that there are altogether four possible states in this problem, and that each state may be mapped from a particular combination of genes: $\omega_1 = \lambda((\alpha_1, \beta_1))$, $\omega_2 = \lambda((\alpha_1, \beta_2))$, $\omega_3 = \lambda((\alpha_2, \beta_1))$, and $\omega_4 = \lambda((\alpha_2, \beta_2))$. However, in Example 2, TT is gradually obtained in two steps. When only \tilde{y}_1 is uncovered, we obtain the function λ_1 such that $\lambda_1(\alpha_1) = \{\omega_1, \omega_2\}$ and $\lambda_1(\alpha_2) = \{\omega_3, \omega_4\}$. $\lambda_1(\alpha_1)$ and $\lambda_1(\alpha_2)$ represent two different "risk types," but for each risk type, disease A is still jointly determined by x and "something else" that is unknown at this stage. It is only when \tilde{y}_2 is also uncovered that the success of x can be perfectly predicted.

The examples above also demonstrate two types of risk determinants: those that are observable before the agent chooses her effort, such as her genes, and those that are only observable after her decision has been made, such as the actual intensity of a hurricane. Depending the timing of the observability, TT may affect behavior through two distinct channels. We shall discuss these two channels separately in the next two sections.

3 | EX ANTE OBSERVABLE RISK DETERMINANTS

In this section, we analyze the behavioral and welfare consequences of TT assuming all risk determinants are observable before the choice of effort. We address ex ante unobservable risk determinants in Section 4.

First, let us review the concept of information partition introduced by Aumann (1976).⁵ Let \mathcal{P} denote an information partition: a partition of Ω into subsets containing subjectively indistinguishable elements. Mathematically, $\mathcal{P} : \Omega \rightarrow \mathcal{F}$ is a function that maps every $\omega \in \Omega$ into $\mathcal{P}(\omega) \subset \Omega$. If ω is the true state, then the agent regards all states within $\mathcal{P}(\omega)$ as possible and all states outside $\mathcal{P}(\omega)$ as impossible. The finer the information partition, the more capable the agent is of distinguishing between states and the closer she is to knowing the true state.

Corollary 2. *When risk determinants are ex ante observable,*

1. *full TT implies $\mathcal{P}(\omega) = \{\omega\}$ for all $\omega \in \Omega$;*
2. *an improvement of TT induced by \tilde{y}_i implies $\mathcal{P}(\omega) = \{\hat{\omega} \in \Omega \mid \lambda_i^{-1}(\hat{\omega}) \cdot \hat{e}_i = \lambda_i^{-1}(\omega) \cdot \hat{e}_i\}$, where \hat{e}_i denotes the column unit vector whose i th row equals 1.*

Together with ex ante observable risk determinants, full TT corresponds to the finest information partition where every element is a singleton, in other words, the ability to predict the exact true state. In the context of Example 2, when both genes \tilde{y}_1 and \tilde{y}_2 are uncovered and agents can conduct genetic tests to learn their genotype, the state space is partitioned into $\{\{\omega_1\}, \{\omega_2\}, \{\omega_3\}, \{\omega_4\}\}$. An agent whose test result is α_1 and β_1 , for example, thus identifies herself in state $\omega_1 = \lambda(\{\alpha_1, \beta_1\})$.

An improvement of TT, on the other hand, corresponds to further refining the information partition along the value of the newly uncovered risk determinant: states in the same partition element are those that share the same realization of that risk determinant. In Example 2, when only \tilde{y}_1 is shown to be a risk determinant and agents can take genetic tests, the state space is partitioned into $\{\{\omega_1, \omega_2\}, \{\omega_3, \omega_4\}\}$ and risk type α_1 (α_2) corresponds to the first (second) partition element. Hence, this refined information partition leads to an update of the states' probabilities.

Now bring effort x back to the picture. The improvement of TT results in—via updating the states' probabilities—also an update of how well the prevention technology works:

Definition 5. Let \mathcal{P}_y be the information partition after an improvement of TT induced by \tilde{y} and let ω be the true state. Given effort x , the *posterior loss probability* $p(x, y)$ is the loss probability conditional on the partition element $\mathcal{P}_y(\omega)$:

$$p(x, y) = \frac{\mu(\{\omega' \in \mathcal{P}_y(\omega) \mid l(\omega', x) = L\})}{\mu(\mathcal{P}_y(\omega))}. \quad (1)$$

Before the improvement of TT, the loss probability $p(x)$ may be seen as the average loss probability across all risk types in the population given effort x . The improvement of TT classifies the population into different risk types along the value of the risk determinant that induces it. For each risk type, the same prevention activity is represented by a different posterior loss probability.

3.1 | Full technological transparency

Let us now examine the behavioral and welfare implications of full TT given ex ante observable risk determinants.

⁵Information partition has also been applied to model financial literacy, see Neumuller and Rothschild (2017).

In the benchmark scenario, we have the classic self-protection problem where the agent optimizes her effort knowing nothing but $p(x)$. We assume x to be the amount of disutility induced by the self-protection effort.⁶ We also assume $p(x)$ to be twice differentiable and satisfy $p' < 0$ and $p'' > 0$. The choice of the optimal self-protection effort corresponds to the following optimization problem:

$$\max_x U(x) = [1 - p(x)]u(w) + p(x)u(w - L) - x, \quad (2)$$

the solution of which, denoted by x^0 , is determined by the first-order condition:

$$-p'(x^0)[u(w) - u(w - L)] = 1. \quad (3)$$

The left-hand side of Equation (3) represents the expected marginal benefit per unit of effort and the right-hand side represents the marginal cost. Define $\hat{x} = u(w) - u(w - L)$, which is the utility premium induced by the loss (M. Friedman & Savage, 1948). It is easy to see that \hat{x} corresponds to the highest effort the agent is willing to undertake to reduce the loss probability from 1 to 0. Hence, Equation (3) can also be written as follows:

$$p'(x^0) = -\frac{1}{\hat{x}}, \quad (4)$$

The second-order condition is fulfilled given the model assumptions.

Now assume there is full TT. How will this affect the agent's optimal effort?

Proposition 1. *Under full TT, when the risk determinants are observed ex ante, the optimal self-protection effort equals the threshold effort if the threshold effort does not exceed \hat{x} ; it equals zero otherwise. Moreover, full TT increases effort with probability $p(x^0) - p(\hat{x})$ and decreases effort with probability $1 - p(x^0) + p(\hat{x})$.*

The intuition underlying Proposition 1 is straightforward: Full TT reveals the true threshold effort before the agent makes her choice. Hence, whenever the loss is preventable at a reasonable cost, that is, a cost smaller than \hat{x} , she chooses to prevent the loss at the lowest possible cost.⁷ If the loss is unpreventable or only preventable at a prohibitive cost, she chooses not to exert any effort. Depending on the revealed threshold effort, full TT may either increase or decrease effort. In fact, full TT and the risk determinants collectively correspond to a conclusive information structure. Such an information structure fully removes risk from the decision problem by providing perfect information, which induces the most efficient decision (see Blackwell, 1951; Gollier, 2001).

We now turn to welfare. An important question to begin with is how $p(x)$ was estimated in the first place before the availability of TT. We assume $p(x)$ to be the unbiased estimation of

⁶Nonmonetary costs are particularly salient for disease prevention, where the effort often takes the form of lifestyle modification such as regular physical exercise, lower cigarette and/or alcohol consumption. Engaging in such activities are usually not associated with lower consumption. However, we acknowledge that monetary costs may be more suitable in other applications. In fact, the majority of our results are independent of the choice of monetary/non-monetary cost function, except in Propositions 4 and 5. We discuss the impact of adopting a monetary cost function for those results in Footnotes 14 and 15.

⁷We restrict ourselves to problems where the loss either does or does not occur exactly once.

expected loss probability in the population. This can be typically achieved by conducting randomized controlled trials (RCTs). After normalizing the number of individuals in the population to 1, we have the following propositions.

Proposition 2. *Full TT:*

1. *leads to a Pareto welfare improvement;*
2. *increases utilitarian social welfare by $\hat{x}p(x^0) + x^0 - \int_0^{\hat{x}} p(t)dt > 0$, out of which*
 - (a) *$\hat{x}p(x^0) - x^0p(\hat{x}) - \int_{x^0}^{\hat{x}} p(t)dt$ results from eliminating underprevention;*
 - (b) *$x^0 - \int_0^{x^0} p(t)dt$ results from reducing the cost of prevention;*
 - (c) *$p(\hat{x})x^0$ results from saving cost from losses that are unpreventable or too costly to prevent.⁸*

Obviously, (a), (b), and (c) are mutually exclusive and collectively comprehensive subsets of the population. Since individuals belonging to all categories become better off, full TT induces a Pareto improvement in welfare. While the number of deaths due to insufficient prevention is often used to emphasize the importance of promoting preventive healthcare (see for instance Danaei et al., 2009; Keeney, 2008), (b) suggests that this number may be reduced by TT.⁹ However, in addition to letting no more preventable losses occur, TT also generates value through saving costs that would otherwise be wasted.

The improvement of social welfare also has a straightforward graphical representation. It is illustrated by the overall area of the shaded regions in Figure 1, where the solid curve represents $p(x)$, the dashed line is the tangent line at x^0 that is parallel to the line connecting the points (0, 1) and $(\hat{x}, 0)$, indicating the fulfillment of Equation (4). In particular, A stands for the welfare gain from saving the cost of prevention, B_1 and B_2 jointly represent the benefit from eliminating underprevention, and C is the benefit from not wasting effort on losses that are unpreventable or too costly to prevent.¹⁰

The following corollary identifies a condition related to technological improvement (see Hoy & Polborn, 2015; Lee, 2015) that leads to a higher welfare improvement by full TT.

Corollary 3. *The welfare improvement by full TT increases when the self-protection technology improves from $p(x)$ to $q(x)$ such that $q(x) < p(x)$, $\forall x \neq x^0$, $q(x^0) = p(x^0)$ and $q'(x^0) = p'(x^0)$.*

As illustrated by Figure 2, whenever there is a global technological improvement such that the marginal productivity of effort is preserved at x^0 and the loss probability becomes lower for all efforts except x^0 , one can expect a larger welfare improvement by full TT. It is easy to see that such a technological improvement is equivalent to a deterioration of the threshold effort in

⁸We acknowledge that our interpretation of utilitarian social welfare makes it mathematically equivalent to an individual's ex ante expected utility before TT. This is in line with Harsanyi's utilitarian theorem (Harsanyi, 1953, 1955). This approach is not without controversy due to the ordinal nature of von Neumann-Morgenstern utility (see Sen, 1976 and Weymark, 2005 for a more recent documentation).

⁹see also Baillon, Bleichrodt, Emirmahmutoglu, Jaspersen, and Peter (2019) for a discussion of underprevention with probability weighting.

¹⁰An important assumption of this paper is the absence of externalities, that is, one agent's loss does not correlate with others'. Discussions on the prevention of interdependent risks can be found in Muermann and Kunreuther (2008), Hofmann and Rothschild (2019), and Kunreuther and Heal (2003).

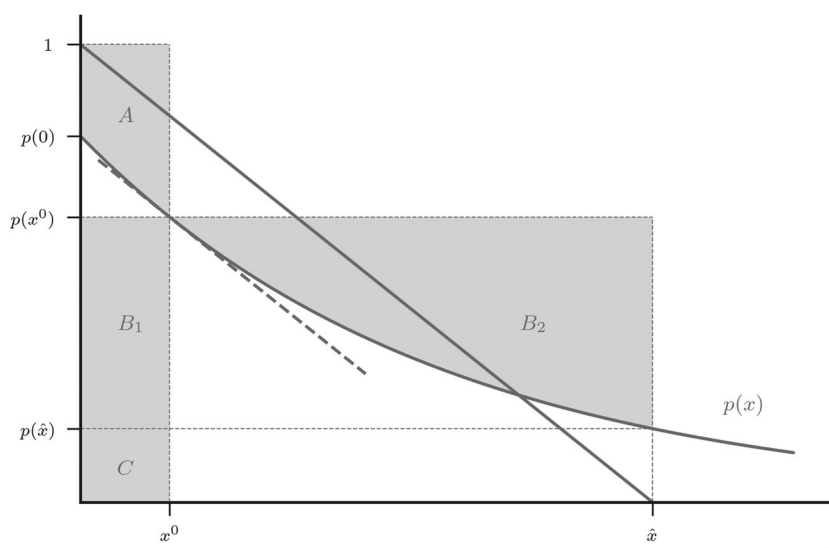


FIGURE 1 Full technological transparency improves utilitarian social welfare. x^0 is the optimal effort in the benchmark case. $\hat{x} = u(w) - u(w - L)$. The total area of the shaded regions equals the improvement of social welfare by full technological transparency. A stands for the welfare gain from reducing the cost of successful prevention. B_1 and B_2 jointly represent the benefit from eliminating underprevention. C is the benefit from not wasting effort on losses that are unpreventable or too costly to prevent.

the sense of first-order stochastic dominance (FSD). Interestingly, without TT, the technological improvement has neither behavioral nor welfare consequence. This is because the optimal effort in the benchmark case is determined solely by the local condition Equation (4), which completely ignores the improved outcome for every effort other than x^0 . However, full TT takes advantage of the deterioration of every potential realization of the threshold effort and enhances the value of the technological improvement by allowing the latter to be fully (globally) exploited.

3.2 | Insurable risks

We now extend the analysis to situations where the risk can be insured through private insurance markets. Hoy (1989) analyzes the welfare effect of increasing the precision of risk categorization for two given risk types under different insurance contracting possibilities. In a way, this section also extends Hoy (1989) to the extreme case where any risk type is fully decomposed into a combination of infinitely many degenerate risks.¹¹

Consider first the benchmark case without TT. The agent faces the joint decision of both her preventive effort x and the level of insurance. We assume a perfectly competitive market where the insurer earns zero expected profit and the premium is actuarially fair. Under symmetric

¹¹We assume TT to be publicly available, for example, through scientific publications. We also assume symmetric information and costless observation of the risk determinants. Related discussions that focus on asymmetric information can be found in for example, Doherty and Posey (1998), Hoy and Witt (2007), Bardey and De Donder (2013), Peter, Richter, and Steinorth (2016), and Peter, Richter, and Thistle (2017).

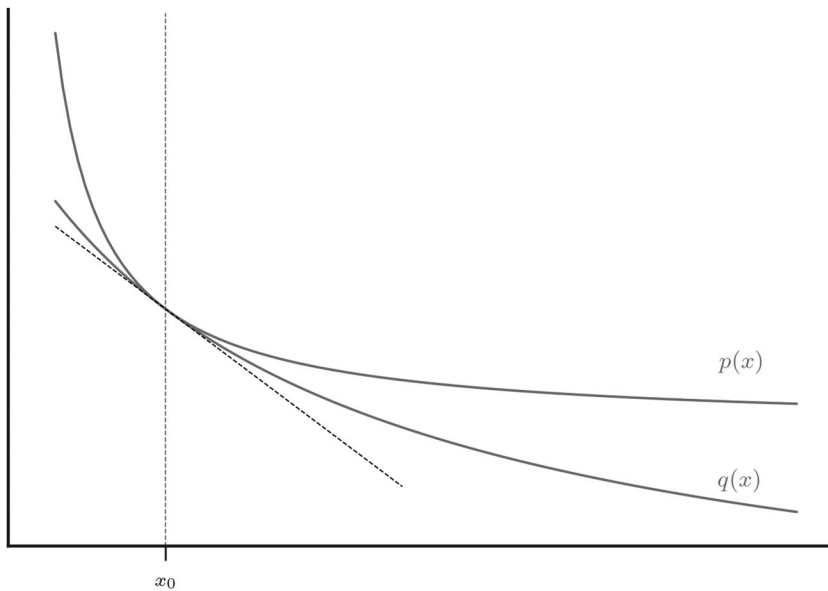


FIGURE 2 A technological improvement that increases the welfare improvement of full technological transparency

information, the insurer observes the level of prevention the agent undertakes and prices it into the insurance contract. Formally, let α stand for the level of coinsurance, that is, the agent receives αL from the insurer in case the loss occurs. The premium she pays equals the expected indemnity payment $p(x)\alpha L$, which decreases with her preventive effort. First of all, it is easy to see that the agent always opts for full insurance ($\alpha = 1$) conditional on any effort level since the elimination of the risk is available at fair cost. Her decision therefore reduces to a univariate optimization problem:

$$\max_x U(x) = u(w - p(x)L) - x.$$

As before, we let x^0 denote the optimal effort in the benchmark case, which satisfies the first-order condition

$$u'(w^0)p'(x^0)L = -1,$$

where $w^0 = w - p(x^0)L$.

Let us now switch to full TT, where the loss is solely determined by the agent's effort. In this case, the risk is no longer existent, which is why the insurance market for the risk also no longer exists.¹² Therefore, the level of insurance is always zero ($\alpha = 0$) and the optimal

¹²The fact that the insurance market no longer exists under full TT also holds under asymmetric information. Suppose only the policyholders themselves have access to the realizations of their risk determinants, as in the case where insurance companies are not allowed to access the genetic test results of their clients. As long as the insurer knows the fact that her clients can observe their own risk determinants, she loses the incentive to sell insurance, as the only clients that are still willing to buy insurance are those who will incur a sure loss.

effort is exactly as described in Proposition 1. If an agent finds out her threshold effort equals zero, she enjoys a loss-free world without having to exert any effort, which is obviously better than in the benchmark case where she has lower wealth due to paying the insurance premium and a positive expenditure on prevention, both of which turn out to be unnecessary. The case is similar if the threshold effort is positive but comparably low. At the other end of the spectrum, if the loss is unpreventable or too costly to prevent, then under full TT, the agent faces a sure loss without being able to do anything about it, whereas in the benchmark case, the loss still occurs but gets fully indemnified through insurance, which she purchased at a lower price than her actual risk type deserves. Obviously, the utility of such an “unlucky” agent is reduced by TT. Therefore, TT can no longer lead to a Pareto welfare improvement.

From the utilitarian perspective, TT introduces two effects. First, there is a distributional effect through unraveling the insurance market, which favors the “lucky” but harms the “unlucky” individuals, therefore exaggerating social disparity and harming social welfare. The distributional effect of TT also resonates with Hirshleifer (1971)’s well-known result on the social value of information when agents can trade state-contingent claims. At the same time, TT also makes prevention more efficient as discussed in Section 3.1, which in itself increases social welfare. Taken together, the overall net welfare effect of full TT depends on the tradeoff between the efficiency effect and the distributional effect.

Proposition 3. *When the risk is insurable, full TT*

1. *never leads to a Pareto welfare improvement;*
2. *may increase or decrease utilitarian social welfare. The net welfare effect of full TT equals $u(w) - u(w^0) + x^0 - \int_0^{\check{x}} p(t)dt$.*

The impact of full TT on utilitarian social welfare is illustrated by the difference between A and B in Figure 3, where $\check{x} = u(w) - u(w^0) + x^0$ represents an agent’s utility gain from full TT if her threshold effort equals 0. As the threshold effort gets larger, the utility gain reduces and eventually becomes negative. Another interpretation of \check{x} is the largest threshold effort for full TT to increase an agent’s utility. Agents whose threshold effort are below \check{x} benefit from full TT, whereas those whose threshold effort exceed \check{x} are made worse off by full TT. Obviously, the larger \check{x} gets, the larger (smaller) A (B) becomes and the more likely full TT will lead to an increase of social welfare.

3.3 | An improvement of technological transparency

In this section, we demonstrate that while the results in Section 3.1 qualitatively carry over to partial improvements of TT, they may be undermined or even reversed by the incomplete disclosure of information, which is in fact not uncommon in reality. We also relax the assumption of an unbiased $p(x)$ and examine the impact of biased prior beliefs on the value of improving TT.

Many risks are a result of highly complex interactions of a number of risk determinants. This is particularly true for complex diseases involving the interaction of genetic and lifestyle factors (see Willett, 2002, for instance). As a result, researchers are often still in the process of gradually improving TT. Consider an improvement of TT induced by the discovery of the risk

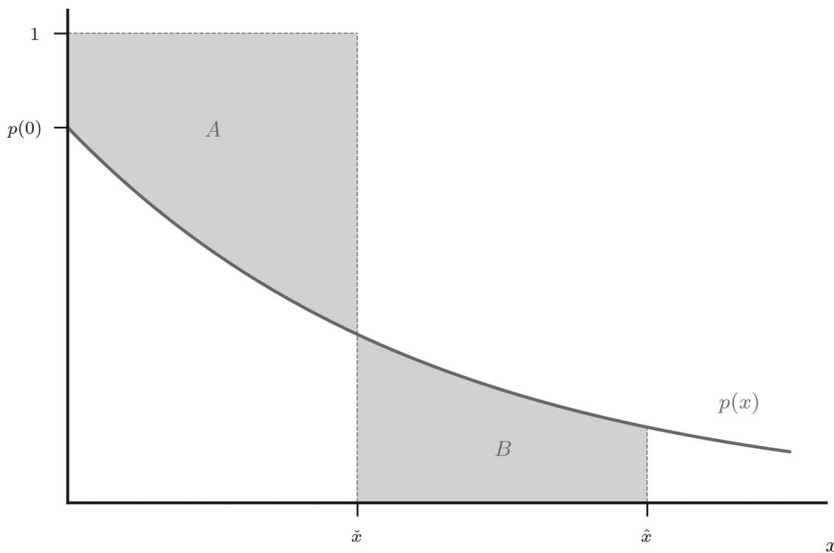


FIGURE 3 The impact of full technological transparency on utilitarian social welfare equals $A - B$ with availability of insurance before the acquisition of full technological transparency. $\hat{x} = u(w) - u(w - L)$. $\check{x} = u(w) - u(w - p(x^0)L) + x^0$.

determinant \tilde{y}_1 , which results in the posterior loss probability $p(x, y_1)$. We now compare this situation to the one before the improvement of TT, that is, when agents are aware of none of the risk determinants and only know $p(x)$.¹³

Assume $p_1(x, y_1) < 0$, $p_{11}(x, y_1) > 0$, $y_1 \in [\underline{y}_1, \bar{y}_1]$, and $\delta(x) = p(x, y_1) - p(x, y'_1) > 0$ whenever $y'_1 > y_1$ so that a larger y_1 corresponds to a smaller revealed risk level. Following the terminology of Hoy (1989), we call $\delta(x)$ the difference function with respect to the risk determinant \tilde{y}_1 . Although we do not impose monotonicity on $\delta(x)$, in cases where $\delta'(x)$ does have a consistent sign, we may obtain some interesting unambiguous comparative statics. We follow Hoy (1989) and make the following distinction:

Definition 6. The self-protection technology has:

1. increasing difference (ID) with respect to \tilde{y}_1 if $\delta'(x) > 0$;
2. constant difference (CD) with respect to \tilde{y}_1 if $\delta'(x) = 0$;
3. decreasing difference (DD) with respect to \tilde{y}_1 if $\delta'(x) < 0$;

Definition 6 characterizes the relationship between the productivity of the effort and the revealed risk type. In particular, ID (DD) means the effort is more effective when the risk is high (low), whereas CD means the effectiveness is independent of the risk type. Note that the property of our difference function is specific to the revealed risk determinant \tilde{y}_1 : if a technology has DD with respect to \tilde{y}_1 , it may still have ID, CD or a nonmonotonic difference function with respect to other risk determinants. In their study of the impact of genetic tests when individuals

¹³We study the generic case where an improvement of TT is induced by uncovering one additional risk determinant, but the generality of our model allows the results to be easily extended to an improvement of TT induced by uncovering multiple risk determinants.

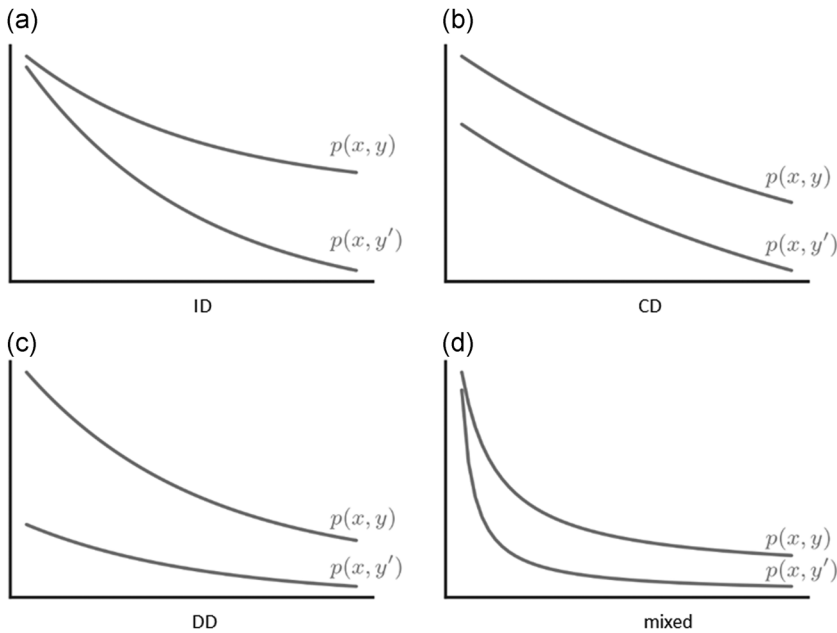


FIGURE 4 Properties of the difference function $\delta(x) = p(x, y_1) - p(x, y_1')$ where $y_1 \leq y_1' \leq \bar{y}_1$. (a), (b), and (c) represent ID, CD, and DD, respectively. (d) stands for a mixed case with ID for small x 's and DD for large x 's. CC, constant difference; DD, decreasing difference; ID, increasing difference

can both purchase insurance and prevent the loss, Bardey and De Donder (2013) assume the genetic test reveals two different posterior loss probabilities. Their model is restricted to DD.

Figure 4 illustrates properties of $\delta(x)$.

When there is no knowledge about risk determinants, $p(x)$ is commonly obtained through experience. Experience, however, may be strongly subject to bias. The next definition addresses the potentially biased estimation of the prior loss probability $p(x)$. Suppose \tilde{y}_1 is distributed in the population with the cumulative distribution function $G(\cdot)$. Then,

Definition 7. $p(x)$ is said to be unbiased if $p(x) = \int_{\underline{y}_1}^{\bar{y}_1} p(x, y_1) dG(y_1)$.

In other words, for each x , the unbiased loss probability must correspond to the population average of the posterior loss probabilities. A common reason for its violation is the so-called selection bias (Allcott, 2015; Cleave, Nikiforakis, & Slonim, 2013; Harrison & List, 2004), that is, the sample used in the estimation of $p(x)$, either via RCTs or through the experience of some individuals, is not representative of the entire population. Selection bias may occur, for instance, because participants of RCTs can only be recruited via certain channels such as universities or local clinics, because some groups of participants are more likely than others to self-select into the studies, or because of the deliberate exclusion of certain population groups (such as women in their pregnancy) due to ethical or liability concerns (Shields & Lysterly, 2013).

Proposition 4. Consider an improvement of TT induced by the risk determinant \tilde{y}_1 . Let $x(y_1)$ denote the optimal effort conditional on y_1 being the realization of \tilde{y}_1 . It holds that:

1. $x(y_1)$ increases (decreases) with y_1 if the technology has ID (DD) with respect to \tilde{y}_1 .¹⁴
2. $x(y_1) \equiv x^0$ if the technology has CD with respect to \tilde{y}_1 .

Furthermore, the improvement of TT:

- (a) leads to a Pareto welfare improvement if the technology has ID or DD with respect to \tilde{y}_1 , but improves welfare no more than full TT does.
- (b) does not affect welfare if the technology has CD with respect to \tilde{y}_1 ;
- (c) leads to higher welfare improvement when the estimation of $p(x)$ is subject to selection bias than when it is not.

The first part of Proposition 4 focuses on the behavioral impact of an improvement of TT and is consistent with Hoy's result with two risk types. As a direct consequence of Equation (4), it depends on the interaction between the revealed risk type and the effectiveness of prevention. The optimal effort always balances the marginal cost and the marginal benefit. Since the former is constant, the relationship between the optimal effort and the revealed risk type is entirely determined by how the marginal productivity interacts with y_1 , which is governed by exactly the difference function. Under DD, a worse revealed risk, or a lower y_1 , means higher marginal benefit, which leads to an increase of effort, whereas the opposite is true under ID. In disease prevention where \tilde{y}_1 is an individual's genetic makeup, evidence shows that a higher effort often attenuates the influence of genes, suggesting DD is more likely to apply (see Graff et al., 2017; L. Qi et al., 2008, 2012, for instance). In this case, individuals with high-risk genes are expected to exert higher effort after learning their risk profile through a genetic test.

The second part of Proposition 4 addresses the welfare impact of an improvement of TT. An improvement of TT is equivalent to an imperfect signal that is less informative than full TT, but still serves to improve the quality of decision-making and therefore increases social welfare, although to a lesser extent than full TT does. In particular, welfare is only improved if observing the signal changes one's optimal action, which is true for ID and DD, but not for CD.

Moreover, the more biased the prior knowledge $p(x)$, the more value the improvement of TT generates. A biased prior leads to a suboptimal choice of effort in the benchmark case since it yields an incorrect estimation of the marginal benefit. If the sample is biased towards better risks, the estimated marginal benefit is also closer to that of the better risks. Under DD, this means a smaller marginal benefit and hence a benchmark effort that is too low. However, since the selection bias does not affect welfare after the improvement of TT, the latter must lead to higher welfare improvement than without the selection bias. Proposition 4 suggests that whenever ill-informed decision making exists due to selection bias, the suboptimal choice can be corrected by an improvement of TT. This is particularly meaningful for situations where the cost for improving TT is lower than the cost of eliminating selection bias.

An important implication of Proposition 4 is that knowledge about a new risk determinant, such as the result of a genetic test, will not necessarily improve the quality of one's decision if the test result is not communicated along with knowledge about the gene-effort interaction. This is summarized by the following Corollary.

¹⁴The relationship between $x(y_1)$ and y_1 when the technology exhibits DD is slightly modified when a monetary cost function is assumed to incorporate the effect of risk aversion, see Li and Peter (2019).

Corollary 4. *An improvement of TT induced by the risk determinant \tilde{y}_1 may reduce welfare if properties of the difference function are undisclosed or misperceived.*

Many personal genetic testing services charge extra money for revealing individuals' health risk profile, for example, by reporting whether the tested individual possesses genetic variants that increase the risk of certain types of diseases. However, these test results say nothing about how the revealed genetic variants affect the marginal productivity of preventive effort. Suppose DD is true, meaning that high risks should exert more effort after obtaining their test result. However, if people do not also know that DD applies to the revealed genes, they might mistakenly perceive ID to be the case and reduce their effort instead if they see themselves as being "too unfortunate to benefit from anything." The latter is particularly relevant if the cost of effort is high, such as when fast food becomes increasingly cheap to produce and easy to access.

As the incomplete disclosure of improved knowledge creates leeway for biased beliefs to form, people may feel as if they were learning more about themselves, but end up making worse choices, which we refer to as a harmful "illusion of knowledge." Hollands et al. (2016) show that revealing DNA-based risk estimates through personal genetic tests does not lead to significant behavioral change. We argue that this none-finding may be partly explained by incomplete disclosure of information. As argued by L. Qi et al. (2008), medical research on the gene–lifestyle interaction in disease prevention is scarce compared to those targeting genes or lifestyle in isolation. Corollary 4 shows that studying the interaction as well as communicating these findings to the public has crucial importance in turning research findings into real value.

4 | EX POST OBSERVABLE RISK DETERMINANTS

We now turn to situations where the risk determinants are ex ante unobservable. Such situations are very common. For instance, one only knows the exact intensity of the next earthquake after the earthquake occurs. In the penalty kick of a soccer game, the goalkeeper only realizes his opponent's strategy at the end of the kick.

When risk determinants are only observable ex post, TT no longer affects a rational, forward-looking agent's choice since it neither removes nor signals the risk ex ante. However, we argue that by revealing the threshold effort, full TT may trigger ex post regret as the agent observes the outcome and realizes what she "should have done" in the past. Regret, if anticipated and incorporated into the decision-making ex ante, serves as a second, indirect channel for TT to affect behavior.

Ample evidence shows people are not always forward looking as assumed by classic decision theories. Regret is a concept well documented by psychologists since more than a century ago (see Zeelenberg & Pieters, 2007, for a survey). Regret theory, which is initially discussed in the economic literature by Loomes and Sugden (1982) and Bell (1982) (see also Bleichrodt & Wakker, 2015, for a recent review), assumes people experience disutility from realizing having made a suboptimal choice (see Bleichrodt, Cillo, & Diecidue, 2010; Camille et al., 2004; Loomes & Sugden, 1987, for empirical supports for regret theory). While the original form of regret theory is restricted to binary choice sets, Sugden (1993) and Quiggin (1994) generalize the theory to arbitrary choice sets based on a set of axioms. More recently, regret theory has been applied to various economic decisions including insurance demand

(Braun & Muermann, 2004), the equilibria of the insurance market (Huang, Muermann, & Tzeng, 2016), auctions (Engelbrecht-Wiggans, 1989; Engelbrecht-Wiggans & Katok, 2008) and portfolio choice (Muermann & Volkman Wise, 2006; Muermann, Mitchell, & Volkman, 2006) and is shown to explain observed deviations from predictions of the expected utility theory including the Allais paradox, preference for low deductible insurance contracts and the disposition effect.

Since the self-protection problem has a continuous choice set, we follow Braun and Muermann (2004) and adopt the approach of regret theoretical expected utility (RTEU) as the basis of our analysis. The RTEU approach features an arbitrary choice set and is consistent with both Sugden (1993)'s axiomatic approach and Quiggin (1994)'s Irrelevance of Statewise Dominated Alternatives (ISDA) assumption. It assumes regret is expressed as a function of the difference between the utility that would be obtained from the foregone optimal decision and the utility obtained from the actual decision:

$$\psi(x, s) = \phi(x, s) - k \cdot g[\phi(x^{opt}(s), s) - \phi(x, s)], \quad (5)$$

where x is the choice variable, s is the realization of the random state variable, ϕ is the classic Bernoulli utility function of the choice and the state (also referred to as choiceless utility), $x^{opt}(s)$ is the foregone optimal action given the realized state s , g with $g > 0$, $g' > 0$, $g'' > 0$ and $g(0) = 0$ represents regret, and $k \geq 0$ stands for the intensity of regret aversion. Hence, the decision problem is written as follows:

$$\max_x \mathbb{E}\psi(x, s) = \mathbb{E}\{\phi(x, s) - k \cdot g[\phi(x^{opt}(s), s) - \phi(x, s)]\}, \quad (6)$$

Notably, without TT and the state-dependent self-protection model, the concept of regret seems almost incompatible with the self-protection problem: the agent would never be able to find out the foregone optimal decision since the states within the loss (no loss) event are not distinguishable from each other. However, x^{opt} is revealed if full TT is available in combination with the ex post observation of the risk determinants. Consider again Example 1 on the prevention for hurricane disasters. Suppose there is full TT, that is, the decision-maker knows the threshold effort given each potential intensity of the hurricane as well as the probability distribution of the intensity. Based on this information, she chooses effort x^0 that protects her house from a hurricane up to y_1^0 : the intensity whose threshold effort coincides with x^0 . In addition, she anticipates four potential future scenarios: (a) The hurricane is weaker than y_1^0 , her house remains safe, but she would have obtained the exact same outcome had she put in less effort. (b) The hurricane has exactly the intensity y_1^0 and her house remains safe. (c) The hurricane is stronger than y_1^0 and destroys her house, but she would have avoided the loss had she chosen a higher effort. (d) The hurricane is so strong that it cannot be prevented at any reasonable cost. Whichever scenario occurs, the agent will realize in hindsight what she should have done, which, except for in the second scenario, differs from what she actually did and therefore generates regret. If the ex post regret is anticipated ex ante, it will in turn affect the optimal effort since the agent wants to additionally mitigate the expected amount of regret. Formally, the scenarios above are summarized by the following objective function:

$$\begin{aligned}
\max_x V(x) = & F(0)[u(w) - x - k \cdot g(x - 0)] + \int_0^x [u(w) - x - k \cdot g(x - t)]f(t)dt \\
& + \int_x^{\hat{x}} [u(w - L) - x - k \cdot g(u(w) - u(w - L) + x - t)]f(t)dt \\
& + \int_{\hat{x}}^{\infty} [u(w - L) - x - k \cdot g(x - 0)]f(t)dt,
\end{aligned} \tag{7}$$

The first line of Equation (7) is the RTEU of situations where the actual effort exceeds the threshold effort, no loss occurs and the decision-maker regrets spending too much effort. Note that the first line is decomposed into two parts due to the discontinuous distribution of the threshold effort at 0. The second line stands for when the actual effort is lower than the threshold effort, the loss occurs and the agent regrets spending too little effort. The third line is when the loss is impossible to prevent at reasonable cost and the decision-maker regrets spending any effort at all. Note that if we eliminate g from Equation (7), it collapses to the original decision problem in our benchmark case described by Equation (2). The optimal effort of a regret-averse decision-maker x^r is therefore determined by the first-order condition of Equation (7), which is obtained by applying the Leibniz rule:

$$\begin{aligned}
V'(x^r) = & f(x^r)\hat{x} + f(x^r)kg(\hat{x}) - \int_0^{x^r} kg'(x^r - t)f(t)dt - \int_{x^r}^{\hat{x}} kg'(\hat{x} + x^r - t)f(t)dt \\
& - [1 - F(x^r)]kg'(x^r) - F(0)kg'(x^r) - 1 = 0.
\end{aligned} \tag{8}$$

By evaluating the sign of $V'(x^0)$, we can compare the optimal effort of a regret-averse decision-maker with that of an expected utility maximizer.

Proposition 5. *With full TT and ex post observable risk determinants, the demand for self-protection increases with regret aversion.¹⁵*

Generally speaking, an increase of effort is always associated with two types of marginal benefits and two types of marginal costs. On the one hand, since the loss probability becomes further reduced, the decision-maker is both more likely to obtain higher wealth and less likely to regret letting a loss occur that she could have prevented. On the other hand, the effort itself costs more and the amount of regret increases due to the higher sunk cost. Taken together, when evaluated at x^0 , the net effect of higher effort is positive because the strongest regret comes from realizing having spent too little effort, and the convexity of g makes the agent disproportionately averse to large regrets. Hence, anticipating future regret makes the agent willing to undertake more self-protection ex ante. TT plays an essential role in this process by revealing the threshold effort, which is the crucial reference point without which a regret-averse agent would not be able to objectively attribute the observed event to internal (her effort) or external (the realizations of the risk determinants) causes.

An interesting related question is how a regret-averse agent would behave when TT is unavailable or only partially improved. In both cases, we have a situation with unknown counterfactuals, in which case it becomes less obvious how regret should be incorporated into the decision-making process. One possible answer to this question is regret is irrelevant whenever the foregone optimal action cannot be perfectly predicted, as

¹⁵If the cost is monetary, then generally, the effect of regret aversion needs to be weighted against the effect of risk aversion. Our result continues to hold if the agent is risk neutral or if the loss probability is sufficiently low.

commonly adopted in the auction literature, which assumes regret to be triggered exactly by the revelation of the foregone optimal action (see Engelbrecht-Wiggans & Katok, 2008, for instance).

Another answer to this question would require the agent to perform an ex post Bayesian update of the distribution of her threshold effort, and then experience the conditional expected regret. One can show that such an assumption is in fact behaviorally equivalent to full TT. Consider a partial improvement of TT which leads to two different risk types. Ex ante, the agent knows her probability of belonging to either risk type. Upon the (non-)occurrence of the loss, the agent learns her risk type, but still does not know her exact threshold effort. Together, there would be four potential combinations of risk type and loss: {high risk, low risk} \times {loss, no loss}. In each combination, she has a posterior loss probability function, which she can use to update the distribution of her threshold effort conditional on the (non-)occurrence of the loss. Such an update would tell her how much to regret “on average.” Ex ante, if the four expected amounts of regret are weighted by the probabilities of the corresponding combinations of risk type and loss, Bayesian update implies that the agent’s objective function looks exactly the same as when full TT were available.

We believe both answers above represent extreme considerations. While the idea behind the first approach may seem intuitively appealing, it is incapable of capturing the effect of gradual information acquisition, which is how TT becomes available in most cases. The second approach is applicable to partial improvements of TT, but demands an arguably excessive cognitive load (One must objectively expect what one will objectively expect in the future under different scenarios, and then incorporate them all to make the decision). To reconcile the conflict between both approaches, we propose that instead of prescribing any specific decision-making rule for cases with unknown counterfactuals¹⁶, improving TT can be interpreted as simply increasing k , that is, magnifying the intensity of regret. The closer to perfectly knowing the threshold effort, the more salient regret becomes.

Another reason for us not to prescribe any normative rules for regret with unknown counterfactuals is the widespread documentation of counterfactual thinking in behavioral science. Phenomena such as hindsight bias (Christensen-Szalanski & Willham, 1991), outcome bias (Baron & Hershey, 1988), or different attributional styles (Abramson, Seligman, & Teasdale, 1978) all suggest there is an innate tendency for people to subjectively assign reasons to past events even when they do not possess adequate information to do so. Therefore, the way regret spells out with unknown counterfactuals may also be affected by contextual and behavioral factors. For instance, the amount of regret may be much higher for an extremely pessimistic agent who always attributes failures to herself and successes to luck than an extremely optimistic agent who believes in the exact opposite. Incorporating biased beliefs into the analysis also requires understanding whether a decision-maker subject to biased beliefs can foresee the bias ex ante (see the similar distinction between naïve and sophisticated present bias and self control in Ali, 2011; O'Donoghue & Rabin, 1999). We leave these questions to future research but believe our analysis serves as a benchmark against which the consequences of biased beliefs may be evaluated.

¹⁶Bell (1983) analyzed regret with unknown consequence of the foregone action when the choice set is binary, where he discusses a potential willingness to pay to avoid resolving the outcome of the alternative action. More recently, Gabillon (2018) extends the discussion to an arbitrary choice set. Both discussions are based on preassumed normative conditions on the decision-maker's preference.

5 | ENDOGENOUS RISK DETERMINANTS

So far, we have assumed risk determinants to be exogenous, that is, their values are beyond the agent's control. In this section, we extend our framework by considering the discovery of risk determinants that the agent can manipulate.

As knowledge advances, it is not uncommon for new measures of risk mitigation to be identified. Smoking, for instance, had not been considered detrimental to people's health until the middle of the 20th century. Currently, its negative health effects are so widely recognized that it is among the very few factors allowed to be used in the pricing of health insurance policies (A. S. Friedman, Schpero, & Busch, 2016). In a more recent example, researchers have identified *porphyromonas gingivalis*—a bacterium that causes periodontal disease—as a potential cause of Alzheimer's disease (Dominy et al., 2019). Since this finding, maintaining good oral hygiene has been recommended to reduce the risk of Alzheimer's disease in addition to preventive activities that are previously known, such as adequate physical and intellectual exercise.

Obviously, endogenous risk determinants are *ex ante* observable, as they themselves are also prevention technologies. Once they are identified, the agent faces a multivariate decision problem. We shall demonstrate that while such a problem shares certain properties in common with our discussion on exogenous risk determinants in Section 3.3, its multidimensional nature generates additional features that may be worthy of practical attention. In addition, motivated by the observation that the efficacy of different prevention technologies are often disclosed separately in reality, we also discuss the potential danger of ignoring the interaction between prevention technologies.

Consider the discovery of an endogenous risk determinant $x_1 \in [0, \infty)$. For generality, we assume x and x_1 do not perfectly explain the occurrence of the loss. Let $p(x, x_1)$ be the posterior loss probability. Assume $p_1(x, x_1) < 0$, $p_{11}(x, x_1) > 0$, $p_2(x, x_1) < 0$, and $p_{22}(x, x_1) > 0$. We first establish the counterpart of Definition 6 for the case of an endogenous risk determinant.

Definition 8. Prevention is called supermodular (submodular, modular) with respect to technologies x and x_1 if the function $-p(x, x_1)$ is supermodular (submodular, modular), that is, if $p_{12}(x, x_1) \leq (\geq, =) 0$

Definition 8 is adopted from Hofmann and Peter (2015). It characterizes the relationship between different types of prevention technologies. Supermodularity means that an increased use of one technology not only reduces the loss probability, but also reinforces the effectiveness of the other technology. It is the counterpart of ID/CD in the exogenous risk determinant case except that the agent can now choose the value of the new risk determinant. The opposite is true for submodularity and DD/CD. Under modularity, the effectiveness of efforts is independent of each other, which corresponds to CD. The decision problem after the improvement of TT becomes:

$$\max_{x, x_1} U(x, x_1) = [1 - p(x, x_1)]u(w) + p(x, x_1)u(w - L) - x - x_1. \quad (9)$$

Its solution (x^*, x_1^*) satisfies the first-order conditions

$$p_1(x^*, x_1^*) = -\frac{1}{\hat{x}}; \quad (10)$$

$$p_2(x^*, x_1^*) = -\frac{1}{\hat{x}}. \quad (11)$$

As before, we assume that before x_1 is identified as a risk determinant, $p(x)$ was estimated empirically via RCTs. Although unknown to the researchers at that time, $p(x)$ is actually shaped by x_1 in two ways. First, it is affected by the way x_1 influences the loss probability. If every subject in the RCT sample turns out to have chosen the same $x_1 = x_1^0$ during the study period, then $p(x)$ is simply equal to $p(x, x_1^0)$. Second, $p(x)$ is also affected by the distribution of x_1 in the RCT sample. Suppose subjects chose different levels of x_1 during the study period, and that their chosen x_1 follow the cumulative distribution function $H(\cdot)$. Then, $p(x)$ is essentially the weighted average of $p(x, x_1)$ according to this distribution:

$$p(x) = \int_0^\infty p(x, x_1) dH(x_1). \quad (12)$$

Essentially, $H(\cdot)$ describes people's status-quo choice of x_1 without knowing x_1 being a risk determinant. We argue the shape of $H(\cdot)$ is largely context-dependent. In an extreme case where x_1 is a newly invented vaccine that did not even exist when $p(x)$ was estimated, it is reasonable to assume $x_1 \equiv 0$. In the example of oral hygiene and Alzheimer's disease mentioned at the beginning of this section, it is more realistic to treat x_1 as random. $H(\cdot)$ influences the benchmark optimal effort x^0 through shaping people's knowledge about the effectiveness of x . Therefore, it also determines the behavioral impact of the improvement of TT. As we show in the next proposition, this impact heavily depends on the interaction between the technologies.

Proposition 6. *Consider an improvement of TT induced by the endogenous risk determinant x_1 . Then:*

- (a) *The improvement of TT always leads to a Pareto improvement in welfare as well as an increase of utilitarian social welfare.*
- (b) *If prevention is supermodular (submodular) with respect to x and x_1 , $x^* - x^0$ is non-increasing (nondecreasing) as $H(\cdot)$ undergoes an FSD improvement.*
- (c) *If prevention is modular with respect to x and x_1 , $x^* = x^0$ independently of $H(\cdot)$.*

Similar to the case with exogenous risk determinants, the endogenous risk determinant also alters the demand for x through affecting the marginal productivity of x . The difference between Proposition 6 and 4 lies in the second dimension of the decision problem. In addition to balancing the marginal cost and marginal benefit of x , the agent now has the freedom to do the same for x_1 . This explains why an improvement of TT through endogenous risk determinants *always* leads to a Pareto improvement of welfare even when the marginal productivity of x is independent of x_1 .

In particular, when the distribution of x_1 in the RCT sample is “good” in the first-order sense (for instance, in regions with high awareness of oral hygiene and easy access to dental care), a steeper $p(x)$ would be estimated in case of supermodularity, which makes the change from x^0 to x^* , that is, the behavioral impact of improving TT, lower and also more likely to be negative.

Since x and x_1 enhance the productivity of each other, their demand also reinforce each other. This observation is in line with the well-known connection between supermodularity and complementarity. The opposite holds under submodularity.

As revealed by Proposition 6, whether prevention is super- or submodular plays a crucial role in determining the demand relationship between x and x_1 . What if this crucial aspect is ignored in the disclosure of knowledge? Said differently, what if the efficacy of x and x_1 are disclosed independently from each another? In this case, a harmful illusion of knowledge may arise. To see this, consider two groups of researchers who simultaneously and independently study the prevention of the same risk, but Group A focuses exclusively on x , whereas Group B focuses solely on x_1 . The two groups disclose their findings as two separate functions $p(x)$ and $q(x_1)$. Suppose our agent who used to know $p(x)$ newly learns about $q(x_1)$, and uses it to guide her choice of x_1 . While it may seem that she is carefully following the guidance of scientific findings, the independent disclosure of $p(x)$ and $q(x_1)$ completely ignores the interaction between the two technologies. As this crucial piece of information is not conveyed to the agent, learning $q(x_1)$ may in fact make her worse off. This is summarized by the next corollary.

Corollary 5. *An improvement of TT induced by the endogenous risk determinant x_1 may reduce welfare if the effectiveness of x_1 is disclosed independently of x .*

As noted before, $p(x)$ is affected by $H(\cdot)$: the distribution of x_1 in Group A's RCT sample, whereas $q(x_1)$ is affected by $J(\cdot)$: the distribution of x in Group B's RCT sample. Having learned $q(x_1)$, the agent may feel as if she acquired new information and chooses her demand for x_1 accordingly while keeping her x^0 guided by $p(x)$. However, only when prevention is modular will she become surely better off by doing so. If prevention is strictly supermodular or strictly submodular, choosing x_1 according to $q(x_1)$ may be harmful if $J(\cdot)$ is very different from x_0 . Hence, similar to Corollary 4, when technological interactions are ignored, the positive value of knowledge may be undermined despite the agent appearing to make two separate informed choices.

Finally, our framework allows us to flesh out the fundamental nature of the interaction between technologies through the dimension of the underlying state space. As Hofmann and Peter (2015) points out, supermodularity (submodularity) is associated with a complementary (substitutable) relationship between the optimal demand for different prevention technologies. We shall demonstrate that this relationship is not only reflected by demand, but also has a deeper underpinning.

To do this, let us first extend the definition of the threshold effort $t(\omega)$ in Corollary 1 to incorporate the high dimensionality caused by endogenous risk determinants.

Definition 9. In multivariate self-protection with technologies x, x_1, \dots, x_m , the *threshold effort* is a T -dimensional random variable $t(\omega) = (t_1(\omega), \dots, t_T(\omega))$ satisfying $l(\omega, x, x_1, \dots, x_m) = L \cdot \mathbb{I}\{\tau_i(x, x_1, \dots, x_m) < t_i(\omega), \forall i \in \{1, \dots, T\}\}$, where $T \leq m + 1$ is a positive integer, $\tau_i(\cdot)$'s are functions that are nondecreasing in each argument.

Definition 10. In multivariate prevention, technologies are said to be

- (a) perfect complements if $T = m + 1$, $\tau_1(x, x_1, \dots, x_m) = x$, $\tau_{i+1}(x, x_1, \dots, x_m) = \gamma_i x_i$, where γ_i 's are a positive constants for all $i \in \{1, \dots, T\}$.
- (b) perfect substitutes if $T = 1$ and $\tau_1(x, x_1, \dots, x_m) = x + \sum_{i=1}^m \gamma_i x_i$, where γ_i 's are positive constants for all $i \in \{1, \dots, m\}$.

Definition 10 describes two distinct ways for different prevention technologies to jointly influence the risk. It is illustrated by the following two examples.

Example 3. When oral hygiene was identified as a new effort to prevent Alzheimer's disease, researchers also found that Alzheimer's disease is likely to be the common endpoint of multiple causal pathways: while good oral hygiene serves to block one of the pathways, successful prevention still requires the rest of the pathways to be blocked by other types of efforts such as sufficient intellectual exercise and social activities. In other words, different technologies complement each other in preventing Alzheimer's disease.

Under full TT, perfect complementarity between technologies is represented by a $(m + 1)$ -dimensional threshold effort, each dimension corresponding to one particular technology. Under perfect complementarity, *all* efforts have to exceed their corresponding thresholds to successfully prevent the loss, and the threshold effort has its largest possible number of dimensions.

Example 4. Consider the health benefits of engaging in physical exercise and healthy diet. Evidence suggests that both types of efforts largely operate through common biological pathways (see Vuori, 2001), indicating a substitutable relationship.

Under full TT, perfect inter-technological substitutability is represented by a unidimensional threshold effort. As long as this threshold is exceeded by a linear combination of all efforts, the loss is successfully prevented.

The dimension of the threshold effort indicates the number of parallel pathways leading to the risk. A larger T means the coexistence of more pathways so that successful prevention requires many efforts to be individually adequate. When T is between 1 and $m + 1$, there exists pathways specific for individual efforts as well as pathways through which multiple efforts operate. Therefore, T indicates the degree of inter-technological complementarity.

Proposition 7. *It holds that*

- (a) *prevention is supermodular with respect to any pair of technologies if technologies are perfect complements;*
- (b) *prevention is submodular with respect to any pair of technologies if technologies are perfect substitutes.*

Figure 5 illustrates Proposition 7 with two examples where x and x_1 are the only two technologies ($m = 1$). In (a), we assume the loss occurs unless both x and x_1 exceed one common threshold. Mathematically, this corresponds to $T = 2$, $\tau_1(x, x_1) = x$, $\tau_2(x, x_1) = x_1$ and $t_1(\omega) = t_2(\omega)$ follow the same cumulative distribution function $F(\cdot)$. In this case, we have $p(x, x_1) = 1 - F(\min(x, x_1))$. As can be seen from the graph, the contour lines of $p(x, x_1)$ are parallel either to the x or to the x_1 axis and make a 90-degree turn at the 45-degree diagonal—a shape that clearly reflects perfect complementarity. In (b), the loss is prevented as long as the sum of x and x_1 exceeds the threshold, so $T = 1$, $\tau_1(x, x_1) = x + x_1$ and $p(x, x_1) = 1 - F(x + x_1)$. The contour lines are perpendicular to the 45-degree diagonal, indicating perfect substitution.

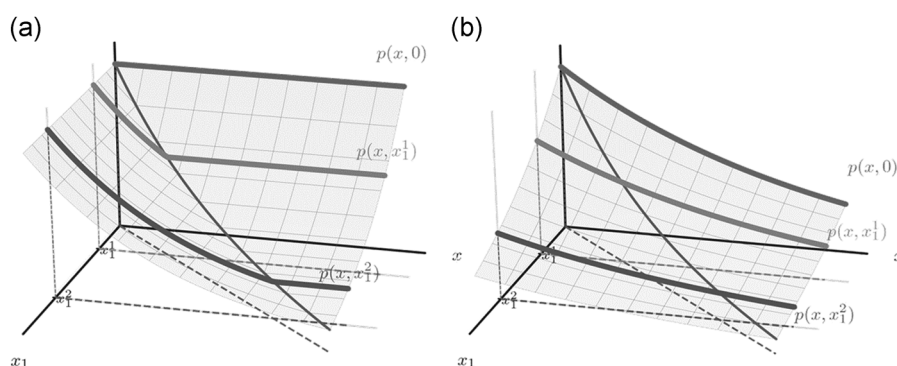


FIGURE 5 Loss probability as a function of two action variables. (a) perfect complements: $p(x, x_1) = 1 - F(\min(x, x_1))$. (b) perfect substitutes: $p(x, x_1) = 1 - F(x + x_1)$

Proposition 7 also implies that the super- or submodularity of prevention contains useful information that may guide future research towards further uncovering the mechanism of prevention. Whenever supermodularity is observed, it suggests efforts may operate through parallel pathways and successful prevention may require each effort to be high enough. In case of submodularity, efforts are likely to operate through common channels and prevention may succeed as long as efforts are adequate in the aggregate.

6 | CONCLUSION

In this article, we propose the concept of TT by explicitly interpreting the outcome of utilizing self-protection technologies as being jointly determined by underlying risk determinants. TT allows one to predict the success of prevention by revealing the risk determinants together with the mapping from their ranges to the underlying state space.

When risk determinants are ex ante observable, full TT corresponds to the acquisition of perfect information and induces the most efficient use of the prevention technology. In addition, full TT may enhance the value of technological improvements by allowing the latter to be fully (globally) exploited. However, for an insurable risk, although full TT increases the efficiency of prevention, it also completely unravels the insurance market. This introduces a negative distributional effect due to the exaggeration of social disparity.

A marginal improvement of TT also increases the efficiency of prevention, although to a lesser extent than full TT does. However, the positive welfare effect of an improvement of TT is no longer guaranteed if the interaction between the revealed risk type and the effectiveness of prevention is not disclosed, as the interaction crucially determines the posterior optimal effort. Improving TT also has the potential of neutralizing biased estimations of the prior loss probability.

When the uncovered risk determinants are endogenous, an improvement of TT turns prevention into a multivariate decision problem. Knowledge about a new prevention technology affects the optimal demand for the original prevention technology depending on the interaction between the technologies, which is characterized by the supermodularity/submodularity of prevention. Ignoring this interaction may be harmful as it may lead to seemingly informed choices that are in fact inefficient. Through the lens of full TT, we also reveal the connection

between inter-technological complementarity and the potential existence of parallel pathways underlying the occurrence of the loss.

When the risk determinants are observed *ex post*, TT allows the agent to objectively attribute the (non-)occurrence of a loss to herself and to external causes. This hindsight makes the *ex ante* self-protection effort increase with the degree of regret aversion. In addition, TT in combination with *ex post* observable risk determinants also serves to prevent potential biased beliefs from distorting the impact of regret aversion.

Our framework facilitates a deeper understanding of the connection between adequate risk mitigation and scientific research uncovering hidden risk determinants. It also allows a straightforward assessment of the welfare improvement resulting from understanding determinants of risks, which informs cost-benefit analyses upon making resource allocation decisions.

Our results also have implications for the design of public education campaigns aiming to promote preventive activities. To make prevention more efficient, not only should a prevention technology be made transparent by research, it needs to be made transparent in the eyes of the decision-maker as well. Instead of communicating the effectiveness of prevention based on population average statistics, policymakers may consider tailoring the information to different subpopulations to the extent allowed by current knowledge so that each subpopulation may choose the effort most suitable to their needs. In particular, for knowledge to turn into real value, it is crucial to disclose not only the risk level of each subpopulation, but also the efficacy of prevention associated with the risk level. Surprisingly, the regret channel shows that even when individuals are not yet perfectly aware of which subpopulation they belong to, simply anticipating knowing this in the future suffices to increase the current preventive effort.

In case of insurable risks with *ex ante* observable risk determinants, our results indicate that advancing our understanding of the mechanism of prevention—while making prevention more efficient—may eventually make it impossible for private insurance to exist. For such risks, an additional wealth redistribution may be necessary to recover the welfare loss resulting from the distributional effect introduced by TT.

While this paper focuses on the benefit side of TT, the optimal investment in improving TT has to consider its cost as well. A natural extension would be to treat the improvement of TT as an endogenous decision by incorporating the cost of acquiring TT (see the literature on rational inattention, for example, Sims, 2006, for the cost of information acquisition).

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REFERENCES

- Abramson, L. Y., Seligman, M. E., & Teasdale, J. D. (1978). Learned helplessness in humans: Critique and reformulation. *Journal of Abnormal Psychology*, 87(1), 49.
- Ali, S. N. (2011). Learning self-control. *The Quarterly Journal of Economics*, 126(2), 857–893.
- Allcott, H. (2015). Site selection bias in program evaluation. *The Quarterly Journal of Economics*, 130(3), 1117–1165.
- Aumann, R. J. (1976). Agreeing to disagree. *The Annals of Statistics*, 4, 1236–1239.
- Baillon, A., Bleichrodt, H., Emirmahmutoglu, A., Jaspersen, J. G., & Peter, R. (2019). When risk perception gets in the way: Probability weighting and underprevention. *Operations Research*. <https://pubsonline.informs.org/doi/pdf/10.1287/opre.2019.1910>
- Bardey, D., & De Donder, P. (2013). Genetic testing with primary prevention and moral hazard. *Journal of Health Economics*, 32(5), 768–779.
- Baron, J., & Hershey, J. C. (1988). Outcome bias in decision evaluation. *Journal of Personality and Social Psychology*, 54(4), 569.
- Bell, D. E. (1982). Regret in decision making under uncertainty. *Operations Research*, 30(5), 961–981.
- Bell, D. E. (1983). Risk premiums for decision regret. *Management Science*, 29(10), 1156–1166.
- Blackwell, D. (1951). *Comparison of experiments*. Howard University, Washington, United States. Technical report.
- Bleichrodt, H., Cillo, A., & Diecidue, E. (2010). A quantitative measurement of regret theory. *Management Science*, 56(1), 161–175.
- Bleichrodt, H., & Wakker, P. P. (2015). Regret theory: A bold alternative to the alternatives. *The Economic Journal*, 125(583), 493–532.
- Braun, M., & Muermann, A. (2004). The impact of regret on the demand for insurance. *Journal of Risk and Insurance*, 71(4), 737–767.
- Camille, N., Coricelli, G., Sallet, J., Pradat-Diehl, P., Duhamel, J.-R., & Sirigu, A. (2004). The involvement of the orbitofrontal cortex in the experience of regret. *Science*, 304(5674), 1167–1170.
- Christensen-Szalanski, J. J., & Willham, C. F. (1991). The hindsight bias: A meta-analysis. *Organizational Behavior and Human Decision Processes*, 48(1), 147–168.
- Cleave, B. L., Nikiforakis, N., & Slonim, R. (2013). Is there selection bias in laboratory experiments? The case of social and risk preferences. *Experimental Economics*, 16(3), 372–382.
- Courbage, C., Rey, B., & Treich, N. (2013). Prevention and precaution. In G. Dionne (Ed.), *Handbook of Insurance* (pp. 185–204). New York, NY: Springer. Chapter 8.
- Danaei, G., Ding, E. L., Mozaffarian, D., Taylor, B., Rehman, J., Murray, C. J., & Ezzati, M. (2009). The preventable causes of death in the United States: Comparative risk assessment of dietary, lifestyle, and metabolic risk factors. *PLOS Medicine*, 6(4), e1000058.
- Doherty, N. A., & Posey, L. L. (1998). On the value of a checkup: Adverse selection, moral hazard and the value of information. *The Journal of Risk and Insurance*, 65(2), 189–211.
- Dominy, S. S., Lynch, C., Ermini, F., Benedyk, M., Marczyk, A., Konradi, A., ... Potempa, J. (2019). *Porphyromonas gingivalis* in alzheimer's disease brains: Evidence for disease causation and treatment with small-molecule inhibitors. *Science Advances*, 5(1), eaau3333.
- Ehrlich, I., & Becker, G. (1972). Market insurance, self-insurance, and self-protection. *Journal of Political Economy*, 80(4), 623–648.
- Engelbrecht-Wiggans, R. (1989). The effect of regret on optimal bidding in auctions. *Management Science*, 35(6), 685–692.
- Engelbrecht-Wiggans, R., & Katok, E. (2008). Regret and feedback information in first-price sealed-bid auctions. *Management Science*, 54(4), 808–819.
- Frayling, T. M. (2007). Genome-wide association studies provide new insights into type 2 diabetes aetiology. *Nature Reviews Genetics*, 8(9), 657–662.
- Friedman, A. S., Schpero, W. L., & Busch, S. H. (2016). Evidence suggests that the ACA's tobacco surcharges reduced insurance take-up and did not increase smoking cessation. *Health Affairs*, 35(7), 1176–1183.
- Friedman, M., & Savage, L. (1948). The utility analysis of choices involving risk. *Journal of Political Economy*, 56(4), 279–304.

- Gabillon, E. (2018). *When choosing is painful: A psychological opportunity cost model*. Working paper.
- Gollier, C. (2001). *The Economics of Risk and Time*. Cambridge, MA: The MIT Press.
- Graff, M., Scott, R. A., Justice, A. E., Young, K. L., Feitosa, M. F., Barata, L., ... Kilpeläinen, T. O. (2017). Genome-wide physical activity interactions in adiposity—A meta-analysis of 200,452 adults. *PLOS Genetics*, 13(4), e1006528.
- Harrison, G. W., & List, J. A. (2004). Field experiments. *Journal of Economic Literature*, 42(4), 1009–1055.
- Harsanyi, J. C. (1953). Cardinal utility in welfare economics and in the theory of risk-taking. *Journal of Political Economy*, 61(5), 434–435.
- Harsanyi, J. C. (1955). Cardinal welfare, individualistic ethics, and interpersonal comparisons of utility. *Journal of Political Economy*, 63(4), 309–321.
- Hirshleifer, J. (1971). The private and social value of information and the reward to inventive activity. *American Economic Review*, 61(4), 561–574.
- Hofmann, A., & Peter, R. (2015). Multivariate prevention decisions: Safe today or sorry tomorrow? *Economics Letters*, 128, 51–53.
- Hofmann, A., & Rothschild, C. (2019). On the efficiency of self-protection with spillovers in risk. *The Geneva Risk and Insurance Review*, 44(2), 207–221.
- Hollands, G. J., French, D. P., Griffin, S. J., Prevost, A. T., Sutton, S., King, S., & Marteau, T. M. (2016). The impact of communicating genetic risks of disease on risk-reducing health behaviour: Systematic review with meta-analysis. *The BMJ*, 352, i1102.
- Hoy, M. (1989). The value of screening mechanisms under alternative insurance possibilities. *Journal of Public Economics*, 39(2), 177–206.
- Hoy, M., & Polborn, M. K. (2015). The value of technology improvements in games with externalities: A fresh look at offsetting behavior. *Journal of Public Economics*, 131, 12–20.
- Hoy, M., & Witt, J. (2007). Welfare effects of banning genetic information in the life insurance market: The case of *brca1/2* genes. *Journal of Risk and Insurance*, 74(3), 523–546.
- Huang, R. J., Muermann, A., & Tzeng, L. Y. (2016). Hidden regret in insurance markets. *Journal of Risk and Insurance*, 83(1), 181–216.
- Keeney, R. L. (2008). Personal decisions are the leading cause of death. *Operations Research*, 56(6), 1335–1347.
- Kunreuther, H., & Heal, G. (2003). Interdependent security. *Journal of Risk and Uncertainty*, 26(2–3), 231–249.
- Landsteiner, K. (1900). Zur kenntnis der antifermentativen, lytischen und agglutinierenden wirkungen des blutserums und der lymph. *Zentralblatt für Bakteriologie*, 27, 357–362.
- Lee, C.-M. (2015). Technological advances in self-insurance and self-protection. *Economics Bulletin*, 35(3), 1488–1500.
- Li, L., & Peter, R. (2019). *Should we do more when we know less?: optimal risk mitigation under technological uncertainty*. Working paper.
- Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The Economic Journal*, 92(368), 805–824.
- Loomes, G., & Sugden, R. (1987). Testing for regret and disappointment in choice under uncertainty. *The Economic Journal*, 97(Suppl), 118–129.
- Muermann, A., & Kunreuther, H. (2008). Self-protection and insurance with interdependencies. *Journal of Risk and Uncertainty*, 36(2), 103–123.
- Muermann, A., Mitchell, O. S., & Volkman, J. M. (2006). Regret, portfolio choice, and guarantees in defined contribution schemes. *Insurance: Mathematics and Economics*, 39(2), 219–229.
- Muermann, A., & Volkman, J. (2006). *Regret, pride, and the disposition effect*. Working paper.
- Neumuller, S., & Rothschild, C. (2017). Financial sophistication and portfolio choice over the life cycle. *Review of Economic Dynamics*, 26, 243–262.
- O'Donoghue, T., & Rabin, M. (1999). Doing it now or later. *American Economic Review*, 89(1), 103–124.
- Peter, R., Richter, A., & Steinorth, P. (2016). Yes, no, perhaps? Premium risk and guaranteed renewable insurance contracts with heterogeneous incomplete private information. *Journal of Risk and Insurance*, 83(2), 363–385.
- Peter, R., Richter, A., & Thistle, P. (2017). Endogenous information, adverse selection, and prevention: Implications for genetic testing policy. *Journal of Health Economics*, 55, 95–107.

- Qi, L., Hu, F. B., & Hu, G. (2008). Genes, environment, and interactions in prevention of type 2 diabetes: A focus on physical activity and lifestyle changes. *Current Molecular Medicine*, 8(6), 519–532.
- Qi, Q., Chu, A. Y., Kang, J. H., Jensen, M. K., Curhan, G. C., Pasquale, L. R., ... Hu, M. D. (2012). Sugar-sweetened beverages and genetic risk of obesity. *New England Journal of Medicine*, 367(15), 1387–1396.
- Quiggin, J. (1994). Regret theory with general choice sets. *Journal of Risk and Uncertainty*, 8(2), 153–165.
- Sen, A. (1976). Welfare inequalities and rawlsian axiomatics. *Theory and Decision*, 7(4), 243–262.
- Shields, K. E., & Lysterly, A. D. (2013). Exclusion of pregnant women from industry-sponsored clinical trials. *Obstetrics & Gynecology*, 122(5), 1077–1081.
- Sims, C. A. (2006). Rational inattention: Beyond the linear-quadratic case. *American Economic Review*, 96(2), 158–163.
- Sugden, R. (1993). An axiomatic foundation for regret theory. *Journal of Economic Theory*, 60(1), 159–180.
- Vuori, I. M. (2001). Health benefits of physical activity with special reference to interaction with diet. *Public Health Nutrition*, 4(2b), 517–528.
- Weymark, J. A. (2005). Measurement theory and the foundations of utilitarianism. *Social Choice and Welfare*, 25(2–3), 527–555.
- Willett, W. C. (2002). Balancing life-style and genomics research for disease prevention. *Science*, 296(5568), 695–698.
- Zeelenberg, M., & Pieters, R. (2007). A theory of regret regulation 1.0. *Journal of Consumer Psychology*, 17(1), 3–18.

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