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Abstract

This study provides a behavioral model that allows us to identify if an agent holds an optimistic or pessimistic bias, based on his insurance decisions. Specifically, we say that an agent has an optimistic bias if he purchases less insurance than optimal, and conversely for the pessimistic case. We propose the notion of Risk Awareness Informational Campaigns in which a policymaker increases the awareness of the bad event to improve the insurance decisions of the agents. We give sufficient behavioral conditions to ensure the success of such campaigns.

Keywords: Optimistic Bias, Risk Awareness, Insurance, Behavioral Decision-Making

JEL Classification: D01 , D04 , D81 , D91 , G22

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1 Introduction

The interplay between emotions and decision-making has drawn significant attention in recent years, challenging traditional economic theories that predominantly view individuals as rational agents (see Loewenstein (2000),Gennaro and Ash (2022),Bennett, Mekelburg, and Williams (2023), Bellet, De Neve, and Ward (2024), among others). This view constitutes one of the main assumptions of Decision Theory models. On the other hand, the field of Behavioral Economics has opened the door to understanding how psychological factors and emotional responses influence choices in real-world scenarios (see Alhadeff (2024)). In this paper, we focus on the insurance market, one of the economic scenarios in which we can observe the effects of emotions on decisions. Consider a decision-maker who is facing a lottery with good and bad outcomes and needs to choose his level of insurance against the bad scenario. He will base his decision on his belief of being affected by the bad outcome. In this process, he quantifies the probability of this event by considering both rational and emotional factors. This paper proposes a behavioral model of the insurance market that allows us to study these decisions, characterize optimistic and pessimistic agents, and how a policymaker could design campaigns to improve these decisions.

Our starting point is the Affective Decision-Making model introduced by Bracha and Brown (2012). In their work, the authors model individual decisions involving an agent's rational and emotional sides with a simultaneous game between these two sides. In this game, the rational player chooses an optimal level of insurance against the bad event while the emotional player chooses the optimal probability for the insurance level while also minimizing a mental cost. This cost arises when the agent convinces himself that the probabilities he is facing differ from the ones he is aware of, and is minimal when these probabilities coincide. One crucial assumption in the model of Bracha and Brown (2012) is that the agent is aware of the true probabilities. In this paper we relax that assumption by allowing the agents to be aware of different probabilities. These differences could be given by emotions, access to the information or framing effects, as shown by Kunreuther (1996), Browne and Hoyt (2000), and Etner, Cohen, and Jeleva (2008).

In real-life insurance decisions, the rational and emotional components of the agent are key aspects of their decision-making process (see Marini (2023); Sjöberg (2007)). However, one can only observe the insurance level chosen by the agent, namely the rational choice, while the choice of probability remains hidden. In addition, people make decisions based on these perceived probabilities, which often differ from the actual ones, as they are shaped by personal experiences, anticipatory emotions or framing effects, as established in the literature of Behavioral Economics. For instance, in experience-based choices, as in de Palma et al. (2014), individuals tend to underestimate the true probability of rare events while overestimating the likelihood of events with medium to high probabilities. Although, in the case of decisions based on descriptions, the direction is the opposite[1] (see Abdellaoui, l'Haridon, and Paraschiv (2011); Aydogan (2021); Aydogan and Gao (2020); Faulkner, Feduzi, and Runde (2017); Fox, Erner, and Walters (2015); Glöckner, Hilbig, Henninger, and Fiedler (2016); Kopsacheilis (2018)). Our study combines these insights to develop a behavioral model that differentiates between optimistic and pessimistic agents based solely on the observed insurance decisions. Furthermore, from a behavioral perspective, in which agents subjectively assess event probabilities, we propose an informational campaign framework for policymakers to enhance decision-making.

[1] This phenomenon is known as Availability Bias in the literature.

Our first result establishes that the optimal insurance level is monotonically increasing in the likelihood of the bad event. We define a baseline insurance level that assumes a fully rational agent that chooses an insurance level that aligns with the probabilities that he is aware of. Deviations from this value allow us to define a pessimistic and optimistic agent. For example, if the agent's insurance level is higher, it means that he thinks that the probability of the bad event is higher than the one he is aware of and, hence, we say that this agent holds a pessimistic bias. Consequently, this result allows us to infer whether an individual is optimist or pessimist based on his insurance level.

Our second result focuses on policy design aimed at increasing the risk awareness and, therefore, at increasing the insurance levels. We define the Risk Awareness Informational Campaigns as a mechanism implemented by a policymaker who seeks to improve the agent's awareness of a risky event through informational nudges. Using behavioral insights, policymakers can shift perceived probabilities that the agent is considering by bringing them closer to the true value. Hence, by designing campaigns around the perceived probability, policymakers can affect optimal insurance decisions without knowing the agent's actual risk perception. We say that a campaign is successful if providing more information increases the perceived probability, bringing it closer to the true probability and thus leading to higher insurance levels. These campaigns align individual behavior more closely with actual risk, thereby enhancing protection and ensuring adequate insurance coverage. We establish sufficient conditions for a successful campaign. These conditions closely relate to the agent's absolute risk aversion, calculated with respect to the insurance level rather than the traditional welfare-based approach in individual decision-making under risk. Furthermore, the Risk Awareness Informational Campaigns are particularly effective for agents with beliefs that deviate significantly from the actual probabilities, suggesting that more aggressive campaigns are essential to correct these misperceptions and improve risk awareness.

The rest of the paper is organized as follows: In Section 2, we formally introduce our behavioral affective decision model. In Section 3 presents the concept of Risk Awareness Informational Campaigns and examines the conditions required for a successful campaign using behavioral insights. Finally, Section 4 provides concluding remarks. All the proofs are given in the Appendix.

2 Behavioral Affective Decision Model

In this section, we introduce a model of behavioral affective decision-making in insurance markets. We start from the Affective Decision-Making (ADM) model established in Bracha and Brown (2012). We extend the analysis to allow a more general class of policy interventions aimed at changing endogenous probability perceptions to improve the optimal insurance levels.

Consider an agent who faces two possible states of the world, Bad (B) and Good (G) with associated wealth levels w_B and w_G, respectively, where $w_B < w_G$. The agent derives utility from wealth, which is captured by the strictly increasing, strictly concave smooth function u with $\lim_{w\to-\infty} u'(w) = \infty$, $\lim_{w\to\infty} u'(w) = 0$. The agent's perception of risk is defined by the probability $p \in [0, 1]$ that the Bad state occurs. The agent needs to decide on an insurance level $I \in \mathbb{R}$ against the Bad state of the world at the fixed insurance premium rate $\gamma \in (0, 1)$.

The ADM consider a two-player simultaneous game to find the optimal insurance level I^* and the endogenous perceived probability p^*. The players in this game represent the two parts of the agent's behavior, namely the rational and the emotional parts. On one side, the rational agent maximizes his utility by choosing an optimal insurance level I^* given the probabilities p. On the other side, the emotional agent maximizes his utility by choosing the perceived probabilities p^* given an insurance level I. The emotional agent faces a mental cost when convincing himself that the probability (p) that he is choosing is different from the one he is aware of (p_0).

This interpersonal game can be modeled as a potential game with potential function[2] given by $\theta(I,p) = pu(w_B + (1-\gamma)I) + (1-p)u(w_G - \gamma I) - J(p, po)$, where $J(p, p_0)$ represents the mental cost from ignoring the *real*[3] baseline probability p_0 of the Bad state and optimizing with the respective perceived probability p.

In Bracha and Brown (2012), the mental cost function J takes the baseline probability p_0 as a parameter and increases with the difference between the perceived probability, p, and the baseline probability, p_0. Therefore, the function $J(p, p_0)$ is non-negative, strictly convex, and reaches its minimum at $p = p_0$. Additionally, this cost function is essentially smooth-smooth on (0,1) with $\lim_{p\to 0} J^{\cdot}(p, p_0) = \lim_{p\to 1} J^{\cdot}(p, p_0) = +\infty$ and $\lim_{p\to 0} |DJ^{\cdot}(p, p_0)| = \lim_{p\to 1} |DJ^{\cdot}(p, p_0)| = +\infty$. In this paper, we consider an extension of J to allow it to be a function of p_0. This extension will be useful when studying policy interventions based on changes in p_0, which is a key component of our model. For simplicity and consistency with the literature, we impose the same conditions of J as a function of p over J as a function of p_0. Notice that, even though the agent considers now that p_0 is a variable of the model, he does not have any control over it, hence it will not enter his optimization problem.

The first-order conditions (FOC) of the model with respect to p and I are given by Equations (1) and (2). Finally, it follows from Bracha and Brown (2012), that the pair (I^*, p^*) that solves the system of equations defined by the FOC corresponds to a Nash Equilibrium of the game.

$$\frac{\partial \theta(I,p,p_0)}{\partial I} = pu'(w_B + (1-\gamma)I)(1-\gamma) + (1-p)u'(w_G - \gamma I)(-\gamma) \tag{1}$$

$$\frac{\partial \theta(I,p,p_0)}{\partial p} = u(w_B + (1-\gamma)I) - u(w_B - \gamma I) - J'(p, p_0) \tag{2}$$

[2]The choice of functional form of the potential function would mean that the agent is risk neutral since for a risk-averse it holds that $u\left(p(w_B + (1-\gamma)I) + (1-p)(w_G - \gamma I)\right) > pu(w_B + (1-\gamma)I) + (1-p)u(w_G - \gamma I)$. Now, since being risk-neutral is a stronger behavioral assumption, our results will also hold for risk-averse agents.

[3]The baseline probabilities are given by evidence, facts or past results.

2.1 Behavioral Model of Insurance

In this section, we define whether an agent behaves as an optimist or pessimist based on his insurance decisions. Let us define $I^*(p_0)$ as the baseline insurance level, assuming that the probabilities p and p_0 coincide. This level reflects the choice of a rational agent who maximizes his utility as if the mental cost is either absent or minimal. For this reason, to assess optimism or pessimism, we examine deviations from this baseline level. The first step involves analyzing the effect of p on its corresponding optimal insurance level $I^*(p)$. This result is presented in Proposition 1. This proposition allows us to rank the perception of the bad event with respect to the baseline probability from their optimal insurance levels. Consequently, Corollary 1 defines whether an agent exhibits an optimistic or pessimistic behavior. In particular, given p_0, a policymaker can determine $I^*(p_0)$ and compare it to the agent's insurance levels (which we assume equal to $I^*(p)$) to infer the agent's behavior. These findings enable the design of policy interventions aimed at reducing the gap between the agent's insurance level $I^*(p)$ and the baseline insurance level $I^*(p_0)$.

Proposition 1. *If the agent has a strictly increasing and strictly concave utility function, then his optimal insurance level ($I^*(p)$) is monotone increasing in p.*

Corollary 1 (of Proposition 1)**.** *The difference between the optimal insurance levels $I^*(p)$ and $I^*(p_0)$ determines whether the agent is optimistic ($I^*(p) < I^*(p_0)$) or pessimistic ($I^*(p) > I^*(p_0)$).*

3 Policy Design and Awareness of Risk

In Section 2, we defined a measure of optimism and pessimism relative to a given baseline probability level. This measure could help policymakers to design campaigns to improve agents' insurance decisions. In Bracha and Brown (2012), one of the main assumptions of the model is that agents know the true baseline probability. Let $\tilde{p}_0$ be this probability. We need to relax this assumption as we want to study the behavior of agents that ignore the true $\tilde{p}_0$ and instead consider as baseline probability $p_0 < \tilde{p}_0$. This relaxation helps us to widen the applications of this model, as real information behaves in an imperfect, qualitative, and incomplete manner, as discussed in Aliev, Pedrycz, and Huseynov (2013). These imperfections lead to asymmetric knowledge of actual probabilities among agents, making it challenging to apply the assumption of a common baseline probability. Moreover, the baseline probability that each agent consider could vary depending on how he processes, updates and trusts this information and its sources (see Stern, Gonzalez, Welsh, and Taylor (2010)).

In general, policymakers want to increase the insurance levels of optimistic agents, since they will be under-insured. The intuition behind this comes from Corollary 1, as an optimist agent is someone whose perceived probability p is smaller than the probability he is aware of and, therefore, smaller than $\tilde{p}_0$. On the remaining in this paper, we will focus on this type of agent.

There are two main ways to design policy interventions to increase the insurance levels of an optimistic agent. First, one could make the bad state outcome relatively worse by either increasing w_G or decreasing w_B, this type of intervention is studied in Bracha and Brown (2012). On the other hand, one could increase the agent's baseline probability p_0 to bring it closer to $\tilde{p}_0$. For example, people who decide to drive under the influence of alcohol because they are not aware of the real statistics of drunk-driving accidents, and as a response to this behavior governments increase the awareness of the potential risk via a campaign in collaboration with the alcohol producers and sellers. Another example of these campaigns is the display of the risks of smoking in the cigarette packages, since at the beginning smokers were unaware of the true risk because there were no medical studies available at that time. We refer to one these campaigns as *a Risk Awareness Informational Campaign* (RAIC) since the policymaker wants to improve the awareness that the agent has of the risk through informational nudges.

The design of campaigns based on changes in p_0 allows the policymaker to affect the agent's optimal insurance decisions without ever knowing the agent's true risk perception p. The main intuition for the design of campaigns comes from Proposition 1, which states the monotonicity conditions of the insurance levels with respect to the risk perception level p. Then, if by increasing the value of p_0 one can increase the value of p, the agents will approach the policy-desired insurance levels $I^*(\tilde{p}_0)$. This would mean that the campaign better align individual behavior with the true risk $\tilde{p}_0$, thereby enhancing their protection and ensuring they are adequately insured. We say that the RAICs are successful if they have this effect.

We can express the conditions for a successful campaign in terms of the partial derivative of p with respect to p_0, i.e., $\partial p/\partial p_0$. To be able to define this derivative we need to study the implicit function resulting from the optimal conditions of the potential game described in Section 2. In Proposition 2 we establish a sufficient condition to have a successful informational campaign.

Proposition 2. *We say a* a Risk Awareness Informational Campaign *is successful if*

$$L = \frac{-\left[(1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I)\right]^2}{p(1-\gamma)^2 u''(w_B + (1-\gamma)I) + (1-p)\gamma^2 u''(w_G - \gamma I)} < \frac{\partial^2 J(p, p_0)}{\partial p \partial p} \tag{3}$$

The parameter L is related to the absolute risk aversion but instead of being computed with respect to the welfare level, in our setup is determined by the insurance level. To formalize this statement consider an agent with utility given by $\theta(I) := pu(\psi(I)) + (1-p)u(\phi(I)) - J(p, po)$. Then, the absolute risk aversion[4] of such agent with respect to his insurance level I is given by Equation (4).

[4] $r = -u''(\cdot)/u'(\cdot)$

$$r(\theta(I)) = -\frac{\frac{\partial^2\theta(I,p)}{\partial I\partial I}}{\frac{\partial\theta(I,p)}{\partial I}} = -\frac{p(\psi'(I))^2u''(\psi(I)) + (1-p)(\phi'(I))^2u''(\phi(I))}{p(\psi'(I))u'(\psi(I)) + (1-p)(\phi'(I))u'(\phi(I))} \tag{4}$$

Note that our agent of interest described by the potential function of the Interpersonal Game described in Section 2 has a utility function $\theta(I)$ when $\psi(I) = w_B + (1-\gamma)I$ and $\phi(I) = w_G - \gamma I$. Hence, under this notation $L = -\frac{\left[\psi'(I)u'(\psi(I))-\phi'(I)u'(\phi(I))\right]^2}{p(\psi'(I))^2u''(\psi(I))+(1-p)(\phi'(I))^2u''(\phi(I))}$, which we can rewrite as in Equation (5).

$$L = \left[\frac{1}{r(\theta(I))}\frac{\left[\psi'(I)u'(\psi(I)) - \phi'(I)u'(\phi(I))\right]^2}{p(\psi'(I))u'(\psi(I)) + (1-p)(\phi'(I))u'(\phi(I))}\right] \tag{5}$$

This formalization allows us to compare the condition from Proposition 2 with the one obtained in (Bracha & Brown, 2012, See Prop. 5), resulting in a condition of similar structure[5]. Now, regarding the interpretation of the sufficient conditions of Proposition 2, the fact that $L < \frac{\partial^2 J(p,p_0)}{\partial p\partial p}$ means that the RAIC is effective for agents whose beliefs are far from the real probabilities, indicating a significant discrepancy, needing aggressive campaigns to change the situation and make them more aware.

We can compare the effectiveness of two policies: increasing the distance between w_G and w_B or raising the actual probability p_0. The optimal choice is not fixed and depends on the relative impact of these variables.

For instance, through numerical computations[6], we can determine how much the optimal insurance level increases when γ is fixed and either greater than or equal to p_0, and we increase the distance between w_G and by 10%. We can also analyze the effect of raising p_0 by the same percentage. With a cost function defined as $\frac{1}{10}(p \cdot (\ln(p) - \ln(p_0)) + (1-p)\cdot(\ln(1-p) - \ln(1-p_0)))$, we find that increasing the relative distance between w_G and w_B results in an increase in the insurance level from 5.7 to 6.11, which is a 7.1% increase. In contrast, if we analyze the effect of increasing

[5] In (Bracha & Brown, 2012, See Prop. 5), the authors study the conditions under which the campaigns would backfire and lead to an unintended result of reducing insurance levels.
[6] Available upon request.

the actual probability while keeping w_G and w_B constant, the insurance level rises by 10.5%, reaching a value of 6.3. It is crucial to acknowledge that the relationship between the two policies is not always uniform. Various circumstances may arise in which one policy demonstrates greater effectiveness than the other, depending on the specific context and objectives at hand.

4 Conclusion

This paper investigates how optimism or pessimism can be measured through behavior in the insurance market. Specifically, purchasing less insurance than the optimal amount reflects optimism, as the individual believes the likelihood of a negative event is lower than it is. Conversely, purchasing more insurance than necessary indicates pessimism, as the individual perceives the risk of a negative event to be higher than the true probability.

Considering the relationship between behavior and mood, policymakers can enhance awareness of negative events, leading to greater societal benefits as individuals adjust their insurance choices closer to the level that reflects the true probability of such events. This approach to defining and evaluating a campaign is grounded in behavioral perspectives, emphasizing the importance of information in improving awareness.

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A Supplementary Material for Section 2

Proof of Proposition 1. We focus on the Rational Player to find the optimal level of insurance for a given risk perception. From the F.O.C of θ with respect to I, we can obtain Equation (6), which represents the relationship between the risk perception, the risk prime, and the utility levels when considering the optimal insurance level.

$$\frac{p}{(1-p)}\frac{(1-\gamma)}{\gamma} = \frac{u'(w_G - \gamma I^*(p))}{u'(w_B + (1-\gamma)I^*(p))} \tag{6}$$

Let us define the baseline insurance level as the insurance level $I^*(p_0)$ that satisfies Equation (6) when considering $p = p_0$. Now, to verify the monotonicity of the optimal insurance levels, we need to verify different configurations of the parameters p_0 and γ.

1. Suppose that $p_0 = \gamma$. From Equation (6) we know that $I^*(p_0) = w_G - w_B$.

   Now suppose that the agent's perception of risk is higher than the baseline probability, hence, $p_0 < p$. From the RHS of (6) we know that $\frac{p(1-\gamma)}{(1-p)\gamma} > \frac{p_0(1-\gamma)}{(1-p_0)\gamma} = 1$ and, therefore, $\frac{u'(w_G-\gamma I^*(p))}{u'(w_B+(1-\gamma)I^*(p))} > 1$. Then, thanks to the properties of u we can conclude that $w_G - \gamma I^*(p) < w_B + (1-\gamma)I^*(p)$ which we can rewrite as $I^*(p_0) < I^*(p)$. The case when the agent becomes more optimistic ($p < p_0$) is analogous.

   The case of $\gamma = p_0$ can be interpreted as one in which the baseline probability corresponds with the insurance prime. In this case agent's optimal baseline insurance level corresponds with the difference in outcomes between the good and the bad state. Moreover, when the agent becomes more pessimistic (respectively optimistic), he will choose higher (respectively lower) insurance levels.

2. Suppose that $p_0 > \gamma$. From Equation (6) we know that $I^*(p_0) > w_G - w_B$. First, suppose that $p > p_0 > \gamma$. Using a similar analysis as in the previous case, we know that $\frac{u'(w_G-\gamma I^*(p))}{u'(w_B+(1-\gamma)I^*(p))} > \frac{u'(w_G-\gamma I^*(p_0))}{u'(w_B+(1-\gamma)I^*(p_0))} > 1$. Then, from the properties of u, we can conclude that $w_G - \gamma I^*(p) - w_B - (1-\gamma)I^*(p) < w_G - \gamma I^*(p_0) - w_B - (1-\gamma)I^*(p_0) < 0$ which implies that $I^*(p_0) < I^*(p)$. Second, suppose that

$p_0 > p > \gamma$. We know that $\frac{u'(w_G - \gamma I^*(p_0))}{u'(w_B + (1-\gamma) I^*(p_0))} > \frac{u'(w_G - \gamma I^*(p))}{u'(w_B + (1-\gamma) I^*(p))} > 1$. Similarly, as before, we can conclude that $I^*(p) < I^*(p_0)$. Finally, suppose that $p_0 > \gamma > p$. In this case, we know that $\frac{u'(w_G - \gamma I^*(p_0))}{u'(w_B + (1-\gamma) I^*(p_0))} > 1 > \frac{u'(w_G - \gamma I^*(p))}{u'(w_B + (1-\gamma) I^*(p))}$. Which implies that $I^*(p) < I^*(p_0)$, using the properties of u.

In this case, if the baseline probability is higher than the premium rate, it means that the insurance is relatively cheap, and therefore the agent will over-insure in the baseline scenario. Now, when the agent becomes more pessimistic, the insurance becomes even cheaper (relative to the baseline scenario) and, therefore, the agent will increase their insurance levels. Analogously, when the agent becomes more optimistic, the insurance becomes more expensive (relative to the baseline scenario), and, therefore, the agent will reduce his insurance level. Note that the case when $p_0 > \gamma$ is analogous to $p_0 < \gamma$.

We can conclude that, independently of the relation between p_0 and γ, the optimal insurance level $I^*(p)$ satisfies the desired property. □

B Supplementary Material for Section 3

Let us define a function $\hat{I} : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ such that $\frac{\partial \theta(\hat{I}(p,p_0),p,p_0)}{\partial p} = 0$. The expression of $\hat{I}(p, p_0)$ allows us to express the investment with respect to (p, p_0) at the level curve determined by the best response from the emotional player perspective. Similarly, let us define the function $\tilde{I} : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ denoted by $\tilde{I}(p, p_0)$ such that $\frac{\partial \theta(\tilde{I},p,p_0)}{\partial I} = 0$. This function expresses the optimal investment for the rational agent and allows us to express such an amount for the pair (p, p_0). Note that the functions $\hat{I}(p, p_0)$ and $\tilde{I}(p, p_0)$ constitute the best responses of the game. Note that the existence of $\hat{I}$ and $\tilde{I}$ rely on the existence of u^{-1} and u'^{-1}, which are well-defined since u is strictly concave.

Lemma 1 (Properties of Best Responses)**.** *Consider the extension of the potential game defined in Section 2 to one that considers p_0 as an additional variable of the* *model. Then, the functions* $\tilde{I}(p, p_0) = \tilde{I}(p)$ *and* $\hat{I}(p, p_0)$ *are well-defined, and*

$$\frac{\partial \tilde{I}}{\partial p} = \frac{-((1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I))}{p(1-\gamma)^2 u''(w_B + (1-\gamma)I) + (1-p)\gamma^2 u''(w_G - \gamma I)}$$
$$\frac{\partial \hat{I}}{\partial p} = \frac{-\frac{\partial^2 J(p,p_0)}{\partial p \partial p}}{(1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I)}$$
$$\frac{\partial \hat{I}}{\partial p_0} = \frac{\frac{\partial^2 J}{\partial p \partial p_0}}{(1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I)}$$

Proof. From the definition of $\tilde{I}$ we know that $\frac{\partial \theta(\tilde{I},p,p_0)}{\partial I} = 0$ and, therefore, $\frac{\partial^2 \theta(\tilde{I},p,p_0)}{\partial I \partial p} = 0$. We can explicitly compute this derivative as $\frac{\partial^2 \theta(\tilde{I},p,p_0)}{\partial I \partial \tilde{I}} \frac{d\tilde{I}}{dp} + \frac{\partial^2 \theta(\tilde{I},p,p_0)}{\partial I \partial p} \frac{dp}{dp} + \frac{\partial^2 \theta(\tilde{I},p,p_0)}{\partial I \partial p_0} \frac{dp_0}{dp} = 0$ which implies the desired result, since we know that $\frac{\partial^2 \theta(I,p,p_0)}{\partial I \partial p_0} = 0$ from Equation (1). Then,

$$\frac{d\tilde{I}}{dp} = \frac{-\frac{\partial^2 \theta(I,p)}{\partial I \partial p}}{\frac{\partial^2 \theta(I,p)}{\partial^2 I}} = \frac{-((1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I))}{p(1-\gamma)^2 u''(w_B + (1-\gamma)I) + (1-p)\gamma^2 u''(w_G - \gamma I)}$$

Now, from the definition of $\hat{I}$ we know that $\frac{\partial \theta(\hat{I},p,p_0)}{\partial p} = 0$, and, therefore, $\frac{\partial^2 \theta(\hat{I},p,p_0)}{\partial^2 p} = 0$. By following a similar process as before we can compute $\frac{\partial \theta^2(I,p,p_0)}{\partial p \partial p} = \frac{\partial \hat{I}}{\partial p}$ and $\frac{\partial \theta^2(I,p,p_0)}{\partial p \partial p_0} = \frac{\partial \hat{I}}{\partial p_0}$ we obtain

$$\frac{\partial \hat{I}}{\partial p} = -\frac{\frac{\partial^2 \theta(I,p,p_0)}{\partial p \partial p}}{\frac{\partial \theta(I,p,p_0)}{\partial p \partial I}} = \frac{-\frac{\partial^2 J(p,p_0)}{\partial p \partial p}}{(1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I)}$$
$$\frac{\partial \hat{I}}{\partial p_0} = -\frac{\frac{\partial^2 \theta(I,p,p_0)}{\partial p \partial p_0}}{\frac{\partial \theta(I,p,p_0)}{\partial p \partial I}} = \frac{\frac{\partial^2 J}{\partial p \partial p_0}}{(1-\gamma)u'(w_B + (1-\gamma)I) + \gamma u'(w_G - \gamma I)}$$

□

Now, to measure the effect of p_0 in p, we need to study such effect under the best response behavior for both players. For that, in Lemma 2 we define the implicit function $F(p, p_0)$ and verify the assumptions required in the Implicit Function Theorem which allows us to define ${}^{\partial p}/_{\partial p_0}$.

Lemma 2 (Implicit Function Conditions)**.** *Let* $F(p, p_0) = \frac{\partial \theta(\tilde{I}(p,p_0),p,p_0)}{\partial I} - \frac{\partial \theta(\hat{I}(p,p_0),p,p_0)}{\partial p}$ *and assume that* $u'(w_B + (1-\gamma)I)(1-\gamma) + u'(w_G - \gamma I)\gamma \neq {}^{\partial^2 J(p,p_0)}/_{\partial^2 p}$*, then:*

i) There exists p^* *and* p_0 *such that* $F(p^*, p_0) = 0$.

ii) ${}^{\partial F(p^*,p_0)}/_{\partial p}$*, and* ${}^{\partial F(p^*,p_0)}/_{\partial p_0}$ *exist.*

iii) ${}^{\partial F(p^*,p_0)}/_{\partial p} \neq 0$

Proof. The condition i) holds by definition of the best responses. Notice that for each p_0 there exists p^* (and also I^*) such that $F(p^*, p_0) = 0$. We can compute, $\frac{\partial F}{\partial p} = \frac{\partial^2 \theta(I,p,p_0)}{\partial p \partial I} - \frac{\partial^2 \theta(I,p,p_0)}{\partial p \partial p} = u'(w_B + (1-\gamma)I)(1-\gamma) + u'(w_G - \gamma I)\gamma - \frac{\partial^2 J(p,p_0)}{\partial^2 p}$. Note that the condition iii) follows from this calculation and the assumption. Note that, since u is strictly concave to I and J is strictly convex with respect to p, then $\frac{\partial F}{\partial p_0}$ is also well-defined. Formally $\frac{\partial F}{\partial p_0} = \frac{\partial^2 \theta(I,p,p_0)}{\partial p_0 \partial I} - \frac{\partial^2 \theta(I,p,p_0)}{\partial p_0 \partial p} = \frac{\partial^2 J(p,p_0)}{\partial p_0 \partial p}$. The above two computations state the part condition ii), which concludes the desired result. $\square$

Proof of Proposition 2. Note that there exists open sets $V \subseteq \mathbb{R}^2$ and $W \subseteq \mathbb{R}$ with $(p^*, p_0) \in V$ and $p_0 \in W$ such that for each p_0 there exists a unique p, with $(p, p_0) \in V$ and $F(p, p_0) = 0$. Then, there exists a function $g : W \to \mathbb{R}$ that is continuously differentiable such that $F(g(p_0), p_0) = 0$ for all $p_0 \subseteq W$. Since there exists such function g, we can apply the Implicit Function Theorem to get the expression of ${}^{\partial p}/_{\partial p_0}$ in Equation (7). Moreover, by using the results of Lemma 1, we can simplify the expression into Equation (8), where L is given by Equation (3).

$$\frac{\partial p}{\partial p_0} = -\frac{\frac{\partial F}{\partial p_0}}{\frac{\partial F}{\partial p}} = -\frac{\frac{\partial I^*}{\partial p_0} - \frac{\partial \tilde{I}}{\partial p_0}}{\frac{\partial I^*}{\partial p} - \frac{\partial \tilde{I}}{\partial p}} \tag{7}$$

$$= \frac{\frac{\frac{\partial^2 J}{\partial p \partial p_0}}{(1-\gamma)u'(w_B+(1-\gamma)I)+\gamma u'(w_G-\gamma I)}}{\frac{-((1-\gamma)u'(w_B+(1-\gamma)I)+\gamma u'(w_G-\gamma I))}{p(1-\gamma)^2u''(w_B+(1-\gamma)I)+(1-p)\gamma^2u''(w_G-\gamma I)} + \frac{-\frac{\partial^2 J(p,p_0)}{\partial p \partial p}}{(1-\gamma)u'(w_B+(1-\gamma)I)+\gamma u'(w_G-\gamma I)}}$$

$$= \frac{\frac{\frac{\partial^2 J}{\partial p \partial p_0}}{(1-\gamma)u'(w_B+(1-\gamma)I)+\gamma u'(w_G-\gamma I)}}{\frac{L-\frac{\partial^2 J(p,p_0)}{\partial p \partial p}}{(1-\gamma)u'(w_B+(1-\gamma)I)+\gamma u'(w_G-\gamma I)}}$$

$$\frac{\partial p}{\partial p_0} = \frac{\frac{\partial^2 J}{\partial p \partial p_0}}{L - \frac{\partial^2 J(p,p_0)}{\partial p \partial p}} \tag{8}$$

Note that ${}^{\partial p}/_{\partial p_0} > 0$ if both numerator and denominator of Equation (8) have the same sign. This means that $L > \frac{\partial^2 J(p,p_0)}{\partial p \partial p}$ and $\frac{\partial^2 J}{\partial p \partial p_0} > 0$, or, $L < \frac{\partial^2 J(p,p_0)}{\partial p \partial p}$ and $\frac{\partial^2 J}{\partial p \partial p_0} < 0$. Note that, since $J(p, p_0)$ is strictly convex, the cross-derivative with respect to p and p_0 cannot be positive. We can conclude that if $L < \frac{\partial^2 J(p,p_0)}{\partial p \partial p}$ and $\frac{\partial^2 J}{\partial p \partial p_0} < 0$, then the informational campaign has the desired effect (${}^{\partial p}/_{\partial p_0} > 0$ and, by Proposition 1, higher insurance levels).

At first glance the conditions established in Proposition 2 appear disconnected from existing results like the one of (Bracha & Brown, 2012, See Prop. 5). Nevertheless, we can rewrite our conditions following the same structure. Consider an agent with utility given by $\theta(I) := pu(\psi(I)) + (1-p)u(\phi(I)) - J(p, po)$. Then absolute risk aversion ($r = -{}^{u''(.)}/_{u'(.)}$) of such agent with respect to his insurance level I is given by $r(\theta(I)) = -\frac{\partial^2\theta(I,p)/\partial I \partial I}{\partial\theta(I,p)/\partial I} = -\frac{p(\psi'(I))^2u''(\psi(I))+(1-p)(\phi'(I))^2u''(\phi(I))}{p(\psi'(I))u'(\psi(I))+(1-p)(\phi'(I))u'(\phi(I))}$. Note that, in general, the absolute risk aversion is computed with respect to welfare levels, which, in our setup are determined by the insurance level I. Note that our agent of interest described in the Interpersonal Game satisfies this equation when $\psi(I) = w_B + (1-\gamma)I$ and $\phi(I) = w_G - \gamma I$. Under this notation $L = -\frac{\left[\psi'(I)u'(\psi(I))-\phi'(I)u'(\phi(I))\right]^2}{p(\psi'(I))^2u''(\psi(I))+(1-p)(\phi'(I))^2u''(\phi(I))}$. Then, after simple calculations we conclude that $L = [r(\theta(I))({}^{A}/_{B})]^{-1}$, where $A =$

$p(\psi'(I))u'(\psi(I)) + (1-p)(\phi'(I))u'(\phi(I))$ and $B = [\psi'(I)u'(\psi(I)) - \phi'(I)u'(\phi(I))]^2$. Moreover, under this new definition of L, the conditions of Proposition 2 are equivalent to ${}^{B}/_{r(\theta(I)A} > {}^{\partial^2 J}/_{\partial p \partial p_0}$, which follow a similar structure to those of (Bracha & Brown, 2012, See Prop. 5). $\square$