

# Persuading an inattentive and privately informed receiver

Pietro Dall'Ara\*

*Boston College*

August 4, 2024

## Abstract

This paper studies the persuasion of a receiver who accesses information only if she exerts costly attention effort. A sender designs an experiment to persuade the receiver to take a specific action. The experiment affects the receiver's attention effort, that is, the probability that she updates her beliefs. As a result, persuasion has two margins: extensive (effort) and intensive (action). The receiver's utility exhibits a supermodularity property in information and effort. By leveraging this property, we prove a general equivalence between experiments and persuasion mechanisms à la Kolotilin et al. (2017). Censoring favorable states is an optimal strategy for the sender in applications.

Keywords: Persuasion, Inattention, Information Acquisition, Information Design.

JEL Codes: D82, D83, D91.

---

\*I am grateful for helpful comments froms from Jacopo Bizzotto, Giacomo Calzolari, Ryan Chahrour, Vincenzo Denicolò, Mehmet Ekmekci, Marco Errico, Jan Knoepfle, Hideo Konishi, Stephan Lauermann, Chiara Margaria, Laurent Mathevet, Teddy Mekonnen, Stefano Piasenti, Guillaume Pommey, Giacomo Rubbini, Fernando Stragliotto, Utku Ünver, Dong Wei, Bumin Yenmez, and participants in the 2023 Spring meeting of young economists, 2023 Econometric Society European meeting, BC-BU-Brown theory workshop, EUI (Micro group), U. of Bologna, Brown theory/experimental lunch seminar, BU reading group, and Queen Mary PhD workshop. An earlier version of this paper bore the title “The extensive margin of Bayesian persuasion.” Contact: [pietro.dallara@gmail.com](mailto:pietro.dallara@gmail.com).

# Contents

<b>1</b>	<b>Introduction</b>	<b>3</b>
<b>2</b>	<b>Model</b>	<b>7</b>
2.1	Players, actions, and payoffs . . . . .	7
2.2	Information and timing . . . . .	7
2.3	Information policies . . . . .	8
2.4	Discussion and interpretation . . . . .	10
<b>3</b>	<b>Persuasion</b>	<b>11</b>
3.1	Receiver’s action and effort . . . . .	11
3.2	Interval structure of the extensive margin . . . . .	13
<b>4</b>	<b>Persuasion mechanisms</b>	<b>14</b>
<b>5</b>	<b>Optimality properties of upper censorships</b>	<b>17</b>
<b>6</b>	<b>Conclusion</b>	<b>21</b>
	<b>Appendices</b>	<b>21</b>
A	Equilibrium . . . . .	21
A.1	Preliminaries . . . . .	21
A.2	Equilibrium definition . . . . .	22
B	Proofs . . . . .	23
B.1	Proof of Lemma 2 . . . . .	24
B.2	Proof of Theorem 1 . . . . .	24
B.3	Proof of Theorem 2 . . . . .	27
B.4	Proof of Theorem 3 . . . . .	31
B.5	Proof of Proposition 1 . . . . .	33
B.6	Proof of Proposition 2 . . . . .	35
B.7	Symmetric-information benchmark . . . . .	39
C	Supplementary material . . . . .	40

# 1 Introduction

In the “information age,” consumers evaluate whether information sources are worth their attention because learning takes effort and time (Simon, 1996; Floridi, 2014). The persuasion literature studies how a sender, such as an advertiser or media outlet, provides information to persuade a receiver to take a specific action (Kamenica, 2019). When attention is costly, the sender faces a dual problem: the receiver can be persuaded only if she pays attention to the information. This paper studies a persuasion model in which the sender’s information affects the attention effort of a receiver who privately knows the costs and benefits of information.

The *intensive* margin of persuasion refers to the intensity of the sender’s influence on the receiver’s action, whereas the *extensive* margin refers to whether the receiver pays attention to the information. The study of the extensive margin is important to understand how consumers allocate attention to product advertisements and news content. This allocation of attention ultimately determines the success of marketing campaigns and the spread of information across heterogeneous audiences.

To study the extensive and intensive margins of persuasion, we introduce the receiver’s attention decision into a persuasion game between two players: Sender (he) and Receiver (she). In the first stage of the game, Sender designs a signal, which is a random variable correlated with the unknown state. Receiver chooses her attention *effort* knowing the signal’s distribution but not its realization. Increasing effort is costly and raises the probability of observing the signal’s realization. In the last stage of the game, Receiver takes a binary action: 1 or 0. The players’ interests conflict because Receiver chooses action 1 only if she expects the state to exceed her outside option, whereas Sender wants her to choose 1 regardless of the state. The Receiver’s outside option and effort cost constitute her privately known type. The outside option captures the benefit of information, because it is unlikely that a given piece of information is useful if an extremely beneficial outside option is available. Similar games are applied to study, e.g., the persuasion of voters, electoral manipulation, and credit-rating agencies (Alonso and Câmara, 2016; Gehlbach and Simpson, 2015; Bizzotto and Vigier, 2021).

Sender considers that increasing the correlation between the state and the signal affects both the Receiver’s attention effort  $e$  (the extensive margin) and her action upon observing the signal (the intensive margin). Specifically, Receiver updates her

beliefs with probability  $e$  and does not update with the remaining probability. The choice of effort captures the choice of acquiring information, and the cost of effort may be monetary or cognitive. This model of attention is less general than models of flexible information acquisition (Caplin et al., 2022; Denti, 2022; Pomatto et al., 2023) because Receiver only chooses the probability with which she uniformly observes every signal realization. This parsimonious model allows for including asymmetric information and a general functional form of effort cost.<sup>1</sup>

In the model, the Receiver’s utility is supermodular in information and effort (Corollary 1). In particular, the return from effort increases in a type-specific informativeness order, which agrees with Blackwell’s order whenever possible. This property is a complementarity between information and attention effort. Complementarity is a feature of information acquisition from sources such as news outlets and product advertisements. For instance, voters’ willingness to subscribe to a newspaper increases as the newspaper dedicates more space to election news, and TV audiences are more likely to pay attention during commercial breaks if advertisements are informative.<sup>2</sup> This paper analyzes the extent of persuasion in these scenarios.

We establish the equivalence between persuasion mechanisms and signals (Theorem 1). A persuasion mechanism is a menu of signals, one for every Receiver’s report of her type. Under a persuasion mechanism, Receiver makes a report and chooses her effort. Specifically, Receiver chooses the probability with which she observes the signal that corresponds to her report. For every persuasion mechanism, there is a signal that induces the same action and effort choices of all Receiver’s types. The key step in the proof is to construct a signal that “allocates” to each type  $t$  the same  $t$ -specific informativeness as the incentive-compatible mechanism. This step establishes the equivalence with respect to effort choices. The constructed signal also replicates Receiver’s optimal action, by simple convex analysis given the representation of signals as convex functions (Gentzkow and Kamenica, 2016). Thus, the equivalence in Kolotilin et al. (2017) obtains in the particular case of costless effort. As a result, Sender need not offer a fine collection of information structures and the analysis of

---

<sup>1</sup>Typical applications of flexible information acquisition rely on functional-form assumptions and define cost functions over belief distributions, which this model avoids — the Receiver’s information cost is “experimental” (Denti et al., 2022) because she chooses mixtures of full information and null information about the Sender’s signal, which are represented by effort levels.

<sup>2</sup>Supermodularity implies that Receiver’s equilibrium effort increases as her outside option becomes less extreme. There is empirical evidence that product awareness increases in the informative content of ads (Honka et al., 2017; Tsai and Honka, 2021).

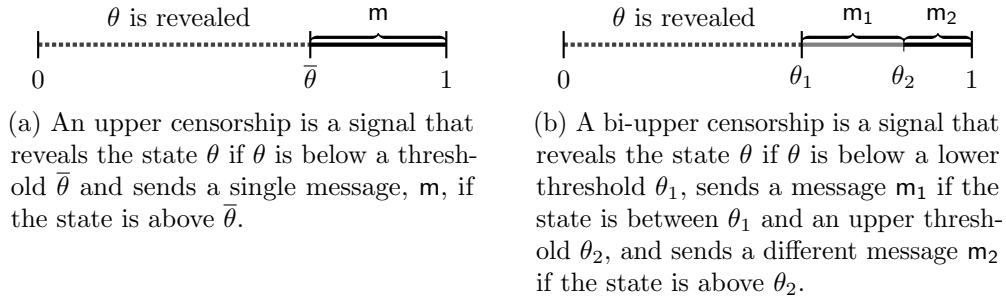


Figure 1: An upper censorship (a) and a bi-upper censorship (b), for a state  $\theta$  with support  $[0, 1]$ .

the extensive margin can focus on single signals.

We characterize the optimal signal in commonly studied applications, which censors high states (Theorem 3). An upper censorship is a signal that reveals low states and pools high states, as shown in Figure 1a. Upper censorships are optimal signals if the Receiver’s outside option follows a single-peaked distribution. In the costless-attention case, the result follows directly from the shape of the noise in the Receiver’s action given her posterior belief. The noise — perceived by Sender — is exogenous and due to asymmetric information. The general result accounts for the endogenous randomness due to the Receiver’s choice of effort. Moreover, any equilibrium upper censorship provides less information if effort is costless than if effort comes at a small positive cost. If Sender values Receiver’s effort directly — i.e., not only because Receiver’s effort ultimately affects her action from the Sender’s point of view —, “bi-upper censorships” are optimal signals (Figure 1b). The additional censorship region allows Sender to separately control the extensive and intensive margins of persuasion in an extension inspired by models of media capture à la Gehlbach and Sonin (2014).

**Related literature** Existing work considers persuasion without Receiver’s information acquisition.<sup>3</sup> The optimality properties of upper censorships are known, and the equivalence between persuasion mechanisms and signals is shown by Kolotilin

<sup>3</sup>*Inter alia*: Rayo and Segal (2010); Kamenica and Gentzkow (2011); Kolotilin (2018); Dworczak and Martini (2019). Note that this paper’s model is not nested in the “single-moment persuasion” because, in equilibrium, effort is a function of the entire posterior-mean distribution — not of a single posterior mean; see Lemma 3 and the Sender’s maximand in Lemma B.3.

et al. (2017).<sup>4</sup> We generalize these results to the case of Receiver’s costly effort and privately known effort cost.

The persuasion of an inattentive Receiver is studied without private information. In Wei (2021), Receiver’s attention cost is posterior separable. As a result of costly attention and symmetric information, the optimal signal is binary, and, in equilibrium, Receiver pays full attention. In the main model of Bloedel and Segal (2021), Receiver’s attention cost is proportional to the entropy reduction in her belief. In a separate model, the authors study the same effort-cost structure as in this paper. The connection with these approaches is discussed in Section 2.4. Certain dynamic models of persuasion include costly Receiver’s attention (Liao, 2021; Jain and Whitmeyer, 2022; Au and Whitmeyer, 2023; Che et al., 2023), although the focus of these binary-state models is on the intertemporal flow of information.<sup>5</sup>

Other work studies Receiver’s information acquisition with different Sender’s incentives or Receiver’s sources than in this paper. The “attention-management” literature considers Receiver’s attention given a benevolent Sender, who maximizes Receiver’s material payoff (without considering her attention cost, Lipnowski et al., 2020, 2022.) The attention model nests this paper’s one in a sense made precise in Section 2.4. The literature on persuasion with “outside-information acquisition” studies Receiver’s costs of acquiring extra information beyond what Sender provides (Brocas and Carrillo, 2007; Felgenhauer, 2019; Bizzotto et al., 2020; Dworczak and Pavan, 2022; Matysková and Montes, 2023). The focus is on how payoffs and information change as outside information becomes cheaper. The belief of a “psychological” Receiver arises from an optimization problem, which typically occurs after the signal realization (Lipnowski and Mathevet, 2018; Galperti, 2019; Beauchêne et al., 2019; de Clippel and Zhang, 2022; Augias and Barreto, 2024) — and not before, as in this paper.

**Outline** Section 2 describes the model and Section 3 analyzes the Receiver’s equilibrium attention and action. Section 4 describes the equivalence between persuasion

---

<sup>4</sup>For upper censorships, see also: Gentzkow and Kamenica (2016); Kleiner et al. (2021); Kolotilin et al. (2022); Arieli et al. (2023); Feng et al. (2024); for persuasion mechanisms, see also: Guo and Shmaya (2019).

<sup>5</sup>Related research includes Knoepfle’s (2020) dynamic model, in which Receiver decides whether to pay attention and Sender only values attention, and the search models in Branco et al. (2016) and Board and Lu (2018).

mechanisms and signals, and Section 5 considers upper censorships and applications. Omitted proofs are in Appendix B.

## 2 Model

### 2.1 Players, actions, and payoffs

Two players, Sender (he) and Receiver (she), play the following persuasion game. Receiver chooses action  $a \in \{0, 1\}$  and effort  $e \in [0, 1]$ , knowing her type  $(c, \lambda) \in [0, 1]^2$ . The material payoff of action  $a$ , given state  $\theta \in [0, 1]$ , is  $a(\theta - c)$ , and the cost of effort  $e$  is  $\lambda k(e)$ , for a continuous function  $k: [0, 1] \rightarrow \mathbb{R}$  and given the Receiver's type  $(c, \lambda)$ .<sup>6</sup> For type  $(c, \lambda)$ , the *cutoff type*  $c$  represents the opportunity cost of taking the risky action, 1, and the *attention type*  $\lambda$  scales the effort cost. The Receiver's utility  $U_R$  is her material payoff net of effort cost and is given by

$$U_R(\theta, a, e, c, \lambda) := a(\theta - c) - \lambda k(e).$$

Sender chooses a signal about the state, i.e., a measurable  $\pi: [0, 1] \rightarrow \Delta M$ , in which  $\Delta M$  is the set of Borel probability distributions over the rich message space  $M$ .<sup>7</sup> The Sender's utility is given by  $U_S(a) := a$ .

### 2.2 Information and timing

**Information** The state  $\theta$  is distributed according to an atomless distribution  $F_0 \in \mathcal{D}$ , the *prior belief*, with mean  $x_0$ , letting  $\mathcal{D}$  be the set of distributions over  $[0, 1]$  identified by their distribution functions. The Receiver's type is independent of  $\theta$  and admits a marginal distribution of the attention type  $\lambda$ ,  $G \in \mathcal{D}$ , and a conditional distribution of the cutoff  $c$  given  $\lambda$ ,  $G(\cdot|\lambda) \in \mathcal{D}$ .

**Timing** First, Sender chooses a signal, without knowing either the state or the Receiver's type  $(c, \lambda)$ . Second, Receiver chooses effort  $e$ , knowing her type  $(c, \lambda)$  and the signal. Third, Nature draws the state  $\theta$  according to  $F_0$ , and the signal realization

---

<sup>6</sup>The results extend to the case of nonlinear cost in  $\lambda$  (see, e.g., Appendix B.2), linearity is maintained to ease interpretation.

<sup>7</sup>For this game, letting  $M = [0, 1]$  is sufficient (Appendix A.2); the representation of signals as convex functions used in the rest of the paper is in Section 2.3.

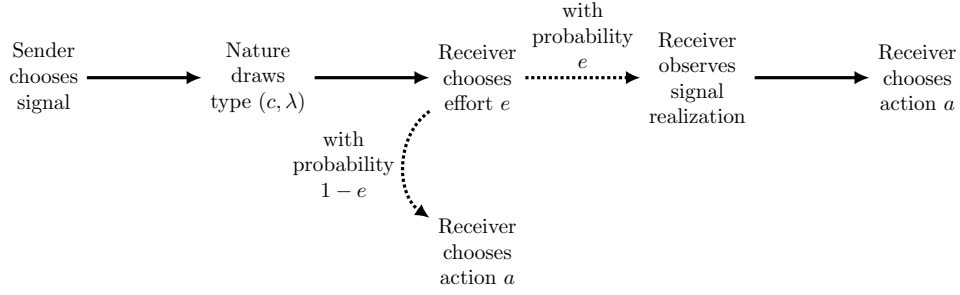


Figure 2: The timeline of the game.

from  $\pi(\theta)$ . Afterwards, with probability  $e$ , Receiver observes the signal realization, she updates her belief about the state using Bayes' rule, and she chooses an action given her *posterior* belief; with probability  $1 - e$ , Receiver does not observe the signal realization and chooses an action given the prior belief. The equilibrium notion is Perfect Bayesian Equilibrium (Appendix A.2).

## 2.3 Information policies

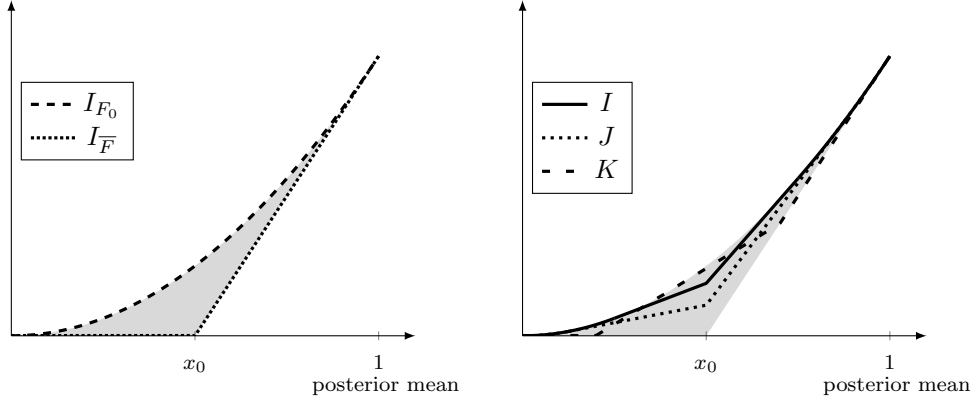
Without loss, signals can be represented by the distributions of the posterior belief's mean induced on a Bayesian player who observes the signal realization.<sup>8</sup> Given the presence of Receiver's effort, it pays off to represent signals by the integrals of such distributions, called “information policies” (Lemma 2). We introduce the notation necessary to state the second equivalence, i.e., between posterior-mean distributions and their integrals. Let's define the *information policy* of  $F \in \mathcal{D}$  as the function  $I_F: \mathbb{R}_+ \rightarrow \mathbb{R}_+$  such that

$$I_F: x \mapsto \int_0^x F(y) dy,$$

the set of feasible distributions  $\mathcal{F} := \{F \in \mathcal{D} \mid I_F(1) = I_{F_0}(1), I_F(x) \leq I_{F_0}(x) \text{ for all } x \in \mathbb{R}\}$ , and the set of information policies  $\mathcal{I} := \{I: \mathbb{R}_+ \rightarrow \mathbb{R}_+ \mid I \text{ is convex, } I_{\bar{F}}(x) \leq I(x) \leq I_{F_0}(x) \text{ for all } x \in \mathbb{R}_+\}$ , in which  $\bar{F}$  is the distribution of an atom at the prior mean, so  $I_{\bar{F}}: x \mapsto (x - x_0)_+$ ; we let  $I'$  denote the right derivative of  $I \in \mathcal{I}$ . Figure 3 illustrates the set  $\mathcal{I}$  and Blackwell's order on  $\mathcal{I}$ . Signals are identified with

<sup>8</sup>Signals can be represented by their posterior-mean distributions in mean-measurable models — as this model — with costless Receiver's attention — unlike this model. Appendix A.1 shows that this equivalence holds for this model.





(a) The set  $\mathcal{I}$  is the set of convex functions that lie between  $I_{F_0}$ , corresponding to a fully informative signal, and  $I_{\bar{F}}$ , corresponding to an uninformative signal, so that  $I$  takes values in the shaded region. (b) Information policy  $I$  is more informative than information policy  $J$  in the Blackwell sense iff:  $I(x) \geq J(x)$  for all  $x \in \mathbb{R}_+$ . Information policies  $K$  and  $I$  are not comparable.

Figure 3: Panel (a) illustrates the set of information policies, panel (b) illustrates the Blackwell's order of information policies; the prior  $F_0$  is a uniform distribution for these figures and the following ones.

information policies via to the following result.

**Lemma 1.** *The following hold:*

1. If  $F \in \mathcal{F}$ , then  $I_F \in \mathcal{I}$ ;
2. If  $I \in \mathcal{I}$ , then  $I' \in \mathcal{F}$ , extending  $I$  to take value 0 at every  $x < 0$ .

*Proof.* See [Gentzkow and Kamenica \(2016\)](#) and [Kolotilin \(2018\)](#).

**QED**

As an implication, Sender chooses  $I \in \mathcal{I}$  in the first stage of the game. Thus, the Receiver's posterior mean is drawn from the distribution  $I'$  with probability corresponding to her effort, and is equal to  $x_0$  with the remaining probability (Figure 2).

**Definition 1.** An *equilibrium* is a tuple  $\langle I^*, e(\cdot), \alpha \rangle$ , in which  $I^* \in \mathcal{I}$  is the Sender's information policy,  $e(c, \lambda, I) \in [0, 1]$  is the Receiver's effort given her type  $(c, \lambda)$  and information policy  $I$ , and  $\alpha(c, \lambda, x) \in [0, 1]$  is the probability that Receiver chooses action 1 given type  $(c, \lambda)$  and posterior mean  $x$ , in a Perfect Bayesian Equilibrium (Appendix A.2).

**Notation** The subdifferential of  $I \in \mathcal{I}$  at  $x \in \mathbb{R}_+$  is denoted by  $\partial I(x)$ . The function  $g: \mathbb{R}^2 \rightarrow \mathbb{R}$  exhibits *increasing differences* if  $t \mapsto g(s', t) - g(s, t)$  is nondecreasing for all  $s', s \in \mathbb{R}$  with  $s < s'$ , and exhibits *strictly increasing differences* if  $t \mapsto g(s', t) - g(s, t)$  is increasing for all  $s', s \in \mathbb{R}$  with  $s < s'$ .

## 2.4 Discussion and interpretation

**Attention effort** The term  $\lambda k(e)$  in the Receiver’s utility represents her attention cost. In particular, let  $e$  represent the Receiver’s attention effort and look at the effort-choice stage for nondecreasing  $k$ . An increase in attention effort implies more Receiver’s information in the Blackwell sense (Figure 3) and higher costs. The functional form of the effort cost is general and includes fixed costs. The model captures a plethora of attention- and non-attention-related phenomena. Examples of attention costs include cognitive difficulties that are psychologically taxing to overcome and memory limits. In contrast, the opportunity cost of being attentive is relevant if a newspaper’s subscription or the probability of being exposed to the media are the objects of choice.

**Costless-attention benchmark** The special case of the model in which effort is costless — i.e., the distribution of  $\lambda$  puts full mass at 0 — is studied by prior work (Kolotilin et al., 2017). There exists an optimal signal that is an upper censorship for a single-peaked distribution of the cutoff type (Theorem 3), and signals are equivalent to persuasion mechanisms (Theorem 1).

**Symmetric-information benchmark** Receiver does not have private information if the type distribution is degenerate. Wei (2021) considers such a model with binary state and two more differences. First, Receiver’s attention cost is posterior separable. Second, Receiver’s strategy space contains the present one: she chooses signals about the Sender’s signal realization, which include mixtures between no information and full information about the Sender’s signal realization. These mixtures constitute the class of signals induced by the choice of effort.

Bloedel and Segal (2021) analyze a model in which: the state space is a continuum, the cost of attention is proportional to an expected entropy reduction taking into account Receiver’s learning about the Sender’s signal, and the Receiver’s strategy

space is fully general.<sup>9</sup> The optimal signal is an upper censorship, although for a different reason than this paper. In particular, Sender perceives Receiver’s action as random, given a signal realization, because of her attention strategy; in our model, instead, the randomness arises due to both the Receiver’s effort and asymmetric information (as discussed in Section 5.) Bloedel and Segal (2021) also consider the symmetric-information benchmark, as one of the alternatives to their model. Due to the binary action and symmetric information, there exists an optimal signal that is a binary signal. There also exists an optimal signal that is an upper censorship (Lemma B.9), and signals are equivalent to persuasion mechanisms (Theorem 1).

### 3 Persuasion

#### 3.1 Receiver’s action and effort

This section studies Receiver’s equilibrium choices, given type  $(c, \lambda)$ .

Given the posterior mean  $x$ , Receiver chooses action 1 if  $x > c$  and action 0 if  $x < c$ . Because  $\theta \mapsto U_R(\theta, a, e; c, \lambda)$  is affine, we express the Receiver’s expected utility from choosing the action optimally given posterior mean  $x$  as

$$U_R(x, e, c, \lambda) := \max_{a \in \{0,1\}} U_R(x, a, e, c, \lambda).$$

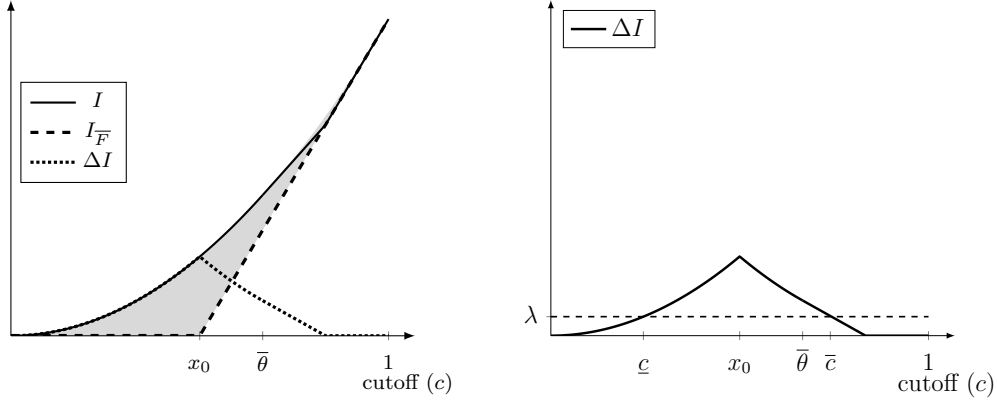
To characterize the equilibrium effort, let’s define the *marginal benefit of effort given information policy  $I$*  as the difference in expected utility with and without the information contained in  $I$ :  $\int_{[0,1]} U_R(x, e, c, \lambda) - U_R(x_0, e, c, \lambda) dI'(x)$ .<sup>10</sup> The *net informativeness of information policy  $I$*  is defined as the difference between  $I$  and the uninformative-signal information policy,  $I_{\bar{F}}$  (Figure 4a). Using the operator  $\Delta: I \mapsto I - I_{\bar{F}}$ , the following result shows that the marginal benefit of effort is given by the net informativeness evaluated at  $c$ , for all  $I$ .

**Lemma 2** (Net informativeness). *Given information policy  $I$  and Receiver’s effort  $e$ ,*

---

<sup>9</sup>We refer to the case in which Sender’s utility is  $U_S$  and the attention cost is entropic, even if their model encompasses other possibilities.

<sup>10</sup>The marginal benefit of effort given  $I$  is also referred to as the value of information in the literature.



(a) The net informativeness of  $I$  at cutoff  $c$ ,  $\Delta I(c)$ , is obtained by subtracting the value of the uninformative-signal information policy at  $c$ ,  $I_{\bar{F}}(c)$ , to  $I(c)$ . The function  $c \mapsto \Delta I(c)$  is single peaked, with peak at the prior mean  $x_0$ , by construction.

(b) The marginal benefit of effort equals the marginal cost for cutoff types  $\underline{c}$  and  $\bar{c}$ , given attention type  $\lambda$  (Lemma 2). Receiver chooses effort 1 if  $c \in (\underline{c}, \bar{c})$ , and does not exert effort if  $c \in [0, 1] \setminus [\underline{c}, \bar{c}]$ .

Figure 4: Panel (a) illustrates the construction of the net informativeness of information policy  $I$ , panel (b) illustrates the subset of cutoff types that exert positive effort, given  $I$  and linear  $k$ , which is an interval. The information policy  $I$  is an “upper censorship” in both panels, defined in Section 5.

the following holds:

$$\int_{[0,1]} U_R(x, e, c, \lambda) - U_R(x_0, e, c, \lambda) dI'(x) = \Delta I(c).$$

The net informativeness  $\Delta I$  is single peaked, with a peak at the prior mean  $x_0$ , by construction (Lemma 1). Extreme-cutoff types benefit the least from observing the signal realization because, intuitively, they are the most certain about the optimal action at the prior.

The following result characterizes Receiver’s equilibrium choices.

**Lemma 3** (Receiver’s rationality). *If  $\langle I^*, e(\cdot), \alpha \rangle$  is an equilibrium, then, for every information policy  $I$ :*

1.  $1 - \int_{[0,1]} \alpha(c, \lambda, x) dI'(x) \in \partial I(c);$
2.  $e(c, \lambda, I) \in \text{Arg max}_{e \in [0,1]} e\Delta I(c) - \lambda k(e).$

*Proof.* Part 1. follows from the definition of information policies and the equilibrium properties of  $\alpha$ , part 2. follows from Lemma 2 and the equilibrium properties of  $e$ . QED

The takeaway of Lemma 3 is Part 2., which identifies the net informativeness of  $I$  at the Receiver's cutoff as a sufficient statistic for her effort decision. As an implication, the two dimensions of Receiver's type,  $c$  and  $\lambda$ , represent her private information about, respectively, her benefit and cost of attention. Part 1. restates the equilibrium conditions that the Receiver's action satisfies.

### 3.2 Interval structure of the extensive margin

This section studies the Receiver's choice of effort.

The Receiver's *value of information policy*  $I$ , given her type  $(c, \lambda)$  and effort  $e$ , is  $V_\lambda(e, \Delta I(c)) := e\Delta I(c) - \lambda k(e)$ .<sup>11</sup> By Lemma 3, part 2., type- $(c, \lambda)$  Receiver's effort in equilibrium maximizes her value given the Sender's information policy. The value of  $I$  exhibits strictly increasing differences in net informativeness and effort, by Lemma 3.

**Corollary 1** (Supermodularity). *The Receiver's value of information policy  $I$ ,  $V_\lambda(e, \Delta I(c))$ , exhibits strictly increasing differences in  $e$  and  $\Delta I(c)$ .*

As an implication, a more informative Sender's information policy, in the Blackwell sense, makes Receiver better off. In particular,  $I$  is Blackwell more informative than  $J$  iff:  $J \leq I$ . Hence, if  $I$  is more informative than  $J$ ,  $I$  allocates more net informativeness to every type than  $J$ . By the increasing-differences property and the envelope theorem (Lemma C.10), Receiver is better off facing  $I$  than  $J$ .<sup>12</sup> The following result characterizes the set of cutoff types that exert positive effort, given  $\lambda$ .

**Lemma 4** (Interval structure). *Let  $\langle I^*, e(\cdot), \alpha \rangle$  be an equilibrium and define the function  $e_\lambda: c \mapsto e(c, \lambda, I)$  for information policy  $I$  and attention type  $\lambda$ . The set  $e_\lambda^{-1}((0, 1])$  is an interval if type  $(x_0, \lambda)$  chooses positive effort, i.e.,  $e_\lambda(\Delta I(x_0)) > 0$ , and is empty otherwise.*

---

<sup>11</sup>Receiver's expected utility equals  $V_\lambda(e, \Delta I(c))$  plus a constant,  $V_\lambda(e, \Delta I(c)) = \int_{[0,1]} U_R(x, e, c, \lambda) dI'(x) + x_0 - c + I_F(c)$ .

<sup>12</sup>This observation is also an implication of Blackwell's theorem, Corollary 1 is a stronger result (see Section 4.)

*Proof.* Let  $\langle I^*, e(\cdot), \alpha \rangle$  be an equilibrium, and let's fix  $\lambda \in [0, 1]$  and  $I \in \mathcal{I}$ . We start with three preliminary observations. First,  $e(c, \lambda, I)$  equals  $e^* \circ \Delta I(c)$  for some selection  $e^*$  from  $\Delta J(c) \mapsto \text{Arg max}_{e \in [0, 1]} V_\lambda(e, \Delta J(c))$ , via Lemma 3. Second, every selection from  $\Delta J(c) \mapsto \text{Arg max}_{e \in [0, 1]} V_\lambda(e, \Delta J(c))$  is nondecreasing, because  $V_\lambda$  satisfies strictly increasing differences, via Corollary 1 and known results (Topkis, 1978, Theorem 6.3). From these observations, it follows that  $e^* \circ \Delta I$  is nondecreasing on  $[0, x_0]$  and nonincreasing on  $[x_0, 1]$  because  $\Delta I$  is nondecreasing on  $[0, x_0]$  and  $\Delta I$  is nonincreasing on  $[x_0, 1]$ .

If  $e^*(\Delta I(x_0)) = 0$ , then every cutoff  $c$  has  $e^*(\Delta I(c)) = 0$ , by the above observations. Let's suppose that  $e^*(\Delta I(x_0)) > 0$ . We define  $\underline{c}_\lambda(\Delta I) = \sup\{c \in [0, x_0] : e^* \circ \Delta I(c) = 0\}$ , if  $\{c \in [0, x_0] : e^* \circ \Delta I(c) = 0\} \neq \emptyset$ , and  $\underline{c}_\lambda(\Delta I) = 0$  otherwise. We define  $\bar{c}_\lambda(\Delta I) = \inf\{c \in [x_0, 1] : e^* \circ \Delta I(c) = 0\}$ , if  $\{c \in [x_0, 1] : e^* \circ \Delta I(c) = 0\} \neq \emptyset$ , and  $\bar{c}_\lambda(\Delta I) = 1$  otherwise. First, we note that  $e^* \circ \Delta I(c) > 0$  only if:  $c \in [\underline{c}, \bar{c}]$ ; second,  $c \in (\underline{c}, \bar{c})$  only if  $e^* \circ \Delta I(c) > 0$ . Thus, either no type  $(c, \lambda)$  chooses positive effort or  $e_\lambda^{-1}((0, 1])$  is an interval. The lemma follows from the fact that  $\Delta I(x_0) \geq \Delta I(c)$  for all  $c \in [0, 1]$ . **QED**

For intuition, let's consider a linear effort cost, which captures a price or fixed cost of gathering information, i.e.,  $k(e) = e$ . Receiver compares her marginal cost,  $\lambda$ , and marginal benefit,  $\Delta I(c)$ , of effort. As shown in Figure 4b, in equilibrium, exerting effort 1 is optimal only if  $\Delta I(c) \geq \lambda$ , and no effort is optimal only if  $\Delta I(c) \leq \lambda$ . Moreover, the net informativeness of  $I$  at a cutoff is single peaked as a function of the cutoff (Figure 3). As an implication, the set of cutoff types that exert positive effort is an interval.<sup>13</sup> The proof of Lemma 4 generalizes the first part of the argument. Specifically, Receiver's effort is nondecreasing in net informativeness at her cutoff type, by supermodularity of  $V_\lambda$  through comparative statics à la Topkis (1978).

## 4 Persuasion mechanisms

This section studies the equivalence between information policies and persuasion mechanisms.

**Definition 2.** A *persuasion mechanism*  $I_\bullet$  is a list of information policies:  $I_\bullet =$

---

<sup>13</sup>Receiver's effort at the boundary is determined through equilibrium selection. The selection is not relevant in equilibrium, for atomless cutoff distributions (Lemma B.3).

$(I_r)_{r \in R}$ , with  $R$  equal to the support of the Receiver's type. A persuasion mechanism  $I_\bullet$  is *incentive-compatible* if

$$\max_{e \in [0,1]} V_\lambda(e, \Delta I_{(c,\lambda)}(c)) \geq \max_{e \in [0,1]} V_\lambda(e, \Delta I_r(c)),$$

for every type  $(c, \lambda)$  and report  $r$ .

Our focus on IC mechanisms references to an auxiliary game. First, Sender publicly commits to a mechanism that selects an information policy for every *type report*. Second, Receiver makes a report  $r \in R$ , knowing her true type  $(c, \lambda)$ . The rest of the game unfolds as in Section 2.2: Receiver chooses effort  $e$ , then she observes the realization of a signal corresponding to information policy  $I_r$  with probability  $e$ , and lastly chooses an action. We are interested in equilibria in which Receiver truthfully reports the type, which is without loss via a revelation-principle argument.

We consider a persuasion mechanism  $I_\bullet$  to be implementable by information policy  $J$  if: every Receiver's type chooses the same action and effort under truthful reporting given  $I_\bullet$  as in some equilibrium of the subgame that starts with the Sender's choice of information policy  $J$  (Section 2.2).

**Definition 3.** An IC persuasion mechanism  $I_\bullet$  is *equivalent to information policy  $J$*  if, for every type  $(c, \lambda)$ :

1.  $\text{Arg max}_{e \in [0,1]} V_\lambda(e, \Delta I_{(c,\lambda)}(c)) \subseteq \text{Arg max}_{e \in [0,1]} V_\lambda(e, \Delta J(c))$ ,
2.  $\partial I_{(c,\lambda)}(c) \subseteq \partial J(c)$  if  $(0, 1] \cap \text{Arg max}_{e \in [0,1]} V_\lambda(e, \Delta I_{(c,\lambda)}(c)) \neq \emptyset$ .

If attention is costless, Definition 3 is the same as in Kolotilin et al. (2017, p. 1954). The novelty is item 1., which requires type  $(c, \lambda)$  to choose the same effort under  $I_\bullet$  as under the signal that implements  $I_\bullet$ .<sup>14</sup> Item 2. in Definition 3 does not deal with a type who only exerts effort 0 under truthful reporting given  $I_\bullet$ . The reason is that the equilibrium action given the prior belief does not depend on Sender's information.<sup>15</sup>

<sup>14</sup>Theorem 1 holds under a slightly stronger version of item 1. in Definition 3, see the proof in Section B.2.

<sup>15</sup>Formally, the reason is that the equivalence of the action decision holds as a consequence of item 1. "for this type." Specifically,  $\text{Arg max}_{e \in [0,1]} V_\lambda(e, \Delta I_{(c,\lambda)}(c)) = \{0\}$  implies that  $0 \in \text{Arg max}_{e \in [0,1]} V_\lambda(e, \Delta J(c))$  by item 1., and the optimal action at the prior belief given  $I_\bullet$  is the same as given  $J$ , possibly via equilibrium selection.

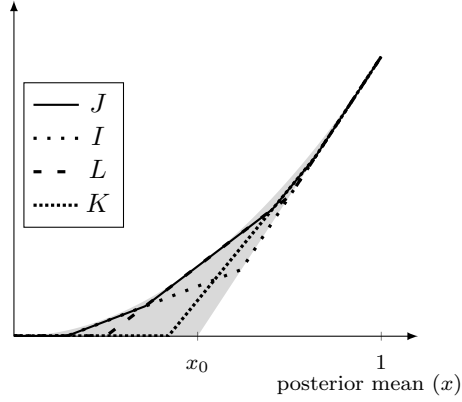


Figure 5: The upper envelope  $J$  of the information policies in the persuasion mechanism  $I_\bullet = (I, L, K)$  is an information policy. The proof of Theorem 1 shows that the upper envelope of an IC persuasion mechanism  $I_\bullet$  implements the equilibrium action and effort of Receiver.

Every IC persuasion mechanism is equivalent to a signal.

**Theorem 1.** *Every persuasion mechanism is equivalent to an information policy.*

This result guarantees that the characterization of the extensive margin of persuasion in Section 3 holds in more general environments, including applications in which multiple information structures are available to decision-makers.

We sketch the intuition and proof of Theorem 1, which leverage Corollary 1. The proof verifies that supermodularity is key by establishing the result for more general Receiver’s payoff functions (Appendix B.2). Let’s claim that the IC mechanism  $I_\bullet$  is equivalent to its upper envelope  $J$  (Figure 5), defined as  $J: x \mapsto \sup_{r \in R} I_r(x)$ , under positive Receiver’s effort. A report  $r$  is *active* at  $x$  if  $I_r(x) \geq I_{r'}(x)$  for all  $r' \in R$ . Let’s also fix Receiver’s type  $(c, \lambda)$ . First, we observe that an active report at  $c$  maximizes Receiver’s expected utility. By Lemma 3, report  $r$  affects Receiver’s utility only through the local net informativeness  $\Delta I_r(c)$ . By increasing differences, an active report at  $c$  makes type  $(c, \lambda)$  weakly better off than any other report (Corollary 1, via the envelope theorem for supermodular programming, Lemma C.10.) Hence, an active report at  $c$  maximizes Receiver’s expected utility at the reporting stage.

Towards the equivalence with respect to effort, we strengthen the observation: A non-active report makes Receiver *strictly* worse off than an active report. This conclusion uses both the fact that Corollary 1 establishes strictly increasing differences and type  $(c, \lambda)$ ’s positive effort (Lemma C.10). To build on this conclusion, let’s order



information policies according to the type-specific relation  $\leq_c$ , defined by  $\hat{I} \leq_c \hat{J}$  iff  $\Delta\hat{I}(c) \leq \Delta\hat{J}(c)$ . The linear order  $\leq_c$  is a completion of Blackwell's order and ranks the menu's items according to Receiver's expected utility. By the IC property of the mechanism  $I_\bullet$ , the policy  $I_r$  maximizes  $\leq_c$  on  $I_\bullet$  only if  $\Delta I_r(c) = \Delta I_{(c,\lambda)}$ .<sup>16</sup> Hence,  $J(c) = I_{(c,\lambda)}(c) \geq I_r(c)$ , for every report  $r$ . An application of Lemma 3 completes the argument for the equivalence with respect to effort. In particular, the net informativeness,  $\Delta J(c)$ , is the only component of the information policy  $I_{(c,\lambda)}$  that affects the effort decision in the IC mechanism  $I_\bullet$ .

The equivalence with respect to action decisions follows from simple convex analysis, due to our results. In particular, it holds that  $\partial I_r(x) \subseteq \partial J(x)$  if report  $r$  is active at  $x$ . The proof uses a continuity argument to cover the case of zero effort.

## 5 Optimality properties of upper censorships

This section discusses the properties of the following class of information policies.

**Definition 4.** The  $\bar{\theta}$  *upper censorship*, for state  $\bar{\theta} \in [0, 1]$ , is the unique information policy  $I_{\bar{\theta}} \in \mathcal{I}$  such that

$$I_{\bar{\theta}}(x) = \begin{cases} I_{F_0}(x), & x \in [0, \bar{\theta}] \\ \max\{I_{F_0}(\bar{\theta}) + F_0(\bar{\theta})(x - \bar{\theta}), I_{\bar{F}}(x)\}, & x \in (\bar{\theta}, \infty). \end{cases}$$

The case of a single-peaked marginal distribution of the cutoff type is relevant for applications (Romanyuk and Smolin, 2019; Kolotilin et al., 2022; Gitmez and Molavi, 2023; Shishkin, 2024; Augias and Barreto, 2024; Sun et al., 2024).

**Assumption 1.** The conditional distribution of the cutoff type given attention type  $\lambda$  admits a density  $g(\cdot|\lambda)$  such that: (i)  $g(\cdot|\lambda)$  is absolutely continuous, and (ii) there exists  $p \in [0, 1]$  such that: for all  $\lambda$ ,  $g(\cdot|\lambda)$  is nondecreasing on  $[0, p]$  and nonincreasing on  $[p, 1]$ .

The class of single-peaked distributions includes the standard uniform and the  $[0, 1]$ -truncated normal. The assumption rules out the symmetric-information bench-

---

<sup>16</sup>Blackwell's theorem does not suffice for this conclusion, which uses (i) Corollary 1, (ii) the envelope theorem (Appendix, Lemma C.10), and (iii) completeness of  $\leq_c$ .

mark, which is treated in Appendix. We say that *strict single-peakedness* holds if: Assumption 1 holds and  $g(\cdot|\lambda)$  is increasing on  $[0, p]$  and decreasing on  $[p, 1]$ .

We first establish that an equilibrium exists and that the Sender’s equilibrium expected utility is unique.

**Theorem 2.** *Under Assumption 1, there exists an equilibrium and the Sender’s expected utility is the same in every equilibrium.*

In the Appendix (Lemma B.3), we establish that continuity of the cutoff distribution ensures that Sender is indifferent among all Receiver’s best responses.<sup>17</sup>

The next result shows that an optimal signal that is an upper censorship exists.

**Theorem 3.** *Under Assumption 1, there exists an equilibrium in which the Sender’s information policy is an upper censorship.*

Given Theorem 1, Theorem 3 shows that the extensive margin of a complicated optimal persuasion mechanism can be studied via an upper censorship. Moreover, Theorem 3 reduces the Sender’s optimization to a uni-dimensional problem.

In the case of costless attention and Sender-optimal equilibria, the argument for Theorem 3 rests on the shape of the exogenous noise in Receiver’s action given a posterior belief, from the Sender’s perspective. The Sender’s expected utility at posterior mean  $x$  is  $H(x)$ , letting  $H$  denote the distribution of the cutoff type. By single-peakedness,  $H$  is “S shaped.” So, Sender is risk lover conditionally on low posterior means, i.e.,  $x < p$ , and he is risk averse for high posterior means. In particular, a mean-preserving spread around a low posterior mean increases Sender’s expected utility. Second-order dominance is related to the informativeness of Sender’s strategy because:  $F \in \mathcal{F}$  is a mean-preserving spread of  $\hat{F} \in \mathcal{F}$  iff  $I_F$  is more Blackwell informative than  $I_{\hat{F}}$ . Moreover, the upper censorship  $I_{\bar{\theta}}$  induces either full information conditionally on the state being lower than the threshold  $\bar{\theta}$ , or no information except that  $\theta > \bar{\theta}$ . Thus, intuitively, upper censorships induce posterior-mean distributions that align with the Sender’s interests. In the next paragraph, we adjust the intuition for the case of endogenous effort, i.e., in which the relevant information policy is  $x \mapsto eI(x) + (1 - e)I_{\bar{F}}(x)$ .

---

<sup>17</sup>Lipnowski et al. (2024) show that uniqueness obtains in a general model, which does not nest ours. Their Corollary 1 is similar to our observation, even if our proof leverages the convexity of (i) information policies and (ii) Receiver’s interim utility  $a \mapsto \max_{e \in [0,1]} V_{\lambda}(e, a)$ . The latter result obtains from the envelope theorem for supermodular optimization, Lemma C.10.)

We claim that Receiver’s effort is affected by the signal’s informativeness in a way that aligns with Sender’s interests. In particular, let’s suppose that Sender increases the net informativeness of posterior mean  $x$ :  $\Delta I(x)$ . This change induces cutoff-type  $x$  to pay extra attention, via the envelope theorem for supermodular optimization (lemmata 3 and C.10.) If cutoff-type  $x$  increases her effort, she gathers more information, because  $x \mapsto eI(x) + (1 - e)I_{\bar{F}}(x)$  increases in the Blackwell’s order as  $e$  increases. Thus, by increasing the net informativeness of  $I$  at  $x$ , Sender spreads out the Receiver’s posterior-mean distribution around  $x$ . This argument, however, is “local.” Specifically, net informativeness  $\Delta I(x)$  increases only via a new information policy that satisfies the convexity constraint in  $\mathcal{I}$ . The proof uses this argument to construct  $I_{\bar{\theta}} \in \mathcal{I}$  that improves upon  $I$ , for arbitrary  $I$ .

Sender optimally provides more information as Receiver’s attention cost increases, for small attention costs. We say that  $I \in \mathcal{I}$  is an *optimal* if there exists an equilibrium in which Sender chooses  $I$ .

**Proposition 1.** *Let strict single-peakedness hold,  $F_0$  admit a density,  $k$  be linear, and the attention type put full mass at  $\lambda$ . Let  $I_{\theta_\varepsilon}$  be an optimal upper censorship if  $\lambda = \varepsilon$ , and  $I_\eta$  be an optimal upper censorship if  $\lambda = 0$ , with  $\eta \in (0, 1)$ . We have:  $\theta_\varepsilon > \eta$  for all sufficiently small  $\varepsilon > 0$ .*

The same qualitative result holds in Wei (2021, Proposition 7). Let’s describe the intuition in the symmetric-information benchmark, for  $c > x_0$ . Sender solves the maximization of the Receiver’s action, given the constraint that she exerts effort 1. Let’s observe that the “participation constraint” binds (Lemma B.4). Let’s suppose this were not the case. Sender increases the probability of a posterior mean  $x$  with  $x \geq c$  as much as possible. Specifically, he induces the mean  $x = c$  with the highest probability that satisfies Bayes’ rule (Kamenica and Gentzkow, 2011). Hence, Receiver faces two possibilities: she is indifferent between the actions, with some probability; she finds it optimal to choose the riskless action, 0, with the remaining probability. So, information brings no value, and the constraint binds. Thus, Sender provides “better” information if  $\lambda > 0$  than if  $\lambda = 0$ .<sup>18</sup> Proposition 1 shows that the insight generalizes, for small  $\lambda$ . In general, a change in the censorship state  $\theta_\varepsilon$  affects the extensive margin given Receiver’s private information. However, only the extensive

---

<sup>18</sup>Lemma B.4 implies that Sender provides more Blackwell information to Receiver if  $\lambda > 0$  than if  $\lambda = 0$  under symmetric information.

margin's upper bound ( $\bar{c}$  in Figure 4b) is affected by small changes in  $\theta_\varepsilon$  around  $\eta$ , because a nontrivial upper censorship is optimal if  $\lambda = 0$ .<sup>19</sup> This argument leads to Proposition 1.

In applications to media capture, Sender cares directly about Receiver's material payoff (Kolotilin et al., 2022) and attention (Gehlbach and Sonin, 2014). In the former case, Sender is a government that weighs social utility. In the latter case, Sender is a dictator and owns a state's media, so he collects advertisement revenues. The next result shows that an extension of the class of upper censorships contains an optimal information policy for general Sender's utility functions.<sup>20</sup> A *bi-upper censorship* is an information policy  $I$  such that

$$I(x) = \begin{cases} I_{F_0}(x), & x \in [0, \theta_1], \\ I_{F_0}(\theta_1) + F_0(\theta_1)(x - \theta_1), & x \in (\theta_1, x_1], \\ I_{\bar{F}}(x_2) - m(x_2 - x), & x \in (x_1, x_2], \end{cases}$$

for  $m = \frac{I_{\bar{F}}(x_2) - [I_{F_0}(\theta_1) + F_0(\theta_1)(x_1 - \theta_1)]}{x_2 - x_1}$  and  $0 \leq \theta_1 \leq x_1 \leq x_2 \leq 1$  (Figure 1).

**Proposition 2.** *Let Assumption 1 hold with  $p \geq x_0$ ,  $k$  be linear, the attention type put full mass at  $\lambda$ , and the Sender's utility be given by  $U_G(\theta, a, e, c, \lambda) := a + \gamma e + \rho U_R(\theta, a, e, c, \lambda)$  for  $\gamma \geq 0$  and  $\rho \geq 0$ . For every equilibrium  $\langle I, e(\cdot), \alpha \rangle$ , there exists a bi-upper censorship with a weakly greater Sender's expected utility than  $I$ , given  $e(\cdot)$  and  $\alpha$ .*

The case of  $\gamma = 0$  is studied by Kolotilin et al. (2022), who find that upper censorships are optimal signals, and by Gitmez and Molavi (2023) who also assume binary state and  $\rho = 0$ . Sender's preferences given  $\rho = 0$  are introduced by Gehlbach and Sonin (2014), who assume binary state and Sender's signal. The requirement that the cutoff's peak satisfies  $p \geq x_0$  represents sufficient ex-ante disagreement between Sender and Receiver, as in Shishkin (2024) and for symmetric cutoff densities. The proof constructs a bi-upper censorship that replicates the same extensive margin as

<sup>19</sup>The net informativeness of  $I_{\bar{\theta}}$  is 0 at a cutoff type weakly greater than the conditional expectation of  $\theta$  given  $\theta \geq \bar{\theta}$  (Figure 4).

<sup>20</sup>Equilibrium existence is not established for this extension. The difficulty lies in establishing continuity of the extensive margin — i.e., continuity of  $F \mapsto \underline{c}_\lambda(\Delta I_F)$  and  $F \mapsto \bar{c}_\lambda(\Delta I_F)$ , defined in the proof of Lemma 4, when  $\mathcal{F}$  is endowed with the  $L^1$ -norm topology (which makes  $\mathcal{F}$  compact, see Kleiner et al., 2021.)

an arbitrary  $I \in \mathcal{I}$ , and that improves upon  $I$  in terms of expected Receiver’s action and utility. Thanks to the same intuition as for Theorem 3, we construct an upper censorship  $I_{\bar{\theta}}$  that improves upon  $I$  for  $\gamma = 0$ , because the argument for  $\rho = 0$  is preserved if  $\rho > 0$  (as in Kolotilin et al., 2022.) The role of the additional censorship region is to modify  $I_{\bar{\theta}}$  in a way that replicates the extensive margin of  $I$ . Specifically, the additional threshold state is constructed to increase the marginal benefit of effort of certain types in case  $I_{\bar{\theta}}$  induces fewer cutoff types than  $I$  to exert effort, for  $\gamma > 0$ .

## 6 Conclusion

This paper proposes a model of attention within the canonical persuasion framework, which underscores the complementarity between information and attention effort. This complementarity leads to the equivalence of persuasion mechanisms and experiments. The sender’s optimization problem is solved by censoring favorable states — a strategy relevant in contexts in which attention is directly valued, such as media capture.

In general, the complementarity may hold only “locally”, across audiences and information structures, for instance due to information overload and psychological constraints. A study of the extensive margin of persuasion that incorporates these distinctions offers an open avenue for future research.

## Appendix

### A Equilibrium

#### A.1 Preliminaries

We claim that the Sender’s signal affects the decisions and payoffs of both Sender and Receiver only through the distribution of the posterior mean that it induces on a Bayesian agent who always observes the signal realization.

Type- $t$  Receiver’s optimal action, given posterior belief  $\mu \in \mathcal{D}$  and  $t = (c, \lambda)$ , depends on the belief  $\mu$  only through its mean  $\bar{x}_\mu := \int_{[0,1]} \theta d\mu(\theta)$ . The Receiver’s *material payoff at belief  $\mu$*  is her expected material payoff given belief  $\mu$  and is given

by

$$v_t(\mu) := \begin{cases} \int_{[0,1]} (\theta - c) d\mu(\theta), & \text{if } \bar{x}_\mu \geq c, \\ 0, & \text{if } \bar{x}_\mu < c. \end{cases}$$

We note that  $v_t(\mu)$  depends on the belief  $\mu$  only through  $x_\mu$ . If the Sender's signal induces the Bayes-plausible distribution over posterior beliefs  $p$  (Kamenica and Gentzkow, 2011), type- $t$  Receiver chooses effort to maximize her expected utility

$$e \int_{\mathcal{D}} v_t(\mu) dp(\mu) + (1 - e)v_t(F_0) - \lambda k(e). \quad (1)$$

Thus, Receiver's action, effort, and her payoff depend on the Sender's signal only via the distribution of the posterior mean (i.e., the distribution of  $x_\mu$  implied by  $p$ .) The claim follows from the Sender's payoff function, which depends on the signal only via the Receiver's choice of action. The same conclusion holds under the hypothesis of Proposition 2.

## A.2 Equilibrium definition

We define a Perfect Bayesian Equilibrium in which Sender directly chooses an experiment  $F \in \mathcal{F}$ . From Section A.1, this approach is without loss. From Lemma 1, the equilibrium notion is essentially the same as in the text (Section 2.2). Let  $T$  denote the support of Receiver's type. Given  $F \in \mathcal{F}$  and effort  $\varepsilon \in [0, 1]$ , we define  $\varepsilon \odot F = \varepsilon F + (1 - \varepsilon)\bar{F}$ , and note that  $\varepsilon \odot F \in \mathcal{F}$ . An equilibrium is a tuple  $\langle F, e, \alpha \rangle$ , in which  $F \in \mathcal{F}$ ,  $e(\cdot, \hat{F}): T \rightarrow [0, 1]$  is measurable for all  $\hat{F} \in \mathcal{F}$ ,  $\alpha(\cdot, x): T \rightarrow [0, 1]$  is measurable for all  $x \in [0, 1]$ , and  $\alpha(c, \lambda, \cdot): [0, 1] \rightarrow [0, 1]$  is measurable for all  $(c, \lambda) \in T$ , such that:

1.  $\alpha$  satisfies  $a$  Opt:

$$\alpha(c, \lambda, x) > 0 \text{ only if } 1 \in \underset{a \in \{0,1\}}{\text{Arg max}} a(\theta - c)$$

for all  $x \in [0, 1]$ ,  $(c, \lambda) \in T$ ;

2.  $e$  satisfies  $e$  Opt:

$$e(c, \lambda, \hat{F}) \in \operatorname{Arg\,max}_{e \in [0,1]} \int_{[0,1]} \max_{a \in \{0,1\}} U_R(x, a, e, c, \lambda) \, d(e(c, \lambda, \hat{F}) \odot \hat{F})(x)$$

for all  $(c, \lambda) \in T$ ,  $\hat{F} \in \mathcal{F}$ ;

3.  $F$  is rational for Sender given  $(\alpha, e)$ , that is:  $F$  maximizes

$$\hat{W}(\cdot, e, \alpha): \hat{F} \mapsto \int_{[0,1]} \int_{[0,1]} \int_{[0,1]} \alpha(x, c, \lambda) \, d(e(c, \lambda, \hat{F}) \odot \hat{F})(x) \, dG(c|\lambda) \, dG(\lambda)$$

on  $\mathcal{F}$ .

Note that: (i.)  $e \mapsto U_R(x, a, e, c, \lambda)$  is continuous for all  $x, a, c, \lambda$ , so the set of maximizers in  $e$  Opt is nonempty; (ii.) lemmata B.1 and B.3 establish that the maximization in (3.) is well-defined given  $(\alpha, e)$  satisfying items (1.) and (2.).

## B Proofs

We endow  $\mathcal{F}$  with the  $L^1$  norm, which metrizes weak convergence (Machina, 1982, Lemma 1). We endow  $\mathcal{I}$  with the pointwise order, denoted by  $\leq$ . We define the functions

$$\begin{aligned} W: F &\mapsto \int_{[0,1]} \int_{[0,1]} V_\lambda(\Delta I_F(c)) \frac{\partial g}{\partial c}(c|\lambda) \, dc \, dG(\lambda), \\ W_\lambda: F &\mapsto \int_{[0,1]} V_\lambda(\Delta I_F(c)) \frac{\partial g}{\partial c}(c|\lambda) \, dc. \end{aligned}$$

**Definition 5.** The experiment  $F$  is  $W$  maximal if  $F$  maximizes  $W$  on  $\mathcal{F}$ . The experiment  $\hat{F} \in \mathcal{F}$  is an *equilibrium experiment* if there exists an equilibrium  $\langle F, e, \alpha \rangle$  with  $\hat{F}(x) = F(x)$  for all  $x \in \mathbb{R}$ . The Receiver's *value of*  $F \in \mathcal{F}$  is  $V_\lambda(\Delta I_F(c)) := \max_{e \in [0,1]} V_\lambda(e, \Delta I_F(c))$ . There are *multiple Sender's payoffs* if there exist equilibria  $\langle F, e, \alpha \rangle$  and  $\langle \tilde{F}, \tilde{e}, \tilde{\alpha} \rangle$  such that  $\hat{W}(F, e, \alpha) \neq \hat{W}(\tilde{F}, \tilde{e}, \tilde{\alpha})$ .

**Remark B.1.** Let's fix an equilibrium  $\langle F, e(\cdot), \alpha \rangle$ . We have  $e(c, \lambda, I) = e_\lambda^* \circ \Delta I(c)$  for some selection  $e_\lambda^*$  from  $\Delta J(c) \mapsto \operatorname{Arg\,max}_{e \in [0,1]} V_\lambda(e, \Delta J(c))$  by  $e$  Opt. We define  $\underline{e}_\lambda(\Delta I) = \sup\{c \in [0, x_0] : e_\lambda^* \circ \Delta I(c) = 0\}$ , if  $\{c \in [0, x_0] : e_\lambda^* \circ \Delta I(c) = 0\} \neq \emptyset$ ,

and  $\underline{c}_\lambda(\Delta I) = 0$  otherwise. We define  $\bar{c}_\lambda(\Delta I) = \inf\{c \in [x_0, 1] : e_\lambda^* \circ \Delta I(c) = 0\}$ , if  $\{c \in [x_0, 1] : e_\lambda^* \circ \Delta I(c) = 0\} \neq \emptyset$ , and  $\bar{c}_\lambda(\Delta I) = 1$  otherwise.

### B.1 Proof of Lemma 2

*Proof.* Let's fix Receiver's type  $(c, \lambda)$  and  $I \in \mathcal{I}$ . By definition of  $U_R$ , letting  $\alpha(c, x)$  be any probability measure over  $\{0, 1\}$  such that  $\alpha(c, x)(\text{Arg max}_{a \in \{0, 1\}} a(x - c)) = 1$  for all  $x \in [0, 1]$ , we have

$$\begin{aligned} \int_{[0, 1]} U_R(x, e, c, \lambda) dI'(x) + \lambda k(e) &= \int_{[c, 1]} x - c dI'(x) \\ &\quad - (1 - \alpha(c, c)(\{1\}))(I'(c) - I'(c^-))(c - c), \\ &= \int_{[c, 1]} x - c dI'(x). \end{aligned}$$

Moreover,

$$\begin{aligned} \int_{[0, 1]} U_R(x, e, c, \lambda) dI'(x) + \lambda k(e) &= (1 - c) - \int_{[c, 1]} I'(x) dx, \\ &= x_0 - c + I(c). \end{aligned}$$

in which the first equality is due to Riemann–Stieltjes integration by parts ([Machina, 1982](#), Lemma 2) and the second to absolute continuity of  $I$ . It follows that

$$\int_{[0, 1]} U_R(x, e, c, \lambda) dI'(x) - \int_{[0, 1]} U_R(x, e, c, \lambda) d\bar{F}(x) = \Delta I(c).$$

**QED**

### B.2 Proof of Theorem 1

Theorem 1 is implied by the result proved in this section as Proposition [B.1](#). For this section, we fix a function  $f: [0, 1] \times [0, 1] \rightarrow \mathbb{R}^2$  that satisfies strictly increasing differences, and such that:  $f(\cdot, a)$  is continuous for all  $a \in [0, 1]$ ,  $f(e, \cdot)$  is nondecreasing for all  $e \in [0, 1]$ , the derivative with respect to the variable  $a$ ,  $\frac{\partial f}{\partial a}(e, \cdot)$ , exists, is nonnegative and bounded for all  $e \in [0, 1]$ , and  $f(e, \cdot)$  is increasing for all  $e \in (0, 1]$ . We maintain the definitions of the main text except that the following definitions replace the corresponding ones in the main text: The *value of*  $I \in \mathcal{I}$ , given type  $(c, \lambda)$



and effort  $e$ , is  $V_\lambda(e, \Delta I(c)) := f(e, \Delta I(c)) - K(e, \lambda)$ , and the cost of effort  $e \in [0, 1]$  is  $K(e, \lambda)$  for a continuous function  $K(\cdot, \lambda)$ . We use the shorthand  $t = (c_t, \lambda_t)$  and we define the set of optimal efforts

$$E_{\lambda_t}(\Delta I(c_t)) := \text{Arg max}_{e \in [0,1]} V_{\lambda_t}(e, \Delta I(c_t)),$$

and  $V_{\lambda_t}(\Delta I(c_t)) := \max_{e \in [0,1]} V_{\lambda_t}(e, \Delta I(c_t))$ , for  $I \in \mathcal{I}$ . A persuasion mechanism  $I_\bullet$  is *incentive compatible* (IC) if:

$$t \in \text{Arg max}_{r \in R} V_{\lambda_t}(\Delta I_r(c_t)), \text{ for all types } t \in T.$$

**Definition 6.** An IC persuasion mechanism  $I_\bullet$  is *equivalent to an experiment* if there exists information policy  $I$  such that, for all  $t \in T$ :

$$1. E_{\lambda_t}(\Delta I_t(c_t)) \subseteq E_{\lambda_t}(\Delta I(c_t)), \quad (2)$$

$$2. \partial I_t(c_t) \subseteq \partial I(c_t) \text{ if } (0, 1] \cap E_{\lambda_t}(\Delta I_t(c_t)) \neq \emptyset. \quad (3)$$

**Proposition B.1.** *Every IC persuasion mechanism is equivalent to an experiment.*

*Proof.* Let's fix an IC persuasion mechanism  $I_\bullet$ . The proof has three steps: (1) we define an information policy  $J$ , (2) we show that  $J$  induces the same effort and (3) action as  $I_\bullet$ .

**(1) Definition of information policy  $J$**  Let's define the function  $I: [0, 1] \rightarrow [0, 1]$  as

$$I(c) := \sup_{r \in R} I_r(c), \quad c \in [0, 1]. \quad (4)$$

$I(c)$  is well defined because  $0 \leq I_r(c) \leq I_{F_0}(c) \leq 1 - x_0$ ,  $c \in [0, 1]$ .  $I$  is the pointwise supremum of a family of convex functions, so  $I$  is convex. It holds that  $I_{\bar{F}}(c) \leq I(c) \leq I_{F_0}(c)$ ,  $c \in [0, 1]$ , because  $I_r \in \mathcal{I}$ ,  $r \in R$ . We extend  $I$  on  $(1, \infty)$ , so that the resulting extended function  $J: \mathbb{R}_+ \rightarrow \mathbb{R}_+$  is an information policy, by defining  $J(c) = I_{F_0}(c)$ ,  $c \in (1, \infty)$ , and  $J(c) = I(c)$ ,  $c \in [0, 1]$ . Thus,  $J \in \mathcal{I}$ .

**(2) Effort distribution** There are two cases.

1.  $E_{\lambda_t}(\Delta I_t(c_t)) \cap (0, 1] \neq \emptyset$ .
2.  $E_{\lambda_t}(\Delta I_t(c_t)) = \{0\}$ .

First, we consider case (1.). By the envelope theorem (Lemma C.10), we have:

$$V_{\lambda_t}(a) - V_{\lambda_t}(\Delta I_t(c_t)) = \int_{\Delta I_t(c_t)}^a \frac{\partial f}{\partial e}(\tilde{a}, e(\tilde{a})) d\tilde{a},$$

for a selection  $e$  of  $E_{\lambda_t}$ . Because  $f$  exhibits strictly increasing differences,  $e(\tilde{a}) \geq e(\Delta I_t(c_t))$  if  $\tilde{a} \geq \Delta I_t(c_t)$ . By the assumption that  $\frac{\partial f}{\partial e}(\tilde{a}, \cdot) > 0$  on  $(0, 1]$  for all  $\tilde{a}$

$$V_{\lambda_t}(a) - V_{\lambda_t}(\Delta I_t(c_t)) > 0, \text{ for all } a > \Delta I_t(c_t).$$

Thus, in case (1.), IC implies that

$$\sup_{r \in R} \Delta I_r(c_t) = \Delta I_t(c_t).$$

Let's consider case (2.), and, towards a contradiction, let's suppose  $0 \notin E_{\lambda_t}(\Delta J(c_t))$ . By Berge's Maximum Theorem (Aliprantis and Border, 2006, Theorem 17.31),  $E_{\lambda_t}$  is upper hemi-continuous and has compact values. Hence, by the sequential characterization of upper hemi-continuity of compact-valued correspondences (Aliprantis and Border, 2006, Theorem 17.16), there exists  $\bar{a} \in (\Delta I_t(c_t), \Delta J(c_t))$  and  $f > 0$  such that  $f \in E_{\lambda_t}(\bar{a})$  (else, define  $a_n := \frac{1}{n}\Delta I_t(c_t) + (1 - \frac{1}{n})\Delta J(c_t)$ ,  $n \in \mathbb{N}$ , to get:  $a_n \rightarrow \Delta J(c_t)$  as  $n \rightarrow \infty$ ,  $E_{\lambda_t}(a_n) = \{0\}$ ,  $n \in \mathbb{N}$ , and  $0 \notin E_{\lambda_t}(\Delta J(c_t))$ , which contradicts upper hemi-continuity of  $E_{\lambda_t}$ .) By the assumption that  $\frac{\partial f}{\partial e}(\tilde{a}, \cdot) > 0$  on  $(0, 1]$  for all  $\tilde{a}$

$$V_{\lambda_t}(\Delta J(c_t)) - V_{\lambda_t}(\bar{a}) > 0.$$

The above inequality and the envelope theorem imply that

$$V_{\lambda_t}(\Delta J(c_t)) - V_{\lambda_t}(\Delta I_t(c_t)) > 0.$$

Hence, IC does not hold, which is a contradiction. Thus,  $0 \in E_{\lambda_t}(\Delta J(c_t))$ .

**(3) Action distribution** Let's suppose that  $d \in \partial I_s(c_s)$  and  $d \notin \partial J(c_s)$  for some type  $s \in T$ . Because  $I_s$  and  $J$  are information policies, they have the same extension on  $(-\infty, 0)$  and, so,  $c_s > 0$ . We have that  $d$  is a subgradient of  $I_s$  at  $c_s$ , and  $d$  is not subgradient of  $J$  at  $c_s$ ; from the fact that  $J(c_s) = I_s(c_s)$  — established above —, there exists  $x \in \mathbb{R}$  such that

$$I_s(x) \geq I_s(c_s) + d(x - c_s) > J(x),$$

which implies  $I_s(x) > J(x)$ . The last inequality contradicts the definition of  $J$ . **QED**

### B.3 Proof of Theorem 2

In this section, we maintain the assumption that: the conditional density of the cutoff type given the attention type  $\lambda$ ,  $g(\cdot|\lambda)$ , is absolutely continuous for all  $\lambda$ .

**Lemma B.1.** *The function  $W$  is continuous on  $\mathcal{F}$ .*

*Proof.* Let's fix  $\lambda$ ,  $F \in \mathcal{F}$ , and  $\varepsilon > 0$ , and define  $p_\lambda := \int_{[0,1]} \left| \frac{\partial g}{\partial c}(c|\lambda) \right| dc$ . Let  $\delta := \frac{\varepsilon}{p_\lambda}$  if  $p_\lambda > 0$ , and let  $\delta$  be an arbitrary positive number otherwise. Let  $H \in \mathcal{F}$  be such that  $\int_{[0,1]} |H(x) - F(x)| dx < \delta$ .

We first establish the claim that:  $|V_\lambda(\Delta I_H(c)) - V_\lambda(\Delta I_F(c))| < \delta$ . By definition of  $V_\lambda$  and the envelope theorem (Lemma C.10), there exists a selection  $e$  from  $c \mapsto \text{Arg max}_{e \in [0,1]} e \Delta I_F(c) - \lambda k(e)$  such that:

$$|V_\lambda(\Delta I_H(c)) - V_\lambda(\Delta I_F(c))| = \int_{[\min\{\Delta I_H(c), \Delta I_F(c)\}, \max\{\Delta I_H(c), \Delta I_F(c)\}]} e(a) da.$$

The codomain of  $e$  is  $[0, 1]$ , so, by the above equality:

$$|V_\lambda(\Delta I_H(c)) - V_\lambda(\Delta I_F(c))| \leq |\Delta I_H(c) - \Delta I_F(c)|.$$

We have the following chain of inequalities,

$$\begin{aligned} |V_\lambda(\Delta I_H(c)) - V_\lambda(\Delta I_F(c))| &\leq \left| \int_{[0,c]} H(x) - F(x) dx \right| \\ &\leq \int_{[0,c]} |H(x) - F(x)| dx \\ &\leq \delta, \end{aligned}$$

which establishes the claim.

We establish the continuity of the function  $W_\lambda$  on  $\mathcal{F}$ . We have the following chain of inequalities,

$$\begin{aligned} |W_\lambda(H) - W_\lambda(F)| &\leq \int_{[0,1]} |V_\lambda(\Delta I_H(c)) - V_\lambda(\Delta I_F(c))| \left| \frac{\partial g}{\partial c}(c|\lambda) \right| dc \\ &\leq \delta p_\lambda \\ &\leq \varepsilon. \end{aligned}$$

Thus,  $W_\lambda$  is continuous on  $\mathcal{F}$ . The result follows from the following chain of inequalities,

$$\begin{aligned} |W(H) - W(F)| &\leq \int_{[0,1]} |W_\lambda(H) - W_\lambda(F)| dG(\lambda) \\ &\leq \varepsilon. \end{aligned}$$

**QED**

**Lemma B.2.** *There exists a measurable selection from  $(c, \lambda, x) \mapsto \text{Arg max}_{a \in \{0,1\}} a(\theta - c)$ , for all  $e \in [0, 1]$ , and there exists a measurable selection from  $(c, \lambda) \mapsto \text{Arg max}_{e \in [0,1]} e\Delta I_F(c) - \lambda k(e)$ , for all  $F \in \mathcal{F}$ .*

*Proof.* The nontrivial part is the second one. The maximand is a real-valued function that is continuous in  $c$ ,  $\lambda$ , and  $e$ . So, the Measurable Maximum Theorem holds (Aliprantis and Border, 2006, Theorem 18.19). **QED**

The next result establishes that the Sender's expected utility given  $I \in \mathcal{I}$  the same in every equilibrium adopting a slightly stronger uniqueness condition than in Definition 5. The comparison holds for two reasons. First, Definition 5 compares Sender's expected utility given the *equilibrium information policy* across equilibria, whereas the proof compares Sender's expected utility given an arbitrary and fixed information policy across equilibria. Second, the proof looks at the conditional expected utility given  $\lambda$ .

**Lemma B.3.** *The experiment  $F$  is an equilibrium experiment if, and only if:  $F$  is  $W$  maximal. Moreover, there are not multiple Sender's payoffs.*

*Proof.* We first show that:  $F$  is  $W$  maximal if, and only if:  $F$  is rational for Sender, given  $(\alpha, e)$ ,  $\alpha$  satisfies  $a$  Opt, and  $e$  satisfies  $e$  Opt. It suffices to that the mapping

$$D_\lambda(\cdot, \alpha, e): F \mapsto \int_{[0,1]} \int_{[0,1]} \alpha(x, c, \lambda) d(e(c, \lambda, F) \odot F)(x) dG(c|\lambda) - W_\lambda(F)$$

is constant (in  $F$ ), for all  $\lambda$ . First, let's express the Sender's equilibrium-conditional-expected utility given  $\lambda$  as

$$\begin{aligned} \hat{W}_\lambda(F) := \int_{[0,1]} \int_{[0,1]} e_\lambda^*(\Delta I_F(c))(\alpha(x, c, \lambda) - \alpha(x_0, c, \lambda)) dF(x) dG(c|\lambda) \\ + \int_{[0,1]} \alpha(x_0, c, \lambda) dG(c|\lambda), \end{aligned}$$

for a selection  $e_\lambda^*$  from  $a \mapsto \text{Arg max}_{e \in [0,1]} V_\lambda(e, a)$ , via Remark B.1. By Lemma 3, there exists a selection  $d_I^1$  from the subdifferential of  $\Delta I_F$  on  $[0, x_0]$  and a selection  $d_I^2$  from the subdifferential of  $\Delta I_F$  on  $(x_0, 1]$  such that:

$$-(\hat{W}_\lambda(F) - \hat{W}_\lambda(\bar{F})) = \int_{[0, x_0]} e_\lambda^*(\Delta I_F(c)) d_I^1(c) dG(c|\lambda) + \int_{(x_0, 1]} e_\lambda^*(\Delta I_F(c)) d_I^2(c) dG(c|\lambda)$$

By the envelope theorem (Lemma C.10),  $e_\lambda^*$  is a selection from the subdifferential of the convex and nondecreasing function  $V_\lambda$ . By  $\Delta I_F \in \mathcal{A}$ ,  $\Delta I_F$  is: (i) convex on  $[0, x_0]$ , and (ii) convex on  $(x_0, 1]$ . Hence: by the rules of subdifferential calculus (Fact C.1), there exists a selection  $d$  from the subdifferential of  $V_\lambda \circ \Delta I_F$  such that:  $d(c) = e_\lambda^*(\Delta I_F(c)) d_I^1(c)$ , for all  $c \in [0, x_0]$ , and  $d(c) = e_\lambda^*(\Delta I_F(c)) d_I^2(c)$ , for all  $c \in (x_0, 1]$ . Hence:

$$\begin{aligned} -(\hat{W}_\lambda(F) - \hat{W}_\lambda(\bar{F})) &= \int_{[0, x_0]} d(c) dG(c|\lambda) + \int_{(x_0, 1]} d(c) dG(c|\lambda) \\ &= \int_{[0, x_0]} d(c) dG(c|\lambda) + \int_{[x_0, 1]} d(c) dG(c|\lambda), \end{aligned}$$

in which the second equality uses absolute continuity of  $G(\cdot|\lambda)$ . By Fact C.1, the composition  $V_\lambda \circ \Delta I_F$  is a convex function on  $[0, x_0]$ , so  $V_\lambda \circ \Delta I_F$  is the integral of any selection from the its subdifferential on  $[0, x_0]$  (Rockafellar, 1970, Corollary 24.2.1.) Similarly,  $V_\lambda \circ \Delta I_F$  is a convex function on  $[x_0, 1]$ . By absolute continuity of  $g(\cdot|\lambda)$ ,

we integrate by parts to obtain

$$\begin{aligned} -(\hat{W}_\lambda(F) - \hat{W}_\lambda(\bar{F})) &= V_\lambda \circ \Delta I_F(1)g(1|\lambda) - V_\lambda \circ \Delta I_F(0)g(0|\lambda) \\ &\quad - \int_{[0,1]} V_\lambda \circ \Delta I_F(c) \frac{\partial g}{\partial c}(c|\lambda) dc. \end{aligned}$$

The fact that  $\Delta I_F(1) = \Delta I_F(0) = 0$  implies

$$-(\hat{W}_\lambda(F) - \hat{W}_\lambda(\bar{F})) = (g(1|\lambda) - g(0|\lambda))V_\lambda(0) - \int_{[0,1]} V_\lambda \circ \Delta I_F(c) \frac{\partial g}{\partial c}(c|\lambda) dc.$$

Hence,

$$\hat{W}_\lambda(F) = W(F) + \hat{W}_\lambda(\bar{F}) - (g(1|\lambda) - g(0|\lambda))V_\lambda(0).$$

So,

$$D_\lambda(F, \alpha, e) = \int_{[0,1]} \alpha(x_0, c, \lambda) dG(c|\lambda) - (g(1|\lambda) - g(0|\lambda))V_\lambda(0).$$

As a result,  $D_\lambda(\cdot, \alpha, e)$  is constant on  $\mathcal{F}$ . Hence,  $F$  is  $W$  maximal if, and only if:  $F$  is rational for Sender, given  $(\alpha, e)$ ,  $\alpha$  satisfies  $a$  Opt, and  $e$  satisfies  $e$  Opt.

From the above equivalence, it follows that: if  $\langle \hat{F}, e, \alpha \rangle$  is an equilibrium, then  $\hat{F}$  is  $W$  maximal. For the other direction, let  $F$  be  $W$  maximal. By Lemma B.2, there exist  $e$  and  $\alpha$  that satisfy the equilibrium measurability conditions,  $a$  Opt, and  $e$  Opt, given  $F$ . Because  $F$  is  $W$  maximal,  $F$  is rational for Sender, given  $(\alpha, e)$ , by the above equivalence. Thus,  $\langle F, e, \alpha \rangle$  is an equilibrium.

As an implication, there are not multiple Sender's payoffs.

**QED**

**Proposition B.2.** *An equilibrium exists.*

*Proof.* The set  $\mathcal{F}$  is compact in the topology induced by the  $L^1$  norm (Kleiner et al., 2021, Proposition 1.) The result follows from Lemma B.3 via upper semi continuity of the Sender's maximand in the definition of  $W$  maximality (Lemma B.1). **QED**

## Proof of Theorem 2

*Proof.* Theorem 2 is implied by Lemma B.3 and Proposition B.2, given that Assumption 1 contains the continuity requirements assumed in this section. **QED**

#### B.4 Proof of Theorem 3

Theorem 3 is a consequence of Lemma B.3 and the following property of upper censorship. A version of the following result is in the working paper [Lipnowski et al., 2021](#), Appendix A.5; [Kolotilin et al. \(2017, Theorem 2\)](#) and [Romanyuk and Smolin \(2019, Theorem 2\)](#) establish similar results.

**Lemma B.4.** *Let  $I \in \mathcal{I}$  and  $\zeta \in [0, 1]$ . There exists  $\theta \in [0, \zeta]$  such that:*

$$(1.) \ I_\theta(\zeta) = I(\zeta);$$

$$(2.) \ I'_\theta(\zeta^-) \leq I'(\zeta^-), \text{ and}$$

$$I_\theta(x) - I(x) \geq 0, \text{ for all } x \in [0, \zeta],$$

$$I_\theta(x) - I(x) \leq 0, \text{ for all } x \in [\zeta, \infty).$$

*Proof.* Let  $\zeta \in [0, 1]$ . Let  $M := \{m \in [0, I'(\zeta^-)] : I(\zeta) + m(x - \zeta) \leq I_{F_0}(x) \text{ for all } x \in [0, \zeta]\}$ , and  $m := \min M$ . We construct an information policy starting from the line  $x \mapsto I(\zeta) + m(x - \zeta)$ , via the next three claims.

(1)  *$m$  is well-defined.* (i)  $M$  is nonempty, because  $0 \leq I'(\zeta^-) \leq 1$  (which follows from  $I \in \mathcal{I}$ ),  $I'(\zeta^-) \in \partial I(\zeta^-)$  and  $I(x) \leq I_{F_0}(x)$  for all  $x$ ; (ii)  $M$  is closed, because the mapping  $m \mapsto I(\zeta) + m(x - \zeta)$  is a continuous function on  $[0, I'(\zeta^-)]$ ; (iii)  $M$  is bounded because  $I'(\zeta^-) \leq 1$ , from  $I \in \mathcal{I}$ .

(2) *There exists  $\theta \in [0, \zeta]$  such that  $I_{F_0}(\theta) = I(\zeta) + m(\theta - \zeta)$ .* If  $m = 0$ , then  $0 = I_{F_0}(0) \geq I(\zeta) \geq 0$ . Hence, taking  $\theta = 0$  verifies our claim. Let  $m > 0$ , and suppose there does not exist  $\theta \in [0, \zeta]$  such that  $I_{F_0}(\theta) = I(\zeta) + m(\theta - \zeta)$ . There exists  $\bar{\varepsilon} > 0$  such that:  $I(\zeta) + (m - \varepsilon)(x - \zeta) < I_{F_0}(x)$  for all  $x \in [0, \zeta]$  and  $0 < \varepsilon \leq \bar{\varepsilon}$ . Moreover, for a sufficiently small  $\varepsilon > 0$ , we have  $m - \varepsilon \in M$ . Thus, we have a contradiction with the definition of  $m$ .

(3)  *$m \in \partial I_{F_0}(\theta)$  and  $I(\zeta) + m(x - \zeta) = I_{F_0}(\theta) + (x - \theta)F_0(\theta)$  for all  $x$ .* First, we argue that  $m \in \partial I_{F_0}(\theta)$ . By convexity of  $I_{F_0}$  and definition of  $\theta$ ,  $x \mapsto I(\zeta) + m(x - \zeta)$  is tangent to  $I_{F_0}$  at  $\theta$ . Thus,  $m$  is a subgradient of  $I_{F_0}$  at  $\theta$ . Now, we argue that  $I(\zeta) + m(x - \zeta) = I_{F_0}(\theta) + (x - \theta)F_0(\theta)$  for all  $x$ .  $m = F_0(\theta)$  because  $I_{F_0}$  is differentiable (by the fact that  $F_0(x^-) = F_0(x)$ ,  $x \in \mathbb{R}$ .) The equality follows because  $x \mapsto I(\zeta) + m(x - \zeta)$  is equal to  $I_{F_0}$  at  $x = \theta$ .

We define the following function.

$$I^u: x \mapsto \begin{cases} I_{F_0}(x) & , x \in [0, \theta] \\ I(\zeta) + m(x - \zeta) & , x \in (\theta, \zeta] \\ \max\{I(\zeta) + m(x - \zeta), I_{\bar{F}}(x)\} & , x \in (\zeta, \infty). \end{cases}$$

Now, we claim that  $I^u = I_\theta$ . It suffices to show that: (i) for some  $x_u \in [0, 1]$

$$I^u(x) = \begin{cases} I_{F_0}(x) & , x \in [0, \theta] \\ I_{F_0}(\theta) + (x - \theta)F_0(\theta) & , x \in (\theta, x_u] \\ I_{\bar{F}}(x) & , x \in (x_u, \infty), \end{cases}$$

and (ii)  $I^u \in \mathcal{I}$ . We claim that (i) holds by means of the next three claims.

*There exists  $x_u \in [\zeta, 1]$  such that:*

$$I(\zeta) + m(x - \zeta) \geq I_{\bar{F}}(x) \quad , x \in [0, x_u] \quad (5)$$

$$I(\zeta) + m(x - \zeta) \leq I_{\bar{F}}(x) \quad , x \in (x_u, 1]. \quad (6)$$

Let's note that: (a)  $I(\zeta) \geq I_{\bar{F}}(\zeta)$ ; (b) by  $m \in \partial I_{F_0}(\theta)$  and  $I_{F_0}(1) = I_{\bar{F}}(1)$ , we have that  $I_{\bar{F}}(1) \geq I(\zeta) + m(1 - \zeta)$ , and (c) the two functions,  $x \mapsto I(\zeta) + m(x - \zeta)$  and  $I_{\bar{F}}$ , are affine with slopes, respectively,  $m$  and 1, such that:  $m \leq 1$ .

We proceed to verify that (ii) holds, i.e.  $I^u \in \mathcal{I}$ , via the next two claims.

(1)  $I_{\bar{F}}(x) \leq I^u(x) \leq I_{F_0}(x)$  for all  $x \in \mathbb{R}_+$  and  $I^u$  locally convex at all  $x \notin \{\theta, x_u\}$ . If  $x \in [0, \theta)$ ,  $I^u$  is locally convex and  $I_{\bar{F}}(x) \leq I^u(x) \leq I_{F_0}(x)$ . If  $x \in (\theta, \zeta)$ ,  $I^u$  is affine,  $I_{\bar{F}}(x) \leq I(x) \leq I^u(x)$  by construction of  $I^u$  and definition of  $I$ , and  $I^u(x) \leq I_{F_0}(x)$  by  $m \in \partial I_{F_0}(x)$ . If  $x \in [\zeta, \infty)$ ,  $I$  is locally convex (because it is the maximum of affine functions),  $I_{\bar{F}}(x) \leq I^u(x)$  by construction of  $I^u$ ,  $I^u(x) \leq I_{F_0}(x)$  because: (i)  $m \in \partial I_{F_0}(\zeta)$  and (ii)  $I_{\bar{F}}(x) \leq I_{F_0}(x)$ . To verify global convexity, it suffices to verify the next claim.

(2)  $I^u$  is subdifferentiable at  $x \in \{\theta, x_u\}$ . First, we argue that  $m$  is a subgradient of  $I^u$  at  $\theta$ . This follows from the fact that the slope of  $I^u$  at  $\theta$  is a subgradient of  $I_{F_0}$  at  $\theta$ , and  $I^u(\theta) = I_{F_0}(\theta)$ . On  $[0, \theta]$ ,  $I^u = I_{F_0}$ , and on  $[\theta_u, \infty)$   $I^u$  is above the line  $x \mapsto I(\zeta) + m(x - \zeta)$ . Thus,  $m \in \partial I^u(\theta)$ . Second, the fact that  $m$  is a subgradient of  $I^u$  at  $x_u$  follows from the claim in (5).



We have established that  $I^u = I_\theta$ . (1.) and (2.) hold by construction. **QED**

### Proof of Theorem 3

*Proof.* By Lemma B.3, the optimal experiment maximizes

$$W: F \longmapsto \int_{[0,1]} \int_{[0,p]} V_\lambda(\Delta I_{\hat{F}}(c)) \frac{\partial g}{\partial c}(c|\lambda) dc + \int_{[p,1]} V_\lambda(\Delta I_{\hat{F}}(c)) \frac{\partial g}{\partial c}(c|\lambda) dc dG(\lambda).$$

Suppose two experiments  $F, H \in \mathcal{F}$  such that  $I_F(x) \geq I_H(x)$  for all  $x \in [0, p]$  and  $I_F(x) \leq I_H(x)$  for all  $x \in [p, 1]$ . Because (i)  $V_\lambda$  is nondecreasing, (ii)  $\frac{\partial g}{\partial c}(\cdot|\lambda)$  is nonnegative on  $[0, p]$  and nonpositive on  $[p, 1]$ , it follows that  $W(F) \geq W(H)$ . The result follows from Lemma B.4. **QED**

### B.5 Proof of Proposition 1

The proof has four steps. First, we establish a single-crossing property of the derivative of Sender's payoff from  $I_\theta$  with respect to the threshold state  $\theta$ , in a series of three claims. Second, we establish a strictly increasing property of Sender's payoff from  $I_\theta$  with respect to the threshold state  $\theta$  and the attention-cost type, given certain conditions, in two claims. The third step verifies that the optimality properties and the hypotheses in the statement of the Proposition imply the aforementioned conditions. The final step completes the argument.

*Proof.* Let's fix an equilibrium  $\langle F, e, \alpha \rangle$ .

(1.) Let strict single-peakedness hold. We claim that the function  $(\theta, \zeta) \longmapsto \int_{[\theta, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc$  crosses zero at most once and from above, that is:

$$\int_{[\theta, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc \leq 0 \implies \int_{[\theta', \zeta']} (c - \theta') \frac{\partial}{\partial c} g(c|\lambda) dc < 0,$$

for all  $\theta \leq \theta'$  and  $\zeta \leq \zeta'$ , with  $\theta' < \zeta'$ ,  $\theta < \zeta$ . If  $p \leq \theta'$ , the result holds. If  $\int_{[\theta, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc \leq 0$ , then  $p < \zeta$ . It holds that:

$$\begin{aligned} \int_{[\theta, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc &= \int_{[\theta, \theta']} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc + \int_{[\theta', p]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc \\ &\quad + \int_{[p, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc. \end{aligned}$$

Let  $\int_{[\theta, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc \leq 0$ . Then:

$$\int_{[\theta, \theta']} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc + \int_{[\theta', p]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc \leq - \int_{[p, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc,$$

which implies, by  $\theta' < p$ :

$$\int_{[\theta', p]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc < - \int_{[p, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc.$$

From the above inequality and  $p < \zeta$ , we have:

$$\int_{[\theta', p]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc + \int_{[p, \zeta]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc + \int_{[\zeta, \zeta']} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc < 0,$$

so the claim follows.

**(2.)** Let strict single-peakedness hold.  $\int_{[\theta, \bar{c}]} (c - \theta) \frac{\partial}{\partial c} g(c|\lambda) dc$  is increasing in  $\lambda$  if  $p \leq \bar{c}$ , for  $\bar{c} := \bar{c}_\lambda(\Delta I_\theta)$  and  $\bar{c} \in (x_0, 1)$ . The claim holds because  $\lambda \mapsto \bar{c}_\lambda(\Delta I_\theta)$  is decreasing under our hypotheses.

**(3.)** Let Assumption 1 hold. We claim that  $\bar{c}_\lambda(\Delta I_\theta) > \theta$ ,  $\underline{p} \leq \bar{c}_\lambda(\Delta I_\theta)$ , and  $\bar{c}_\lambda(\Delta I_\theta) \in (x_0, 1)$ , if:  $I'_\theta$  maximizes  $W$  on  $\mathcal{F}$  and  $F_0, \bar{F}$  do not maximize  $W$  on  $\mathcal{F}$ . If  $\bar{c}_\lambda(\Delta I_\theta) \leq \theta$ , then  $F_0$  maximizes  $W$  on  $\mathcal{F}$ . If  $\bar{c}_\lambda(\Delta I_\theta) < \underline{p}$ , then  $F_0$  maximizes  $W$  on  $\mathcal{F}$ . The rest of the claim follows from similar arguments.

**(4.)** Let  $x_{\bar{\theta}} := \frac{\int_{\bar{\theta}}^1 \theta dF_0(\theta)}{1 - F_0(\bar{\theta})}$ , for threshold state  $\bar{\theta} \in [0, 1]$ . By lemmata B.3, we compute the derivative of the Sender's expected utility, given information policy  $I_{\bar{\theta}}$ , with

respect to  $\bar{\theta}$ , which is:

$$\frac{\partial}{\partial \bar{\theta}} W(I'_{\bar{\theta}}) = \begin{cases} \frac{\partial F_0}{\partial \bar{\theta}}(\bar{\theta}) \int_{[\max\{\bar{\theta}, \underline{c}_\lambda(\Delta I_{\bar{\theta}})\}, \bar{c}_\lambda(\Delta I_{\bar{\theta}})]} (x - \bar{\theta}) \frac{\partial g}{\partial c}(x|\lambda) dx, & \text{if } \theta < \bar{c}_\lambda(\Delta I_{\bar{\theta}}) \\ 0, & \text{if } \theta > \bar{c}_\lambda(\Delta I_{\bar{\theta}}). \end{cases}$$

As claimed above, under our hypotheses,  $\theta_\varepsilon < \bar{c}_\lambda(\Delta I_{\theta_\varepsilon})$ . Moreover, by strict single-peakedness, there exists a unique optimal upper censorship  $I_\eta$  if  $\lambda = 0$ , with  $\eta \in (0, 1)$  (Kolotilin et al., 2022, Lemma 7.) Let's complete the proof.

First, claim 1. implies that  $\bar{\theta} \mapsto W(I'_{\bar{\theta}})$  crosses zero only once and from above: at  $\theta_\varepsilon$ . By claims 2. and 3.,  $\theta_\varepsilon > \eta$ , for  $\varepsilon > 0$ . **QED**

## B.6 Proof of Proposition 2

The proof of Proposition 2 has two steps. The first and main step has the same structure as that of Theorem 3. In particular, Lemma B.5 generalizes the construction of Lemma B.4 to construct: an information policy  $I^*$  that preserves the extensive margin and improves upon an arbitrary information policy  $I$ , for large  $p$ .  $I^*$  induces two censorship regions, separated by a full-revelation region. The second step of the proof: (1) adds a second censorship region at the top to include the general case of  $p > x_0$ , and (2) verifies that eliminating the bottom censorship region improves upon Sender's payoff.

For the rest of this section, we omit reference to  $\lambda$  and we fix an equilibrium  $\langle F, e(\cdot), \alpha \rangle$ .

**Lemma B.5.** *Let  $I \in \mathcal{I}$  and define  $c^* := \bar{c}(\Delta I)$ . There exists an information policy  $I^*$  that satisfies the following properties:*

1. (FEAS)  $I^*$  is feasible, i.e.,  $I^* \in \mathcal{I}$ ;
2. (EM)  $I^*$  produces the same extensive margin as  $I$ , i.e.,  $\bar{c}(\Delta I^*) = c^*$  and  $\underline{c}(\Delta I^*) = \underline{c}(\Delta I)$ ;
3. (IMPR)  $\Delta I^*(x) \geq 0$ , for all  $x \in [\underline{c}(\Delta I), c^*]$ ;

4. (CENS) There exist  $x_\ell, \theta_\ell, \theta_m, x_m$  such that  $0 \leq x_\ell \leq \theta_\ell \leq \theta_m \leq x_m \leq 1$  and

$$I^*(x) = \begin{cases} I_{\overline{F}}(x) & , x \in [0, x_\ell] \\ I_{F_0}(\theta_\ell) + F_0(\theta_\ell)(x - \theta_\ell) & , x \in (x_\ell, \theta_\ell] \\ I_{F_0}(x) & , x \in (\theta_\ell, \theta_m] \\ I_{F_0}(\theta_m) + F_0(\theta_m)(x - \theta_m) & , x \in (\theta_m, x_m] \\ I_{\overline{F}}(x) & , x \in (x_m, \infty). \end{cases}$$

*Proof.* We use the notation:  $\bar{c}(I - I_{\overline{F}}) =: \bar{c}$ ,  $\underline{c}(I - I_{\overline{F}}) =: \underline{c}$ . In the first step, we prove the lemma for the case in which there is a feasible information policy that is a straight line between the points  $\underline{p} := (\underline{c}, I(\underline{c}))$  and  $\bar{p} := (\bar{c}, I(\bar{c}))$ . In the second step we analyze the other case.

*First Step.* Let's define the line  $i$  such that  $x \mapsto I(\underline{c}) + \lambda^*(x - \underline{c})$ , with slope  $\lambda^* := \frac{I(\bar{c}) - I(\underline{c})}{\bar{c} - \underline{c}}$ . We claim that  $i^*(x) := \max\{i(x), I_{\overline{F}}(x)\}$  satisfies all properties.  $i^*$  is FEAS by hypothesis.  $i^*$  is EXT because  $i(\underline{c}) = I(\underline{c})$  and  $i(\bar{c}) = I(\bar{c})$ .  $i^*$  is IMPR because  $I$  is convex and  $i^*$  is EXT.  $i^*$  is CENS with  $\theta_\ell = \theta_m = x_m$ , because: (i) EXT of  $i^*$  and convexity of  $I$  imply that  $i^*$  is affine on  $[\underline{c}, \bar{c}]$ , (ii)  $\lambda^* \in [0, 1]$  and EXT imply, with  $I \in \mathcal{I}$ , that there are intersection points  $\tilde{x}_1, \tilde{x}_2$ , with  $\tilde{x}_1 \leq \underline{c} \leq \bar{c} \leq \tilde{x}_2$ , such that:  $i^*(x) = I(x)$  if  $x \in [0, \tilde{x}_1] \cup [\tilde{x}_2, 1]$ .

*Second Step.* In this case,  $i^*$  is not FEAS. Because  $i^*$  satisfies FEAS at  $x$  if  $x \leq \underline{c}$  and if  $x \geq \bar{c}$ , there exists a point  $x^* \in (\underline{c}, \bar{c})$  such that:  $i(x^*) > I_{F_0}(x^*)$ . Let's define:

$$L := \{\lambda \in [I'(\underline{c}), 1] : I(\underline{c}) + \lambda(x - \underline{c}) \leq I_{F_0}(x) \text{ for all } x \in [\underline{c}, \infty)\},$$

$$M := \{\lambda \in [0, I'(\bar{c})] : I(\bar{c}) + \lambda(x - \bar{c}) \leq I_{F_0}(x) \text{ for all } x \in [0, \bar{c}]\},$$

$\ell := \max L$ ,  $m := \min M$ , and the lines

$$y_\ell : x \mapsto I(\underline{c}) + \ell(x - \underline{c}),$$

$$y_m : x \mapsto I(\bar{c}) + m(x - \bar{c}).$$

As part of the rest of the proof, we establish some lemmata.

**Lemma B.6.** *It holds that  $\ell$  and  $m$  are well-defined.*

*Proof.*  $L$  is nonempty because  $I'(\underline{c}) \in L$ , which follows from: (i)  $I_{F_0}(x) \geq I(x)$  for

all  $x$  and (ii)  $I'(\underline{c}) \in \partial I(\underline{c})$ .  $M$  is nonempty because  $I'(\bar{c}) \in M$ , which follows from: (i)  $I_{F_0}(x) \geq I(x)$  for all  $x$  and (ii)  $I'(\bar{c}) \in \partial I(\bar{c})$ .  $L, M$  are closed because  $I_{F_0}$  is continuous.  $L, M$  are bounded. **QED**

**Lemma B.7.** *There exists a unique pair of numbers  $(\theta_\ell, \theta_m) \in [\underline{c}, 1] \times [0, \bar{c}]$  such that:  $y_\ell(\theta_\ell) = I_{F_0}(\theta_\ell)$  and  $y_m(\theta_m) = I_{F_0}(\theta_m)$ .*

*Proof.* Suppose there does not exist such  $\theta_\ell$ . There exists a sufficiently small  $\varepsilon > 0$  such that: (i)  $\ell + \varepsilon \in L$  and (ii)  $I(\underline{c}) + (\ell + \varepsilon)(x - \underline{c}) < I_{F_0}(x)$  for all  $x \in [\underline{c}, \infty)$ ; we note that  $\theta_\ell = 1$  contradicts  $\ell \in L$  because  $I'_{F_0}(x) < 1$  if  $x < 1$ . Uniqueness of  $\theta_\ell$  follows from convexity of  $I_{F_0}$ .

Suppose there does not exist such  $\theta_m$ . There exists a sufficiently small  $\varepsilon > 0$  such that: (i)  $\ell - \varepsilon \in M$  and (ii)  $I(\bar{c}) + (m - \varepsilon)(x - \bar{c}) < I_{F_0}(x)$  for all  $x \in [0, \bar{c})$ ; we note that  $\theta_m = 0$  contradicts  $I \neq I_{\bar{F}}$ . Uniqueness of  $\theta_m$  follows from convexity of  $I_{F_0}$ . **QED**

**Lemma B.8.** *It holds that  $\theta_\ell \leq \theta_m$ .*

*Proof.* Let's first prove that: it suffices to show that  $\ell \leq m$ . Suppose  $\ell \leq m$ , then, from  $\ell \in \partial I_{F_0}(\theta_\ell)$ ,  $m \in \partial I_{F_0}(\theta_m)$ , and  $I_{F_0}$  being strictly convex, we have:  $\theta_\ell \leq \theta_m$ .

Next, we show that  $\ell \leq \lambda^*$ . Suppose that:  $\ell > \lambda^*$ . Then:  $I(x) + \ell(x - \underline{c}) > I(\underline{c}) + \lambda^*(x - \underline{c})$  for all  $x > \underline{c}$ . Therefore, because  $\ell > 0$ , we get:

$$I_{F_0}(x^*) \geq I(\underline{c}) + \lambda^*(x^* - \underline{c}).$$

We reach a contradiction with the definition of  $x^*$ , so:  $\ell \leq \lambda^*$ .

Let's prove that  $m \geq \lambda^*$ . Suppose  $m < \lambda^*$ . Then:  $I(x) + m(x - \bar{c}) > I(\bar{c}) + \lambda^*(x - \bar{c})$  for all  $x < \bar{c}$ . Therefore, because  $m > 0$ , we get:

$$I_{F_0}(x^*) \geq I(\bar{c}) + \lambda^*(x^* - \bar{c}).$$

We reach a contradiction with the definition of  $x^*$ , so:  $m \geq \lambda^*$ . Therefore, we have  $m \geq \lambda^* \geq \ell$ , which implies  $\theta_m \geq \theta_\ell$ . **QED**

We define a candidate  $I^*$  and verify that  $I^*$  has the desired properties.

$$I^*(x) := \begin{cases} \max\{I_{\bar{F}}(x), I(\underline{c}) + \ell(x - \underline{c})\} & , x \in [0, \theta_\ell] \\ I_{F_0}(x) & , x \in [\theta_\ell, \theta_m] \\ \max\{I_{\bar{F}}(x), I(\bar{c}) + m(x - \bar{c})\} & , x \in [\theta_m, \infty) \end{cases}$$

Let's first verify that  $I^*$  is well-defined. We know that  $\ell \in \partial I_{F_0}(\theta_\ell)$  and  $m \in \partial I_{F_0}(\theta_m)$ . Because  $I(\underline{c}) + \ell(0 - \underline{c}) < I_{F_0}(0)$  and  $I(\underline{c}) \geq I_{F_0}(\underline{c})$ ,  $\max\{I_{F_0}(x), I(\underline{c}) + \ell(x - \underline{c})\} = I_{F_0}(x)$  if  $x < x_0$ ; and  $\max\{I_{F_0}(x), I(\underline{c}) + \ell(x - \underline{c})\} = I(\underline{c}) + \ell(x - \underline{c})$  if  $x > x_0$ ; for some  $x_0 \in [0, \theta_\ell]$ . In a similar way, we can show that there exists a  $x_2 \in [\theta_m, 1]$  such that:  $\max\{I_{F_0}(x), I(\bar{c}) + m(x - \bar{c})\} = I_{F_0}(x)$  if  $x > x_2$ , and  $\max\{I_{F_0}(x), I(\bar{c}) + m(x - \bar{c})\} = I(\bar{c}) + m(x - \bar{c})$  if  $x < x_2$ .

1. CENS follows from the definition of  $I^*$  and the conclusion of the above paragraph.
2. IMPR on  $[\underline{c}, \theta_\ell]$  and  $[\theta_m, \bar{c}]$  follows from convexity of  $I$ , and on  $[\theta_\ell, \theta_m]$  follows from FEAS of  $I$  in that region.
3. EM follows by construction of  $I^*$ .
4. FEAS is established as in the last step of the proof of Lemma B.4.

**QED**

## Proof of Proposition 2

*Proof.* Let's define information policy  $J$  by: letting  $J$  equal  $I^*$ , constructed as in Lemma B.5 by replacing  $c^*$  with  $p$ , for  $x \in [0, x_m^\circ]$ , defining the point  $x_m^\circ$  in which  $I^*$  intercepts the line  $j: x \mapsto I(\bar{c}) + I'(\bar{c})(x - \bar{c})$ ; and letting  $J$  equal  $x \mapsto \max\{I_{\bar{F}}(x), j(x)\}$  on  $[x_m^\circ, \infty)$ .

It suffices to show that: if the resulting information policy  $J$  induces a censorship region at the bottom, then there is an improvement over  $J$  that is a bi-upper censorship. Suppose that  $I^*$  is affine on  $[x_\ell, \theta_\ell]$  and  $I^*$  equals  $I_{\bar{F}}$  on  $[0, x_\ell]$ , for  $0 < x_\ell < \theta_\ell$  (for notation, see Lemma B.5.) By construction,  $I^*(\theta_\ell) = I_{F_0}(\theta_\ell)$ . Let's define information

policy  $K$  by

$$K(x) = \begin{cases} I_{F_0}(x) & , 0 \leq x \leq \theta_\ell, \\ J(x) & , x \geq \theta_\ell. \end{cases}$$

$K \geq J$ , so:  $K$  induces a weakly higher Receiver's ex-ante payoff (by Blackwell's theorem) and weakly decreases  $\underline{c}_\lambda$ , with respect to  $J$ . Hence, by  $\rho \geq 0$  and  $\gamma \geq 0$ , it is left to verify that the expected Receiver's action is weakly higher under  $K$  than under  $J$ . Because  $p \geq x_0$ , the argument of Theorem 3 suffices. Specifically, by Lemma B.3, we have that:

$$\begin{aligned} W(K') - W(J') &= \int_{[0, \theta_\ell]} (V_\lambda(\Delta K(c)) - V_\lambda(\Delta J(c))) \frac{\partial g}{\partial c}(c|\lambda) dc \\ &\geq 0, \end{aligned}$$

in which the inequality follows from the definition of  $I^*$ , which includes  $p \geq \theta_\ell$ . Hence  $K$  is a bi-upper censorship that improves upon  $I$ , for arbitrary  $I$ , in terms of  $U_G$ . **QED**

## B.7 Symmetric-information benchmark

For this section, the type distribution puts full mass at  $(\zeta, \kappa)$ ,  $k$  is linear, and  $F_0$  admits a density. The Sender's *problem* is:

$$\max_{I \in \mathcal{I}} (1 - I'(\zeta_-)) \mathbf{1}_{\{I \in \mathcal{I} | \Delta I(\zeta) \geq \kappa\}}(I),$$

because an experiment  $F$  is an equilibrium experiment iff  $I_F$  solves the above maximization, due to a generalization of the argument of Gentzkow and Kamenica (2016). If  $\zeta > 1$ , any information policy is optimal. If  $\zeta < x_0$ ,  $I_{\bar{F}}$  is optimal. Let  $1 \geq \zeta \geq x_0$ .

**Lemma B.9.** *There exists  $\theta \in [0, \zeta]$  such that:  $I_\theta$  solves the Sender's problem and  $\Delta I_\theta \leq \kappa$ , with equality if  $\theta > 0$ .*

*Proof.* Let  $\mathcal{I}^u := \{I \in \mathcal{I} \mid I = I_\theta, \theta \in [0, \zeta]\}$ . Without loss of optimality by Lemma B.4, we consider solutions in  $\mathcal{I}^u$ . Suppose there exists a solution  $I \in \mathcal{I}^u$ , such that  $I = I_{\theta^*}$ , for some  $\theta^* \in (0, 1)$ . We distinguish three cases.

- (1) If  $\Delta I(\zeta) < \kappa$ , then Sender is indifferent between  $I$  and  $I_{\bar{F}}$ , so the lemma holds.  
(2) If  $\Delta I(\zeta) = \kappa$ , the lemma holds. (3) If  $\Delta I(\zeta) > \kappa$ , then, by definition of  $I$  at  $y = I(\zeta)$ ,

$$I_{F_0}(\theta^*) + F_0(\theta^*)(\zeta - \theta^*) - y = 0.$$

By the implicit function theorem, there exists a differentiable function  $t: (0, 1) \rightarrow (0, 1)$  such that  $t: y \mapsto \theta^*$  and

$$t'(y) = \begin{cases} \frac{1}{(\zeta - t(y)) \frac{\partial F_0}{\partial \theta}(t(y))}, & 0 < \zeta < t(y), \\ \frac{1}{\frac{\partial F_0}{\partial \theta}(t(y))}, & 1 > \zeta \geq t(y). \end{cases}$$

Let's define the value of the Sender's maximand at  $I_\theta$  as  $v: (0, 1) \rightarrow [0, 1]$  such that  $v: \theta \mapsto 1 - I'_\theta(\zeta^-)$ . Because  $I'_{\theta^*}(\zeta_-) = F_0(\theta^*)$ ,  $v$  is differentiable in  $\theta$  at  $\theta^*$ . The derivative of  $v$  with respect to  $I(\zeta)$  is:

$$-\frac{\partial F_0}{\partial \theta}(t(I(\zeta))) \frac{1}{(\zeta - t(I(\zeta))) \frac{\partial F_0}{\partial \theta}(t(I(\zeta)))},$$

if  $\zeta > t(I(\zeta))$ , and  $-1$  otherwise. It follows that we can consider without loss solutions  $I \in \mathcal{I}^u$  that satisfy:  $\Delta I_\theta(\zeta) = \kappa$  and  $I = I_\theta$ , or  $\Delta I(\zeta) < \kappa$ . **QED**

## C Supplementary material

**Fact C.1** (Subdifferential of convex functions). *Let  $S \subseteq \mathbb{R}$ ,  $f: S \rightarrow \mathbb{R}$  be convex and  $\varphi: \mathbb{R} \rightarrow \mathbb{R}$  be a nondecreasing convex function on the range of  $f$ . The following hold:*

1. *The function  $\varphi \circ f$  is convex on  $S$ ;*
2. *For all  $y \in S$ , letting  $t = f(y)$ , we have:*

$$\{\alpha u : (\alpha, u) \in \partial \varphi(t) \times \partial f(y)\} = \partial \varphi \circ f(y).$$

*Proof.* See [Bauschke and Combettes \(2011, Proposition 8.21 and Corollary 16.72.\)](#)

**QED**



**Lemma C.10** (Envelope theorem). *Let  $f: [0, 1]^2 \rightarrow \mathbb{R}$  exhibit increasing differences and be such that:  $f(\cdot, a)$  is continuous for all  $a \in [0, 1]$ ,  $f(e, \cdot)$  is nondecreasing for all  $e \in [0, 1]$ , the derivative with respect to the variable  $a$ ,  $\frac{\partial f}{\partial a}(e, \cdot)$ , exists and is bounded for all  $e \in [0, 1]$ . The following hold.*

1. *We have  $\text{Arg max}_{e \in [0, 1]} f(e, a) \neq \emptyset$  for all  $a \in [0, 1]$ .*
2. *The function  $a \mapsto \max_{e \in [0, 1]} f(e, a)$  is nondecreasing and absolutely continuous.*
3. *If  $a \mapsto \frac{\partial f}{\partial a}(e, a)$  is nondecreasing for all  $e \in [0, 1]$ , then  $a \mapsto \max_{e \in [0, 1]} f(e, a)$  is convex.*
4. *If  $f$  exhibits strictly increasing differences,  $a \mapsto \frac{\partial f}{\partial a}(e, a)$  is nondecreasing,  $f(e, \cdot)$  is increasing for all  $e \in (0, 1]$ ,  $\text{Arg max}_{e \in [0, 1]} f(e, a) \cap (0, 1] \neq \emptyset$ , and  $1 \geq a' > a \geq 0$ , then*

$$\max_{e \in [0, 1]} f(e, a') > \max_{e \in [0, 1]} f(e, a).$$

*Proof.* By upper semi-continuity of  $f$ ,  $\text{Arg max}_{e \in [0, 1]} f(e, a) \neq \emptyset$ , so 1. holds. Then, by the increasing-differences property of  $f$ , there exists a nondecreasing selection  $e^*: a \mapsto \text{Arg max}_{e \in [0, 1]} f(e, a)$  on  $[0, 1]$  (Topkis, 1978). By our hypotheses, we apply the envelope theorem (Milgrom and Segal, 2002), letting  $V(a) := \max_{e \in [0, 1]} f(e, a)$ , to establish that  $V$  is absolutely continuous and

$$V(a) = V(0) + \int_{[0, a]} \frac{\partial f}{\partial a}(e^*(\tilde{a}), \tilde{a}) d\tilde{a}.$$

$V$  is nondecreasing because  $\frac{\partial f}{\partial a} \geq 0$ . Hence, 2. holds.

Let's establish that  $V$  is convex if  $a \mapsto \frac{\partial f}{\partial a}(e, a)$  is nondecreasing. By the increasing-differences property of  $f$ : (i)  $e \mapsto \frac{\partial f}{\partial a}(e, a)$  is nondecreasing, and (ii) there exists a nondecreasing  $e^*: a \mapsto \text{Arg max}_{e \in [0, 1]} f(e, a)$ . As a result,  $a \mapsto \frac{\partial f}{\partial a}(e^*(a), a)$  is nondecreasing. Thus,  $V$  is convex (Rockafellar, 1970, Theorem 24.8.) Hence, 3. holds.

Let  $a' > a$ , for  $a', a \in [0, 1]$ , and  $e' \in \text{Arg max}_{e \in [0, 1]} f(e, a) \cap (0, 1]$ . Then:  $V(a') - V(a) = \int_{[a, a']} \frac{\partial f}{\partial a}(e^*(\tilde{a}), \tilde{a}) d\tilde{a}$  for every selection  $e^*$  of  $\text{Arg max}_{e \in [0, 1]} f(e, a) \cap (0, 1]$ . We have the following chain of inequalities under the additional hypotheses stated in part

4.:

$$\begin{aligned} V(a') - V(a) &\geq \int_{[a,a']} \frac{\partial f}{\partial a}(e', \tilde{a}) d\tilde{a} \\ &\geq \int_{[a,a']} \frac{\partial f}{\partial a}(e', a) d\tilde{a}, \end{aligned}$$

in which the first inequality follows from the strict increasing-differences property of  $f$  and the definition of  $e'$ , the second inequality holds because  $a \mapsto \frac{\partial f}{\partial a}(e, a)$  is nondecreasing (for the first inequality, in particular, we note that: (i) every selection  $e^*$  of  $\text{Arg max}_{e \in [0,1]} f(e, a) \cap (0, 1]$  is nondecreasing, (ii) there exists a selection  $e^*$  of  $\text{Arg max}_{e \in [0,1]} f(e, a) \cap (0, 1]$  such that  $e^*(a) = e'$ .) Item 4. holds because  $\int_{[a,a']} \frac{\partial f}{\partial a}(e', a) d\tilde{a} = (a' - a) \frac{\partial f}{\partial a}(e', a)$ . **QED**

## References

- Aliprantis, Charalambos D. and Kim C. Border (2006), *Infinite Dimensional Analysis: A Hitchhiker's Guide*, third edition. Springer Berlin, Heidelberg.
- Alonso, Ricardo and Odilon Câmara (2016), “Persuading voters.” *American Economic Review*, 106(11), 3590–3605.
- Arieli, Itai, Yakov Babichenko, Rann Smorodinsky, and Takuro Yamashita (2023), “Optimal persuasion via bi-pooling.” *Theoretical Economics*, 18(1), 15–36.
- Au, Pak Hung and Mark Whitmeyer (2023), “Attraction versus persuasion: Information provision in search markets.” *Journal of Political Economy*, 131(1), 202–245.
- Augias, Victor and Daniel M. A. Barreto (2024), “Persuading a wishful thinker.” Working Paper.
- Bauschke, Heinz H. and Patrick L. Combettes (2011), *Convex Analysis and Monotone Operator Theory in Hilbert Spaces*, second edition. Springer Cham.
- Beauchêne, Dorian, Jian Li, and Ming Li (2019), “Ambiguous persuasion.” *Journal of Economic Theory*, 179, 312–365.

- Bizzotto, Jacopo, Jesper Rüdiger, and Adrien Vigier (2020), “Testing, disclosure and approval.” *Journal of Economic Theory*, 187, 105002.
- Bizzotto, Jacopo and Adrien Vigier (2021), “Fees, reputation, and information production in the credit rating industry.” *American Economic Journal: Microeconomics*, 13(2), 1–34.
- Bloedel, Alexander W. and Ilya Segal (2021), “Persuading a Rationally Inattentive Agent.” Working Paper.
- Board, Simon and Jay Lu (2018), “Competitive information disclosure in search markets.” *Journal of Political Economy*, 126(5), 1965–2010.
- Branco, Fernando, Monic Sun, and J. Miguel Villas-Boas (2016), “Too much information? information provision and search costs.” *Marketing Science*, 35(4), 605–618.
- Brocas, Isabelle and Juan D. Carrillo (2007), “Influence through ignorance.” *The RAND Journal of Economics*, 38(4), 931–947.
- Caplin, Andrew, Mark Dean, and John Leahy (2022), “Rationally inattentive behavior: Characterizing and generalizing shannon entropy.” *Journal of Political Economy*, 130(6), 1676–1715.
- Che, Yeon-Koo, Kyungmin Kim, and Konrad Mierendorff (2023), “Keeping the listener engaged: A dynamic model of bayesian persuasion.” *Journal of Political Economy*, 131(7), 1797–1844.
- de Clippel, Geoffroy and Xu Zhang (2022), “Non-bayesian persuasion.” *Journal of Political Economy*, 130(10), 2594–2642.
- Denti, Tommaso (2022), “Posterior separable cost of information.” *American Economic Review*, 112(10), 3215–59.
- Denti, Tommaso, Massimo Marinacci, and Aldo Rustichini (2022), “Experimental cost of information.” *American Economic Review*, 112(9), 3106–23.
- Dworzak, Piotr and Giorgio Martini (2019), “The Simple Economics of Optimal Persuasion.” *Journal of Political Economy*, 127(5), 1993–2048.

- Dworczak, Piotr and Alessandro Pavan (2022), “Preparing for the worst but hoping for the best: Robust (bayesian) persuasion.” *Econometrica*, 90(5), 2017–2051.
- Felgenhauer, Mike (2019), “Endogenous persuasion with costly verification.” *The Scandinavian Journal of Economics*, 121(3), 1054–1087.
- Feng, Yiding, Chien-Ju Ho, and Wei Tang (2024), “Rationality-robust information design: Bayesian persuasion under quantal response.” In *Proceedings of the 2024 ACM-SIAM Symposium on Discrete Algorithms, SODA 2024, Alexandria, VA, USA, January 7-10, 2024* (David P. Woodruff, ed.), 501–546, SIAM.
- Floridi, Luciano (2014), *The Fourth Revolution: How the Infosphere is Reshaping Human Reality*. Oxford University Press, Oxford.
- Galperti, Simone (2019), “Persuasion: The art of changing worldviews.” *American Economic Review*, 109(3), 996–1031.
- Gehlbach, Scott and Alberto Simpser (2015), “Electoral manipulation as bureaucratic control.” *American Journal of Political Science*, 59(1), 212–224.
- Gehlbach, Scott and Konstantin Sonin (2014), “Government control of the media.” *Journal of Public Economics*, 118, 163–171.
- Gentzkow, Matthew and Emir Kamenica (2016), “A Rothschild-Stiglitz Approach to Bayesian Persuasion.” *American Economic Review*, 106(5), 597–601.
- Gitmez, A. Arda and Pooya Molavi (2023), “Informational autocrats, diverse societies.”
- Guo, Yingni and Eran Shmaya (2019), “The interval structure of optimal disclosure.” *Econometrica*, 87(2), 653–675.
- Honka, Elisabeth, Ali Hortaçsu, and Maria Ana Vitorino (2017), “Advertising, consumer awareness, and choice: evidence from the u.s. banking industry.” *The RAND Journal of Economics*, 48(3), 611–646.
- Jain, Vasudha and Mark Whitmeyer (2022), “Competitive disclosure of information to a rationally inattentive agent.” Working Paper.

- Kamenica, Emir (2019), “Bayesian Persuasion and Information Design.” *Annual Review of Economics*, 11, 249–272.
- Kamenica, Emir and Matthew Gentzkow (2011), “Bayesian Persuasion.” *American Economic Review*, 101(6), 2590–2615.
- Kleiner, Andreas, Benny Moldovanu, and Philipp Strack (2021), “Extreme Points and Majorization: Economic Applications.” *Econometrica*, 89(4), 1557–1593.
- Knoepfle, Jan (2020), “Dynamic competition for attention.” Working Paper.
- Kolotilin, Anton (2018), “Optimal information disclosure: a linear programming approach.” *Theoretical Economics*, 13(2), 607–635.
- Kolotilin, Anton, Tymofiy Mylovanov, and Andriy Zapechelnyuk (2022), “Censorship as optimal persuasion.” *Theoretical Economics*, 17(2), 561–585.
- Kolotilin, Anton, Tymofiy Mylovanov, Andriy Zapechelnyuk, and Ming Li (2017), “Persuasion of a Privately Informed Receiver.” *Econometrica*, 85(6), 1949–1964.
- Liao, Xiaoye (2021), “Bayesian persuasion with optimal learning.” *Journal of Mathematical Economics*, 97, 102534.
- Lipnowski, Elliot and Laurent Mathevet (2018), “Disclosure to a psychological audience.” *American Economic Journal: Microeconomics*, 10(4), 67–93.
- Lipnowski, Elliot, Laurent Mathevet, and Dong Wei (2020), “Attention management.” *American Economic Review: Insights*, 2(1), 17–32.
- Lipnowski, Elliot, Laurent Mathevet, and Dong Wei (2022), “Optimal attention management: A tractable framework.” *Games and Economic Behavior*, 133, 170–180.
- Lipnowski, Elliot, Doron Ravid, and Denis Shishkin (2021), “Persuasion via weak institutions.” Working Paper. Electronic copy available at: <https://ssrn.com/abstract=3168103>, July 20, 2021.
- Lipnowski, Elliot, Doron Ravid, and Denis Shishkin (2024), “Perfect bayesian persuasion.”

- Machina, Mark J. (1982), “Expected utility analysis without the independence axiom.” *Econometrica*, 50(2), 277–324.
- Matysková, Ludmila and Alfonso Montes (2023), “Bayesian Persuasion With Costly Information Acquisition.” *Journal of Economic Theory*, 211, 105678.
- Milgrom, Paul and Ilya Segal (2002), “Envelope theorems for arbitrary choice sets.” *Econometrica*, 70(2), 583–601.
- Pomatto, Luciano, Philipp Strack, and Omer Tamuz (2023), “The cost of information: The case of constant marginal costs.” *American Economic Review*, 113(5), 1360–93.
- Rayo, Luis and Ilya Segal (2010), “Optimal Information Disclosure.” *Journal of Political Economy*, 118(5), 949–987.
- Rockafellar, R. Tyrell (1970), *Convex Analysis*. Princeton University Press, Princeton.
- Romanyuk, Gleb and Alex Smolin (2019), “Cream skimming and information design in matching markets.” *American Economic Journal: Microeconomics*, 11(2), 250–76.
- Shishkin, Denis (2024), “Evidence Acquisition and Voluntary Disclosure.” Working Paper.
- Simon, Herbert A. (1996), “Working paper no. 96–2 — Knowledge and the time to attend to it.” In *Carnegie Bosch Institute for Applied Studies in International Management*.
- Sun, Junze, Arthur Schram, and Randolph Sloof (2024), “Publicly persuading voters: The single-crossing property and the optimality of interval revelation.” Working Paper.
- Topkis, Donald M. (1978), “Minimizing a submodular function on a lattice.” *Operations Research*, 26(2), 305–321.
- Tsai, Yi-Lin and Elisabeth Honka (2021), “Informational and noninformational advertising content.” *Marketing Science*, 40(6), 1030–1058.
- Wei, Dong (2021), “Persuasion under costly learning.” *Journal of Mathematical Economics*, 94, 102451.