

# Simple Communication

Jacopo Bizzotto Nathan Hancart\*

February, 2026

## Abstract

We study multidimensional cheap talk with simple language and aligned preferences. An expert communicates with a decision-maker using a score that aggregates a multidimensional state into a one-dimensional message. Even though the expert and the decision-maker share the same payoffs, the use of simple language introduces strategic frictions. As a result, equilibrium payoffs may be lower than those achievable under commitment to a score. Additionally, under quadratic-loss utility, any equilibrium score must be linear in the state or discrete. Finally, for normally distributed states, we characterize the set of equilibrium linear scores and show that it consists of the ex-ante best and worst linear scores.

---

\*Bizzotto: Oslo Metropolitan University, Hancart: University of Oslo. We are grateful to Bård Harstad, Bart Lipman, Luca Onnis and Ran Spiegler for useful feedback and suggestions. We also thank Katinka Holtsmark for early discussions on this project.

Give me a one-handed economist.

---

*Harry Truman*

## 1 Introduction

Decision-makers often seek advice on complex issues. Policymakers consult experts about the impact of new policies, while people follow nutritional guidance from professionals. In principle, experts can write volumes on the many impacts of a new policy, and dietitians are available for personalized eating plans. In practice though, advice has to be simple. Experts summarize their findings in executive summaries. Most individuals rely on dietary recommendations, such as “5 a day” or nutritional labels. In this study, we examine the strategic incentives that arise when advice on complex issues has to be simple.

To isolate the effect of simple language, we focus on settings in which the expert and the decision-maker share identical preferences. If the expert could use a language as rich as the object described, revealing every relevant aspect of the object under consideration would be both optimal and an equilibrium strategy. When instead experts communicate using simple language, the nature of optimal and equilibrium communication is not immediately clear.

We explore communication via simple language in a multidimensional cheap talk game with aligned preferences. A sender observes a two-dimensional state of the world, then sends a cheap-talk message to a receiver. The receiver takes a two-dimensional action to minimize a quadratic loss function. Sender and receiver share the same payoffs. The model is also equivalent to one where a sender addresses two different audiences with the same message. For example, a movie critic using a single movie rating for a diverse readership.

We model simple language by requiring that equilibrium strategies map the state space to a real number and satisfy a property we dub *Intermediate Value Property*. We call such mappings *scores*. The Intermediate Value Property requires that small changes in the state of the world only cause small changes in the score. The property captures the idea that the score must represent the underlying physical reality of the state space. All continuous

scores satisfy the property. If the score has a countable image, e.g., a five-star rating, a marginal change in the state cannot make the score change by more than one star.

Both the image in  $\mathbb{R}$  and the Intermediate Value Property are necessary for scores to capture a language “simpler” than the state. The Intermediate Value Property rules out bijections between  $\mathbb{R}$  and  $\mathbb{R}^2$  and therefore prevents the sender from fully revealing the state (see Lemma 1). At the same time, our definition of score is flexible: it does not impose monotonicity or other functional-form assumptions and accommodates both discrete and continuous images of the mapping from states to messages.

We study Perfect Bayesian Equilibria where the sender maps states of the world into messages according to a score. Note that to model simple languages, we propose an equilibrium-selection criterion, not a restriction on the set of strategies. In other words, once the state is observed, the sender can deviate to any message. Proposition 1 shows that equilibrium scores always exist.

Our first result shows that communicating through scores can lead to welfare losses due to strategic frictions: in some situations, no ex-ante optimal score is an equilibrium strategy. This is possible because the sender can deviate from the optimal score to a strategy that is not a score, once the receiver’s expectations are set. Whenever such a deviation is profitable, commitment has value. In fact, the sender is sometimes better off being uninformed about one dimension to reduce the set of deviations available.

We then characterize the shape of equilibrium scores when the state space is  $\mathbb{R}^2$ . We show that strategic frictions impose qualitative restrictions on equilibrium scores. First, for any prior distribution, equilibrium scores are either linear in the state or a discrete coarsening of a linear score (Proposition 2). Second, a linear equilibrium score exists only if the expectation of the state conditional on a linear score is itself affine in the message (Proposition 3). When this condition cannot be satisfied, equilibrium scores must be discrete. That is, the sender needs to use a coarser language to be credible – for example a letter-based rating instead of a continuous one.

For some prior distribution, equilibrium linear scores exist. When the state is normally distributed, Proposition 4 shows that there are exactly two equilibrium linear scores. One score corresponds to the ex-ante worst linear score. In other words, a score may be state-wise optimal yet ex-ante the worst linear one. The other equilibrium linear score cor-

responds to the ex-ante best linear score. One score positively correlates the actions across dimensions, and the other one negatively correlates them. The optimality of each score depends on the correlation between the two dimensions of the state of the world: when the dimensions are positively correlated, the ex-ante best linear score correlates the actions and vice-versa. The key to Proposition 4 is the equivalence between the equilibrium scores and the stationary points of the ex-ante payoff maximization problem over linear scores. These stationary points correspond to the eigenvectors of a matrix that depends on the preference parameters and the correlation structure. We can extend this equivalence between equilibrium linear scores and the stationary points beyond two dimensions. In this case, some stationary points could be neither the maximum nor the minimum.

## 1.1 Related Literature

We introduce a new notion of simple language in cheap-talk models by requiring the sender to use a score, an aggregator of a multidimensional state, in equilibrium. Our definition of score rules out bijections while being flexible enough to allow for discrete and continuous scores. Closest to our paper is the literature studying cheap talk models with aligned preferences and some form of language limitation.<sup>1</sup> Jäger et al. (2011) study a similar model where the sender is constrained to use a finite number of messages. They establish that the ex-ante optimal strategy is an equilibrium and study the stability of the equilibrium. In Blume and Board (2013) and Blume (2018) uncertainty about the language used can impede communication. These three papers find that optimal strategies are equilibrium strategies. Similarly, Lipman (2025) uses the fact that optimal strategies are equilibrium strategies to show that there is always an equilibrium in pure strategy when preferences are aligned in cheap-talk games with a possibly constrained set of messages. We take a different approach and require simplicity to be an equilibrium property instead of a constraint on the strategy space itself. In particular, the optimal scores are not necessarily equilibrium strategies and therefore strategic frictions impose constraints on communication beyond the properties of scores.<sup>2</sup>

---

<sup>1</sup>This literature, like us, looks at the consequences of language limitations, not its causes. On the latter topic see Lipman (2003) and Lipman (2025).

<sup>2</sup>Other papers consider scores that aggregate a multidimensional variable in different settings. For example, Ball (2025) and Bonatti and Cisternas (2020) study linear scores where sender and receiver have different payoffs and the sender can manipulate the score input.

We also relate to the literature on multidimensional cheap talk. This literature has shown that multiple dimensions can be useful for information revelation, e.g., Battaglini (2002), Chakraborty and Harbaugh (2007) and Chakraborty and Harbaugh (2010). In this strand of the literature, the contribution closest to ours is Levy and Razin (2007), who show that correlation across dimensions can limit communication by creating informational spillovers across dimensions. Similar mechanisms are at play in our paper as the sender needs to balance how the score, a one dimensional object, reveals information across both dimensions.

Finally, there is a strand of the literature in information design where the amount of information transmitted is limited. In Gentzkow and Kamenica (2014), the limitation comes from the cost of designing the experiment, while in Bloedel and Segal (2021) it comes from the information-processing cost faced by the receiver. When considering optimal scores, we impose a restriction directly on the shape of the information structure, by limiting the sender to select among scores. In this way we are closer to Le Treust and Tomala (2019) and Aybas and Turkel (2024), who consider exogenous constraints on the capacity or cardinality of the message space.

## 2 Model

There are two players: a sender and a receiver. The sender has private information about a two-dimensional state of the world,  $\theta = (\theta_1, \theta_2) \in \Theta \subseteq \mathbb{R}^2$ , whose distribution admits a density function  $f$  if the state is infinite. Otherwise,  $f$  denotes the probability mass function. We assume that the variance of  $\theta$  is finite. When there is some ambiguity, we use  $\tilde{\theta}$  to denote the random variable with realization  $\theta$ . The receiver takes two actions represented by  $a = (a_1, a_2) \in \mathbb{R}^2$ . Before the receiver takes action, the sender sends a cheap-talk message  $m \in \mathbb{R}$ .<sup>3</sup> Sender and receiver share the same payoff function

$$u(a, \theta) = -\phi(a_1 - \theta_1)^2 - (a_2 - \theta_2)^2,$$

with  $\phi > 0$ . Both players want each action to match the state. The parameter  $\phi$  determines the dimension along which the loss from mismatch is the largest. Let  $\mu : \Theta \rightarrow \mathbb{R}$  and

---

<sup>3</sup>Given our focus on the sender's equilibrium strategies with image in  $\mathbb{R}$ , we directly assume that the message space is  $\mathbb{R}$ . This restriction is without loss of generality as we could have a larger message space and assign to any off-path message a belief associated with an on-path message.

$\alpha : \mathbb{R} \rightarrow \mathbb{R}^2$  denote pure strategies of the sender and the receiver. Also, for any  $m \in \mathbb{R}$  and  $i = 1, 2$ , let  $\alpha_i(m)$  denote the  $i$ -th element of  $\alpha(m)$ .

We are interested in a class of Perfect Bayesian Equilibria that we define in the next section.

An example of this setting is an expert giving advice to a government that needs to design a multidimensional policy. For example, promoting a healthy diet among different subpopulations, choosing tax levels for different groups or taking multiple investment decisions in some technology.

Our model is also equivalent to a model with two receivers, each taking a one-dimensional action. Each receiver minimizes a one-dimensional quadratic loss function and the sender maximizes a weighted sum of the receivers' payoffs. An example here could be an expert directly promoting a healthy diet among different subpopulations.

## 2.1 Scores

A *score*  $s$  is a non-constant function from  $\Theta$  to  $\mathbb{R}$  that satisfies the following property:

Intermediate Value Property (IVP): for any  $\theta, \theta' \in \Theta$  such that  $s(\theta) > s(\theta')$  and any  $m \in [s(\theta'), s(\theta)] \cap s(\Theta)$ , there is a  $\theta'' \in s^{-1}(m)$  such that  $\theta \wedge \theta' \leq \theta'' \leq \theta \vee \theta'$ .<sup>4</sup>

We discuss this definition in more detail below.

The set of scores is denoted by  $\mathcal{S}$ , and we refer to the typical realization of  $s$  as  $m$ . We say that a score is *optimal* if it solves the following maximization problem:

$$\begin{aligned} & \max_{s \in \mathcal{S}} \mathbb{E}[-\phi(\alpha_1(s(\theta)) - \theta_1)^2 - (\alpha_2(s(\theta)) - \theta_2)^2] \\ \text{s.t. } & \alpha(m) = \mathbb{E}[\theta|m], \quad \forall m \in s(\Theta). \end{aligned} \tag{BR}$$

A score is thus optimal if it maximizes the expected payoff among scores, given that the receiver best responds.

We say that a score  $s : \Theta \rightarrow \mathbb{R}$  is an *equilibrium score* if there is a Perfect Bayesian equilibrium (PBE) such that  $\mu(\theta) = s(\theta)$  for all  $\theta$ . A score is thus an equilibrium score if

---

<sup>4</sup>Here,  $\wedge$  is the component-wise minimum and  $\vee$  is the component-wise maximum:  $\theta \wedge \theta' = (\min\{\theta_1, \theta'_1\}, \min\{\theta_2, \theta'_2\})$  and  $\theta \vee \theta' = (\max\{\theta_1, \theta'_1\}, \max\{\theta_2, \theta'_2\})$ .

and only if there is  $\alpha$  that satisfies (BR) and  $\forall m, m' \in s(\Theta)$  and  $\forall \theta \in \Theta$ :

$$s(\theta) = m \Rightarrow -\phi(\alpha_1(m) - \theta_1)^2 - (\alpha_2(m) - \theta_2)^2 \geq -\phi(\alpha_1(m') - \theta_1)^2 - (\alpha_2(m') - \theta_2)^2. \quad (IC)$$

We note that an equilibrium score always exists.

**Proposition 1.** *An equilibrium score exists.*

The proof is in Section A. We show existence of an equilibrium score by showing that there always exists a PBE with two messages in the support of the sender's strategy.<sup>5</sup> Because a non-constant strategy with two messages satisfies all the properties of a score, an equilibrium score exists.

A score aggregates the two-dimensional state of the world into a one-dimensional object. The Intermediate Value Property ensures that the score is a well-behaved aggregator of the two-dimensional state of the world. Its economic interpretation is that it imposes a weak form of continuity: small changes in the state correspond to small changes in the score. We regard this property as a minimal requirement that the score must represent the underlying physical reality of the state space. All continuous mappings from  $\Theta$  to  $\mathbb{R}$  satisfy the property. For discrete mappings instead, the property requires that a minimal increment in the state changes the score by at most one grade. On a mathematical level, the property also rules out bijections between  $\mathbb{R}^2$  and  $\mathbb{R}$ , in line with our original motivation.<sup>6</sup>

**Lemma 1.** *A score  $s : \mathbb{R}^2 \rightarrow \mathbb{R}$  is not a bijection.*

*Proof.* If  $|s(\Theta)| \leq 2$ , then  $s$  cannot be a bijection. Take some messages  $m, m_1, m_2 \in s(\Theta)$  with  $m_1 < m < m_2$ . Take  $\theta, \theta^1, \theta^2$  such that  $s(\theta) = m$ ,  $s(\theta^1) = m_1$  and  $s(\theta^2) = m_2$ .

We can draw a curve from  $\theta^1$  to  $\theta^2$  consisting of straight vertical and horizontal segments such that this curve does not intersect with  $\theta$ . At least one of these segments has end points, denoted  $\theta'$  and  $\theta''$ , such that  $s(\theta') \leq m \leq s(\theta'')$ . By the IVP, there must be  $\theta'''$  on that segment such that  $s(\theta''') = m$ .  $\square$

Figure 1 shows 4 different scores for the finite state space  $\Theta = \{0, 1\}^2$ ; in the figure, dots in the same area represent states to which the score assigns the same signal.

---

<sup>5</sup>Here we adapt the proof of existence in Jäger et al. (2011) to a potentially unbounded state space.

<sup>6</sup>Similarly, one can also show that the IVP rules out bijections for scores of the form  $s : \{1, \dots, n\}^2 \rightarrow \mathbb{R}$ .

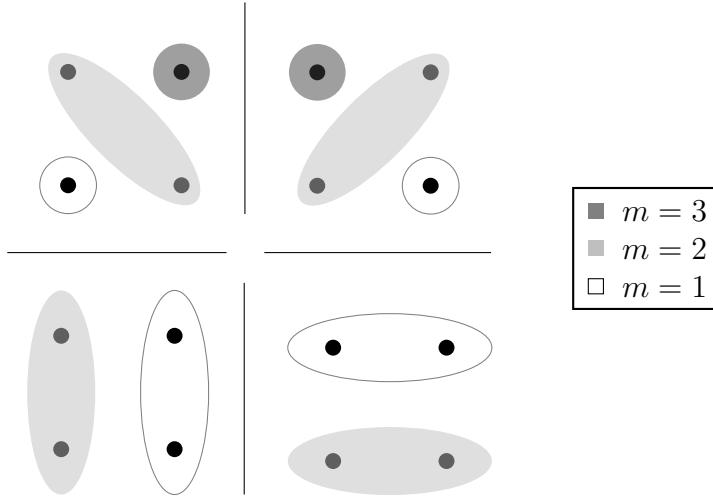


Figure 1: Examples of scores for  $\Theta = \{0, 1\}^2$

Here are some examples of scores for  $\Theta = \mathbb{R}^2$ :

- $s(\theta) = \beta_0 + \beta_1\theta_1 + \beta_2\theta_2;$
- $s(\theta) = \begin{cases} 1 & \text{if } \beta_1\theta_1 + \beta_2\theta_2 \geq c, \\ 0 & \text{otherwise.} \end{cases};$
- $s(\theta) = \sqrt{(\theta_1 - c_1)^2 + (\theta_2 - c_2)^2}.$

These examples show that scores can take many different forms. In particular, they can be continuous functions or take discrete values, e.g., five-star ratings. Scores need not be increasing or decreasing in any dimension. The last example shows a score that measures the distance between the state and a point  $(c_1, c_2)$  on the plane. If the state  $\theta$  represents political positions along two dimensions, this score can be interpreted as a measure of extremism where  $(c_1, c_2)$  would be the political center.

## 3 Analysis

### 3.1 Value of Commitment

We argue that commitment has value, i.e., it can be the case that none of the optimal scores are equilibrium strategies. We make our argument with an example. Let  $\phi = 1$ , the state takes values  $\Theta = \{0, 1\}^2$  and, for simplicity, let  $f(\theta) \neq f(\theta')$  for any two states  $\theta \neq \theta'$ . Let scores  $s_d$  and  $s_D$  be as shown, respectively, in the top left and top right panels of Figure 1. Score  $s_d$  assigns the same message to states  $(0, 1)$  and  $(1, 0)$  while assigning unique messages to the other states. Score  $s_D$  instead assigns the same message to states  $(0, 0)$  and  $(1, 1)$  while assigning unique messages to the other states. Up to an inconsequential relabeling of the messages, the optimal score is either  $s_d$  or  $s_D$ .

**Remark 1.** *The optimal score is either  $s_d$  or  $s_D$ . Score  $s_d$  is optimal if:*

$$\frac{f(0, 0)f(1, 1)}{f(0, 0) + f(1, 1)} \geq \frac{f(0, 1)f(1, 0)}{f(0, 1) + f(0, 1)}; \quad (1)$$

*if the condition holds with a reversed inequality, score  $s_D$  is optimal.*

The proofs of this and the next remark are in Section B. The optimal score is an equilibrium one if and only if the prior probabilities of the two states associated with the same message are not too different.

**Remark 2.** *Suppose the optimal score assigns the same signal to states  $\theta$  and  $\theta'$ . The optimal score is an equilibrium score if and only if*

$$\frac{f(\theta)}{f(\theta')} \in \left[ \sqrt{2} - 1, \frac{1}{\sqrt{2} - 1} \right].$$

The intuition is as follows. Suppose condition (1) holds strictly, so that  $s_d$  is the unique optimal score. Score  $s_d$  is shown on the left-hand side of Figure 2. Suppose also that  $\frac{f(0,1)}{f(1,0)} > \frac{1}{\sqrt{2}-1}$ , so that the posterior associated with  $m = 2$  is “close” to  $(0, 1)$  and “far” from  $(1, 0)$ . In fact, the posterior is so far from  $(1, 0)$  that the score is not an equilibrium strategy: if the receiver expects the sender to communicate according to the score, i.e.,  $\mu(\theta) = s_d(\theta)$  for all  $\theta$ , then the sender has a profitable deviation upon observing state

$(1, 0)$ . The right-hand side of Figure 2 shows one such deviation, which involves message  $\mu(1, 0) = 3$  instead of  $\mu(1, 0) = 2$ .

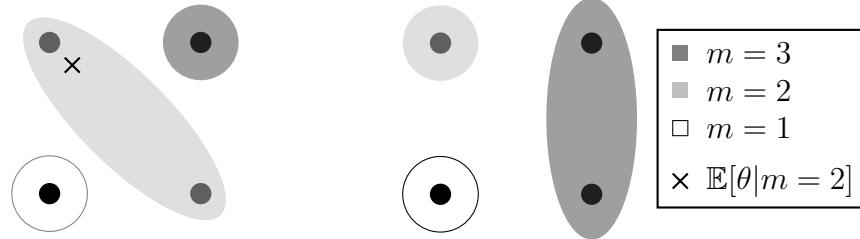


Figure 2: Left: Strategy  $\mu = s_d$ . Right: Profitable deviation from  $\mu = s_d$ .

The deviation leads to a strategy that violates the IVP, as it “jumps” from  $\mu(0, 0) = 1$  to  $\mu(1, 0) = 3$ . This strategy is not a score. In general, optimal scores need not be equilibrium strategies precisely because deviations to strategies that are not scores are possible. Relatedly, in some cases, the players are better off if the sender only observes one dimension of the state of the world (see Section F). The intuition here is that ignorance reduces the set of potential deviations available to the sender. This is in contrast with the rest of the literature that studies cheap talk models with aligned preferences (Jäger et al. (2011), Blume and Board (2013) and Blume (2018)) where the constraints on communication are on the message space directly and not on the properties of the equilibrium.

### 3.2 Infinite State Space

We characterize here equilibrium scores when the state space is  $\mathbb{R}^2$ . We show that equilibrium scores must satisfy specific properties that are imposed by the equilibrium conditions. We first introduce three definitions.

A score  $s$  is *linear* if there exist  $\beta_1$  and  $\beta_2$  such that, for any  $\theta \in \mathbb{R}^2$ ,

$$s(\theta) = \beta_1 \theta_1 + \beta_2 \theta_2.$$

A score  $s$  is *coarsely linear* if it has a discrete image  $M \subseteq \mathbb{Z}$  and there exists  $\beta_1$  and  $\beta_2$  such that

$$s(\theta) = m \Leftrightarrow c_{m-1} < \beta_1 \theta_1 + \beta_2 \theta_2 \leq c_m,$$

with  $-\infty \leq c_{m-1} < c_m \leq +\infty$  for any  $\theta \in \mathbb{R}^2$ .

Essentially, a coarsely linear score can be constructed by taking a linear score and partitioning its image into a countable number of intervals.

The scores  $s$  and  $s'$  are *equivalent* if  $\mathbb{E}[\tilde{\theta}|s(\theta)] = \mathbb{E}[\tilde{\theta}|s'(\theta)]$  for all  $\theta \in \Theta$ .

We are now ready to state the result of this section.

**Proposition 2.** *Suppose  $\Theta = \mathbb{R}^2$ . Any equilibrium score is equivalent to a linear or coarsely linear score.*

The proof is in Section C. To understand how we get Proposition 2, observe that given a belief about the sender's strategy, the receiver takes an action  $\alpha(m) = \mathbb{E}[\theta|m]$ . The sender's objective in state  $\theta$ , given this belief, is to choose the message  $m'$  that minimizes the loss function:

$$\min_{m'} (\phi(\theta_1 - \alpha_1(m'))^2 + (\theta_2 - \alpha_2(m'))^2).$$

As the sender minimizes a weighted Euclidean distance, in any equilibrium the set of states indifferent between any two messages must be a line. Furthermore, the IVP requires that such indifference lines do not cross. These observations imply that every equilibrium score with a discrete image must be coarsely linear. Linear scores can be seen as a limit case of coarsely linear scores. The rest of the proof shows that when the image of the score is not discrete, linear scores are the *only* scores compatible with the equilibrium conditions.

With a loss function that is not quadratic, the equilibrium forces would impose other restrictions on the score's functional form. In light of this observation, Proposition 2 should not be interpreted as showing that linear strategies are special, but rather that strategic frictions impose functional form restrictions on communication.

Finally, we argue that linear equilibrium scores are special cases.

**Proposition 3.** For any  $\beta \in \mathbb{R}^2$ , let  $e_i(m; \beta) = \mathbb{E}[\theta_i | m = \beta_1 \theta_1 + \beta_2 \theta_2]$  for  $i = 1, 2$ . Assume that for any  $\beta \in \mathbb{R}^2$ ,  $e_i(m; \beta)$  is differentiable in  $m$ .

- A linear score with  $\beta_j = 0$  for  $j = 1$  or  $2$  is an equilibrium score only if  $\mathbb{E}[\theta_j | \theta_i]$  is constant in  $\theta_i$ .
- A linear score with  $\beta_i \neq 0$  for  $i = 1, 2$  is an equilibrium score only if  $e_i(m; \beta)$  is affine in  $m$  for  $i = 1, 2$ .

Proposition 3 establishes that revealing one dimension is an equilibrium strategy only when the expectation of one dimension conditional on the other is constant. It also establishes that linear equilibrium scores can exist only if the expectation of the state conditional on the score is itself affine in the message. When this condition is never met, all equilibrium scores are coarsely linear. In these cases, the sender limits the information transmitted to maintain credibility. Indeed, every coarsely linear score can be improved upon by a score using more messages.

To understand the first result, suppose that the sender uses a score that only reveals one dimension, say  $\theta_1$ . Upon observing  $\theta_1$ , the receiver will use the correlation between the two dimensions to make some inferences about  $\theta_2$ . This reasoning from the receiver introduces an incentive for the sender to lie about  $\theta_1$  to potentially correct the inference on  $\theta_2$ . The intuition is that an appropriately chosen marginal change in the score induces a marginal loss of zero along the revealed dimension  $\theta_1$  and a positive marginal benefit along the other dimension. This information spillover is similar to the result in Levy and Razin (2007) who show that misalignment in one dimension can hinder communication in another dimension where receiver and sender have aligned preferences.

Using the score  $m = \theta_1$  reveals that the state lies in the subspace  $\{\theta : \theta_1 = m\}$  and the first condition requires that the message does not change the expectation on the second dimension. The second result generalizes this logic to revealing an arbitrary linear subspace. Using a linear score is equivalent to revealing the state lies in a linear subspace of  $\mathbb{R}^2$ :  $\{\theta : m = \beta_1 \theta_1 + \beta_2 \theta_2\}$ . The condition that the conditional expectation is affine in the message is necessary for the message to not change the expectation on an appropriate other dimension.

### 3.3 Normally Distributed State

There are important classes of distributions — such as the normal distribution — for which the conditional expectations given a linear score are affine. In this case, a linear equilibrium score may exist. We now characterize the linear scores when the state is normally distributed.<sup>7</sup>

Let  $\mathcal{S}_l = \{s : \mathbb{R}^2 \rightarrow \mathbb{R} : s \text{ is linear}\}$ . We refer to a score as an *ex-ante best linear score* if it solves the problem:

$$\max_{s \in \mathcal{S}_l} \mathbb{E}[-\phi(\alpha_1(s(\theta)) - \theta_1)^2 - (\alpha_2(s(\theta)) - \theta_2)^2] \quad \text{s.t. } \alpha(m) = \mathbb{E}[\theta|m], \quad \forall m \in s(\Theta).$$

We instead refer to a score as an *ex-ante worst linear score* if it solves

$$\min_{s \in \mathcal{S}_l} \mathbb{E}[-\phi(\alpha_1(s(\theta)) - \theta_1)^2 - (\alpha_2(s(\theta)) - \theta_2)^2] \quad \text{s.t. } \alpha(m) = \mathbb{E}[\theta|m], \quad \forall m \in s(\Theta).$$

Let

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}$$

be a covariance matrix and

$$\Phi = \begin{pmatrix} \phi & 0 \\ 0 & 1 \end{pmatrix}.$$

We identify a linear score  $s(\theta) = \beta'\theta$  with the weights  $\beta = (\beta_1, \beta_2)'$ .<sup>8</sup>

**Proposition 4.** *Let  $\theta \sim N(0, \Sigma)$ . The equilibrium linear scores are the eigenvectors of  $\Phi\Sigma$ . These are the ex-ante best and worst linear scores.*

The proof is in Section E. Proposition 4 shows that when the state is normally distributed, the best linear score is achievable in equilibrium. However, another linear equilibrium exists, corresponding to the worst possible linear score. The key idea underlying the proof is the following. A linear score  $\beta$ , with corresponding strategy  $\alpha$ , is an equilibrium score if the indifference curve of each type  $\theta$  sending message  $m$ ,  $\{a \in \mathbb{R}^2 : u(a, \theta) = u(\alpha(m), \theta)\}$ , is tangent to the curve  $\{\alpha(m) : m \in \mathbb{R}\}$ . We show that the linear scores

---

<sup>7</sup>The next result remains valid under elliptical distributions — a broader class of distributions that also satisfy the linear conditional expectations property.

<sup>8</sup>We use the convention that when writing a vector as a matrix, it is a column vector.

$\beta$  satisfying these tangency conditions are the eigenvectors of  $\Sigma\Phi$ . These eigenvectors, in turn, solve the first-order conditions of the ex-ante maximization problem.

The proof of Proposition 4 is general and can be extended to arbitrary dimensions of the state and action space. When the dimension is larger than two, the set of equilibrium linear scores coincides with the set of stationary points of the ex-ante maximization problem. In the case of two dimensions, we can explicitly calculate the equilibrium linear scores. Note that for any constant  $c \neq 0$ , two linear scores  $\beta'$  and  $\beta''$  such that  $\beta' = c\beta''$  induce the same distributions over actions. Therefore, any linear score is determined by the ratio  $\beta_1/\beta_2$ , if the ratio exists.

**Corollary 1.** *Suppose  $\sigma_{12} \neq 0$ . The equilibrium linear scores,  $\beta' = (\beta'_1, \beta'_2)$  and  $\beta'' = (\beta''_1, \beta''_2)$ , are determined by the ratios*

$$\frac{\beta'_1}{\beta'_2} = \frac{\phi\sigma_1^2 - \sigma_2^2 + \sqrt{(\phi\sigma_1^2 - \sigma_2^2)^2 + 4\phi\sigma_{12}^2}}{2\sigma_{12}} \neq 0,$$

$$\frac{\beta''_1}{\beta''_2} = \frac{\phi\sigma_1^2 - \sigma_2^2 - \sqrt{(\phi\sigma_1^2 - \sigma_2^2)^2 + 4\phi\sigma_{12}^2}}{2\sigma_{12}} \neq 0.$$

If  $\sigma_{12} = 0$ , then  $\beta'_2 = 0$  and  $\beta''_1 = 0$ , i.e., the equilibrium scores fully reveal one dimension.<sup>9</sup>

When the covariance  $\sigma_{12}$  is different than zero, one equilibrium ratio  $\beta_1/\beta_2$  is positive and the other one is negative. In the score with a positive ratio, a higher message is associated with a higher state:  $\mathbb{E}[\theta_i|m]$  is increasing in  $m$  for  $i = 1, 2$ .<sup>10</sup> If, for instance, the score rates a movie by considering its aesthetic quality,  $\theta_1$ , and entertainment value,  $\theta_2$ , then a higher rating indicates that the movie has a higher expected quality in both dimensions. Instead, the score with a negative ratio can be interpreted as a relative measure: a higher message is associated with a higher expected value in one dimension, but lower in the other.

When the correlation between the two dimensions is positive ( $\sigma_{12} > 0$ ), the optimal linear score satisfies  $\beta_1/\beta_2 > 0$ , which corresponds to inducing positively correlated actions by the receiver. When the correlation is negative, the best linear score is such that  $\beta_1/\beta_2 < 0$ , while the worst is such that  $\beta_1/\beta_2 > 0$ . Note that the worst score can be a natural

---

<sup>9</sup>The proof of the corollary is immediate, therefore omitted.

<sup>10</sup>This statement is true in equilibrium but does not hold for all  $\beta$ . For example, suppose there is negative correlation between the two dimensions,  $\sigma_{12} < 0$ , and the weight on the first dimension is much higher than on the second,  $\beta_1 \gg \beta_2 > 0$ . In this case, a higher message will still be indicative of a high  $\theta_1$  which in turn implies a low  $\theta_2$ .

candidate for an equilibrium score. For example, if movie critics use a rating system where a higher rating indicates higher aesthetic or entertainment value but these two dimensions are negatively correlated, then the equilibrium score has poor welfare properties.

Finally, note that as in Proposition 3, it is an equilibrium to reveal only one dimension only if the two dimensions are uncorrelated. In this case, the best linear score depends on the loss from mismatch  $\phi$  and the variance of each dimension.

## 4 Conclusion

We model a cheap-talk game with aligned preferences where the sender is constrained to use a score in equilibrium. We show that this restriction introduces strategic frictions despite the aligned preferences. These frictions can create a wedge between optimal and equilibrium scores. They also put structure on the shape of equilibrium scores.

The multidimensionality of our model plays a key role in our results. In particular, if the state were one-dimensional, any optimal score would be an equilibrium strategy. In a one-dimensional model, the score can be defined in multiple ways. Let  $\Theta \subseteq \mathbb{R}$  and let the sender send messages in  $M \subseteq \mathbb{R}$ . A score is a function  $s$  that satisfies

1.  $s : \Theta \rightarrow M$  and
2.  $s$  satisfies IVP.

If either  $M = \mathbb{R}$  or  $M = \{1, \dots, n\}$  for some  $n \in \mathbb{N}$ , then any optimal score is an equilibrium strategy. If  $M = \mathbb{R}$ , full revelation is possible so the optimal score is trivially an equilibrium. If  $M = \{1, \dots, n\}$ , the result follows from the fact that for any given score and belief associated with it, the most profitable deviation is also a score. Therefore, if this deviation is profitable, then this score should have been optimal. This is the crucial difference with the two-dimensional case where a profitable deviation could be a strategy that is not a score.

## References

Aybas, Y. C. and Turkel, E. (2024), ‘Persuasion with coarse communication’, *arXiv preprint arXiv:1910.13547* .

Ball, I. (2025), ‘Scoring strategic agents’, *American Economic Journal: Microeconomics* **17**(1), 97–129.

Battaglini, M. (2002), ‘Multiple referrals and multidimensional cheap talk’, *Econometrica* **70**(4), 1379–1401.

Bloedel, A. W. and Segal, I. R. (2021), ‘Persuasion with rational inattention’, *Available at SSRN 3164033* .

Blume, A. (2018), ‘Failure of common knowledge of language in common-interest communication games’, *Games and Economic Behavior* **109**, 132–155.

Blume, A. and Board, O. (2013), ‘Language barriers’, *Econometrica* **81**(2), 781–812.

Bonatti, A. and Cisternas, G. (2020), ‘Consumer scores and price discrimination’, *The Review of Economic Studies* **87**(2), 750–791.

Chakraborty, A. and Harbaugh, R. (2007), ‘Comparative cheap talk’, *Journal of Economic Theory* **132**(1), 70–94.

Chakraborty, A. and Harbaugh, R. (2010), ‘Persuasion by cheap talk’, *American Economic Review* **100**(5), 2361–2382.

Gentzkow, M. and Kamenica, E. (2014), ‘Costly persuasion’, *American Economic Review* **104**(5), 457–462.

Jäger, G., Metzger, L. P. and Riedel, F. (2011), ‘Voronoi languages: Equilibria in cheap-talk games with high-dimensional types and few signals’, *Games and Economic Behavior* **73**(2), 517–537.

Lang, R. (1986), ‘A note on the measurability of convex sets’, *Archiv der Mathematik* **47**, 90–92.

Le Treust, M. and Tomala, T. (2019), ‘Persuasion with limited communication capacity’, *Journal of Economic Theory* **184**, 104940.

Levy, G. and Razin, R. (2007), ‘On the limits of communication in multidimensional cheap talk: a comment’, *Econometrica* **75**(3), 885–893.

Lipman, B. L. (2003), Language and economics, in ‘Cognitive Processes and Economic Behaviour’, Routledge, pp. 75–93.

Lipman, B. L. (2025), ‘Why is language vague?’, *International Journal of Game Theory* **54**(1), 8.

Parlett, B. N. (1998), *The symmetric eigenvalue problem*, SIAM.

## A Proof of Proposition 1

We first establish that there always exists an equilibrium with two messages.

**Lemma 2.** *There exists a Perfect Bayesian Equilibrium in which the sender chooses a strategy  $\mu : \Theta \rightarrow \{1, 2\}$ .*

*Proof.* As a first step, we establish that the function

$$v(\alpha^1, \alpha^2) = \int_{\Theta} \max\{u(\alpha^1, \theta), u(\alpha^2, \theta)\} dF$$

is continuous. To show this, we apply the dominated convergence theorem.

Take two converging sequences in  $\mathbb{R}^2$ ,  $(\alpha^{1,n}, \alpha^{2,n}) \rightarrow (\alpha^1, \alpha^2)$ . Observe that

$$|\max\{u(\alpha^{1,n}, \theta), u(\alpha^{2,n}, \theta)\}| \leq \phi(\alpha_1^{1,n} - \theta_1)^2 + (\alpha_2^{1,n} - \theta_2)^2.$$

For any converging sequence in  $\mathbb{R}^2$ ,  $\alpha^n \rightarrow \alpha$ , the function

$$\phi(\alpha_1^n - \theta_1)^2 + (\alpha_2^n - \theta_2)^2 = (\phi\theta_1^2 + \theta_2^2) - 2(\phi\theta_1\alpha_1^n + \theta_2\alpha_2^n) + \phi(\alpha_1^n)^2 + (\alpha_2^n)^2$$

is dominated by an integrable function. This is the case, because the sequence  $(\alpha^n)$  converges, hence it is bounded and  $\phi(\alpha_1^n)^2 + (\alpha_2^n)^2 \leq M$  for some  $M > 0$ . Similarly, by the Cauchy-Schwarz inequality,  $|\phi\theta_1\alpha_1^n + \theta_2\alpha_2^n| \leq \sqrt{M}(\theta_1^2 + \theta_2^2)$ . Therefore,

$$|\max\{u(\alpha^{1,n}, \theta), u(\alpha^{2,n}, \theta)\}| \leq \phi(\alpha_1^{1,n} - \theta_1)^2 + (\alpha_2^{1,n} - \theta_2)^2 \leq (\phi\theta_1^2 + \theta_2^2) + 2\sqrt{M}(\theta_1^2 + \theta_2^2) + M,$$

for some  $M > 0$ . Because the variance of  $\theta$  is finite, the dominating function is integrable.

It is also clear that

$$\max\{u(\alpha^{1,n}, \theta), u(\alpha^{2,n}, \theta)\} \rightarrow \max\{u(\alpha^1, \theta), u(\alpha^2, \theta)\}, \text{ for each } \theta.$$

Therefore by the dominated convergence theorem,

$$\int_{\Theta} \max\{u(\alpha^{1,n}, \theta), u(\alpha^{2,n}, \theta)\} dF \rightarrow \int_{\Theta} \max\{u(\alpha^1, \theta), u(\alpha^2, \theta)\} dF,$$

and the function  $v(\alpha^1, \alpha^2)$  is continuous.

As a second step, we establish that the following maximization problem has a solution:

$$\max_{\alpha^1, \alpha^2 \in \mathbb{R}^2} v(\alpha^1, \alpha^2) \quad (2)$$

The function  $v(\alpha^1, \alpha^2)$  is bounded above by 0 and therefore a supremum exists, say  $v^*$ . Moreover, setting  $\alpha^1 = \alpha^2 = \mathbb{E}[\theta]$  guarantees a payoff of  $-\phi \text{Var}[\theta_1] - \text{Var}[\theta_2]$  and therefore  $v^* \geq -\phi \text{Var}[\theta_1] - \text{Var}[\theta_2]$ .

If  $v^* = -\phi \text{Var}[\theta_1] - \text{Var}[\theta_2]$ , then the supremum is attained by  $\alpha^1 = \alpha^2 = \mathbb{E}[\theta]$  and therefore a maximum exists.

Suppose instead that  $v^* > -\phi \text{Var}[\theta_1] - \text{Var}[\theta_2]$ . Let  $(\alpha^{1,n}, \alpha^{2,n})$  be a sequence such that  $v(\alpha^{1,n}, \alpha^{2,n}) \rightarrow v^*$ . We want to show that the sequence  $(\alpha^{1,n}, \alpha^{2,n})$  is bounded.

Suppose it is not. If  $\|\alpha^{k,n}\| \rightarrow \infty$ , then  $u(\alpha^{k,n}, \theta) \rightarrow -\infty$  for each  $\theta$ .

If  $\|\alpha^{k,n}\| \rightarrow \infty$  for both  $k = 1, 2$ , then  $\max\{u(\alpha^{1,n}, \theta), u(\alpha^{2,n}, \theta)\} \rightarrow -\infty$  and therefore  $v(\alpha^{1,n}, \alpha^{2,n}) \rightarrow -\infty$  and thus does not converge to  $v^*$ .

If  $\|\alpha^{k,n}\| \rightarrow \infty$  for only one  $k = 1, 2$ , then  $\alpha^{-k,n}$  is bounded and admits a convergent subsequence to  $\alpha^{-k}$ . Taking such subsequence, we get  $\max\{u(\alpha^{k,n}, \theta), u(\alpha^{-k,n}, \theta)\} \rightarrow u(\alpha^{-k}, \theta)$  for each  $\theta$ . Using the dominated convergence theorem in a similar way as above, we get

$$v(\alpha^{k,n}, \alpha^{-k,n}) \rightarrow \int_{\Theta} u(\alpha^{-k}, \theta) dF \leq -\phi \text{Var}[\theta_1] - \text{Var}[\theta_2].$$

But the supremum  $v^* > \phi \text{Var}[\theta_1] + \text{Var}[\theta_2]$ , a contradiction.

Therefore, the sequence  $(\alpha^{1,n}, \alpha^{2,n})$  is bounded and admits a convergent subsequence. By continuity, a maximum then exists.

To conclude the proof, note that the maximization problem (2) gives the Perfect Bayesian Equilibrium strategies of the common interest game where the sender chooses a strategy  $\mu : \Theta \rightarrow \{1, 2\}$  and the receiver chooses  $(\alpha^1, \alpha^2) \in \mathbb{R}^2 \times \mathbb{R}^2$  to maximize

$$\max_{\mu, \alpha} \int_{\Theta} \mathbb{1}[\mu(\theta) = 1] u(\alpha^1, \theta) + \mathbb{1}[\mu(\theta) = 2] u(\alpha^2, \theta) dF. \quad (3)$$

□

Proposition 1 is a corollary of Lemma 2.

*Proof of Proposition 1.* Note first that  $\alpha^1 = \alpha^2 = \mathbb{E}[\theta]$  is not a solution of the maximization problem (3), as any arbitrary partition of  $\Theta$  and the best-reply to it would give strictly higher payoffs. This means that the solution to (3) is a non-constant  $\mu$ . Moreover, the strategy  $\mu : \Theta \rightarrow \{1, 2\}$  trivially satisfies the IVP. Therefore, an equilibrium score exists. □

## B Proof of Remark 1 and Remark 2

Let  $s_1$  denote the score that assigns a signal to  $(0, 0)$  and  $(0, 1)$  and another signal to  $(1, 0)$  and  $(1, 1)$ . Let  $s_2$  denote the score that assigns a signal to  $(0, 0)$  and  $(1, 0)$  and another signal to  $(0, 1)$  and  $(1, 1)$ . It is immediate that the optimal score belongs to the set  $\{s_1, s_2, s_D, s_d\}$ . Let the payoffs associated with  $s_D$ ,  $s_d$ ,  $s_1$  and  $s_2$  be respectively,  $u_D$ ,  $u_d$ ,  $u_1$  and  $u_2$  so that:

$$\begin{aligned} u_D &:= -2g(f(0, 0), f(1, 1)); \\ u_d &:= -2g(f(1, 0), f(0, 1)); \\ u_1 &:= -g(f(0, 0), f(0, 1)) - g(f(1, 0), f(1, 1)); \\ u_2 &:= -g(f(0, 0), f(1, 0)) - g(f(0, 1), f(1, 1)), \end{aligned}$$

where  $g(x, y) := \frac{xy}{x+y}$ .

**Lemma 3.** *If  $f(0, 1) > f(0, 0)$ , then score  $s_2$  is not optimal.*

*Proof.* Suppose first that  $f(1, 0) > f(1, 1)$ . Simple algebra gives:

$$\begin{aligned} u_2 < u_D &\Leftrightarrow \\ g(f(0, 0), f(1, 0)) - g(f(0, 0), f(1, 1)) &> g(f(0, 0), f(1, 1)) - g(f(0, 1), f(1, 1)). \end{aligned}$$

As  $g_x > 0$ , then  $f(1, 0) > f(1, 1)$  ensures that the left side of the last inequality is positive: at the same time,  $f(0, 1) > f(0, 0)$  ensures that the right side is non-positive. We conclude

that the last inequality holds and indeed  $u_2 < u_D$ . So for  $f(1, 0) > f(1, 1)$ , score  $s_2$  is not optimal.

Suppose now that  $f(1, 0) < f(1, 1)$ . We proceed by contradiction. Suppose that  $u_2 \geq \max\{u_D, u_d\}$ . Then

$$g(f(0, 0), f(1, 0)) + g(f(0, 1), f(1, 1)) \leq 2g(f(1, 0), f(0, 1)), \text{ and}$$

$$g(f(0, 0), f(1, 0)) + g(f(0, 1), f(1, 1)) \leq 2g(f(0, 0), f(1, 1)).$$

These two inequalities imply that the sum of the right sides must be larger than the sum of the left sides:

$$2g(f(0, 0), f(1, 0)) + 2g(f(0, 1), f(1, 1)) \leq 2g(f(1, 0), f(0, 1)) + 2g(f(0, 0), f(1, 1)) \Leftrightarrow$$

$$g(f(0, 1), f(1, 1)) - g(f(0, 0), f(1, 1)) \leq g(f(1, 0), f(0, 1)) - g(f(0, 0), f(1, 0)).$$

As  $g_{xy}(\cdot) > 0$ , then  $f(0, 1) > f(0, 0)$  and  $f(1, 0) < f(1, 1)$  together imply that the last inequality is violated. This contradiction implies that  $u_2 < \max\{u_D, u_d\}$ . Hence, for  $f(1, 0) < f(1, 1)$ , score  $s_2$  is not optimal. As  $f(1, 0) \neq f(1, 1)$  by assumption, the lemma follows.  $\square$

*Proof of Remark 1.* Lemma 3 establishes that if  $f(0, 1) > f(0, 0)$ , then score  $s_2$  is not optimal. The same arguments can be used to show that also for  $f(0, 1) < f(0, 0)$  score  $s_2$  is not optimal. As  $f(0, 1) \neq f(0, 0)$  by assumption, we conclude that score  $s_2$  cannot be optimal. The proof that  $s_1$  cannot be optimal follows the same steps and is omitted. We conclude that the optimal score is either  $s_D$  or  $s_d$ . The last part of the remark is immediate.  $\square$

*Proof of Remark 2.* Suppose parameters are such that  $s_d$  is optimal (the argument is identical if  $s_D$  is optimal). Consider a PBE such that  $\mu(\theta) = s_d$ . In such a PBE,  $\mu(0, 0) = 1$ ,  $\mu(0, 1) = \mu(1, 0) = 2$  and  $\mu(1, 1) = 3$ ;  $\alpha(1) = (0, 0)$ ,  $\alpha(2) = (\frac{f(1,0)}{f(1,0)+f(0,1)}, \frac{f(0,1)}{f(1,0)+f(0,1)})$

and  $\alpha(3) = (1, 1)$ . Note that  $u(\alpha(3), (1, 0)) = u(\alpha(1), (1, 0)) = -1$  hence

$$u(\alpha(2), (1, 0)) \geq u(\alpha(1), (1, 0)) \Leftrightarrow u(\alpha(2), (1, 0)) \geq u(\alpha(3), (1, 0)) \Leftrightarrow \frac{f(1, 0)}{f(0, 1)} \geq \sqrt{2} - 1,$$

while

$$u(\alpha(2), (0, 1)) \geq u(\alpha(1), (0, 1)) \Leftrightarrow u(\alpha(2), (0, 1)) \geq u(\alpha(3), (0, 1)) \Leftrightarrow \frac{f(1, 0)}{f(0, 1)} \leq \frac{1}{\sqrt{2} - 1}.$$

A necessary condition for  $s_d$  to be an equilibrium strategy is therefore that

$$\frac{f(1, 0)}{f(0, 1)} \in \left[ \sqrt{2} - 1, \frac{1}{\sqrt{2} - 1} \right].$$

To conclude the proof it is sufficient to note that (a) this condition is also sufficient, as deviations for the sender are unprofitable upon observing some  $\theta \in \{(0, 0), (1, 1)\}$  and (b)

$$\frac{f(1, 0)}{f(0, 1)} \in \left[ \sqrt{2} - 1, \frac{1}{\sqrt{2} - 1} \right] \Leftrightarrow \frac{f(0, 1)}{f(1, 0)} \in \left[ \sqrt{2} - 1, \frac{1}{\sqrt{2} - 1} \right]$$

□

## C Proof of Proposition 2

For a score  $s$ , let  $\alpha(m) = \mathbb{E}[\theta|m]$ , let  $M$  be the image of  $s$  and  $\alpha(M)$  the image of  $\alpha(\cdot)$ . Let  $\Theta(a) = \{\theta : \alpha(s(\theta)) = a\}$ . For any two points,  $x, y \in \mathbb{R}^2$ , with a slight abuse of notation, let  $[x, y] = \text{conv}\{x, y\}$ ,  $(x, y) = [x, y] \setminus \{x, y\}$  and  $[x, y) = [x, y] \setminus \{y\}$ . Finally, let  $\ell(x, y)$  be the line connecting the points  $x, y$ .

The following lemma will be used throughout the proof.

**Lemma 4.** *Let  $a, a' \in \mathbb{R}^2$ . If  $u(a, \theta) \geq u(a', \theta)$ , then  $u(a, \theta') > u(a', \theta')$  for all  $\theta' \in [a, \theta]$ .*

*Proof.* First assume that  $a' \notin \ell(a, \theta)$ . Take  $\theta' \in [a, \theta]$ . Note that

$$\begin{aligned} -u(a, \theta) &\leq -u(\theta, a') \\ \Rightarrow \sqrt{-u(\theta, a)} &\leq \sqrt{-u(\theta, a')} < \sqrt{-u(\theta, \theta')} + \sqrt{-u(\theta', a')}, \end{aligned} \tag{4}$$

where the last inequality holds by the triangle inequality and is strict because  $\theta$ ,  $\theta'$  and  $a'$  are not collinear. Note also that

$$\begin{aligned} \sqrt{-u(\theta', \theta)} + \sqrt{-u(a, \theta')} &= \sqrt{-u(a, \theta)} < \sqrt{-u(\theta, \theta')} + \sqrt{-u(\theta', a')} \\ \Rightarrow -u(a, \theta') &< -u(a', \theta') \\ \Leftrightarrow u(a, \theta') &> u(a', \theta'), \end{aligned}$$

where the equality holds as  $a$ ,  $\theta$  and  $\theta'$  are collinear, and the first inequality follows from (4).

If instead  $a' \in \ell(a, \theta')$ , we must have  $a' \notin (a, \theta]$ , otherwise  $u(a, \theta) < u(a', \theta)$ . But then, either  $a \in (a', \theta')$  or  $\theta \in (\theta', a')$ . In both cases,  $u(a, \theta') > u(a', \theta')$ .  $\square$

We first consider the case in which all points in  $\alpha(M)$  are isolated.

**Lemma 5.** *If all points in  $\alpha(M)$  are isolated, then  $s(\theta)$  is equivalent to a coarsely linear score.*

*Proof.* For any two  $a, a' \in \alpha(M)$ , let  $\Theta^{\geq}(a, a') := \{\theta : u(a, \theta) \geq u(a', \theta)\}$ . This set is a half-space:

$$u(\theta, a) \geq u(\theta, a') \Leftrightarrow -2\theta_1 a_1 \phi + a_1^2 \phi - 2\theta_2 a_2 + a_2^2 \geq -2\theta_1 a'_1 \phi + a'_1^2 \phi - 2\theta_2 a'_2 + a'_2^2.$$

Similarly, let  $\Theta^=(a, a') := \{\theta : u(a, \theta) = u(a', \theta)\}$ . This set is a line.

If  $|\alpha(M)| = 2$ , the set  $\Theta^=(a, a')$  determines the half-space defining a coarsely linear score.

Suppose there are three points  $a^1, a^2, a^3 \in \alpha(M)$  and  $m^i \in \alpha^{-1}(a^i)$  for  $i = 1, 2, 3$  such that (i)  $m^1 < m^2 < m^3$  and (ii) for any action  $a' \in \alpha(M) \setminus \{a^1, a^2, a^3\}$ , every  $m \in \alpha^{-1}(a')$  satisfies  $m > m^3$  or  $m < m^1$ .

Suppose that  $\Theta^=(a^1, a^2)$  and  $\Theta^=(a^2, a^3)$  are not parallel. Then  $\Theta(a^2) \subseteq \Theta^{\geq}(a^2, a^1) \cap \Theta^{\geq}(a^2, a^3)$  and the set  $\Theta^{\geq}(a^2, a^1) \cap \Theta^{\geq}(a^2, a^3)$  is a polyhedron with an extreme point at  $\Theta^=(a^2, a^1) \cap \Theta^=(a^2, a^3)$ .

Clearly  $\{a^1, a^3\} \cap \Theta^{\geq}(a^2, a^1) \cap \Theta^{\geq}(a^2, a^3) = \emptyset$ . Moreover, we can draw a curve from  $a^1$

to  $a^3$  in  $\Theta \setminus (\Theta^{\geq}(a^2, a^1) \cap \Theta^{\geq}(a^2, a^3))$  consisting of straight vertical and horizontal lines. By the IVP, there must be  $\theta'$  on that curve such that  $s(\theta') = m^2$ , a contradiction.  $\square$

We consider next the case in which not all points in  $\alpha(M)$  are isolated.

**Lemma 6.** *Let  $a$  be a limit point in  $\alpha(M)$ . Then  $\text{int } \Theta(a) = \emptyset$ .*

*Proof.* To establish that  $\text{int } \Theta(a) = \emptyset$ , we proceed by contradiction. Suppose  $\text{int } \Theta(a) \neq \emptyset$  and let  $\theta \in \text{int } \Theta(a)$ . Hence  $u(a, \theta) \geq u(a', \theta)$  for all  $a' \in \alpha(M)$ . Let  $a''$  be such that  $u(a, \theta) = u(a'', \theta)$ . Because  $\theta \in \text{int } \Theta(a)$ , there is  $\epsilon > 0$ , such that for all  $\theta' \in B_\epsilon(\theta)$ ,  $\theta \in \Theta(a)$ . Therefore,  $(\theta, a''] \cap B_\epsilon(\theta)$  is not empty. But by Lemma 4,  $\theta' \in (\theta, a'']$  implies  $u(a'', \theta') > u(a, \theta')$ , contradicting  $\theta' \in \Theta(a)$ . Hence  $u(a, \theta) > u(a', \theta)$  for all  $a' \in \alpha(M) \setminus \{a\}$ .

Now we argue that  $\text{int } \Theta(a)$  is convex. Let  $\theta, \theta' \in \text{int } \Theta(a)$  and  $\theta'' \in [\theta, \theta']$ . First observe that

$$u(\theta, a) > u(\theta, a') \Leftrightarrow -2\theta_1 a_1 \phi + a_1^2 \phi - 2\theta_2 a_2 + a_2^2 > -2\theta_1 a'_1 \phi + a'_1^2 \phi - 2\theta_2 a'_2 + a'_2^2. \quad (5)$$

The inequality is preserved under convex combinations, so  $u(a, \theta'') > u(a', \theta'')$  for all  $a' \in \alpha(M) \setminus \{a\}$ , and thus  $\theta'' \in \Theta(a)$ .

We show next that  $\theta'' \in \text{int } \Theta(a)$ . Take  $\epsilon > 0$ , such that  $B_\epsilon(\theta) \subset \text{int } \Theta(a)$ . If  $\theta'' \in B_\epsilon(\theta)$ , we are done. Suppose  $\theta'' \notin B_\epsilon(\theta)$ . Take two points  $\theta^1, \theta^2 \in B_\epsilon(\theta)$  such that  $\theta'' \notin [\theta^i, \theta']$  for  $i = 1, 2$ , and  $\theta \in (\theta^1, \theta^2)$ . This implies that  $\theta^1, \theta^2$  and  $\theta'$  are not collinear.<sup>11</sup> In that case, the convex hull  $\text{conv}\{\theta^1, \theta^2, \theta'\} \subseteq \Theta(a)$  has a non-empty interior and contains  $\theta''$ . Since  $\theta''$  is not on the boundary of  $\text{conv}\{\theta^1, \theta^2, \theta'\}$ , it is in its interior. There exists thus an  $\eta > 0$  such that  $B_\eta(\theta'') \subseteq \text{conv}\{\theta^1, \theta^2, \theta'\} \subseteq \Theta(a)$ . Therefore,  $\theta'' \in \text{int } \Theta(a)$ , and  $\text{int } \Theta(a)$  is convex.

If  $\text{int } \Theta(a)$  is not empty and convex, then the boundary of  $\Theta(a)$  has measure zero in  $\mathbb{R}^2$  (see e.g., Lang, 1986). Moreover, since  $\mathbb{E}[\theta | s(\theta) = m] = a$  for all  $m \in \{m' \in M : \alpha(m') =$

---

<sup>11</sup>For example, two points whose segment  $[\theta^1, \theta^2] \subseteq B_\epsilon(\theta)$  is perpendicular to  $[\theta, \theta']$  satisfy these conditions.

$a\}$ , we have

$$\mathbb{E}[\theta|\theta \in \Theta(a)] = a.$$

Therefore,

$$\mathbb{E}[\theta|\theta \in \Theta(a)] = \mathbb{E}[\theta|\theta \in \text{int } \Theta(a)] = a,$$

which implies  $a \in \text{int } \Theta(a)$ . But then, because  $a$  is a limit point of  $\alpha(M)$ , it means that  $\text{int } \Theta(a)$  intersects with  $\alpha(M)$  at a point different than  $a$ , i.e., there is a point  $a' \in \alpha(M)$  and associated message  $m'$  with  $\alpha(m') = a'$  such that  $0 > u(a', a) \geq u(a', \alpha(m')) = 0$ . A contradiction. Hence,  $\text{int } \Theta(a) = \emptyset$ .  $\square$

**Lemma 7.** *Let  $a$  be a limit point in  $\alpha(M \setminus \{\inf M, \sup M\})$ . Then  $\Theta(a) = \ell(\theta, \theta')$  for some  $\theta$  and  $\theta'$ . Moreover, for all limit points  $a$  in  $\alpha(M \setminus \{\inf M, \sup M\})$ , the lines  $\Theta(a)$  are parallel.*

*Proof.* First, we show that there are  $\theta$  and  $\theta'$  such that  $\Theta(a) \subseteq \ell(\theta, \theta')$ .

From the proof of Lemma 1,  $|\Theta(a)| > 1$  and therefore  $\Theta(a) \neq \{a\}$ .

Note that  $a$  cannot be an extreme point of  $\text{conv } \Theta(a)$  as  $\mathbb{E}[\theta|\theta \in \Theta(a)] = a$  and  $\Theta(a) \neq \{a\}$ . This means that there exist  $\theta, \theta' \in \Theta(a)$  such that  $a \in [\theta, \theta']$ .

By Lemma 4, we can assume that for  $\theta^\dagger \in \{\theta, \theta'\}$  we have  $u(\theta^\dagger, a) > u(\theta^\dagger, a')$  for all  $a' \in \alpha(M) \setminus \{a\}$ . Otherwise, we can just take a smaller interval contained in  $[\theta, \theta']$ .

Suppose there is  $\theta'' \notin \ell(\theta, \theta')$  such that  $\theta'' \in \Theta(a)$ . Again, we can take  $\theta''$  such that  $u(\theta'', a) > u(\theta'', a')$  for all  $a' \in \alpha(M) \setminus \{a\}$ . As argued in the proof of Lemma 6, the set  $\text{conv}\{\theta, \theta', \theta''\} \subseteq \Theta(a)$ . Since these points are not aligned,  $\text{conv}\{\theta, \theta', \theta''\}$  has a non-empty interior and therefore  $\text{int } \Theta(a)$  has a non-empty interior. A contradiction.

To prove that  $\Theta(a) = \ell(\theta, \theta')$ , it is then enough to show that the set  $\Theta(a)$  is unbounded in both directions. To see this, take some  $\theta \in \Theta(a)$  and let  $m = s(\theta)$ . We can repeat the same argument as in Lemma 1. Let  $m_1$  and  $m_2$  satisfy  $m_1 < m < m_2$  and pick  $\theta^1$  and  $\theta^2$  such that  $s(\theta^1) = m_1$  and  $s(\theta^2) = m_2$ .

If  $\Theta(a)$  is bounded in one direction, we can find a curve consisting of straight horizontal and vertical lines such that this curve does not intersect with  $\Theta(a)$ . By the IVP, there must be  $\theta'$  on that curve such that  $s(\theta') = m$  and therefore  $\theta' \in \Theta(a)$ , a contradiction. Therefore,  $\Theta(a) = \ell(\theta, \theta')$ .

Let  $a$  and  $a'$  be limit points of  $\alpha(M \setminus \{\inf M, \sup M\})$  such that  $a \neq a'$ . Because  $\Theta(a) \cap \Theta(a') = \emptyset$ , the lines  $\Theta(a)$  and  $\Theta(a')$  must be parallel.  $\square$

Let  $A_I$  be the set of isolated points in  $\alpha(M)$  and  $A_L$  be the set of limit points in  $\alpha(M)$ . Denote by  $\ell_s(a)$  the line that goes through  $a$  and has the same slope as  $\Theta(a')$  for some  $a' \in A_L$ .

**Lemma 8.** *If there are some limit points in  $\alpha(M)$ , then all points in  $\alpha(M)$  are limit points.*

*Proof.* Let  $\Theta^\dagger = \bigcup_{a \in \text{cl}A_L} \Theta(a) = \bigcup_{a \in \text{cl}A_L} \ell_s(a)$ .

Take  $a \in \arg \max_{a' \in A_I} \sup_{\theta \in \Theta^\dagger} u(a', \theta)$  and  $\theta^\dagger \in \arg \max_{\theta \in \Theta^\dagger} u(a, \theta)$ . The points  $a$  and  $\theta^\dagger$  are the two points in  $A_I$  and  $\Theta^\dagger$  with minimal (weighted) distance between the two. Moreover, this distance is bounded away from zero either by the definition of isolated points if  $\theta^\dagger \in A_L$  or by the optimality of generating an action in  $A_L$  for states arbitrarily close to  $\theta^\dagger$  if  $\theta^\dagger \notin A_L$ .

Note that  $\theta^\dagger$  is on the boundary of  $\Theta^\dagger$ , otherwise there is another point in  $\Theta^\dagger$  closer to  $a$ . Take  $\tilde{a} \in \text{cl}A_L$  such that  $\theta^\dagger \in \ell_s(\tilde{a})$ . Because the  $\Theta^\dagger$  is a union of lines, if  $\theta^\dagger \in \ell_s(\tilde{a})$  is on the boundary of  $\Theta^\dagger$ , then  $\ell_s(\tilde{a})$  is on the boundary of  $\Theta^\dagger$ . We can therefore find a sequence  $\theta^n \notin \Theta^\dagger$  with  $\theta^n \rightarrow \tilde{a}$ . By definition of isolated points, there is  $\epsilon > 0$  such that  $u(a, \tilde{a}) < -\epsilon$  for all  $a \in A_I$ . But then for  $n$  large enough,  $\theta^n$  prefers to induce an action in  $A_L$ , a contradiction.  $\square$

**Lemma 9.** *If there are some limit points in  $\alpha(M)$ , any equilibrium score is equivalent to a linear score.*

*Proof.* By Lemma 8, if there are some limit points in  $\alpha(M)$ , then all points in  $\alpha(M)$  are limit points.

If  $\inf M \notin M$  and  $\sup M \notin M$ , then by Lemma 7, the score is equivalent to an equilibrium score.

To conclude the proof, we will show that  $\inf M \notin M$  and  $\sup M \notin M$ . Suppose it is not the case and that  $m = \min M$  exists. By Lemma 8, because there are some limit points in  $\alpha(M)$ ,  $\alpha(m)$  is a limit point of  $\alpha(M)$ . Therefore, there is a neighborhood of  $\alpha(m)$ , denote it  $\Theta^\dagger$ , such that for all  $\theta \in \Theta^\dagger$ , it is the case that  $\sup_{a \in A_L} u(\theta, a) > \sup_{a \in A_I} u(\theta, a)$  and for

all  $a \in \Theta^\dagger \cap \alpha(M)$ , it is the case that  $a \in A_L$ . That is, types in  $\Theta^\dagger$  are closer to points in  $A_L$  than to points in  $A_I$ .

Take a point in  $\theta \in \ell_s(\alpha(m)) \cap \Theta^\dagger$ . It cannot be that  $\alpha(s(\theta)) \in A_I$  by definition of  $\Theta^\dagger$ . It also cannot be that  $\alpha(s(\theta)) \in A_L \setminus \{\alpha(m)\}$  as  $\theta \in \ell_s(\alpha(m))$ . Therefore,  $\alpha(s(\theta)) = \alpha(m)$  and there is more than one point in  $\Theta(\alpha(m))$ . By a similar argument as above, it must be that  $\Theta(\alpha(m)) \subseteq \ell_s(\alpha(m))$ .

Let  $\Theta^+$  and  $\Theta^-$  denote the two open half-spaces defined by the line  $\ell_s(\alpha(m))$ . Suppose  $a^+ \in \Theta^+$  and  $a^- \in \Theta^-$  such that  $a^+, a^- \in \Theta^\dagger \cap \alpha(M)$ , i.e., there are actions played in equilibrium in  $A_L$  that are on both sides of  $\ell_s(\alpha(m))$ . Note that  $\ell_s(a^-) \subset \Theta^-$ .

Suppose without loss of generality that  $m^+ = s(a^+) > m^- = s(a^-)$ . By definition,  $m^- > m$ . Take two points  $\theta^+ \in \ell_s(a^+)$ ,  $\theta^m \in \Theta(\alpha(m))$  such that  $\theta^+ > \theta^m$  or  $\theta^+ < \theta^m$ . We can draw a curve between  $\theta^+$  and  $\theta^m$  that is entirely in  $\Theta^+$  (except at  $\theta^m$ ) that consists only of straight horizontal and vertical lines. By IVP, there must be  $\theta'$  on that curve such that  $s(\theta') = m^-$ . But  $\theta' \in \Theta^+$  and  $\theta' \notin \ell_s(a^-) = \Theta(a^-)$ , a contradiction.

Therefore all  $\theta \in \Theta^\dagger \cap \alpha(M)$  are in the same half-space, say  $\Theta^-$ . But types in  $\Theta^+ \cap \Theta^\dagger$  should prefer sending messages that induce  $a \in A_L$ , contradicting that  $\Theta(a) \subseteq \ell_s(a)$ .  $\square$

*Proof of Proposition 2.* Proposition 2 follows from Lemmas 5 and 9.  $\square$

## D Proof of Proposition 3

Let  $s(\theta) = \beta_1\theta_1 + \beta_2\theta_2$  be a linear score.

Assume first that  $\beta_j = 0$  for  $j = 1$  or  $2$ . Without loss we can set  $\beta_i = 1$  and therefore the message perfectly reveals the state  $\theta_i$ . Let  $e_j(\theta_i) = \mathbb{E}[\theta_j | \theta_i]$  and assume that it is not constant in  $\theta_i$ .

Assume  $i = 1$ . In equilibrium we must have for each  $\theta$  that it is optimal to play  $m = \theta_1$ , i.e.,

$$\theta_1 \in \arg \max_m -\phi(\theta_1 - m)^2 - (\theta_2 - e_2(m))^2.$$

Taking FOC, we obtain

$$\phi(\theta_1 - m) + e'_2(m)(\theta_2 - e_2(m)).$$

This expression is equal to zero at  $m = \theta_1$  if either  $e'_2(\theta_1) = 0$  or  $\theta_2 = e_2(\theta_1)$ . Since the FOCs must hold for all  $\theta_2$ , we must have  $e'_2(\theta_1) = 0$ .

The reasoning for  $i = 2$  is the same.

Now assume that  $\beta_i \neq 0$  for  $i = 1, 2$ . Let  $e_i(m) = \mathbb{E}[\theta_i|m]$ .

We must show that if for all  $\theta$ ,

$$\beta_1\theta_1 + \beta_2\theta_2 \in \arg \max_m -\phi(\theta_1 - e_1(m))^2 - (\theta_2 - e_2(m))^2, \quad (6)$$

then  $e_i(m) = a_i m + b_i$  for some  $a_i, b_i \in \mathbb{R}$ .

If (6) holds, then for  $m = \beta_1\theta_1 + \beta_2\theta_2$ , we have

$$\begin{aligned} & \phi e'_1(m)(\theta_1 - e_1(m)) + e'_2(m)(\theta_2 - e_2(m)) = 0 \\ \Leftrightarrow & \phi e'_1(m)\theta_1 + e'_2(m)\theta_2 = \phi e'_1(m)e_1(m) + e'_2(m)e_2(m) \end{aligned} \quad (7)$$

First, we show that there is a function  $\lambda : \mathbb{R} \rightarrow \mathbb{R}$  such that  $e'_1(m) = \lambda(m)\beta_1/\phi$  and  $e'_2(m) = \lambda(m)\beta_2$ . To see this, fix a message  $m$  and write the derivative conditional expectations as  $e'_1(m) = \lambda_1\beta_1/\phi$  and  $e'_2(m) = \lambda_2\beta_2$ . Take  $\theta, \theta'$  such that  $s(\theta) = s(\theta') = m$ . Note that given  $\beta_i \neq 0$ , we have  $\theta_1 \neq \theta'_1$ . Since the RHS of (7) does not depend on the state, we get

$$\phi \frac{\lambda_1}{\phi} \beta_1 \theta_1 + \lambda_2 \beta_2 \theta_2 = \phi \frac{\lambda_1}{\phi} \beta_1 \theta'_1 + \lambda_2 \beta_2 \theta'_2.$$

If  $\lambda_2 = 0$ , we must also have  $\lambda_1 = 0$  as  $\theta_1 \neq \theta'_1$ . If  $\lambda_2 \neq 0$ , we can rearrange the expression to obtain

$$\begin{aligned} & \beta_1\theta_1 + \beta_2\theta_2 + \left(\frac{\lambda_1}{\lambda_2} - 1\right)\theta_1\beta_1 = \beta_1\theta'_1 + \beta_2\theta'_2 + \left(\frac{\lambda_1}{\lambda_2} - 1\right)\theta'_1\beta_1 \\ \Leftrightarrow & \left(\frac{\lambda_1}{\lambda_2} - 1\right)\theta_1\beta_1 = \left(\frac{\lambda_1}{\lambda_2} - 1\right)\theta'_1\beta_1, \end{aligned}$$

where we have used on the last line that  $s(\theta) = s(\theta') = m$ . Again using that  $\theta_1 \neq \theta'_1$ , we

obtain  $\lambda_1 = \lambda_2$ .

Plugging the functional form of  $e'(m)$  in the FOC again, we obtain,

$$\lambda(m)\beta_1\theta_1 + \lambda(m)\beta_2\theta_2 = \lambda(m)\beta_1e_1(m) + \lambda(m)\beta_2e_2(m) \Leftrightarrow \beta_1\theta_1 + \beta_2\theta_2 = \beta_1e_1(m) + \beta_2e_2(m).$$

Since  $\beta_1\theta_1 + \beta_2\theta_2 = m$ , the last equation is  $m = \beta_1e_1(m) + \beta_2e_2(m)$ . Differentiating on both sides with respect to  $m$ , we get

$$1 = \beta_1e'_1(m) + \beta_2e'_2(m) \Leftrightarrow 1 = \lambda(m)\frac{\beta_1^2}{\phi} + \lambda(m)\beta_2^2 \Leftrightarrow \lambda(m) = \frac{1}{\frac{\beta_1^2}{\phi} + \beta_2^2}.$$

Therefore,  $\lambda(m)$  is independent of  $m$  and thus  $e_1(m) = \frac{\frac{\beta_1}{\phi}}{\frac{\beta_1^2}{\phi} + \beta_2^2}m + b_1$  and  $e_2(m) = \frac{\beta_2}{\frac{\beta_1^2}{\phi} + \beta_2^2}m + b_2$  for some  $b_1, b_2 \in \mathbb{R}$ .

## E Proof of Proposition 4

*Proof of Proposition 4.* For any strategy  $s(\theta) = \beta'\theta$ , we have the unconditional distribution over messages  $m$  induced by the score  $s$ ,  $m \sim N(0, \sigma_s^2)$  where  $\sigma_s^2 = \beta_1^2\sigma_1^2 + \beta_2^2\sigma_2^2 + 2\beta_1\beta_2\sigma_{12} = \beta'\Sigma\beta$ . We also have that  $Cov(\theta_i, m) = \sigma_{is} = \beta_i\sigma_i^2 + \beta_j\sigma_{12}$ . Therefore,  $(\sigma_{1s}, \sigma_{2s})' = \Sigma\beta$ .

The payoff of the sender can be rewritten, up to a constant, as

$$-a'\Phi a + 2a'\Phi\theta.$$

Therefore, the ex-ante payoff – given that the best-reply to  $m$  is  $\alpha(m) = \frac{\Sigma\beta}{\beta'\Sigma\beta}m$  – is

$$\begin{aligned} & \mathbb{E}[-\alpha(m)'\Phi\alpha(m) + 2\alpha(m)'\Phi\theta] \\ &= \mathbb{E}\left[-\frac{\beta'\Sigma}{\beta'\Sigma\beta}m\Phi\frac{\Sigma\beta}{\beta'\Sigma\beta}m + 2\frac{\beta'\Sigma}{\beta'\Sigma\beta}m\Phi\theta\right] \\ &= \frac{\beta'\Sigma\Phi\Sigma\beta}{\beta'\Sigma\beta}, \end{aligned}$$

where the last equality follows from  $\mathbb{E}[m^2] = \beta'\Sigma\beta$  and  $\mathbb{E}[\theta m] = \Sigma\beta$ . The matrix  $\Sigma\Phi\Sigma$  is

positive semidefinite and symmetric. Therefore,  $\frac{\beta' \Sigma \Phi \Sigma \beta}{\beta' \Sigma \beta}$  is a generalized Rayleigh quotient (see e.g., Parlett, 1998, Chapter 15) and the two stationary points, up to a rescaling of  $\beta$ , of  $\frac{\beta' \Sigma \Phi \Sigma \beta}{\beta' \Sigma \beta}$  are the eigenvectors of  $\Sigma^{-1}(\Sigma \Phi \Sigma) = \Phi \Sigma$ , i.e., the points  $\beta$  such that there is  $\lambda \in \mathbb{R}$  such that  $\Phi \Sigma \beta = \lambda \beta$ . Moreover, as generalized Rayleigh quotients attain a maximum and a minimum, one of the stationary points must correspond to a maximizer, the other to a minimizer.<sup>12</sup>

The equilibrium problem can be expressed as follows. Given a belief that the sender uses a linear strategy  $\beta$ , the receiver chooses  $\alpha(m) = \frac{\Sigma \beta}{\beta' \Sigma \beta} m$ . In equilibrium, the sender chooses a signal  $m$  for each realization of  $\theta$ :

$$\max_m -\frac{\beta' \Sigma m \Phi \Sigma \beta m}{(\beta' \Sigma \beta)^2} + 2 \frac{\beta' \Sigma m \Phi \theta}{\beta' \Sigma \beta}.$$

The objective function is quadratic in  $m$  and therefore the maximizer must satisfy the first-order condition:

$$m = \beta' \Sigma \beta \frac{\beta' \Sigma \Phi}{\beta' \Sigma \Phi \Sigma \beta} \theta.$$

Therefore, any equilibrium strategy must satisfy

$$\beta' = \beta' \Sigma \beta \frac{\beta' \Sigma \Phi}{\beta' \Sigma \Phi \Sigma \beta} \Leftrightarrow \beta = \frac{\beta' \Sigma \beta}{\beta' \Sigma \Phi \Sigma \beta} \Phi \Sigma \beta.$$

Take any equilibrium strategy  $\beta$ . From the equilibrium condition,  $\beta$  is an eigenvector of  $\Phi \Sigma$  with eigenvalue  $\frac{\beta' \Sigma \Phi \Sigma \beta}{\beta' \Sigma \beta}$ .

Conversely, take an eigenvector  $\beta$  of  $\Phi \Sigma$ , with eigenvalue  $\lambda$ . Plugging in the equilibrium condition, we get

$$\beta = \beta' \Sigma \beta \frac{\Phi \Sigma \beta}{\beta' \Sigma \Phi \Sigma \beta} \Leftrightarrow \beta = \frac{\beta' \Sigma \beta}{\lambda \beta' \Sigma \beta} \lambda \beta, \quad (8)$$

where the equivalence follows from  $\Phi \Sigma \beta = \lambda \beta$  and  $\beta' \Sigma \Phi = \lambda \beta'$ . Equation (8) is satisfied and therefore  $\beta$  is an equilibrium strategy.  $\square$

---

<sup>12</sup>If the state had more than two dimensions, there would be more stationary points/eigenvectors; yet, it would still be the case that one of the eigenvectors corresponds to a maximizer of the Rayleigh quotient, another to the minimizer.

## F Value of Ignorance

We show here, by way of an example, that sender and receiver *can* be better off if the sender is less informed.

Let  $\phi = 1$ ,  $\Theta = \{0, 1, 2\} \times \{0, 2\}$ ,  $f(0, 0) = f(1, 2) = f(2, 2) = \frac{\epsilon}{3}$  and  $f(0, 2) = f(1, 0) = f(2, 0) = \frac{1-\epsilon}{3}$ , for some  $\epsilon < \frac{5}{24}$ . We consider the standard setting and a setting in which the sender does not observe  $\theta_2$  and therefore can only select strategies that assign the same message to any two states with the same  $\theta_1$ . In Figure 3, empty circles denote low-probability states and filled circles high-probability ones. The figure illustrates a score that assigns to each state  $(\theta_1, \theta_2)$  a message equal to  $\theta_1$ . We refer to this as *score*  $s_1$ .

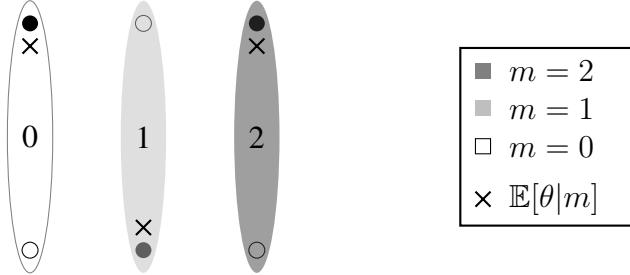


Figure 3

If the sender does not observe  $\theta_2$ , then score  $s_1$  is an equilibrium strategy.<sup>13</sup> We show next that any equilibrium score in the standard setting is associated with a larger loss than  $s_1$ .

We proceed in two steps. First, we establish that any score such that  $s(\theta) = s(\theta')$  for two high-probability states is associated with a larger loss than  $s_1$ .

The expected loss associated with  $s_1$  is:  $4\epsilon(1 - \epsilon)$ . Consider a score  $s$  such that  $s(0, 2) = s(1, 0) = m'$ . In any equilibrium in which  $\mu(\theta) = s(\theta)$  for all  $\theta$ , the loss conditional on  $\theta \in \{(0, 2), (1, 0)\}$  is minimized if  $\alpha(m') = (0.5, 1)$ . For such action, the loss conditional on  $\theta \in \{(0, 2), (1, 0)\}$  is  $\frac{5}{4}$ . Thus

$$Pr(\theta \in \{(0, 2), (1, 0)\}) \times \frac{5}{4}$$

<sup>13</sup>For this strategy,  $E(\theta|m = 0) = (0, 2(1 - \epsilon))$ , and  $E(\theta|m = 1) = (1, 2\epsilon)$ . The expected loss, conditional on  $\theta = 0$ , is  $4\epsilon(1 - \epsilon)$ . Deviating to report  $m = 1$  upon observing  $\theta = 0$  induces a loss, conditional on  $\theta = 0$ , equal to  $1 + 4(1 - \epsilon)(1 - 2\epsilon)^2$ . As  $1 + 4(1 - \epsilon)(1 - 2\epsilon)^2 > 4\epsilon(1 - \epsilon)$ , the deviation is not profitable. Similar arguments show that the sender does not have *any* profitable deviation.

is a lower bound on the loss from any score pooling  $(0, 2)$  and  $(1, 0)$  together. Note that

$$Pr(\theta \in \{(0, 2), (1, 0)\}) \times \frac{5}{4} = (1 - \epsilon) \frac{5}{6} > 4\epsilon(1 - \epsilon) \Leftrightarrow \epsilon < \frac{5}{24}.$$

Hence any score  $s$  such that  $s(0, 2) = s(1, 0)$  is associated with a larger loss than  $s_1$ . Similar arguments apply for any score such that  $s(\theta) = s(\theta')$  for any two high-probability states.

The second step amounts to showing that any score such that  $s(0, 2) \neq s(1, 0) \neq s(2, 2)$  is not an equilibrium score.

To see this, let score  $s$  satisfy  $s(0, 2) \neq s(1, 0) \neq s(2, 2)$ . The IVP requires  $s(1, 2) = 1$ . We consider two cases:  $s(1, 0) = 1$  and  $s(1, 0) \neq 1$ .

If  $s(1, 0) = 1$ , let, without loss,  $s(0, 2) = 0$  and therefore  $s(2, 2) = 2$ . In this case, the IVP requires  $s(0, 0) \neq 2$  and  $s(2, 0) \neq 0$ . This in turn implies that - in any equilibrium such that  $\mu(\theta) = s(\theta)$  for all  $\theta$  - the receiver chooses  $\alpha(0) = (0, x)$ , where  $x \geq 2(1 - \epsilon)$  and  $\alpha(1) = (y, z)$ , where  $z \leq 2\epsilon$ . For any value of  $x, y$  and  $z$ , in state  $(1, 2)$  the sender has a profitable deviation to report  $m = 0$  instead of  $m = 1$ . So the score is not an equilibrium score.

If instead  $s(1, 0) \neq 1$ , let, without loss,  $s(1, 0) = 2$ ,  $s(0, 2) = 0$  and  $s(2, 2) = 1$ . The IVP requires  $s(0, 0) = s(1, 2) = 1$  and  $s(2, 0) \in \{1, 2\}$ . Regardless of whether  $s(2, 0) = 1$  or  $s(2, 0) = 2$ , in any equilibrium such that  $\mu(\theta) = s(\theta)$  for all  $\theta$ , in state  $(0, 0)$  - the sender has a profitable deviation to report  $m = 0$  instead of  $m = 1$ .

We conclude that any equilibrium score in the standard setting is associated with a larger loss than  $s_1$ : in this example, sender and receiver can be better off if the sender does not observe the realization of  $\theta_2$ .