

Correcting Optimism: Informational Interventions in Affective Decision-Making*

Julián Chitiva, Penélope Hernández, Maria Murgui

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Abstract

We develop a behavioral model of insurance choice where a rational and an emotional self engage in a simultaneous game, expanding the affective decision-making framework of Bracha and Brown (2012) to accommodate diverse subjective beliefs. Optimal coverage increases with the perceived probability of an adverse event. Relative to a benchmark, an agent who under-insures is optimistic, while one who over-insures is pessimistic. A single choice reveals an agent’s behavioral type but not the bias source, whereas population-level distributions are recovered. We propose Risk Awareness Informational Campaigns (RAICs) to align perceived probabilities with objective ones without changing payoffs. We identify conditions under which a RAIC increases coverage, based on absolute risk aversion related to insurance levels.

Keywords: Optimism Pessimism Insurance Beliefs Affective decision-making Information

JEL classification: D01; D81; D82; D91; G22

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1 Introduction

Standard decision theory treats the agent as a rational expected-utility maximizer whose beliefs are exogenous inputs to choice. A large body of work relaxes this separation by letting beliefs themselves enter utility. Agents derive anticipatory pleasure or anxiety from what they expect, and may therefore hold beliefs that depart from objective probabilities (Loewenstein, 2000; Caplin and Leahy, 2001). When beliefs are valued rather than merely held, they become objects of choice, and the resulting distortions have first-order consequences for economic behavior. A central manifestation is optimism bias, the tendency to underestimate the likelihood of adverse events relative to the evidence (Camerer and Lovallo, 1999; Weinstein et al., 2005). Such misperception is not merely anecdotal; experimental studies that elicit how individuals weight the probability of low-probability adverse events find systematic distortion, including outright neglect of small probabilities, in insurance decisions themselves (Robinson and Botzen, 2019). Because such distortions are not directly observable, a natural question is whether, and to what extent, they can be recovered from the choices agents make.

We study this question in insurance markets, where coverage decisions turn on how an individual evaluates a low-probability adverse event. The probability an agent acts on is subjective and shaped by emotional factors, by the information environment, and by past experience, and it need not coincide with the objective frequency of the event (Kunreuther, 1996; Browne and Hoyt, 2000; Etner et al., 2008). Insurance is a natural laboratory because coverage choices are observable while the perceptions driving them are not, so choices can serve as a window onto underlying beliefs. Field evidence supports this link as homeowners systematically underinsure low-probability, high-consequence risks, and overconfident individuals are less likely to purchase coverage (Cox and Zwinkels, 2016), consistent with belief distortion translating directly into under-insurance.

Our starting point is the affective decision-making (ADM) model of Bracha and Brown (2012), in which a rational and an emotional self play a simultaneous game. The rational self chooses insurance, taking the perceived probability as given. The emotional self chooses the perceived probability, trading off the utility of a more comforting belief against a mental cost of distorting it away from a baseline. In the ADM framework the baseline probability is the belief that minimizes this mental cost, interpreted as the risk perception easiest to justify and, in many settings, as the empirical fre-

quency of the adverse state; it is a reference point in the cost function, not a probability common to all agents. Because informational environments and experiences differ, we treat this baseline as heterogeneous across individuals and, in general, distinct from the objective frequency.

Two features of our framework separate it from the original model. First, allowing baselines to be heterogeneous and subjective lets us distinguish an agent whose distortion is emotional from one whose reference belief is itself miscalibrated. Second, we consider a policy instrument that operates on the baseline belief rather than on payoffs. This belief channel is grounded in the view that agents value and invest in their beliefs (Brunnermeier and Parker, 2005; Bénabou and Tirole, 2011), so that an intervention which changes what an agent perceives can change behavior without altering any financial incentive. This is distinct from, and complementary to, the outcome-severity channel studied by Bracha and Brown (2012), in which campaigns widen the gap between good and bad states; isolating the belief channel is what allows us to attribute a behavioral response to a change in perception rather than to a change in payoffs.

Our first result is that optimal coverage is strictly increasing in the perceived probability of the adverse event. This monotonicity turns coverage into a revealed-preference signal. Given an objective benchmark probability, an agent who covers less than the benchmark implies behaves as if the event were less likely than it objectively is, which we call optimism, and an agent who covers more behaves pessimistically. We are explicit about the scope of this identification. A single choice reveals the total gap between the agent’s acted-on probability and the objective one, but not whether that gap originates in emotional distortion or in a miscalibrated baseline; the two coincide only when the baseline is correct. What a single choice does identify is the behavioral wedge relative to the objective benchmark, which is exactly the object a corrective policy needs, and at the population level the distribution of behavioral types is recovered from the distribution of coverage.

Our second result concerns policy. We define a *Risk Awareness Informational Campaign* (RAIC) as an intervention that shifts perceived baseline probabilities toward the objective frequency through information, leaving payoffs unchanged. We derive a sufficient condition under which a RAIC raises coverage and show that it is governed by a notion of absolute risk aversion measured with respect to the insurance level rather than wealth. The condition is not always met. Outside the region it delineates, a campaign can be counterproductive, which lets us say when information-based

policy is beneficial and when it is not. Empirically, information interventions of exactly this kind have been shown to raise protective coverage, for instance, a randomized field experiment finds that providing flood-risk information increased flood-insurance uptake with no change in premiums (Allaire, 2016), and observational evidence shows that public risk-communication activities crowd in private coverage while hazard-mitigation activities, which lower perceived risk, crowd it out (Borsky and Hennighausen, 2022; Shao et al., 2017).¹

Our contribution is threefold. We develop a tractable affective model of insurance demand with heterogeneous, subjective baseline beliefs; we provide a revealed-preference characterization of optimistic and pessimistic behavior from observed coverage, together with an explicit account of what such choices do and do not identify; and we characterize when informational campaigns raise coverage without altering payoffs. Section 2 introduces the model. Section 3 introduces RAICs and their properties. Section 4 concludes. All proofs are relegated to the Appendix.

2 Behavioral Affective Decision Model

We extend the ADM model of Bracha and Brown (2012) to allow policy interventions that change endogenous perceptions of probability to improve insurance levels.

Consider an agent facing two states of the world, Bad (B) and Good (G), with associated wealth levels $w_B < w_G$. Utility from wealth is captured by a strictly increasing, strictly concave smooth function u satisfying $\lim_{w \rightarrow -\infty} u'(w) = \infty$ and $\lim_{w \rightarrow \infty} u'(w) = 0$. The agent's perception of risk is the probability $p \in [0, 1]$ that the Bad state occurs. The agent chooses an insurance level $I \in \mathbb{R}$ at the fixed insurance premium rate $\gamma \in (0, 1)$.

The optimal pair (I^*, p^*) is the Nash equilibrium of a two-player simultaneous game between the agent's rational and emotional sides. The rational agent maximizes utility by choosing I given p ; the emotional agent chooses p given I subject to a mental cost incurred when the perceived probability p differs from the one he is aware of, p_0 . This interpersonal game admits the

¹Such settings are also those in which the outcome-severity channel is least available. When the adverse state is already catastrophic, as with a destroyed home, there is little scope for a policymaker to make the bad outcome worse in order to motivate coverage, leaving the belief channel as the principal lever.

potential function

$$\theta(I, p, p_0) = pu(w_B + (1 - \gamma)I) + (1 - p)u(w_G - \gamma I) - J(p, p_0), \quad (1)$$

where $J(p, p_0)$ is the mental cost from departing from the *real*² baseline probability p_0 .

Following Bracha and Brown (2012), J is non-negative, strictly convex, attains its minimum at $p = p_0$, and is essentially smooth on $(0, 1)$ with $\lim_{p \rightarrow 0} J(p, p_0) = \lim_{p \rightarrow 1} J(p, p_0) = +\infty$ and $\lim_{p \rightarrow 0} |DJ(p, p_0)| = \lim_{p \rightarrow 1} |DJ(p, p_0)| = +\infty$. We extend J to depend explicitly on p_0 , as policy interventions operate through changes in p_0 . We impose the same regularity conditions on this dependence as on $J(p)$. Since p_0 is exogenous to the agent, it does not constitute a choice variable in the optimization problem.

The first-order conditions of the model are

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

$$\frac{\partial \theta(I, p, p_0)}{\partial p} = u(w_B + (1 - \gamma)I) - u(w_G - \gamma I) - J'(p, p_0), \quad (3)$$

and from Bracha and Brown (2012) the pair (I^*, p^*) that solves (2)–(3) is a Nash equilibrium of the game.

2.1 Behavioral model of insurance

Let $I^*(q)$ denote the insurance level that solves the rational player's first-order condition (2) when the probability conditioned on equals q . The agent's realized choice is $I^*(p^*)$, evaluated at the equilibrium perception p^* . The object of interest for a policymaker is a *benchmark* coverage against which realized choices can be judged. We take this benchmark to be $I^*(\tilde{p}_0)$, the coverage of a rational agent who acts on the objective probability $\tilde{p}_0$ of the adverse event. Crucially, $\tilde{p}_0$ is not a private belief: it is the empirical frequency of the adverse state, which a policymaker can estimate from claims records, actuarial tables, or epidemiological data. The benchmark $I^*(\tilde{p}_0)$ is therefore computable from observables and the model primitives, without access to any agent's subjective beliefs.

Proposition 1 establishes that $I^*(\cdot)$ is strictly increasing, so the benchmark is well defined and the sign of the gap between realized and benchmark

²Baseline probabilities are given by evidence, facts or past results.

coverage is informative about the sign of the gap between perceived and objective probabilities. The monotonicity of optimal coverage in the loss probability, and the resulting characterization in Corollary 1, are standard facts of the expected-utility model; we state them explicitly for completeness, as they provide the benchmark on which the identification and policy results below rest.

Proposition 1. *If u is strictly increasing and strictly concave, then $I^*(q)$ is strictly increasing in q .*

Corollary 1. *Fix the objective probability $\tilde{p}_0$ and the corresponding benchmark $I^*(\tilde{p}_0)$. An agent whose realized coverage satisfies $I^*(p^*) < I^*(\tilde{p}_0)$ behaves as if the adverse event were less likely than it objectively is ($p^* < \tilde{p}_0$); we call such behavior *optimistic*. Symmetrically, $I^*(p^*) > I^*(\tilde{p}_0)$ identifies *pessimistic behavior* ($p^* > \tilde{p}_0$).*

Corollary 1 states what a single choice can and cannot reveal, and it is worth being explicit about the distinction, since it is the crux of identification in this model. Realized under-insurance relative to $I^*(\tilde{p}_0)$ signs the *total behavioral wedge* $p^* - \tilde{p}_0$, but this wedge admits two conceptually distinct sources,

$$p^* - \tilde{p}_0 = \underbrace{(p^* - p_0)}_{\text{affective distortion}} + \underbrace{(p_0 - \tilde{p}_0)}_{\text{miscalibrated baseline}}, \quad (4)$$

where p_0 is the agent's own, privately held baseline belief. The first term is the emotional self pulling perception away from the agent's reference belief; the second is the reference belief itself departing from the objective frequency. These correspond to the two readings of optimism in our title: an agent may under-insure because he is *unaware* (a distortion $p^* < p_0$) or because his baseline is simply *wrong* ($p_0 < \tilde{p}_0$).

Remark 1 (Scope of identification). A single observed choice reveals the total wedge $p^* - \tilde{p}_0$ but does not separate the two terms in (4), because p_0 is not observed. We therefore make no claim to type an individual's *source* of bias from one choice. What is identified is behavioral: relative to what the data say the risk is, the agent acts as if it were lower (optimism) or higher (pessimism). This is the object a policymaker needs, since a Risk Awareness Informational Campaign (Section 3) targets the belief component and is justified precisely when the total wedge is nonzero. At the population level the distribution of $p^* - \tilde{p}_0$ is identified from the distribution of coverage

given $\tilde{p}_0$, so the share of agents behaving optimistically is recovered even when individual types are not.

Remark 2 (The benchmark agent). The benchmark $I^*(\tilde{p}_0)$ is a policy yardstick, the coverage implied by acting on the objective probability, rather than a claim that any agent is free of affective distortion. Indeed, an agent whose baseline is correctly set to $\tilde{p}_0$ still plays the rational–emotional game and reaches an equilibrium perception $p^*(\tilde{p}_0)$ that need not equal $\tilde{p}_0$; his coverage $I^*(p^*(\tilde{p}_0))$ generally differs from the benchmark. Using $I^*(\tilde{p}_0)$ as the reference isolates the belief target of policy from residual affective distortion, and reinforces the *unaware* interpretation: distortion persists even under correct information.

3 Policy Design and Awareness of Risk

As established in Section 2, we allow the baseline belief p_0 to be heterogeneous across agents and, in general, distinct from the objective frequency $\tilde{p}_0$ of the adverse event. This reflects the imperfect nature of real-world information (Aliev et al., 2013) and how individuals process uncertainty (Stern et al., 2010). We focus on optimistic agents, for whom $p_0 < \tilde{p}_0$, which by Corollary 1 manifests as under-insurance relative to the benchmark $I^*(\tilde{p}_0)$.

Two policy levers can raise such an agent’s coverage: widening the wealth gap between states, as studied by Bracha and Brown (2012), or raising the perceived baseline p_0 toward $\tilde{p}_0$. We study the second and call these interventions *Risk Awareness Informational Campaigns* (RAICs). Interventions of this kind are not merely hypothetical. In a randomized field experiment, providing homeowners with practical flood-risk information raised flood-insurance uptake by roughly five percentage points, with no change in premiums (Allaire, 2016); and across U.S. communities, public activities that communicate flood risk crowd in private insurance, whereas hazard-mitigation activities, which lower perceived risk, crowd it out (Borsky and Hennighausen, 2022). Consistent with this, exposure to official flood-risk maps raises voluntary coverage (Shao et al., 2017). These interventions share the feature that they change what agents perceive about the *probability* of the adverse event rather than its severity, which is precisely the channel our model isolates.

The design of RAICs is attractive because changing p_0 allows the policymaker to affect optimal insurance decisions without observing the agent’s

actual risk perception p . The intuition comes from Proposition 1: if increasing p_0 increases p , then by monotonicity insurance levels also increase, bringing them closer to $I^*(\tilde{p}_0)$. We say a RAIC is *successful* when it achieves this upward shift in perceived probability. Mathematically, this requires the comparative static $\partial p / \partial p_0$ to be strictly positive. This derivative is obtained by applying the Implicit Function Theorem to the system formed by Equations (2) and (3), yielding our primary threshold for intervention.

Proposition 2. *A Risk Awareness Informational Campaign is successful if, at the equilibrium (I^*, p^*) , the parameter L satisfies:*

$$L := \frac{-\left[(1-\gamma)u'(w_B + (1-\gamma)I^*) + \gamma u'(w_G - \gamma I^*)\right]^2}{p^*(1-\gamma)^2 u''(w_B + (1-\gamma)I^*) + (1-p^*)\gamma^2 u''(w_G - \gamma I^*)} < \frac{\partial^2 J(p^*, p_0)}{\partial p^2}. \quad (5)$$

The parameter L is closely linked to the agent's absolute risk aversion, specifically with respect to the *insurance level* rather than overall wealth. To illustrate this connection and relate our framework to existing literature, consider an agent with a generalized utility function evaluated at equilibrium, $\theta(I^*) := p^*u(\psi(I^*)) + (1-p^*)u(\phi(I^*)) - J(p^*, p_0)$. His absolute risk aversion³ with respect to I , evaluated at I^* , is:

$$r(\theta(I^*)) = -\frac{p^*(\psi'(I^*))^2 u''(\psi(I^*)) + (1-p^*)(\phi'(I^*))^2 u''(\phi(I^*))}{p^* \psi'(I^*) u'(\psi(I^*)) + (1-p^*) \phi'(I^*) u'(\phi(I^*))}. \quad (6)$$

Because our specific agent corresponds to $\psi(I^*) = w_B + (1-\gamma)I^*$ and $\phi(I^*) = w_G - \gamma I^*$, we can compactly rewrite the parameter L as:

$$L = \frac{1}{r(\theta(I^*))} \frac{B}{A}, \quad (7)$$

where $A = p^* \psi'(I^*) u'(\psi(I^*)) + (1-p^*) \phi'(I^*) u'(\phi(I^*))$ and $B = \left[\psi'(I^*) u'(\psi(I^*)) - \phi'(I^*) u'(\phi(I^*))\right]^2$.

This formalization makes Proposition 2 comparable to the result in Bracha and Brown (2012, Prop. 5). The condition $L < \partial^2 J(p, p_0) / \partial p^2$ offers two insights. First, campaigns are more effective for strongly risk-averse agents because L is inversely related to risk aversion. Second, interventions are

³ $r = -u''(\cdot)/u'(\cdot)$.

most effective when targeting individuals with significant belief distortions, as the convexity of the psychological cost function increases with greater deviations from baseline beliefs.

While Proposition 2 establishes the theoretical threshold for success, we illustrate its *conditional* character numerically. Adopt CARA utility $u(w) = -e^{-w}$ and the relative-entropy mental cost

$$J(p, p_0) = \frac{1}{K} [p(\ln p - \ln p_0) + (1-p)(\ln(1-p) - \ln(1-p_0))],$$

with $w_B = 0$, $w_G = 5$, $K = 10$, $p_0 = 0.525$, and vary the premium rate γ . For each γ we solve the Nash equilibrium (I^*, p^*) and evaluate both sides of condition (5). Table 1 reports the results.

Table 1: Verification of the threshold condition in Proposition 2. Parameters: $w_B = 0$, $w_G = 5$, $K = 10$, $p_0 = 0.525$. The horizontal rule separates the region where the condition holds ($\gamma \leq p_0$) from the region where it fails ($\gamma > p_0$).

γ	I^*	L	$\frac{\partial^2 J}{\partial p^2}$	$L < \frac{\partial^2 J}{\partial p^2}$?	sign $\frac{\partial I^*}{\partial p_0}$
0.30	6.26	0.09	0.42	Yes	+
0.40	5.95	0.20	0.43	Yes	+
0.50	5.60	0.38	0.44	Yes	+
0.525	5.00	0.37	0.40	Yes	+
0.55	5.80	0.63	0.51	No	−
0.65	5.57	1.19	0.56	No	−
0.70	5.50	1.71	0.61	No	−

When $\gamma \leq p_0$ the condition $L < \partial^2 J / \partial p^2$ is satisfied and $\partial I^* / \partial p_0 > 0$: a RAIC successfully raises insurance. When $\gamma > p_0$ the condition fails and a RAIC *reduces* coverage. To quantify the practical stakes in the favorable regime, consider $\gamma = 0.4 < p_0 = 0.525$ ($I^* = 5.95$). A 10% increase in p_0 via a RAIC raises optimal insurance to 6.35 (+6.7%), while a 10% widening of the payoff gap ($w_G : 5 \rightarrow 5.5$) raises it to 6.28 (+5.4%).⁴ Hence, *within the region delineated by Proposition 2*, informational nudges can outperform payoff-based incentives. The superiority is conditional, not unconditional: it is the condition $L < \partial^2 J / \partial p^2$ that separates the two regimes.

⁴Numerical computations, including the underlying code, are available upon request.

4 Conclusion

We have developed an affective model of insurance choice with heterogeneous, subjective baseline beliefs, and used it to ask what observed coverage reveals about an agent’s perception of risk. Because optimal coverage is monotone in the perceived probability, coverage relative to a benchmark computed from the objective probability provides a revealed-preference reading of behavior: under-insurance is optimistic, over-insurance pessimistic. We have been deliberate about the limits of this reading. A single choice identifies the behavioral wedge between an agent’s acted-on probability and the objective one, but not whether that wedge originates in emotional distortion or in a miscalibrated baseline; the two are separated only at the population level, through the distribution of coverage. This is, we think, the honest content of a revealed-preference approach to bias, and it is enough for the policy question we pose.

On the policy side, we introduced Risk Awareness Informational Campaigns, which shift perceived baseline probabilities toward the objective frequency without altering payoffs. Our sufficient condition ties their success to a notion of absolute risk aversion measured with respect to the insurance level rather than wealth, and it is genuinely a condition: outside the region it delineates, a campaign that raises awareness can lower coverage. The framework thus does more than recommend information provision; it characterizes when such provision helps and when it backfires, which is the practical guidance a policymaker needs. These results suggest natural extensions, including the joint use of belief- and payoff-based instruments and the estimation of the behavioral-type distribution from coverage data, which we leave for future work.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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A Proofs and Auxiliary Lemmas

Proof of Proposition 1. The optimal insurance level $I^*(q)$ solves the rational player's first-order condition: $\partial\theta/\partial I = 0$, where q is the probability conditioned on. Applying the Implicit Function Theorem to this condition yields:

$$\frac{dI^*}{dq} = -\frac{\partial^2\theta/\partial I\partial q}{\partial^2\theta/\partial I^2}.$$

Because u is strictly increasing, the cross-partial derivative $\partial^2\theta/\partial I\partial q = (1 - \gamma)u'(w_B + (1 - \gamma)I^*) + \gamma u'(w_G - \gamma I^*)$ is strictly positive. Because u is strictly concave, $\partial^2\theta/\partial I^2 = q(1 - \gamma)^2 u''(w_B + (1 - \gamma)I^*) + (1 - q)\gamma^2 u''(w_G - \gamma I^*)$ is strictly negative. Consequently, the ratio is strictly positive ($dI^*/dq > 0$), meaning $I^*(q)$ is strictly increasing in q . $\square$

Let $\tilde{I}(p, p_0)$ and $\hat{I}(p, p_0)$ implicitly define the rational and emotional best-responses via $\partial\theta/\partial I = 0$ and $\partial\theta/\partial p = 0$, respectively. Because u is strictly concave, these characterize global maxima. Note $\partial\tilde{I}/\partial p_0 = 0$, as rational choices are independent of the baseline.

Lemma 1 (Best-Response Properties). *The partial derivatives of the best-response functions are:*

$$\begin{aligned}\frac{\partial\tilde{I}}{\partial p} &= \frac{-[(1 - \gamma)u'(w_B + (1 - \gamma)I) + \gamma u'(w_G - \gamma I)]}{p(1 - \gamma)^2 u''(w_B + (1 - \gamma)I) + (1 - p)\gamma^2 u''(w_G - \gamma I)}, \\ \frac{\partial\hat{I}}{\partial p} &= \frac{\partial^2 J(p, p_0)/\partial p \partial p}{(1 - \gamma)u'(w_B + (1 - \gamma)I) + \gamma u'(w_G - \gamma I)}, \\ \frac{\partial\hat{I}}{\partial p_0} &= \frac{\partial^2 J(p, p_0)/\partial p \partial p_0}{(1 - \gamma)u'(w_B + (1 - \gamma)I) + \gamma u'(w_G - \gamma I)}.\end{aligned}$$

Proof. Follows directly from total differentiation of $\partial\theta/\partial I = 0$ and $\partial\theta/\partial p = 0$. $\square$

Define the equilibrium intersection $F(p, p_0) := \tilde{I}(p) - \hat{I}(p, p_0)$.

Lemma 2 (Implicit Condition). *At an equilibrium (p^*, p_0) where $F(p^*, p_0) = 0$, if the best-response curves have distinct slopes ($\partial\tilde{I}/\partial p \neq \partial\hat{I}/\partial p$), then F is continuously differentiable at (p^*, p_0) and $\partial F(p^*, p_0)/\partial p \neq 0$.*

Proof. The smoothness of u and J guarantees F is continuously differentiable. By definition, $\partial F/\partial p = \partial \tilde{I}/\partial p - \partial \hat{I}/\partial p$. The distinct slopes assumption ensures $\partial F/\partial p \neq 0$. Moreover, $\partial F/\partial p_0 = -\partial \hat{I}/\partial p_0$, which is well-defined as derived in Lemma 1. $\square$

Proof of Proposition 2. Applying the Implicit Function Theorem to $F(p, p_0) = 0$ yields $\frac{\partial p}{\partial p_0} = \frac{\partial \hat{I}/\partial p_0}{\partial \tilde{I}/\partial p - \partial \hat{I}/\partial p}$. Substituting Lemma 1 and multiplying the numerator and denominator by $D = (1 - \gamma)u'(w_B + (1 - \gamma)I) + \gamma u'(w_G - \gamma I)$ yields:

$$\frac{\partial p}{\partial p_0} = \frac{\partial^2 J(p, p_0)/\partial p \partial p_0}{D \cdot \partial \tilde{I}/\partial p - \partial^2 J(p, p_0)/\partial p^2} = \frac{\partial^2 J(p, p_0)/\partial p \partial p_0}{L - \partial^2 J(p, p_0)/\partial p^2}.$$

For a successful campaign ($\partial p/\partial p_0 > 0$), since J is strictly convex ($\partial^2 J/\partial p \partial p_0 < 0$), the denominator must be strictly negative. This requires $L < \partial^2 J(p, p_0)/\partial p^2$. This strict inequality simultaneously ensures the condition of Lemma 2 ($\partial F/\partial p \neq 0$) is satisfied. Under this condition, p^* rises, and by Proposition 1, I^* rises. $\square$