Biases in Information Choice and its Use: The Role of Strategic Uncertainty*

Michal Szkup
Vancouver School of Economics
University of British Columbia
Vancouver V6T 1L4, Canada

Isabel Trevino
Department of Economics
University of California San Diego
San Diego 92093, USA

July 2025

Abstract

We study experimentally how strategic uncertainty affects the way people choose and use information in a simple game that can be easily transformed into an individual decision task. We identify persistent overacquisition of information and an overall similar pattern of precision choices in both individual and strategic decision environments. In contrast, we find substantial overuse of private information in the strategic, but not in the individual decision setup. Moreover, we find that the overuse bias in the strategic environment is stronger in subjects who overacquire information and this relationship between biases cannot be explained by sunk-cost fallacies or popular models of bounded rationality. By disentangling forces related to the strategic environment, we argue that the overuse of information is driven by factors related to strategic belief formation and tensions in the information structure. We show that the overuse bias has negligible welfare effects, while overacquisition leads to significant welfare losses.

Keywords: information acquisition, information use, behavioral biases, strategic uncertainty.

*Corresponding author: itrevino@ucsd.edu.

1 Introduction

Information processing biases have been extensively documented in psychology and economics. These systematic departures from the Bayesian paradigm can take different forms, depending on the information that is neglected or overweighed. The vast majority of the evidence that has identified these biases comes from individual decision-making environments where agents have to form beliefs about unknown states.[1] However, we have limited knowledge of how information processing biases arise in strategic environments, which are characterized by a complex architecture of beliefs. In games of incomplete information players face not only fundamental uncertainty, but also strategic uncertainty and thus form beliefs, respectively, about states and about the actions and beliefs of others. Game theoretic models of incomplete information typically approach these complex belief systems by assuming that players incorporate new information and update their beliefs according to Bayes' rule. However, in light of our understanding of departures from the Bayesian paradigm in individual decision making, it is an important endeavour to characterize how information processing biases might arise in strategic settings and to identify biases that could be intrinsic to these environments. In this paper we do not aim to fully characterize how specific biases that are well documented in the belief formation literature arise in strategic settings. Instead, we contribute to this conversation by studying how biases in the choice and use of information are related to the presence of strategic uncertainty in a coordination game with private and public information. We use a theoretical framework to give structure to the experimental investigation that is designed to pursue this goal.

We study an environment (based on Morris and Shin (2002)) that features coordination motives and a rich information structure, which leads to non-trivial trade-offs in the choice and use of private and public information. In this setup we can easily shut down strategic uncertainty in order to compare behavior across strategic and non-strategic environments. The framework of Morris and Shin (2002) and its extensions have been used to study theoretically how coordination motives, information structures, and strategic uncertainty interact.[2] Moreover, this framework has been applied to analyze a broad range of problems in economics and finance that feature strategic complementarities where information plays an important role in determining

[1] See Rabin (1998) and Kahneman et al. (2001) for an overview of this literature.

[2] See Angeletos and Pavan (2007), Hellwig and Veldkamp (2009), Myatt and Wallace (2012), Colombo et al. (2014), Ui and Yoshizawa (2015), or Pavan (2024), among others.

outcomes.[3] In this paper we solve a two-player version of the beauty contest model of Morris and Shin (2002), extended to feature an initial stage of costly information acquisition where agents want to choose an action that is close to an unknown state of fundamentals and to the other agent's action.[4] Before choosing their actions, agents observe two noisy signals about the fundamental: a public signal, with a common exogenously given precision, and a private signal whose precision is endogenously and individually chosen, at a cost. Coordination motives and incomplete information give rise to strategic uncertainty as agents have to make inferences not only about the state of fundamentals, but also about the action, beliefs, and information of their opponent, while facing a trade-off between matching the fundamental and the other agent's action. We characterize the equilibrium and derive the corresponding predictions for the individual decision-making version of the model where agents face the same information structure but we remove strategic motives. Our setup leads to a rich set of testable theoretical predictions. Moreover, the equilibrium action rules in the baseline model and in standard behavioral extensions are always linear combinations of private and public information, which makes this a convenient framework to characterize departures from equilibrium predictions. With our theoretical results in hand, we design an experiment to understand how strategic uncertainty affects the choice and use of information in this environment.

In terms of information choices, we observe the same qualitative results in the strategic and non-strategic environments, once behavior has stabilized. In both environments the distributions of precision choices are bimodal with peaks corresponding to the equilibrium prediction and to overacquisition of information. This is robust to changes in the strength of coordination motives and the transparency of public information. However, we observe differences across environments in the initial rounds of the experiment. Strategic uncertainty does have an impact in information acquisition initially, leading to strong overacquisition, compared to the relatively uniform precision choices observed in the individual decision making environment. Learning dynamics, however, eventually make these differences disappear and lead to a similar

[3]This setup has been referred to as a beauty contest model with private and public signals, following the analogy by Keynes (1936) that financial markets in the short run behave like newspaper beauty contests where people want to guess average opinion. For applications to firms' pricing and investment decisions see (Angeletos and Pavan (2004), Adam (2007), Colombo et al. (2014)); for analysis of the effectiveness of monetary policy see (Woodford (2003) or Roca (2010)), for examination of optimal central bank communication see (Morris and Shin (2002), Cornand and Heinemann (2006)), while for a management application see Bolton et al. (2013).

[4]We focus on a two-player setup since this is the simplest departure from the individual setup. This also avoids some of the difficulties that experimental subjects face when coordinating in larger groups (see Weber (2006)).

distribution of choices across environments, suggesting that initial differences across environments are not persistent.

In contrast, we find that the presence of strategic uncertainty has a strong effect in the way subjects use the acquired information. While subjects use information similarly to the Bayesian paradigm in the individual decision environment, they strongly overuse private information in the strategic setup, particularly those subjects who overacquire information. This result is robust to changes in the strength of strategic motives and does not follow identifiable learning dynamics over time.[5] We show that this overuse is not driven by a sunk cost fallacy or by uncertainty about the rationality of others.[6] By isolating different components of the strategic task, we identify how different complexities in the belief formation process affect this bias. In particular, we show that this bias is related specifically to overusing, and not to a general heuristic of "mis-using" private information, since this bias arises only in treatments where there is a clear tension between the quality of public information and the incentives to acquire private information. In other words, this bias arises when the decision to acquire private information is not trivial. Additionally, we show a strong effect in the extent of this bias related to the computational complexity of forming strategic beliefs. When we provide subjects with the Bayesian estimates of their opponent's private information in otherwise identical experimental sessions, the magnitude of this bias (i.e., how much subjects overuse private information with respect to the equilibrium prediction) is drastically reduced.

Finally, we analyze the payoff consequences of the overacquisition and overuse biases. We find that overacquisition of information has significant negative welfare effects but that the overuse of private information has negligible payoff effects, and this is robust across treatment variations. This implies that the departures from the equilibrium use of information that we observe in the coordination game are not costly in terms of payoffs, which might help explain the persistence of this bias since there is not a monetary incentive to 'correct' this behavior. The similar payoffs observed in the coordination game (without taking into account information costs), in turn,

[5] We show that our results cannot be explained by popular models of bounded rationality in games (level-k, regret aversion, quantal response equilibrium, or overconfidence).

[6] To test for sunk cost fallacies we run treatments where we remove the costly information acquisition stage and exogenously endow subjects with different signal precisions. To check if beliefs about the rationality of others might lead to this bias (an aspect of stategic uncertainty that is not present in the theory) we run a treatment where subjects play against a computer that follows the equilibrium strategy, i.e., subjects do not know the signal or the strategy of their opponent, but they know that their opponent behaves optimally. In both treatment variations we find persistent overuse of private information.

help explain why the overacquisition bias leads to such strong welfare losses: since those who overacquire information do not make any additional profits in the game, the higher cost that they pay for information, with respect to subjects who choose lower precisions, leads to welfare losses.

Our results might offer relevant insights for economists and policy makers interested in settings that have been studied using models like ours, such as firms' pricing (Myatt and Wallace (2014)), investment (Angeletos and Pavan (2004)), monetary policy (Adam (2007)) or central banks' communication (Morris and Shin (2007)). For example, the theoretical literature (e.g., Morris and Shin (2002), Colombo et al. (2014)) has emphasized the importance of a careful consideration of the transparency of central banks' communication since public information may sway market participants towards worse outcomes and crowd out private information acquisition. Our results suggest that, given the persistent overuse and overacquisition of private information by subjects, these trade-offs might not be as stark as believed.

Literature Review — Our work relates to the large literature in psychology and economics that documents biases in the choice and use of information in individual decision-making environments (see, for example, Tversky and Kahneman (1974), Kahneman, Knetsch, and Thaler (1991), Thaler and Johnson (1991), Moore and Cain (2007), or Enke and Zimmermann (2018) to name a few). We complement this literature by focusing on the effects of strategic uncertainty on the way that people process information.

We contribute to the literature that studies experimentally coordination games with incomplete information. Dale and Morgan (2012), Cornand and Heinemann (2014), and Baeriswyl and Cornand (2016) test the predictions of Morris and Shin (2002) and Angeletos and Pavan (2007) regarding the equilibrium use of information in a similar theoretical setup of linear-quadratic payoff loss functions but without information acquisition.[7] Dale and Morgan (2012) vary the precision of signals and find that subjects tend to overweight imprecise public signals. Cornand and Heinemann (2014) find qualitative support for the theoretical predictions to changes in the strength of strategic complementarities, but document lower weights to public information than what is predicted by the theory, which is consistent with our results. Similarly, Baeriswyl and Cornand (2016) vary the precision of public information and

[7] Heinemann, Nagel, and Ockenfels (2007), Szkup and Trevino (2020), and Trevino (2020) investigate experimentally how exogenous changes in the information structure affect behavior in global games of regime change (a related family of coordination games), where strategic uncertainty plays a key role determining equilibrium strategies.

find qualitative support for the theoretical predictions but report weaker effects. Our experimental design unifies the themes studied separately in these papers into a single framework, which allows us to understand the interaction and interdependence of these forces and their effect on the way people use information. Unlike these papers, we endogenize the information structure, allowing us not only to study information choices and identify departures from equilibrium predictions, but also to characterize the close relationship between biases in the choice and use of information.

In terms of experimental investigations of costly information acquisition in strategic environments, Szkup and Trevino (2025) show that information choices in global games lead subjects to self-select in terms of the quality of play they exhibit in the game. Gretschko and Rajko (2015) and Battacharya, Duffy, and Kim (2017) show instances of overacquisition of information in auctions and voting committees, respectively. The closest paper to our strategic setup is Baeriswyl, Boun My, and Cornand (2021) who study endogenous attention allocation in an environment where signals have exogenous precisions and their publicity depends on how much attention is allocated to them by all players. Their theoretical predictions show that it is optimal to pay full attention to the signal that is highest weighted in the action, but their results show that subjects allocate less attention to the more common / least private signal than predicted by the theory. Even though our mechanism of endogenous precision choices with explicit costs is different from attention allocation, the results of Baeriswyl, Boun My, and Cornand (2021) reflect a similar phenomenon as ours: people fail to realize how useful public information can be in a coordination game.

Finally, our paper relates to the broader literature that studies theoretically information acquisition and its use in coordination games. Following Morris and Shin (2002), the tensions between increased transparency of public information and welfare have been investigated both when private information is exogenously determined (Angeletos and Pavan (2007), Ui and Yoshizawa (2015)) and when it is endogenized (Hellwig and Veldkamp (2009), Myatt and Wallace (2012), Colombo et al. (2014), Pavan (2024)). These papers assume Bayesian rationality of players. Our experiment validates some of the predictions of this literature, such as widespread use of linear strategies and comparative statics results like the crowding out effects of increased transparency of public information on private information acquisition. However, our results also highlight departures from the theoretical predictions that are robust to different parametrical specifications and have welfare consequences.

2 The model

The theoretical framework used in the experiment is a modified version of Morris and Shin (2002) with two players (as opposed to a continuum) and extended to feature an initial stage of costly information acquisition.[8] Therefore, our model captures the interplay between endogenous information choices and fundamental and strategic uncertainty.

2.1 Preferences

There are two identical agents $i = 1, 2$. Agent i's utility in the coordination game is given by

$$U(a_i, a_j, \theta) = -(1-\alpha)(a_i - \theta)^2 - \alpha (a_i - a_j)^2, \tag{1}$$

where a_i is agent i's action, a_j is the action of the other agent, and θ is a payoff-relevant variable, which we refer to as the state of economic fundamentals. The constant $\alpha \geq 0$ captures the degree of strategic complementarity between the actions of the agents. This utility function illustrates that agents would like to choose an action close to the fundamental θ and close to the other agent's action, with α capturing the relative importance assigned to each of these motives. The higher is α, the more agents care about matching the other agent's action relative to matching the state. When $\alpha = 0$ the strategic motive is absent, in which case the model corresponds to an individual decision making problem. As is standard in the literature, we set $\alpha < 1$ to ensure the existence of equilibrium (see Angeletos and Pavan (2007)). The fundamental state, θ, is not known by the agents, however, it is common knowledge that it is distributed according to a normal distribution with mean μ_θ and precision τ_θ (variance τ_θ^{-1}), that is $\theta \sim N(\mu_\theta, \tau_\theta^{-1})$. In addition, both agents observe the same noisy public signal of θ, y, given by

$$y = \theta + \tau_y^{-1/2} \varepsilon_y,\ \varepsilon_y \sim N(0, 1), \tag{2}$$

where τ_y is the precision of the public signal and ε_y is independent of θ.

2.2 The Information Acquisition Stage

In the first stage of the model each agent chooses privately the precision of their private signal about θ, x_i, that they receive at the beginning of the second stage,

[8] In the Online Appendix we discuss the specific relationship between our model and Morris and Shin (2002).

where

$$x_i = \theta + \tau_i^{-1/2}\varepsilon_i,\ \varepsilon_i \sim N(0,1), \tag{3}$$

with ε_i independent of θ and ε_y, and i.i.d. across agents. τ_i is the precision that agent i chooses for his signal in the information acquisition stage. We assume $\tau_i \in [\underline{\tau}, \infty]$ (with $\underline{\tau} \geq 0$), where choosing $\tau_i = \infty$ implies observing θ perfectly. Acquiring more precise information is costly: choosing τ_i is associated with a cost $C(\tau_i)$.

Assumption 1 *The cost function C is continuously twice differentiable and satisfies the following properties: (i) C is strictly increasing in τ_i ($C'(\cdot) > 0$), (ii) C is strictly convex in τ_i ($C''(\cdot) > 0$), (iii) $C(\underline{\tau}) = C'(\underline{\tau}) = 0$, and (iv) $\lim_{\tau_i \to \infty} C'(\tau_i) = \infty$.*

These are standard assumptions in the literature on costly information acquisition (see, for example, Colombo et al. (2014) or Szkup and Trevino (2015)). The first and second part of Assumption 1 imply that more precise information is more costly and that a marginal increase in precision is more costly when the precision is already high; that is $C(\cdot)$ is increasing and convex. The third part states that acquiring no information is associated with no cost and that an infinitesimal improvement in precision is costless. As a consequence, in equilibrium, both agents will choose to improve the precision of their signals. The last property implies that no agent will ever acquire perfectly informative signals.

After making their precision choices privately, agents move on to the coordination stage.

2.3 The Coordination Stage

In the coordination stage, after observing private and public signals about θ, agents simultaneously choose their actions to maximize their utility, defined in Equation (1). Agent i's strategy corresponds to $a_i : \mathbb{R}^2 \to \mathbb{R}$ that maps agent i's signals $\{x_i, y\}$ into an action. When choosing an action, agents face both fundamental uncertainty (about θ) and strategic uncertainty (about a_j), so actions need to balance the desire to match both the fundamental and the action of the other player. As has been pointed out by Morris and Shin (2002) and Angeletos and Pavan (2007), public information plays a dual role in this setting since, just as private information, it reduces fundamental uncertainty, but it also serves as a tool to address strategic uncertainty because it is observed by both agents.

2.4 Equilibrium

To characterize the equilibrium of our model and derive testable predictions, we solve the model using backward induction. Thus, we first characterize the equilibrium in the coordination stage for any given pair of precision choices, $\{\tau_i, \tau_j\}$, which specifies the equilibrium use of information. We then move on to the information acquisition stage and characterize equilibrium precision choices. The detailed derivations of the theoretical results can be found in the Online Appendix.[9]

2.4.1 Equilibrium Use of Information

Consider agent i who observes private signal x_i with precision τ_i and public signal y with precision τ_y, and who believes that agent j acquires precision τ_j. Therefore, taking as given the strategy of agent j, $a_j(x_j, y)$, the optimal strategy of agent i satisfies

$$a_i^*(x_i, y) = \max_{a' \in \mathbb{R}} \mathbb{E}\left[U\left(a', a_j(x_j, y), \theta\right) \middle| x_i, y; \tau_i, \tau_j\right]$$

Given the functional form of the utility function (Equation (1)), the first order condition associated with the maximization problem implies that

$$a_i^*(x_i, y) = (1-\alpha)\,\mathbb{E}\left[\theta \middle| x_i, y\right] + \alpha \mathbb{E}\left[a_j(x_j, y) \middle| x_i, y\right] \tag{4}$$

Let $z \equiv (\tau_y y + \tau_\theta \mu_\theta) / (\tau_y + \tau_\theta)$ and $\tau_z \equiv \tau_y + \tau_\theta$. Agents' common posterior belief (i.e., the posterior belief based only on public information) is given by $\theta | y \sim N\left(z, \tau_z^{-1}\right)$. In addition, for each $i = 1, 2$, let $\delta_i = \tau_z / (\tau_z + \tau_i)$ so that $\mathbb{E}[\theta | x_i, z] = \delta_i z + (1-\delta_i)\, x_i$, where δ_i is the weight assigned to public information in the posterior of a Bayesian agent after observing both public and private signals. We now characterize equilibrium strategies of the coordination stage.

Lemma 1 *Let $\boldsymbol{\tau} = \{\tau_i, \tau_j\}$. For each player $i = 1, 2$, the unique linear equilibrium strategy of the coordination stage is given by*

$$a_i(x_i, y) = \beta_i^*(\boldsymbol{\tau})\, x_i + \gamma_i^*(\boldsymbol{\tau})\, z, \tag{5}$$

[9] Colombo et al. (2014) consider information acquisition in a general linear-quadratic Gaussian setup but do so in the model with a continuum of agents. Ui and Yoshizawa (2015) consider a general linear-quadratic Gaussian setup with finitely many players but with an exogenous information structure. The model in the Online Appendix contributes to the theoretical literature by solving a general quadratic-Gaussian model with information acquisition and two players.

where

$$\beta_i^*(\boldsymbol{\tau}) = (1-\alpha)(1-\delta_i)\frac{1+\alpha(1-\delta_j)}{1-\alpha^2(1-\delta_i)(1-\delta_j)} \tag{6}$$

and $\gamma_i^*(\boldsymbol{\tau}) = 1-\beta_i^*(\boldsymbol{\tau})$. *If* $\alpha = 0$ *then* $\beta_i^*(\boldsymbol{\tau}) = 1-\delta_i$.

This result shows that in the unique linear equilibrium of the coordination game each agent's action is a weighted sum of private and public information. However, as first pointed our by Morris and Shin (2002), if $\alpha > 0$ then agents rationally attach a weight β_i^* to private information, which is lower than the weight on private information in the Bayesian posterior, $(1-\delta_i)$. This is due to the presence of strategic complementarities (as measured by α) and by the fact that relying more on public information allows agents to better coordinate their actions. Only when we remove strategic motives ($\alpha = 0$) we have $\beta_i^* = 1-\delta_i$. The parameter α measures the "equilibrium degree of coordination" or, equivalently, the private value that agents assign to aligning their choices.[10] It is easy to see that β_i^* is decreasing (or, equivalently, γ_i^* is increasing) in α and in τ_z.

2.4.2 Equilibrium Choice of Information

We now consider choices in the information acquisition stage. The ex-ante utility of agent i, given precision choices $\{\tau_i, \tau_j\}$, is

$$\mathbb{E}\left[U(a_i, a_j, \theta) \middle| \tau_i, \tau_j\right] - C(\tau_i), \tag{7}$$

where expectations are taken over possible realizations of θ and the signals. Agent i's problem is to choose precision τ_i to maximize this ex-ante utility. The first order condition associated with this problem is given by

$$\frac{\partial}{\partial \tau_i}\mathbb{E}\left[U(a_i, a_j, \theta) \middle| \tau_i, \tau_j\right] - C'(\tau_i) = 0 \tag{8}$$

Equation (8) determines agent i's optimal choice of precision, for each precision choice of player j. The next result characterizes the unique equilibrium precision.

[10] In our simple model, the equilibrium degree of coordination is simply the weight in the utility function attached to minimizing the distance between agents' choices. In a more general model, the equilibrium degree of coordination is measured by the slope of agents' best-response functions (see the Online Appendix or Angeletos and Pavan (2007)).

Lemma 2 *In the unique equilibrium of the model, both agents choose precision τ^*, which is the unique solution to*

$$\tau^* = \sqrt{\frac{1}{C'(\tau^*)}} - \frac{1}{1-\alpha}\tau_z \tag{9}$$

Lemma 2 establishes that in the unique equilibrium of the two-stage game, both agents choose τ^*. Therefore, at the coordination stage they use information symmetrically, i.e., $\delta_i = \delta_j$.

Corollary 1 *Consider the equilibrium precision choice τ^*.*

1. *τ^* is decreasing in the precision of public information τ_z, that is $\partial\tau^*/\partial\tau_z < 0$.*
2. *τ^* is decreasing in the degree of strategic complementarities α, that is $\partial\tau^*/\partial\alpha < 0$.*

Corollary 1 states that, ceteris paribus, agents will choose to acquire less private information if the precision of public information, τ_z, is high or if the degree of strategic complementarities, α, is high. These predictions are intuitive: When τ_z is high, agents already receive highly informative signals about the state θ, so the marginal value of acquiring a more precise private signal is lower. When α is high, agents care more about coordinating their actions, rather than matching the state. Since public information is relatively more useful than private information for coordinating actions, the marginal value of private information decreases. Thus, Corollary 1 predicts that agents have the strongest incentive to acquire private information when $\alpha = 0$ (given our restriction that $\alpha \geq 0$).[11]

Notice that if we remove strategic motives by setting $\alpha = 0$, this model corresponds to an individual decision making environment where agents face the same informational constraints described above but desire only to match the state θ. These theoretical results serve as hypotheses for our experiment in the sense that our benchmark is one where agents are Bayesian and, thus, we characterize biases that arise in the data in terms of departures from this paradigm.

[11] We assume $\alpha \geq 0$ to focus on the case with strategic complementarities, but this model can also be used to understand what happens under strategic substitutabilities ($\alpha \leq 0$), in which case precision choices would also be strategic substitues (see Hellwig and Veldkamp (2009)).

2.5 Potential Mechanisms for Biases in the Strategic Environment

The equilibrium analysis imposes strong assumptions both on the behavior of agents and on their beliefs. Optimal use of information, characterized by Bayesian rationality, has been challenged by a large literature in economics and psychology, which motivates us to understand whether departures from this paradigm are present in our setup and how strategic forces might affect them. In this section we decompose best response and utility functions in the strategic environment to foresee how different components of the process that ultimately leads to optimal behavior could lead to biases in our experiment.

Use of Information in the Coordination Game Our starting point is the first order condition that determines optimal choices in the coordination stage. Equation (4) shows that agent i needs to form beliefs about three different objects: (i) the fundamental state, θ, (ii) agent j's private signal, x_j, and (iii) agent j's strategy, $a_j^i(x_j, y)$ (the superscript denotes this being agent i's belief). The model assumes that agents use Bayesian updating and take into consideration coordination motives to determine the weights given to private and public signals when forming each of these beliefs. From a behavioral standpoint, deviations from any of these weights can lead to biases in the use of information, which can then lead to actions that depart from the equilibrium predictions. To better understand these three possible channels, we rewrite agent i's best response function explicitly in terms of each of these weights. We still assume that agent i expects agent j's strategy to be a linear combination of public and private signals and that agent i's expectations are a linear combination of the public posterior belief and his private signal. Under these assumptions, we can write the optimal action of player i as

$$\widehat{a}_i^* = (1-\alpha)\underbrace{\left[\widehat{\delta}_i z + \left(1-\widehat{\delta}_i\right)x_i\right]}_{\mathbb{E}^i[\theta|x_i,y]} + \alpha\underbrace{\left\{\widehat{\gamma}_j z + \left(1-\widehat{\gamma}_j\right)\overbrace{\left[\widehat{\eta}_i z + \left(1-\widehat{\eta}_i\right)x_i\right]}^{\mathbb{E}^i[x_j|x_i,y]}\right\}}_{\mathbb{E}^i\left[a_j^i(x_j,y)\middle|x_i,y\right]}, \tag{10}$$

where $\mathbb{E}^i[\cdot]$ denotes agent i's subjective expectations, $a_j^i(x_j, y)$ denotes agent i's belief about the strategy used by agent j, and $\widehat{a}_i^*$ denotes agent i's optimal action, given these subjective beliefs. In thinking about possible departures from the optimal use of information, we define subjective (non-Bayesian) weights as follows: $\widehat{\delta}_i$ is the subjective weight assigned by agent i to public information in his posterior belief about θ, $\widehat{\eta}_i$ is the subjective weight assigned by agent i to public information in his posterior belief about x_j, and $\widehat{\gamma}_j$ is the weight that agent i believes that agent j assigns to public information when agent j chooses an action. Note that in the equilibrium of Section 2.4, $\widehat{\delta}_i = \widehat{\eta}_j = \delta_i$ and $\widehat{\gamma}_j = \gamma_j$.

Equation (10) provides us with a systematic way to discuss deviations from equilibrium actions in terms of departures from the optimal use of information. Specifically, deviations can be due to biases in the estimation of θ ($\widehat{\delta}_i \neq \delta$, which can also arise in the individual decision environment), biases when forming beliefs about the other agent's signal ($\widehat{\eta}_i \neq \delta$), or biased beliefs about the strategy used by the other player ($\widehat{\gamma}_j \neq \gamma_j$). We will revisit this decomposition in our experimental analysis.

Acquisition of Information Consider now agents' information choices and assume that agent i correctly understands that the signals are unbiased and the noise components of signals are uncorrelated.[12] Under these mild assumptions we can write agent i's expected ex-ante utility in the coordination stage as

$$\begin{aligned} E\left[U\right] = &-\left(1-\widehat{\gamma}_i\right)^2 Var^i\left(\theta - x_i\right) - \widehat{\gamma}_i^2 Var^i\left(\theta - z\right) - C\left(\tau_i\right) \\ &-\alpha\left\{\widehat{\gamma}_j^2 Var^i\left(z-\theta\right) + \left(1-\widehat{\gamma}_j\right)^2 Var^i\left(x_j - \theta\right) - 2\widehat{\gamma}_i\widehat{\gamma}_j Var^i\left(z-\theta\right)\right\}, \end{aligned} \tag{11}$$

where $\widehat{\gamma}_i$ is the weight that agent i assigns to the public signal when choosing an action in the coordination stage (which is given by $\hat{\gamma}_i = (1-\alpha)\widehat{\delta}_i + \alpha\widehat{\gamma}_j + \alpha(1-\widehat{\gamma}_j)\widehat{\eta}_i$), $\widehat{\gamma}_j^i$ is the weight that agent i believes that agent j assigns to public information, and $Var^i(\cdot)$ captures subjective beliefs about the variances of relevant random variables.[13]

Equation (11) helps us identify three mechanisms for possible departures from equilibrium precision choices. First, biases in the use of information ($\widehat{\gamma}_i \neq \gamma_i^*$, described above) may lead agents to choose a non-equilibrium level of precision. Second, biased beliefs about the weight assigned by agent j to the public signal may further distort agent i's information choices. Third, agents may have an incorrect perception of the joint distribution of $\{\theta, x_i, x_j\}$, meaning that they incorrectly asses how a more precise private signal improves their ability to estimate θ, and hence, also the signal of the other player ($Var^i(\cdot) \neq Var(\cdot)$). We will use Equation (11) to discuss the potential mechanisms behind the biases in information choices that we identify in our experiment.

In what follows we refer to precision parameters in terms of standard deviations,

[12] Alternatively, agents may simply ignore taking such considerations into account. See Section A4 of the Online Appendix for derivations.

[13] To keep notation simple, we suppress the dependence of $\widehat{\gamma}_i$, $\widehat{\gamma}_j$, and $Var^i(\cdot)$ on agent i's precision choice and his belief about precision choice of agent j.

since this is the more intuitive language that we used in the implementation of the experiment. This implies the following notation changes: $\tau_\theta^{-1/2} = \sigma_\theta$, $\tau_i^{-1/2} = \sigma_i$, and $\tau_y^{-1/2} = \sigma_y$.

3 Experimental Design

The experiment was conducted using the usual computerized recruiting procedures. All subjects were undergraduate students from the University of British Columbia and the University of California, San Diego. Sessions lasted between 60 and 90 minutes and subjects earned $25 on average. A total of 466 subjects participated in the experiment. The experiment was programmed and conducted using z-Tree (Fischbacher, 2007). We implemented a between-subjects design in order to directly compare the behavior of subjects across treatments. Each session consisted of 40 independent and identical rounds. For the strategic treatment, subjects were randomly matched in pairs in every round. In each round, subjects made decisions simultaneously without a preselected action.[14]

Treatments varied in 3 main dimensions: the strength of strategic motives, α (individual decision environment, mild complementarities, and strong complementarities), the nature of the precision of private signals (exogenous or endogenously determined), and the transparency of public information, σ_y (high or low).[15] Our baseline treatments correspond to the case where private information is endogenously determined, the transparency of public information is high ($\sigma_y = 1$), and the decision environment corresponds to either individual decision making ($\alpha = 0$) or one with mild strategic complementarities ($\alpha = 0.25$).

Since our goal is to study the differences in behavior in environments with and without strategic motives, we choose mild complementarities as a baseline so that the contrast between our treatments in terms of strategic uncertainty would not be too stark. However, we also run treatments with strong strategic complementarities ($\alpha = 0.75$) to test the robustness of our results across different strengths of strategic motives. We choose high transparency of public information in our baseline treatments because this leads to a more pronounced tension with private information acquisition. However, to investigate the effects of changes in the transparency

[14] Instructions can be found at https://econweb.ucsd.edu/~itrevino/pdfs/instructions_st_baseline.pdf.

[15] We included an explicity public signal, on top of the prior, to preserve symmetry between public and private information and to avoid any confounds related to base-rate neglect. For this reason we chose a relatively diffuse prior.

of public information we also run every treatment with low transparency of public information (noisier public signal, $\sigma_y = 15$). In addition, we also run sessions with exogenous private signal precisions to control for any possible effects that private information acquisition could have in the use of information (e.g., sunk cost fallacy), for all variations of α and σ_y. Finally, we run two additional treatments of our baseline strategic condition ($\alpha = 0.25$, $\sigma_y = 1$), one where subjects interact against computers that face the same informational constraints as subjects but follow equilibrium rules (without stating what these rules are), and one where subjects are provided with the best guess for the private signal of their pair member, given their own private and public signals.

The rest of the parameters used in the experiment are the following. For the prior about the state θ we set $\mu = 0$, $\sigma_\theta = 18$, so that $\theta \sim N(0, 18^2)$. For the treatments with endogenous private information we provide subjects a menu of four possible precision choices, specified in Table 1.[16,17]

Precision	σ	$C(\sigma)$
1	0.5	12
2	2	6
3	6	2.5
4	10	1

Table 1: Precision choices in the experiment

For the treatments with exogenous private signal precision we chose two different precisions from Table 1, one corresponding to the equilibrium precision choice and one to a higher precision than equilibrium (the second most popular choice observed in our sessions with endogenous information). Table 2 summarizes our experimental design.

At the beginning of each session, subjects had access to two practice screens. In the information practice screen, subjects could experiment with different levels of precision and generate as many different signals as they wanted, for any given state, and they could also generate different states, in order to familiarize with the

[16] In the experiment we use the term "precision" as a qualitative measure to make it intuitive for subjects. That is, precision level 1 corresponds to the highest precision, precision level 2 to the second highest, and so on. We use the term precision in this qualitative way throughout the rest of the paper.

[17] We decided not to have a default precision chosen for subjects in order to avoid status quo biases. The reason to introduce a discrete choice set for precisions is to simplify the choice for subjects and the data analysis. We believe four is a reasonable number of options to observe dynamics in the level of informativeness that subjects choose, without losing statistical power.

Treatment	Strategic motives (α)	Transparency of public signal (σ_y)	Private signal precision	Opponent
Baseline I	None ($\alpha = 0$)	High (σ_y= 1)	Endogenous	N/A
Baseline S	Mild ($\alpha = 0.25$)	High (σ_y= 1)	Endogenous	Human
Low public I	None ($\alpha = 0$)	Low (σ_y= 15)	Endogenous	N/A
Low public S	Mild ($\alpha = 0.25$)	Low (σ_y= 15)	Endogenous	Human
Strong strat high pub	Strong ($\alpha = 0.75$)	High (σ_y= 1)	Endogenous	Human
Strong strat low pub	Strong ($\alpha = 0.75$)	Low (σ_y= 15)	Endogenous	Human
Belief aid S*	Mild ($\alpha = 0.25$)	High (σ_y= 1)	Endogenous	Human
Computer S*	Mild ($\alpha = 0.25$)	High (σ_y= 1)	Endogenous	Computer
Exogenous 1	Mild ($\alpha = 0.25$)	High (σ_y= 1)	Exogenous ($\sigma = 2$)	Human
Exogenous 2	Mild ($\alpha = 0.25$)	High (σ_y= 1)	Exogenous ($\sigma = 10$)	Human
Exogenous 3	Mild ($\alpha = 0.25$)	Low (σ_y= 15)	Exogenous ($\sigma = 0.5$)	Human
Exogenous 4	Mild ($\alpha = 0.25$)	Low (σ_y= 15)	Exogenous ($\sigma = 2$)	Human

* Sessions run at UCSD. All other sessions were run at UBC.

Table 2: Experimental design

distribution that signals were drawn from and to understand what type of signals were generated by different precisions.[18] The practice screen for actions was devised with the intention of familiarizing subjects with the payoff function. Subjects could input different hypothetical values of the state, the action of the other player (for the strategic treatments), and their own action to calculate how many points they would earn. Subjects had access to a similar calculator in each paying round of the experiment (called a hypothetical payoff calculator).

Subjects were randomly matched with a different person at the beginning of each round and were endowed with 12 points to make up for the cost of information in that round. Each round of the experiment proceeded as follows. First, for the sessions with endogenous private information, subjects privately chose the precision of their private signals from Table 1. Then, in the strategic treatments, they stated their beliefs about their opponent's precision choice, which were incentivized by paying subjects an additional $5 if their guess was correct in the round selected for payment. Then, subjects observed private and public signals and simultaneously chose their action, with the option of clicking a button to use a hypothetical payoff calculator to aid their calculations. At the end of each round, subjects observed feedback about the state, their own signals, the actions and precision choices of both pair members, and

[18] We provided a clear explanation of a normal distribution in the instructions that focused on its intuitive properties and illustrated them. Additionally, in every choice screen during the paying rounds we provided a table that detailed the 95% confidence interval for the signals around the unobserved state that each possible precision choice would induce.

their individual points (payoff) for that round. Subjects observed the same feedback in all treatments, except for precision choices in treatments with exogenous precisions.

One round of the 40 rounds played was randomly selected for payment. The objective function in the second stage of the game was transformed from the specification in Equation (1) by adding 100 points in order for subjects to not think that any outcome would lead to negative points, so in each round the number of points they could earn in the coordination stage was determined by $Points = 100 - (1-\alpha)(a_i - \theta)^2 - \alpha(a_i - a_j)^2$. Despite this transformation, it was still possible for subjects to have negative payoffs in a round. To circumvent this issue, the points earned in the round selected for payment were converted to probabilities in a lottery that paid \$20 with probability p and \$5 with probability $(1-p)$, where p is a linear function of the points earned.[19] In particular, $p = 1$ for $Points = 112$, which is the maximum number of points a subject can make in a round. For symmetry we set $p = 0$ for $Points \leq -112$ and the increment in probability to earn the high lottery prize was 0.446% for every additional point earned in the experiment. To summarize, the payment in dollars was composed of a \$10 show up fee, the outcome of the lottery whose probabilities were determined by each subject's performance in a randomly selected round, and \$5 if the subject guessed correctly the precision choice of their opponent in the round selected for payment (in the strategic treatments).

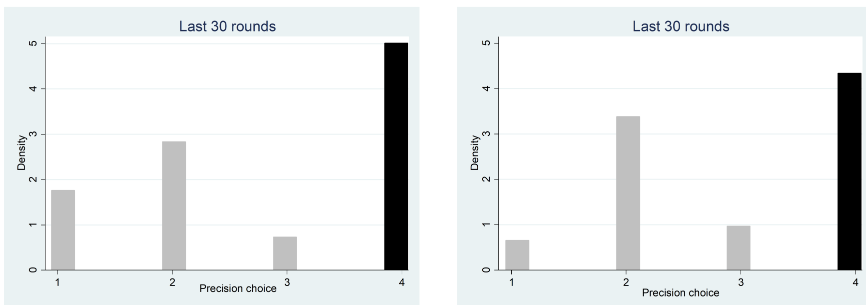
4 Experimental Results

To present our results, we first focus on precision choices and characterize departures from the equilibrium predictions. Then, we study how subjects use the information they observe across the different environments induced by our treatments and characterize biases in the use of information with respect to the equilibrium benchmark of the model. We then quantify welfare effects of the biases we identify by analyzing payoffs. Throughout this section, we present our results by comparing the behavior of subjects in individual and strategic environments. Most of the analysis in this section relates to the last 30 rounds of the experiment, once subjects' behavior has stabilized, unless otherwise specified.

[19] See Roth and Malouf (1979) for a discussion of paying with probability points and the relationship of this method to inducing risk neutrality.

4.1 Choice of Information

Figure 1 presents the histograms of precision choices for the individual and baseline strategic environments (panels (a) and (b), respectively). Three main observations emerge. First, we see that in both environments precision choices are surprisingly similar. Second, in both environments the modal precision choice corresponds to the equilibrium precision (level 4, black bar). Third, in both environments there are significant departures from the equilibrium prediction, mostly to precision level 2, which represents overacquisition of information.



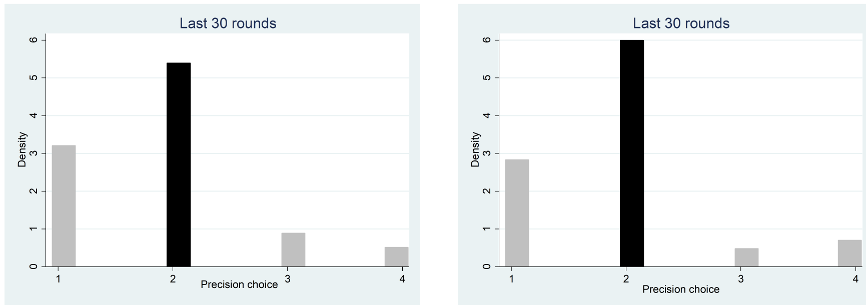
(a) Individual (b) Strategic

Figure 1: Precision choices, baseline treatment

Since the equilibrium precision choice in our baseline treatment is level 4, the lowest precision (mostly driven by the fact that the public signal is very precise), departures from equilibrium can only imply overacquisition of information. To check the robustness of our results, Figure 2 presents similar histograms for the treatments with the same parameters, except for the transparency of public information, which is now low ($\sigma_y = 15$). In this case, the public signal is very noisy, which increases the incentives to acquire more precise private information. The equilibrium precision choice in this case corresponds to precision level 2 (black bar). We make the same three qualitative observations as in our baseline treatment: The distribution of precision choices in the individual and strategic environment is very similar, the modal precision choice corresponds to the equilibrium prediction, and most of the departures from equilibrium correspond to subjects overacquiring information.[20]

The robustness of our findings allows us to identify overacquisition of private information as a systematic departure from the equilibrium prediction, which does

[20] Figures 1 and 2 support the theoretical prediction for the strategic environment that an increase in the transparency of public information crowds out private information acquisition (see Colombo et al. (2014)) and show that this prediction holds both for equilibrium and non-equilibrium choices.



(a) Individual (b) Strategic

Figure 2: Precision choices, low transparency

not depend on the presence of strategic uncertainty.[21] Our results illustrate a clear heterogeneity between subjects who acquire the equilibrium precision and those who overacquire information. While we are agnostic about the specific sources of the observed heterogeneity (such as intrinsic preferences for better information), we investigate how this pattern arises in each environment by focusing on learning dynamics in the early rounds of the experiment.[22]

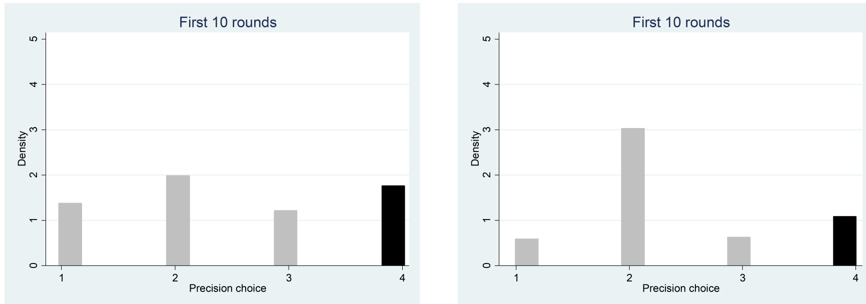
4.1.1 Learning Dynamics

To better understand precision choices once behavior has stabilized (last 30 rounds), we turn our attention to the first ten rounds of the experiment where most learning and experimentation takes place. Figure 3 presents similar histograms to Figure 1 for both environments in our baseline treatment, but for the first 10 rounds.

As we can see in Figure 3, initial precision choices in the individual decision making environment are similarly spread out across all four precision levels, whereas in the strategic setup precision 2 is clearly favored. This illustrates a difference across environments and, also, within environments if we compare the first 10 and last 30 rounds. The differences observed in Figure 3 suggest the following interpretation. First, the balanced distribution of precision choices in the individual task in the early rounds might reflect purely heterogeneous preferences for information. In contrast, the presence of strategic uncertainty might lead subjects to choose initially a high

[21] Theoretically, precision choices in the strategic environment are strategic complements due to the complementarity in actions (Hellwig and Veldkamp (2009)), so we could imagine that strategic considerations could affect precision choices off-equilibrium and lead to different off-equilibrium choices than in the individual decision case.

[22] Szkup and Trevino (2025) study selection via precision choices in a strategic environment and find limited evidence for strategic anticipation as a driver of heterogeneity in precision choices, suggesting that pure selection, due to differences in preferences, is more likely to lead to this heterogeneity.



(a) Individual (b) Strategic

Figure 3: Precision choices in initial rounds, baseline treatment

precision for their private signal, in an effort to reduce the uncertainty they face in the coordination stage. Despite these initial differences, behavior converges once learning takes place, as illustrated by Figure 1 where precision levels 2 and 4 become clear favorites and the differences across environments disappear.[23] Therefore, it is not that strategic uncertainty has no effect on the choice of information, but rather that learning dynamics erase the initial differences across environments, leading to convergence to the same typology of precision choices.

To understand how this shift takes place we turn to Figure 4, which presents, for each environment, the transition matrices of precision choices for rounds 1-10. In each matrix the entry a_{ij} corresponds to the implied probability of a subject choosing precision level j in round $t+1$, given their choice of precision level i in round t, for $i, j \in [1, 4]$. The transition matrices for the first 10 rounds can help us understand the level of experimentation with different precisions in the early rounds of the experiment. Figure 10 in the Appendix presents similar transition matrices for rounds 11-40, which illustrate how subjects' choices veer towards Precisions 2 and 4 once initial learning has taken place.

Individual ($\alpha = 0$)

	P 1	P 2	P 3	P 4
P 1	0.73	**0.17**	0.09	*0.01*
P 2	0.13	0.64	0.15	*0.08*
P 3	0.11	**0.23**	0.43	**0.23**
P 4	0.02	0.06	0.08	0.84

Strategic ($\alpha = 0.25$)

	P 1	P 2	P 3	P 4
P 1	0.55	**0.32**	0.13	*0*
P 2	0.07	0.79	0.07	*0.07*
P 3	0.06	**0.34**	0.42	**0.18**
P 4	0.02	0.16	0.05	0.77

Figure 4: Transition matrices of precision choices in rounds 1-10

[23] In the individual decision making environment precision choices become stable by round 20. In the strategic environment convergence occurs by round 30, but after round 20 it is clear that precision levels 2 and 4 are absorbent states.

Figure 4 shows that even in the first ten rounds precision choices are relatively stable, in the sense that the probability of a subject choosing the same precision in two consecutive rounds (main diagonal) is larger than the probability of choosing any other precision (off main-diagonal), for all precisions and environments. However, we see two main transitions across precision levels in both environments. First, we can see that subjects converge towards precision levels 2 and 4 and away from levels 1 and 3 by noting that the most likely transition from precision level 1 is towards level 2 and from level 3 is towards both levels 2 and 4 (numbers in bold). Second, notice that subjects who initially choose high precision levels (1 and 2) have an extremely low rate of experimentation with cheaper precisions, one of which is the equilibrium (the numbers in italics show a negligible probability of choosing precision level 4 after choosing levels 1 or 2). This implies that subjects who start the experiment choosing high precisions do not get to learn the benefits of cheaper, less precise private information.[24] To further establish lack of experimentation in the early rounds, specifically for subjects who choose high precisions, Figures 8 and 9 in the Appendix contain histograms of precisions choices in the first 10 rounds, controlling for the precision level at which subjects individually converge in the last 30 rounds of the experiment (their preferred precision choice). As we can see, both in the individual and strategic setup, subjects who eventually converge to choosing precisions 1 or 2 very rarely experiment with the lower (and cheaper) precisions 3 and 4. We quantify the cost of this behavior later on when we analyze realized payoffs in the experiment.

From the transition matrices for rounds 11-40, we can see in Figure 10 in the Appendix that individual choices of all precision are relatively stable in both environments, in the sense that the probability of choosing the same precision in two consecutive periods is at least 66%. Precision levels 2 and 4 are clearly the most stable as they have the largest probabilities of consecutive choices in both environments. Moreover, most of the movement off the main diagonals is directed from precision levels 1 or 3 towards precision levels 2 or 4 (numbers in bold), reinforcing the pattern of convergence that we observe in the first 10 rounds. Figures 11 and 12 in the Appendix show the histograms of precision choices in rounds 11-40, separating subjects by their preferred precision choice, and we can see very stable individual choices (individual convergence in precision).

[24] The difficulties to engage in hypothetical thinking have been documented in the experimental literature (e.g., Esponda and Vespa (2014) and Martinez-Marquina et al. (2019)). For this reason, experimentation is especially important to learn the potential benefits of cheaper, less precise information. These benefits are particularly large in our baseline treatments because the public signal is very informative about the state.

We defer the discussion of possible theoretical mechanisms that could drive overacquisition of information to Section 4.3, as we need to understand first how subjects use information to be able discuss the incentives to overacquire information.

4.2 Use of information

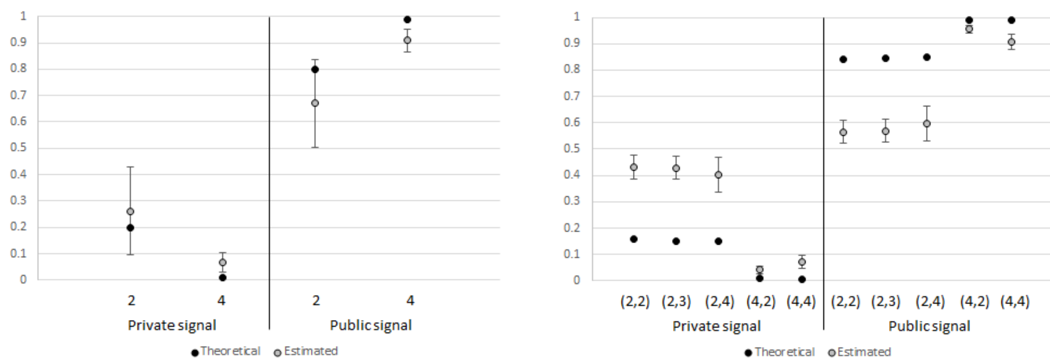
We now turn our attention to the analysis of how subjects use the different signals at their disposal. To do this, we estimate the weights subjects assign to private and public signals when choosing their actions in the coordination stage. Recall from Equation (5) that optimal actions are linear combinations of private and public signals. The theoretical weights given to these signals depend on the noise parameters and on the coordination motive α. We run random-effects linear regressions for each treatment to estimate these weights, conditioning on individual precision choices and beliefs about the opponent's precision choice (for the strategic treatments), since when $\alpha > 0$ beliefs about the precision choice of the other agent affect the equilibrium weights given to signals (see Equations (6)).[25] All standard errors were clustered at the individual level.

We present the coefficients of these regressions for the individual and strategic baseline treatments in Figure 5 (panels (a) and (b), respectively). In each graph, the vertical axis indicates the weights given to the different types of signals. The vertical line in the horizontal axis separates the weights estimated to private and public signals (left and right of the line, respectively). Each indicator on the horizontal axis corresponds to a specific precision choice (individual treatment) or to a combination of individual precision choice and belief about the opponent's precision choice (strategic treatment). Black dots indicate the theoretical weights predicted by the theory and gray dots correspond to the weights estimated with the data, for a given precision choice and beliefs about the other's precision choice, with their corresponding error bars that illustrate confidence intervals ($\pm$ 2 standard errors). Given the results from Section 4.1, we focus on the weights corresponding to the two most popular precision choices, levels 4 (equilibrium) and 2 (overacquisition).

In Panel (a) of Figure 5 we can see that the use of information in the individual decision making treatment is qualitatively similar to the Bayesian weights predicted by the theory.[26] However, we see a starkly different pattern in the use of information in

[25] We tested the assumption of linearity by running regressions with higher order terms, which were statistically insignificant in all specifications. Therefore, we only focus on linear specifications.

[26] The weights to private and public signals are not statistically different to the theoretical weights when subjects choose precision 2. For precision level 4, estimated weights are statistically different from theoretical weights to the 1% level of significance, but they are qualitatively very similar (0.068



(a) Individual (b) Strategic ($\alpha = 0.25$)

Figure 5: Weights given to signals baseline treatments.

the strategic setup (Panel (b) of Figure 5).[27] Since public information is very precise ($\sigma_y = 1$), the theory predicts that most of the weight should be assigned towards it, but instead subjects overuse private information, particularly those subjects who overacquire information (choose precision level 2), regardless of their beliefs about the precision choice of their opponent.

Panel (b) of Figure 5 illustrates a strong relationship between overacquiring information and overusing it. To check whether the overuse of private information might be due to a sunk-cost fallacy, i.e., where subjects who acquire more precise information use it more in an effort to "make up" for the high cost paid for it, Figure 13 in the Appendix extends Panel (b) of Figure 5 to include the estimated weights for the strategic treatment where the precision of private signals was exogenously determined (one treatment where precision was set at level 2 and one at level 4). We still see a significant overuse of private information, but the magnitude of this bias is decreased for subjects in the treatment with exogenously set precision 2. While this shows partial support for the sunk-cost fallacy, the overuse bias is still present.

To check for robustness of this result, Figure 14 in the Appendix finds similar qualitative patterns in the treatment with strong complementarities ($\alpha = 0.75$): subjects overuse private signals with respect to the equilibrium prediction, in particular those who overacquire information. In this case, we find no support for the sunk-cost fallacy argument since the magnitude of the bias is invariant when precision is exogenously determined. This shows that our results on the overuse of private information, in particular for overacquirers, are robust to changes in the strength of

vs 0.01 for the private signal and 0.905 vs 0.987 for the public signal).

[27] In all cases the estimated weights are different to the theoretical weights at the 1% level of significance.

strategic motives.

The strong overuse of private information that we identify for overacquirers in Panel (b) of Figure 5 and in Figure 14 in the Appendix implies that the weights given to private and public signals are "closer" to each other than what the theory suggests. This could be interpreted as suggesting that the overuse bias we identify might just be a product of subjects using a simple heuristic in the strategic environment where they give roughly the same weight ("50-50") to both signals.[28] If such a heuristic were responsible for our results, we would expect to see a similar "50-50" pattern for weights, across all treatments. We find no support for this conjecture when we vary the precision of the public signal to an environment of low transparency of public information where $\sigma_y = 15$, for both weak and strong complementarities. The decision environments are identical, except that in the baseline cases ($\sigma_y = 1$), equilibrium predicts higher weights to private information due to the low precision of the public signal. Figure 15 in the Appendix presents the estimated weights to private and public signals, for each combination of precision choice and belief about the opponent's precision choice, for the case where $\sigma_y = 15$ and where $\alpha = 0.25$ or $\alpha = 0.75$. We can see that, contrary to our baseline case, subjects not only set weights clearly far from the "50-50" midpoint, but their use of information is surprisingly close to the equilibrium prediction for both endogenous and exogenous information structures.[29]

This observation helps us to better characterize our bias in the use of information as true overuse, and not *misuse*, of private information, and it hints towards a mechanism based on the complexity of the environment that could be related to this bias. When public information is noisy ($\sigma_y = 15$), there is little competition between private and public information because subjects do not have a high-accuracy public signal, so it is optimal to predominantly rely on the private signal, which is what our subjects do. However, when public information is precise ($\sigma_y = 1$, as in the baseline treatment), there is a tension between private and public information that starts in the information acquisition stage. This tension might difficult the assessment of strategic actions, which can affect the emergence of biases like the overuse of private information.[30]

[28] See Benjamin (2019) for a review of biases in probabilistic updating.

[29] Note that in the treatments with $\sigma_y = 15$ we do not observe overuse of private information because the theoretical weights given to private information are large enough that there is barely any scope to overuse this signal.

[30] Notice that the tension that arises when public information is very precise has not been present in other papers that study these games experimentally, like Cornand and Heinemann (2014) and Baeriswyl and Cornand (2014). These studies focus on environments where there is little tension

4.2.1 Overuse of Private Information in the Strategic Environment

To understand why subjects use information differently in the individual and strategic environments we turn our attention to the forces that are unique to strategic reasoning. In both cases, subjects observe signals about the state, θ, and have to form a series of beliefs. In the individual setup the mapping between signals and beliefs is direct since subjects have to form beliefs only about the state. However, in the strategic environments they have to form beliefs about the state, but also about the actions and beliefs of others, so the mappings between signals and beliefs are necessarily more complex due to strategic uncertainty.

We refer to strategic uncertainty broadly as the uncertainty related to the behavior of the other player. In our experiment this manifests in three ways, each related to a different exercise in belief formation. The first, also captured by the theoretical model, refers to not knowing the other agent's signal realization. While this uncertainty implies not knowing the other person's action, in the theoretical equilibrium agents do know the mapping between signals and actions (strategy). The second manifestation of strategic uncertainty in our experiment, but not in the model, is that subjects do not know the strategy of the other player so they have to form beliefs about the mapping between signals and actions. Third, in our experiment strategic uncertainty can also manifest as uncertainty about the rationality of other subjects.

To understand whether the overuse of private information in the strategic environment can be due to the complexity of strategic belief formation, we run two additional treatments where we shut down the first and third manifestations separately. First, we explore whether uncertainty about the rationality of others is responsible for our results. Second, we revisit the decomposition of Equation (10) in an effort to pin down the belief formation channel that could be behind this bias.

Uncertainty about the Rationality of Others Intuitively, if subjects are unsure about the rationality of their opponent they might be inclined to offset this added (strategic) uncertainty with a desire to purchase better private information because it is the only tool at their disposal to reduce overall uncertainty and then using this information more than they should, leading to the overuse bias that we document. This force is clearly present only in the experiment, since the theory assumes rationality and common knowledge of rationality.

---

between private and public information because both signals have identical precision and subjects do not have the option to choose the precision of their private signal.

To explore this hypothesis, we run a treatment identical to the baseline strategic treatment, except that subjects interact with a computer. They are told in the instructions that their opponent is a computer that chooses and uses information optimally. Subjects are not told what the computer's strategy is, in an effort to not influence their own strategy. Therefore, in this treatment we shut down only the uncertainty about the rationality of the opponent, while preserving the uncertainty about the action taken by the opponent.[31] We provided the same feedback as in the main treatments.

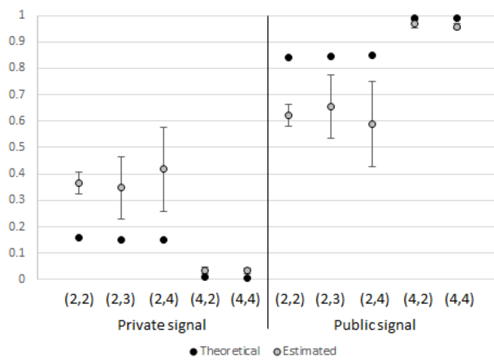


Figure 6: Weights given to private and public signals, computer opponent

Figure 6 plots the estimated weights given to private and public signals in this treatment, controlling for individual precision choices and beliefs about the computer's precision choice, just as in Figure 5. We see the same qualitative findings as in our baseline treatment, i.e., a clear and significant overuse of private information by those subjects who overacquire information. In terms of information choices, Panel A of Figure 16 in the Appendix shows strikingly similar patterns in precision choices as in the individual and strategic baseline treatments (Figure 1).

We conclude that uncertainty about the rationality of others is not the driving force of the overacquisition of information or the overuse of private information by overacquirers.[32]

[31] By telling subjects that their computer opponent behaves optimally, we decrease the likelihood with which subjects believe that their opponent does not fully understand the game or knows how to use information to choose an action, regardless of the mechanism the opponent uses to form posterior beliefs.

[32] As pointed out by Morris and Shin (2002), strategic models like ours capture the forces behind the beauty contest model first described by Keynes (1936). Following Keynes (1936), if we think of these games as an approximation to decision making in financial markets, we could interpret these results as suggesting that the information processing bias we observe might not be due to the presence of noise traders, but rather to forces inherent to the uncertainty in the environment.

Decomposition of Beliefs in the Strategic Environment We revisit the decomposition of the best-response functions of the strategic environment described in Section 2.5 in an effort to better understand how the overuse bias we identify in the game is related to the way individuals form beliefs about the beliefs and actions of others. From Equation (10), we know that there are three instances that can potentially lead to biases where subjects use their private and public signals to form beliefs. The first one is when subject i uses signals x_i and y to form beliefs about the fundamental θ. Notice that there is no strategic component to this belief and that this is precisely the exercise that subjects perform in the individual decision environment. Our results suggest that subjects are relatively good at forming beliefs about θ (as illustrated in Panel (a) of Figure 5). This is consistent with the findings of Szkup and Trevino (2020) and Baeriswyl et al. (2021) who found that subjects form accurate beliefs about fundamentals in coordination games with incomplete information. In addition, since we are comparing behavior between strategic and individual decisions, differences in the use of information across environments are unlikely driven by fundamental uncertainty since it is present in both cases. For these reasons, we hypothesize that the overuse bias that we observe in the strategic environment is unlikely to come from a bias in the (non-strategic) beliefs about the state, θ.

The two other instances where subjects have to form beliefs using private and public signals are unique to the strategic setup. Subject i uses signals x_i and y to form beliefs about the private signal observed by subject j, $E^i\left(x_j|x_i, y\right)$, and about the action taken by subject j, $E^i\left(a_j\left(x_j, y\right)|x_i, y\right)$. Equation (10) illustrates how we can decompose these two expectations into weighted sums of public and private signals. In order to disentangle these two objects, we run an additional treatment where we shut down the first channel, that is, we provide subjects with $E^i\left(x_j|x_i, y\right)$. This experiment is identical to the baseline strategic treatment, except that subjects are provided with the Bayesian estimates of their opponent's private signal, referred to in the instructions as the best statistical guess, based on each subject's observed signals. The instructions are clear about this being a statistical guess, and not the actual signal observed by the other subject.

Figure 7 plots the estimated weights given to private and public signals in this treatment, controlling for individual precision choices and beliefs about the other's precision choice, just as in Panel (b) of Figure 5. For subjects who choose the equilibrium precision (level 4), providing subjects with the best guess about the private signal of the other player removes any biases in the use of information, i.e., the estimated weights coincide with the theoretical predictions and the noise in these

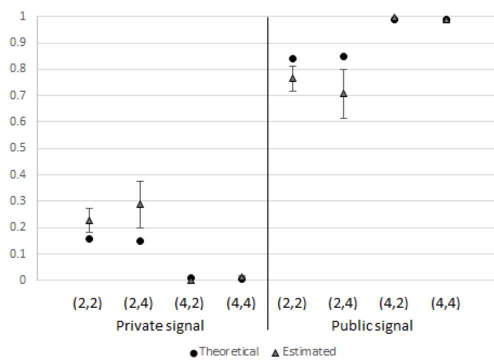


Figure 7: Weights given to signals, best guess of other's signal provided

estimations is very small. That is, we see an improvement in the use of information for those subjects who choose information optimally when we help them with the calculation about the information observed by their opponent (i.e., when we reduce their cognitive load). It is relevant to note that the equilibrium precision is the modal choice, just as in the baseline treatments, but the proportion of subjects who choose the equilibrium precision is higher in this treatment than in the baseline treatment, as shown by the histogram of precision choices in Panel b of Figure 16 in the Appendix. Subjects who overacquire information still use their private signal more than what the theory suggests (estimated weights are larger than the theoretical predictions to the 1% level of significance), but the magnitude of the overuse bias is significantly reduced with respect to the baseline case. The results from this treatment suggest that the overuse bias that we observe in the strategic setup can be related to the complexity of forming beliefs about the information held by others that is only present under strategic uncertainty.

4.3 Mechanisms behind overacquisition of information

Similar to the discussion of possible mechanisms behind the overuse bias, we now discuss possible drivers of the overacquisition of information that we identify in our experiment. From Section 2.5, recall that using Equation (11) we identified three theoretical channels that can lead to deviations in precision choices with respect to the equilibrium prediction. First, the overuse of information that we observe in the coordination game may encourage subjects to overacquire information. Second, this incentive can be further reinforced if agents expect other agents to overuse information. Third, subjects may have incorrect beliefs about the way their information choices improve their ability to predict θ and x_j. We investigate how these mechanisms affect the incentives to overacquire information, which we measure by the difference between the ex-ante expected utility from choosing the equilibrium precision (level 4) and deviating to precision level 2 unilaterally. The details of these calculations can be found in Section B in the Appendix.

Our calculations suggest that overusing private information at the coordination stage and expecting that the other agent also overuses information do increase the incentives to overacquire information, but not enough to make that choice optimal. Following the decomposition of Equation (11), we hypothesize that the third channel, i.e., an incorrect perception of the joint distribution of $\{x_i, x_j, \theta\}$ (in particular, an incorrect assessment of how a more precise private signal improves their ability to estimate θ and x_j) might play a role in driving overacquisition. Panel (b) of Figure 16 in the Appendix, which shows the histogram of precision choices in the treatment where we provide subjects with the correct estimate of the other player's signal, provides indirect evidence in support of this channel. Moreover, this treatment allows us to better understand the first two channels that relate the overuse of private information and overacquisition through the lens of the third channel. As shown in Panel (b) of Figure 16 in the Appendix, we observe less overacquisition of information in this treatment than in the other treatments that share the same parameters but lack the aid in calculating $E^i\left(x_j | x_i, y\right)$ (baseline and baseline with computer opponent, Panel (a) of Figure 1 and Panel (a) of Figure 16, respectively). This suggests that the complexity of forming strategic beliefs, in this case about the information held by the other player, can also affect precision choices. One can interpret the reduction in overacquisition as being driven by partially correcting subjects' perceptions of the joint distribution of $\{\theta, x_i, x_j\}$ due to being given an estimate of x_j.[33]

4.4 Welfare

In this section, we analyze realized payoffs in the experiment and compare them to the payoffs that would result if players behaved according to the theoretical benchmark, given the realized states and signals in the experiment. We do this with the objective of quantifying the welfare effects of the two biases we identify. That is, we investigate what is the cost, in terms of foregone payoffs, of overacquiring information, for both the individual and strategic treatments, and the cost of overusing private information in the strategic treatment.

Table 3 reports the median payoffs for subjects in our baseline treatments as well

[33] Due to the intricacies related to this channel, our experimental setup does not permit to do a deep investigation of this mechanism. We deem this an exciting avenue for future research.

as payoffs that subjects would have obtained had they followed equilibrium strategies in the coordination game, separated by precision choices that correspond to the equilibrium prediction and to the higher level of precision that represents overacquisition.[34] The second and third column correspond to the median payoffs of the two stage game, whereas the fourth and fifth columns correspond to the payoffs only in the coordination stage, that is, we abstract from payoffs related to precision choices.

	Two-stage Model		Coordination Stage	
	Individual	*Strategic*	*Individual*	*Strategic*
Equilibrium σ	110.1	110.2	99.1	99.2
Overacquirers	105.3***	105.1***	99.3	99.1
Theoretical	110.4	110.8	99.4	99.8

Statistical difference wrt theoretical equilibrium payoffs at levels:*** 1%, ** 5%, * 10%.

Table 3: Realized payoffs for subjects who choose equilibrium precision and for overacquirers, baseline treatment

We see similar payoff patterns in the strategic and non-strategic environments. In particular, average payoffs of subjects who choose the equilibrium precision are not different from the theoretical benchmark in both environments. In terms of the two biases that we identify, we find that the overuse of private information has a negligible effect on payoffs, since there is no significant difference in the payoffs in the coordination stage across precision choices (equilibrium vs. overacquirers, column 5 of Table 3). This suggests that the bias in the use of information is not costly, so subjects do not have monetary incentives to correct this bias. However, the overacquisition of information leads to significant welfare losses due to the higher cost of more precise information.[35] These results are robust to treatment and parameter variations, as shown in Tables 4 and 5 in the Appendix.

5 Discussion

We have identified two biases that arise in our environment, one related to the way in which people choose information and one to the way they use this information, which are robust to different parametrical specifications. First, we observe sustained

[34] Theoretical payoffs are computed given the signals and state realizations observed in the experiment, assuming that the other pair member also behaves optimally.

[35] Welfare losses clearly depend on the cost function, but our qualitative results are unlikely dirven by the specific cost function since payoffs in the coordination game are not different for overacquirers and equilibrium choosers.

overacquisition of information both in individual and strategic decision environments. Despite observing initial differences across environments, learning dynamics eventually erase any effects of strategic uncertainty in precision choices and lead to similar behavior in the choice of information in both setups. Second, we identify a bias in the use of information that, in contrast, is present only in the strategic environment: subjects overuse their private signal, specifically those who overacquire information.

Our investigation suggests that different factors related to the complexity of the decision environment affect how subjects use information. In particular, by removing individual components that affect the complexity of the decision in our strategic setup we are able to identify significant reductions in the magnitude of the overuse bias. We identify such a reduction in three separate treatments: (i) when we exogenously determine the precision of the private signals (so subjects do not have to choose them), which could reflect some type of sunk-cost fallacy, (ii) when we set a low precision for the public signal and, as a result, remove the tension between very precise public information and private information acquisition, and (iii) when we provide subjects with the correct estimate of the information held by others, thus helping their belief formation process. While these interventions do not remove the overuse bias completely, they separately reduce it, suggesting that this bias is not due to one specific mechanism, but to a collection of factors that, together, make this decision non trivial. In addition, we show that the overuse bias has a negligible effect on payoffs across treatments, implying that it does not carry a quantifiable cost to subjects, i.e., subjects do not have an incentive to correct it. In contrast, the overacquisition of information entails significant payoff losses.

To complete the investigation of possible mechanisms behind our results, we explore alternative explanations for our findings based on popular models of bounded rationality in games. We formally study variations of our model where we allow for limited depth of reasoning (Level-k), anticipated regret minimization, quantal response equilibrium, and overconfidence, separately, and argue that each of these models is unlikely to explain our results. This is because, even if these models assume specific behavioral mechanisms that lead to departures from the standard theory, they all tend to move in the direction of Bayesian updating and imply that subjects should rely more on public information in the presence of strategic complementarities, which is the opposite to the overuse of private information that we observe. This, in turn, implies that it is hard for these models to induce overacquisition for reasonable values of parameters. All proofs and detailed descriptions of each of these environments are relegated to the Online Appendix.

Acknowledgements

We are grateful to participants at various conferences and seminars for insightful comments and suggestions. Linchen Zhang provided outstanding research assistance. All errors remain ours. Michal Szkup is supported in part by funding from the Social Sciences and Humanities Research Council.

References

[1] Adam, K. (2007). Optimal monetary policy with imperfect common knowledge. *Journal of monetary Economics*, 54(2), 267-301.

[2] Angeletos, G. M., & Pavan, A. (2004). Transparency of information and coordination in economies with investment complementarities. *American Economic Review*, 94(2), 91-98.

[3] Angeletos, G.M. and Pavan, A., (2007). Efficient use of information and social value of information. *Econometrica*, 75(4), pp.1103-1142.

[4] Bansal, R. and Shaliastovich, I., (2013). A long-run risks explanation of predictability puzzles in bond and currency markets. *Review of Financial Studies*, 26(1), pp.1-33.

[5] Baeriswyl, R. and Cornand, C., (2016). The Predominant Role of Signal Precision in Experimental Beauty Contests. *The B.E. Journal of Theoretical Economics*, 16(1), pp. 267-301.

[6] Baeriswyl, R., Boun My, K. and Cornand, C., (2021). Double overreaction in beauty contests with information acquisition: Theory and experiment. *Journal of Monetary Economics*, 118, pp.432-445.

[7] Benhabib, J., Liu, X. and Wang, P., (2016). Endogenous information acquisition and countercyclical uncertainty. *Journal of Economic Theory*, 165, pp.601-642.

[8] Benjamin, D., (2019), Errors in Probabilistic Reasoning and Judgment Biases. Chapter for the Handbook of Behavioral Economics (Bernheim, DellaVigna, and Laibson, eds.) Elsevier Press.

[9] Bhattacharya, S., Duffy, J., and Kim, S., (2017). Voting with endogenous information acquisition: Experimental evidence. *Games and Economic Behavior*, 102:316–338.

[10] Bolton, P., Brunnermeier, M. K., and Veldkamp, L. (2013). Leadership, coordination, and corporate culture. *Review of Economic Studies*, 80(2), 512-537.

[11] Colombo, L., Femminis, G. and Pavan, A., (2014). Information acquisition and welfare. *Review of Economic Studies*, 81(4), pp.1438-1483.

[12] Conlon, J., Healy, P. J., and Yoon, Y. (2016). Information Cascades With Informative Ratings: An Experimental Test. Mimeo.

[13] Cornand, C. and Heinemann, F., (2014). Measuring agents' reaction to private and public information in games with strategic complementarities. *Experimental Economics*, 17(1), pp.61-77.

[14] Costa-Gomes, M. A., and Crawford, V. P. (2006). Cognition and behavior in two-person guessing games: An experimental study. American economic review, 96(5), 1737-1768.

[15] Crawford, V. P., and Iriberri, N. (2007). Level-k auctions: Can a nonequilibrium model of strategic thinking explain the winner's curse and overbidding in private-value auctions?. *Econometrica*, 75(6), 1721-1770.

[16] Dale, D.J. and Morgan, J., (2012). Experiments on the social value of public information. Mimeo.

[17] Enke, B. and Zimmermann, F., (2019). Correlation neglect in belief formation. *Review of Economic Studies*, 86(1), pp.313-332.

[18] Fischbacher, U., (2007). z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental Economics* 10(2).

[19] Gervais, S., Heaton, J. B., and Odean, T. (2011). Overconfidence, compensation contracts, and capital budgeting. *Journal of Finance*, 66(5), 1735-1777.

[20] Goree, J., Holt, C., and Palfrey T. R. (2016). Quantal Response Equilibrium: A Stochastic Theory of Games. Princeton University Press.

[21] Gretschko, V. and Rajko, A., (2015). Excess information acquisition in auctions. *Experimental Economics*, 18(3):335–355.

[22] Griffin, D., and Tversky, A. (1992). The weighing of evidence and the determinants of confidence. *Cognitive psychology*, 24(3), 411-435.

[23] Hellwig, C. and Veldkamp, L. (2009)., Knowing what others know: Coordination motives in information acquisition, *Review of Economic Studies* 76(1).

[24] Kahneman, D., Gilovich, T., and Griffin, D. (eds.), (2002), *Heuristics and Biases, The Psychology of Intuitive Judgement*, Cambridge University Press.

[25] Keynes, J. M. (1936), *The general theory of employment, interest, and money.* Macmillan.

[26] Martínez-Marquina, A., Niederle, M. and Vespa, E., (2019). Failures in contingent reasoning: The role of uncertainty. *American Economic Review*, 109(10), pp.3437-74.

[27] McKelvey, R. D., and Palfrey, T. R. (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior*, 10(1), 6-38.

[28] Moore, D.A. and Healy, P.J., (2008). The trouble with overconfidence. Psychological review, 115(2), p.502.

[29] Morris, S. and Shin, H.S., (2002). Social value of public information. *American Economic Review*, 92(5), pp.1521-1534.

[30] Morris, S. and Shin, H.S. (2007), Optimal Communication. *Journal of the European Economic Association*, 5: 594-602.

[31] Myatt, D.P. and Wallace, C., (2012). Endogenous information acquisition in coordination games. *Review of Economic Studies*, 79(1), pp.340-374.

[32] Myatt, D. P., & Wallace, C. (2015). Cournot competition and the social value of information. *Journal of Economic Theory*, 158, 466-506.

[33] Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *Journal of Finance*, 53(6), 1887-1934.

[34] Pavan A. (2024). Attention, Coordination, and Bounded Recall. Mimeo.

[35] Rabin, M. (1998). Psychology and economics. *Journal of Economic Literature*, 36(1), 11-46.

[36] Reshidi, P., Lizzeri, A., Yariv, L., Chan, J., and Suen, W., (2025). Sequential Sampling by Individuals and Groups: An Experimental Study. *American Economic Review: Insights,* forthcoming.

[37] Roth, A. E., and Malouf, M. W., (1979). Game-theoretic models and the role of information in bargaining. *Psychological Review*, 86(6), 574–594.

[38] Shapiro, D., Shi, X., and Zillante, A. (2014). Level-k reasoning in a generalized beauty contest. *Games and Economic Behavior*, 86, 308-329.

[39] Szkup, M. and Trevino, I., (2015). Information acquisition in global games of regime change. *Journal of Economic Theory*, 160, pp.387-428.

[40] Szkup, M. and Trevino, I., (2020). Sentiments, strategic uncertainty, and information structures in coordination games. *Games and Economic Behavior*, 124, pp.534-553.

[41] Szkup, M. and Trevino, I., (2025). Selection through information acquisition in coordination games. Mimeo.

[42] Trevino, I., (2020). Informational channels of financial contagion. *Econometrica*, 88(1), pp. 297-335.

[43] Tversky, A. and Kahneman, D., (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), pp.1124-1131.

[44] Ui, T. and Yoshizawa, Y., (2015). Characterizing social value of information. *Journal of Economic Theory*, 158, pp.507-535.

[45] Weber, R., (2006), Managing Growth to Achieve Efficient Coordination in Large Groups. *American Economic Review*, 96 (1): 114-126.

Appendix

A Empirical analysis

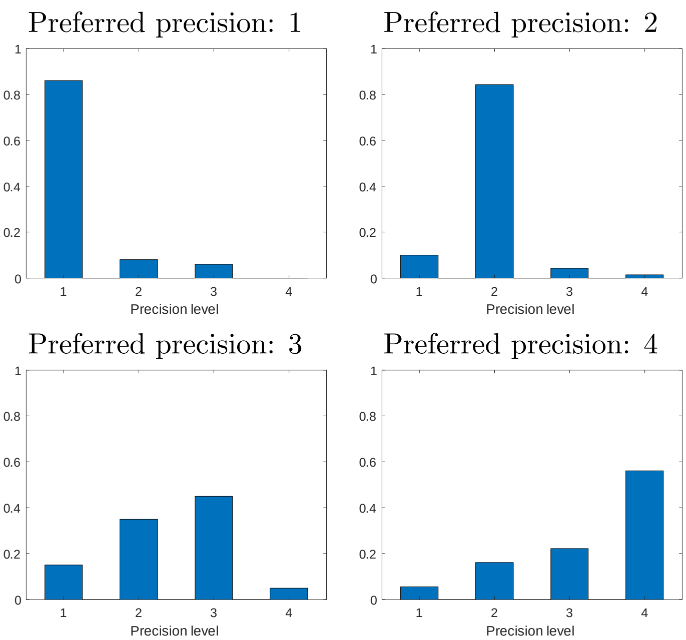


Figure 8: Precision choices in rounds 1-10, by preferred precision, individual decision setup

	$\sigma_y = 1$, $\alpha = 0.25$	$\sigma_y = 1$, $\alpha = 0.75$	$\sigma_y = 15$, $\alpha = 0.25$
Equilibrium	110.72	110.86	102.49
Endogenous, σ_i^{eq}	110.16	110.07	100.59**
Exogenous, σ_i^{eq}	109.35	109.49	101.09
Endogenous, σ_i^{over}	105.05***	104.51***	98.76***
Exogenous, σ_i^{over}	105.27**	105.08**	-

Statistical difference with respect to efficient payoffs at levels:*** 1%, ** 5%, * 10%.

Table 4: Median realized payoffs for subjects who choose equilibrium precision and for overacquirers, strategic treatments

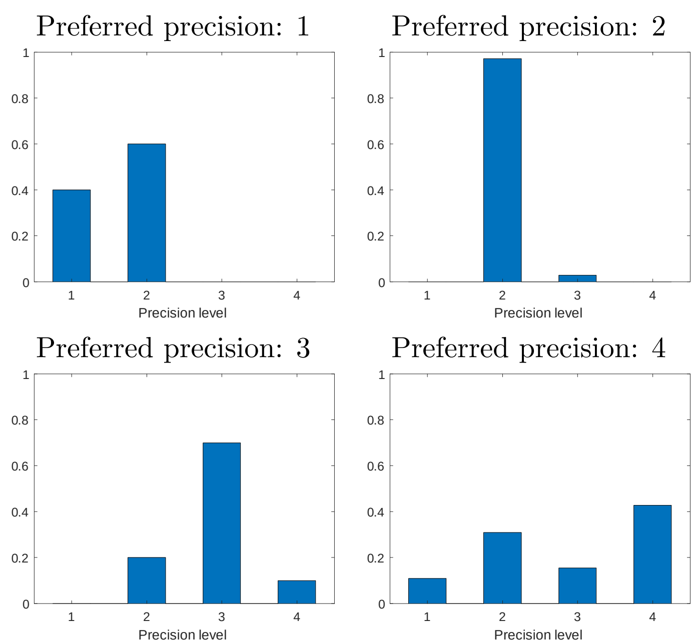


Figure 9: Precision choices in rounds 1-10, by preferred precision, strategic setup

Individual ($\alpha = 0$)

	P 1	P 2	P 3	P 4
P 1	0.85	**0.1**	0.03	0.02
P 2	0.06	0.85	0.04	0.05
P 3	0.02	**0.14**	0.67	**0.17**
P 4	0.01	0.03	0.01	0.95

Strategic ($\alpha = 0.25$)

	P 1	P 2	P 3	P 4
P 1	0.66	**0.31**	0	0.03
P 2	0.06	0.86	0.06	0.02
P 3	0	**0.18**	0.7	**0.12**
P 4	0	0.01	0.01	0.98

Figure 10: Transition matrices of precision choices in rounds 11-40

	$\sigma_y = 1$, $\alpha = 0.25$	$\sigma_y = 1$, $\alpha = 0.75$	$\sigma_y = 15$, $\alpha = 0.25$
Equilibrium	99.72	99.86	96.49
Endogenous, σ_i^{eq}	99.16	99.07	94.59
Exogenous, σ_i^{eq}	98.35	99.49	95.09
Endogenous, σ_i^{over}	99.05	98.51	**98.76**
Exogenous, σ_i^{over}	99.27	99.08	-

Statistical difference with respect to efficient payoffs at levels:*** 1%, ** 5%, * 10%.

Table 5: Median realized payoffs in coordination stage for subjects who choose equilibrium precision and for overacquirers, strategic treatments

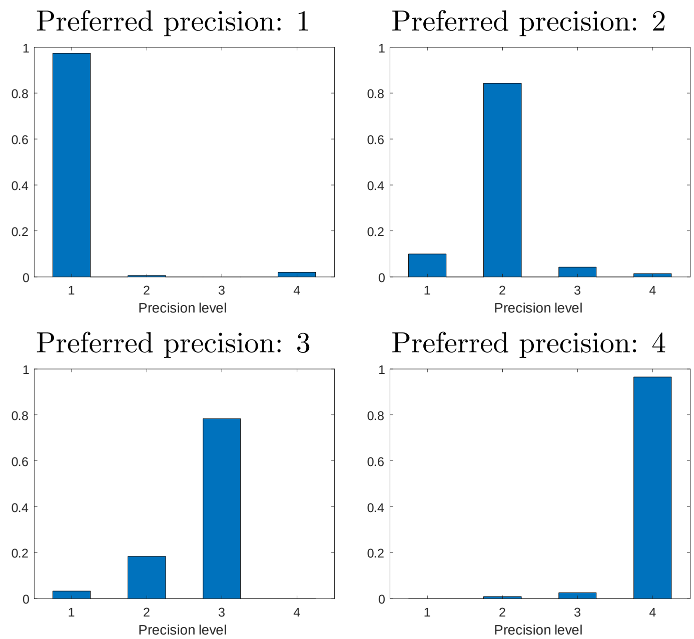


Figure 11: Precision choices in rounds 11-40, by preferred precision, individual decision setup

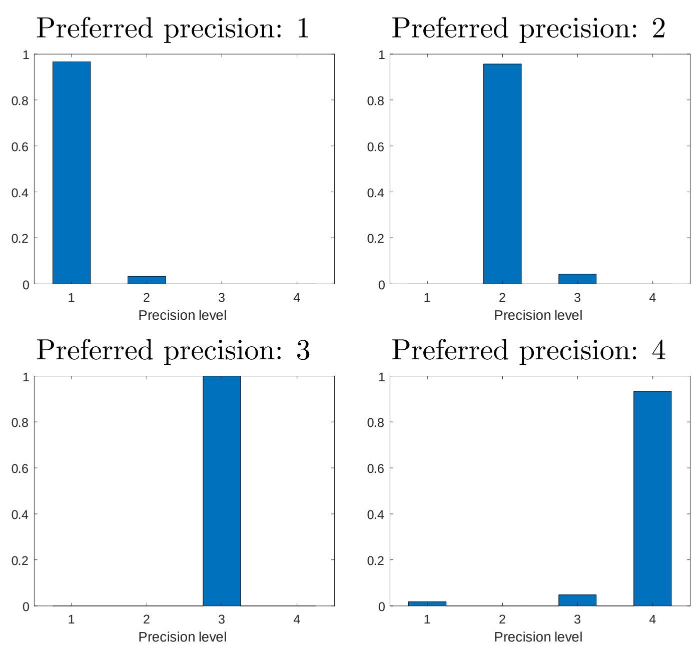


Figure 12: Precision choices in rounds 11-40, by preferred precision, strategic setup

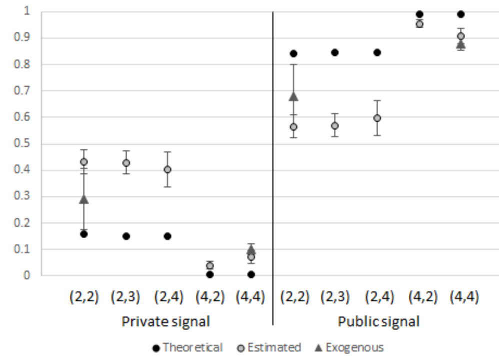


Figure 13: Weights given to signals, baseline treatment and exogenous treatments.

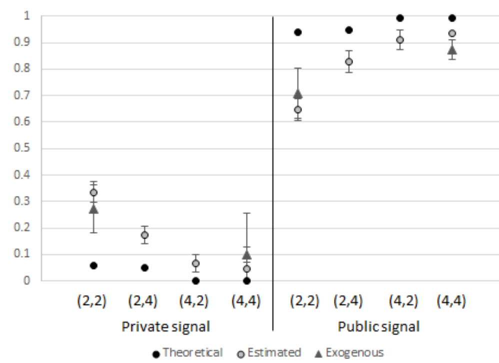


Figure 14: Weights given to signals, strong complementarities ($\alpha = 0.75$).

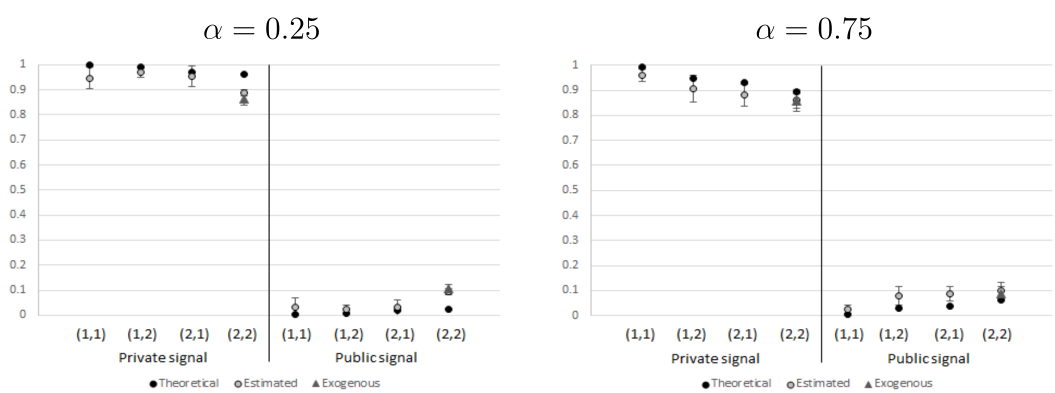
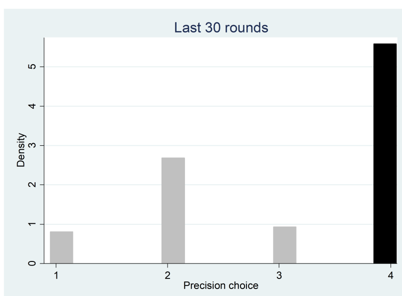
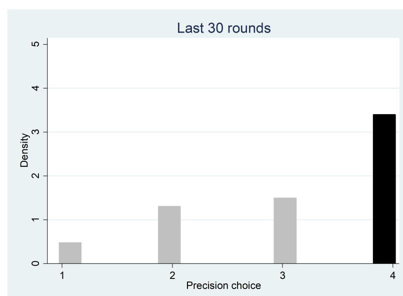


Figure 15: Weights given to signals, low transparency of public information



(a): Computer opponent



(b): Best guess about x_j provided

Figure 16: Precision choices in robustness treatments.

B Incentives to Overacquire Information

We measure the incentives to overacquire information by looking at the difference in the ex-ante utility of an agent that chooses to overacquire information (precision level 2) and acquiring the equilibrium precision (level 4):

$$\begin{aligned} E\left[U\left(\tau_2\right)\right]-E\left[U\left(\tau_4\right)\right] \quad = \quad & -\left(1-\widehat{\gamma}_i\left(\tau_2\right)\right)^2 Var_{\tau_2}^i\left(\theta-x_i\right)-\widehat{\gamma}_i^2\left(\left(\tau_2\right)\right) Var_{\tau_2}^i\left(\theta-z\right) \\ & +\left(1-\widehat{\gamma}_i\left(\tau_4\right)\right)^2 Var_{\tau_4}^i\left(\theta-x_i\right)+\widehat{\gamma}_i^2\left(\tau_4\right) Var_{\tau_4}^i\left(\theta-z\right) \\ & +2\alpha\widehat{\gamma}_j\left(\widehat{\gamma}_i\left(\tau_2\right)-\widehat{\gamma}_i\left(\tau_4\right)\right)-\left(C\left(\tau_2\right)-C\left(\tau_4\right)\right), \end{aligned} \tag{12}$$

where $Var_{\tau_i}^i(\cdot)$ is the variance conditional on agent i choosing precision τ_i.[36]

We consider first the effect of overusing information on agent i's incentives to overacquire information when agent i (i) expects the other agent to follow the equilibrium strategy and (ii) has the correct perception of the joint distribution of $\{x_i x_j, \theta, y\}$.[37] From our experiment, we know that subjects that overacquire information (and expect their partners to choose precision level 4) assign weight $\widehat{\gamma}_i(\tau_2, \tau_4) = 0.596$ to public information. While we do not observe directly the weight these subjects would use had they chosen precision level 4, we use the data from sessions with exogenous information to impute this weight indirectly.[38] The imputed weight is $\widehat{\gamma}_i(\tau_4, \tau_4) = 0.84$. Using these weights in Equation (11), we find that the expected utility from following the equilibrium prediction is still higher than from deviating to precision level 2 (i.e., $E[U(\tau_4)] - E[U(\tau_2)] > 0$), but the loss from the deviation decreases by 42.5% compared to the case where both agents behave optimally, both on and off the equilibrium path. This suggests that while the overuse of information by itself cannot explain overacquisition of information, it does increase the incentives to overacquire information.

We next consider how agents' beliefs about other agents' use of information affect the

[36] To keep notation simple, we suppress the dependence of utility and weights on agent i's beliefs about agent j's choice of information and agent j's beliefs about agent i's choice of information. Throughout this section, we assume that player j chooses the equilibrium precision (i.e., precision level 4) and expects agent i to do the same.

[37] In terms of Equation (12) this implies that $\widehat{\gamma}_j = \gamma^*(\tau_4, \tau_4) \approx 0.9925$, $Var^i(\theta - x_i|\tau_4) = \tau_4^{-1}$, $Var^i(\theta - x_i|\tau_2) = \tau_2^{-1}$, and $Var^i(\theta - z|\tau_4) = \tau_z^{-1}$.

[38] To impute this weight, based on our experimental evidence, we assume that there are two types of agents: (1) those that choose the equilibrium precision level and (2) those that overacquire information. Based on subjects' information choices in our benchmark treatment, we compute the proportion of these types in our benchmark treatment. Assuming that (1) the distribution of subjects' types is the same in the treatment with exogenous information and (2) both types of subjects use information in the same way as in the baseline treatment, we can interpret the estimated weight on the public signal in the treatment with exogenously provided signals with precision level 4 as the weighted average of the weight used by both types of agents. We can then obtain $\widehat{\gamma}_i(\tau_4, \tau_4)$ by simply computing the necessary weight that implies the average weight in the treatment with exogenously provided signals with precision level 4 to be 0.878.

incentives to overacquire information. To do so, we continue assuming that agent i overuses information, but we also assume that he also expects the other agent to overuse information (while still believing that the other agent chooses precision 4 so that agent i expects $\widehat{\gamma}_j^i = 0.84$). Under these assumptions, the loss from deviation is decreased by 43%, compared to the case where both agents follow the equilibrium predictions. If, instead, we assume that agent i believes that the other agent completely neglects public information ($\widehat{\gamma}_j^i = 0$), the loss from deviating decreases by 45% compared to the equilibrium benchmark. Thus, we see that beliefs about other agent's use of information play only a minor role in determining agent i's incentives to overacquire information. This is intuitive since the other agent's use of information affects agent i's incentive to deviate only through the term $2\alpha\widehat{\gamma}_j\left(\widehat{\gamma}_i\left(\tau_4\right) - \widehat{\gamma}_i\left(\tau_2\right)\right)$ (see Equation (12)). If α is low and agent i overuses information (so $\widehat{\gamma}_i$ are low), then the belief about $\widehat{\gamma}_j$ has little impact on $E\left[U\left(\tau_4\right)\right] - E\left[U\left(\tau_2\right)\right]$.

Biases in Information Choice and its Use: The Role of Strategic Uncertainty
ONLINE APPENDIX

Michal Szkup
University of British Columbia

Isabel Trevino
University of California, San Diego

February 2025

A Theoretical Model

We solve a general quadratic-Gaussian model with information acquisition, strategic complementarities, and two players. The results stated in the paper follow as simple corollaries of the general results established below. Our analysis complements the results of Colombo et al. (2014) who considered a general linear-Gaussian model with information acquisition and continuum of players and the results of Ui and Yoshizawa (2015) who considered a general quadratic-Gaussian model with finitely many players but with exogenous information structure.

We begin by describing the general quadratic-Gaussian model with information acquisition, of which our setup described in Section 2 is a special case, and characterize its equilibrium.

A.1 General Setup

The structure of the model is the same as of the setup described in Section 2 except that we allow for more general utility specification. The utility function in our general setup is given by

$$U(a_i, a_j, \theta) = \frac{1}{2}U_{aa}a_i^2 + U_{aa'}a_ia_j + U_{a\theta}a_i\theta + \frac{1}{2}U_{a'a'}a_j^2 + U_{a'\theta}a'\theta + \frac{1}{2}U_{\theta\theta}\theta^2 + Linear\ Terms, \quad (1)$$

where "linear terms" can be expressed as $\begin{pmatrix} v_a & v_{a'} & v_\theta \end{pmatrix} \times \begin{pmatrix} a_i & a_j & \theta \end{pmatrix}'$. Note that Equation (1) implies that U_{aa} is the second derivative of U with respect to own action, a_i, $U_{a'a'}$ is the second derivative of U with respect to action of the other player, a_j, and so on. The linear terms are grouped together as they play little role in the analysis. The information structure and the sequence of agents' is the same as in the setup described in Section 2.

We impose the standard regularity conditions on the utility function (see Angeletos and Pavan (2007) and Colombo et al. (2014)).

Assumption 1 $U_{aa} < 0$ *and* $-U_{aa'}/U_{aa} \in (0,1)$

Assumption 1 ensures that the best-response function are well defined, that the coordination stage has unique equilibrium, and that actions in the coordination stage are strategic complementarities.

It is easy to see that the game we consider in Section 2 is a special case of the general game described above with $U_{aa} = -2$, $U_{aa'} = 2\alpha$, and $U_{a'a'} = -2\alpha$ and $v_a = v_{a'} = v_\theta = 0$. Therefore, Assumption 1 is satisfied in the model of Section 2 as long as $\alpha \in (0,1)$.

A.2 Equilibrium under Complete Information

Consider the general model of Section A.1, but assume that both agents observe θ. The equilibrium under complete information is pair of action choices for player 1 and player 2, $\{a_1, a_2\}$, such that for each $i = 1, 2$, a_i solves

$$\frac{\partial}{\partial a_i} U(a_i, a_j, \theta) = 0, \;\; j \neq i \tag{2}$$

Using the fact the utility function is quadratic, it follows that the best-response function is given by

$$a_i(\theta, a_j) = -\frac{v_a}{U_{aa}} - \frac{U_{a\theta}}{U_{aa}}\theta - \frac{U_{aa'}}{U_{aa}} a_j \tag{3}$$

Following Angeletos and Pavan (2007) and Colombo et al. (2014), we refer to the slope of the best-response function as the equilibrium degree of coordination and denote it by α^*, where

$$\alpha^* \equiv \frac{\partial a_i}{\partial a_j} = -\frac{U_{aa'}}{U_{aa}} \tag{4}$$

Assumption 1 implies that $\alpha^* \in (0,1)$.[1] Solving simultaneously F.O.C.s of both agents we obtain the following result.

Lemma 1 *The unique equilibrium of the complete information model is the pair of action* $\{a_i, a_j\}$ *such that*

$$a_i = a_j = \kappa_0^* + \kappa_1^* \theta \tag{5}$$

where

$$\kappa_0^* \equiv -\frac{v_a}{U_{aa} + U_{aa'}} \tag{6}$$

$$\kappa_1^* \equiv -\frac{U_{a\theta}}{U_{aa} + U_{aa'}} \tag{7}$$

A.3 Equilibrium of the Model with Incomplete Information

A.3.1 The Coordination Stage

Suppose that agents chose precisions $\{\tau_i, \tau_j\}$ in the information acquisition stage. In this section, we characterize agents' optimal actions in the coordination stage given that both agents have correct beliefs about each other precision choices. That is, we characterize the optimal play along a potential equilibrium path.

In the coordination stage, the problem of player i is given by

$$\max_{a_i} E\left[U(a_i, a_j, \theta) | x_i, y\right], \tag{8}$$

where τ_i and τ_j affect the expectations through the joint distribution of $\{\theta, y, x_i, x_j\}$. The first-order condition is associated with the above problem is given by

$$E\left[\frac{\partial}{\partial a_i} U(a_i, a_j, \theta) | x_i, y\right] = 0 \tag{9}$$

Since the utility function U is quadratic in its arguments, the above first-order equation can be simplified to the following expression for a_i:

$$a_i = E\left[\alpha^* a_j + (1 - \alpha^*) \kappa^*(\theta) | x_i, y\right]$$

where, $\alpha^* \in (0,1)$ is the equilibrium degree of coordination (see Equation (4)) and $\kappa^*(\theta) = \kappa_0^* + \kappa_1^* \theta$ is the optimal action choice under the complete information.

[1] In our simple model of Section 2, $\alpha^* = -U_{aa'}/U_{aa} = \alpha$.

A strategy is a function that maps signals $\{x_i, y\}$ into actions. Denote the strategy of player i by $a_i(x_i, y)$, $i = 1, 2$. The equilibrium strategies of player i and j have to satisfy simultaneously

$$a_i(x_i, y) = E[\alpha^* a_j(x_j, y) + (1 - \alpha^*)\kappa(\theta) | x_i, y] \quad (10)$$

$$a_j(x_j, y) = E[\alpha^* a_i(x_i, y) + (1 - \alpha^*)\kappa(\theta) | x_j, y] \quad (11)$$

Lemma 2 *Let* $\boldsymbol{\tau} = \{\tau_i, \tau_j\}$. *For each player* i, $i = 1, 2$, *the unique linear equilibrium strategy is*

$$a_i^*(x_i, y) = \kappa_0^* + \kappa_1^*(\beta_i^*(\boldsymbol{\tau}) x_i + \gamma_i^*(\boldsymbol{\tau}) z), \quad (12)$$

where

$$\beta_i^*(\boldsymbol{\tau}) = (1 - \alpha^*)(1 - \delta_i)\frac{1 + \alpha^*(1 - \delta_j)}{1 - \alpha^{*2}(1 - \delta_i)(1 - \delta_j)} \quad (13)$$

and $\gamma_i^*(\boldsymbol{\tau}) = 1 - \beta_i^*(\boldsymbol{\tau})$.

Proof. We guess that player i and j use the following linear strategies

$$a_i^*(x_i, y) = \zeta_i^*(\boldsymbol{\tau}) + \beta_i^*(\boldsymbol{\tau}) x_i + \gamma_i^*(\boldsymbol{\tau}) z \quad (14)$$

$$a_j^*(x_j, y) = \zeta_j^*(\boldsymbol{\tau}) + \beta_j^*(\boldsymbol{\tau}) x_j + \gamma_j^*(\boldsymbol{\tau}) z \quad (15)$$

respectively. Combining the guess (14) with Equation (10) and using the observation that $E[\theta | x_i, y] = (1 - \delta_i) x_i + \delta_i z$, where $\delta_i = \tau_z / (\tau_i + \tau_z)$, we obtain

$$\begin{aligned} a_i^*(x_i, y) = {} & \left[\alpha^* \zeta_j^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_0^*\right] + (1 - \delta_i)\left(\alpha^* \beta_j^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_1^*\right) x_i \\ & + \left(\alpha^* \beta_j^*(\boldsymbol{\tau})\delta_i + \alpha^* \gamma_j^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_1^* \delta_i\right) z \end{aligned} \quad (16)$$

Following the same steps we get

$$\begin{aligned} a_j^*(x_j, y) = {} & [\alpha^* \zeta_i^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_0^*] + (1 - \delta_j)(\alpha^* \beta_i^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_1^*) x_j \\ & + (\alpha^* \beta_i^*(\boldsymbol{\tau})\delta_j + \alpha^* \gamma_i^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_1^* \delta_j) z \end{aligned} \quad (17)$$

Comparing the coefficients in Equations (14) and (15) with those in (16) and (17), we see that the constants ζ_i^* and ζ_j^* have to satisfy

$$\zeta_i^*(\boldsymbol{\tau}) = \left[\alpha^* \zeta_j^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_0^*\right]$$

$$\zeta_j^*(\boldsymbol{\tau}) = [\alpha^* \zeta_i^*(\boldsymbol{\tau}) + (1 - \alpha^*)\kappa_0^*]$$

From these equations we obtain that $\zeta_i^* (\boldsymbol{\tau}) = \zeta_j^* (\boldsymbol{\tau}) = \kappa_0^*$.

Next, comparing coefficients on x_i and x_j in Equations (14) and (15) with those in (16) and (17), we obtain a system of linear equations that $\{\zeta_i^* (\boldsymbol{\tau}), \beta_i^* (\boldsymbol{\tau}), \gamma_i^* (\boldsymbol{\tau})\}$ and $\left\{\zeta_j^* (\boldsymbol{\tau}), \beta_j^* (\boldsymbol{\tau}), \gamma_j^* (\boldsymbol{\tau})\right\}$ have to satisfy. Solving this system of equations for these unknowns yields the desired result. ■

A.3.2 The Coordination Stage after an Undetected Deviation

Suppose now that in a candidate equilibrium agents were to choose precisions $\{\tau_i, \tau_j\}$. Furthermore, suppose that agent i deviated from this prescribed behavior and chose instead precision, $\widehat{\tau}$. To keep notation simple let $\widehat{\boldsymbol{\tau}} = \{\widehat{\tau}, \{\tau_i, \tau_j\}\}$, so that $\widehat{\boldsymbol{\tau}}$ is a vector that contains precision choice to which player i deviated and the precision choices $\{\tau_i, \tau_j\}$, which agents were supposed to make in the information acquisition stage. Note that since precision choices are made privately, agent j is unaware of this deviation and behaves as if the agent i chose τ_i. On the other hand, agent i has correct believes about precision choice of agent j.

Given that agent j believes that agent i chose the prescribed equilibrium precision, agent j finds it optimal to follows a linear strategy $a_j^* (x_j, y) = \kappa_0^* + \kappa_1^* \left(\beta_j^* (\boldsymbol{\tau}) x_j + \gamma_j^* (\boldsymbol{\tau}) z\right)$ as characterized in Section A.3.1. Agent i's optimal action choice is the best-response to this strategy employed by agent j. That is, agent i solves

$$\max_{a_i} E \left[U \left(a_i, a_j^*, \theta\right) | x_i, y\right],$$

where his precision choice is $\widehat{\tau}$ instead of τ_i. The following result follows immediately from solving the above maximization problem.

Lemma 3 *Suppose that agents were expected to choose precisions $\{\tau_i, \tau_j\}$. Suppose further that agent i instead chose precision $\widehat{\tau}$. Then, in the coordination stage, player i's optimal strategy is given by*

$$\widehat{a}_i (x_i, y) = \kappa_0^* + \kappa_1^* \left(\widehat{\beta}_i (\widehat{\boldsymbol{\tau}}) x_i + \widehat{\gamma}_i (\widehat{\boldsymbol{\tau}}) z\right) \tag{18}$$

where, $\widehat{\boldsymbol{\tau}} = \{\widehat{\tau}, \{\tau_i, \tau_j\}\}$,

$$\widehat{\beta}_i (\widehat{\boldsymbol{\tau}}) = (1 - \alpha^*) \left(1 - \widehat{\delta}\right) \frac{1 + \alpha^* (1 - \delta_j)}{1 - \alpha^{*2} (1 - \delta_i) (1 - \delta_j)}, \tag{19}$$

$\widehat{\delta} = \tau_z / (\tau_z + \widehat{\tau})$, *and* $\widehat{\gamma}_i (\widehat{\boldsymbol{\tau}}) = 1 - \widehat{\beta}_i (\widehat{\boldsymbol{\tau}})$.

A.3.3 The Information Acquisition Stage

We now consider agents optimal precision choices. A pair of precision choices $\{\tau_i, \tau_j\}$ constitutes an equilibrium if and only if neither agent has incentives to unilaterally deviate from it. Thus, our first goal is to determine agents' optimal unilateral deviations in the information acquisition stage from a candidate equilibrium precision choices.

Suppose that in a candidate equilibrium, agents are expected to choose precisions, $\{\tau_i, \tau_j\}$. Consider agent i who is deciding whether to unilaterally deviate from the prescribed precision choice. That is, agent i is choosing an optimal precision choice in response to agent j (i) choosing precision τ_j and (ii) acting in the coordination stage according to the belief that precision levels chosen in the first-stage were $\{\tau_i, \tau_j\}$. Agent i's problem is then given by

$$\max_{\widehat{\tau}} E\left[U\left(\widehat{a}_i^*, a_j^*, \theta\right)\right] - C\left(\widehat{\tau}\right) \tag{20}$$

where the expectations are taken over $\{\theta, y, x_1, x_2\}$, $C\left(\widehat{\tau}\right)$ is the cost of purchasing precision $\widehat{\tau}$, $\widehat{a}_i^*$ is agent i's optimal strategy in the coordination stage following an undetected deviation (see Lemma 3), and a_j^* is agent j's optimal strategy in coordination stage given that agent j believes that both agents will make prescribed precision choices.

Lemma 4 *Let $\widehat{\tau}\left(\boldsymbol{\tau}\right)$ denote agent i's optimal deviation from any prescribed precision choice $\boldsymbol{\tau} = \{\tau_i, \tau_j\}$. Then for any $\boldsymbol{\tau} \in \mathbb{R}_+^2$, $\widehat{\tau}\left(\boldsymbol{\tau}\right)$ is defined as the unique solution to*

$$F\left(\widehat{\boldsymbol{\tau}}\right) \equiv \frac{|U_{aa}|\left(\kappa_1^* \widehat{\beta}_i^*\left(\widehat{\boldsymbol{\tau}}\right)\right)^2}{2\widehat{\tau}^2} - C'\left(\tau_i\right) = 0, \tag{21}$$

where $\widehat{\boldsymbol{\tau}} = \{\widehat{\tau}, \{\tau_i, \tau_j\}\}$.

Proof. The first-order condition associated with agent i's problem stated in (20) is given by

$$\begin{aligned} &\int_{(\theta,y)} \int_{\{x_i,x_j\}} U\left(\widehat{a}_i^*, a_j^*, \theta\right) \frac{\partial p\left(x_i|\theta, y\right)}{\partial \tau_i} p\left(x_j|\theta, y\right) dx_i dx_j dP\left(\theta, y\right) \\ &+ \int_{(\theta,y)} \int_{\{x_i,x_j\}} U_k\left(\widehat{a}_i^*, a_j^*, \theta\right) \frac{\partial \widehat{a}_i^*}{\partial \tau_i} dP\left(x_i, x_j|\theta, y\right) dP\left(\theta, y\right) - C'\left(\tau_i\right) = 0 \end{aligned} \tag{22}$$

Note that the second integral in Equation (22) can be written as

$$\int_{(x_i,y)} \frac{\partial \widehat{a}_i^*}{\partial \tau_i} \left\{ \int_{\{\theta,x_j\}} U_k\left(\widehat{a}_i^*, a_j^*, \theta\right) \frac{\partial \widehat{a}_i^*}{\partial \tau_i} dP\left(\theta, x_j | x_i, y\right) \right\} dP\left(x_i, y\right) = 0,$$

where we used the observation that the inner integral in the above expression corresponds to agent i's F.O.C. at the coordination stage following undetected deviation. Next, we use integration by parts and simplify the first integral in Equation (22). Following these steps we find that the above F.O.C. can be written as

$$\frac{|U_{aa}| \left(\kappa_1^* \widehat{\beta}_i^* \left(\widehat{\boldsymbol{\tau}}\right)\right)^2}{2\widehat{\tau}^2} - C'\left(\widehat{\tau}\right) = 0, \tag{23}$$

where $\widehat{\beta}_i^*$ is defined in Equation (19) and is a function of $\widehat{\boldsymbol{\tau}} = \{\widehat{\tau}, \{\tau_i, \tau_j\}\}$.

Let $F\left(\widehat{\boldsymbol{\tau}}\right)$ denote the LHS of Equation (23). It is straightforward to see that $\partial F\left(\widehat{\boldsymbol{\tau}}\right)/\partial \widehat{\tau} < 0$, $F\left(\widehat{\boldsymbol{\tau}}\right) > 0$ at $\widehat{\tau} = 0$, and $\lim_{\widehat{\tau}\to\infty} F\left(\widehat{\boldsymbol{\tau}}\right) = -\infty$. Therefore, Equation (23) has always a unique interior solution implying that $\widehat{\tau}\left(\boldsymbol{\tau}\right)$ is well defined. ■

Lemma 5 $\widehat{\tau}\left(\boldsymbol{\tau}\right)$ *is increasing in both* τ_i *and* τ_j.

Proof. Using the definition of $\widehat{\beta}_i^*$ (see Equation (19)) is is straightforward to see that $\widehat{\beta}_i^*/\partial \tau_j > 0$ and $\partial \widehat{\beta}_i^*/\partial \tau_i > 0$ implying that $\partial F\left(\widehat{\boldsymbol{\tau}}\right)/\partial \tau_j > 0$ and $\partial F\left(\widehat{\boldsymbol{\tau}}\right)/\partial \tau_i > 0$. Since, $\partial F\left(\widehat{\boldsymbol{\tau}}\right)/\partial \widehat{\tau} < 0$, by the implicit function theorem applied to Equation (21), we conclude that $\widehat{\tau}\left(\boldsymbol{\tau}\right)$ is increasing in both τ_i and τ_j. ■

Before proceeding further, note that if $\widehat{\boldsymbol{\tau}} = \{\tau_i, \{\tau_i, \tau_j\}\}$ then $\widehat{\beta}_i^*\left(\widehat{\boldsymbol{\tau}}\right) = \beta_i^*\left(\boldsymbol{\tau}\right)$, where $\boldsymbol{\tau} = \{\tau_i, \tau_j\}$. Therefore, if $\boldsymbol{\tau}^* = \left\{\tau_i^*, \tau_j^*\right\}$ is a vector of equilibrium precision choices, then $\boldsymbol{\tau}^*$ has to satisfy

$$\frac{|U_{aa}| \left(\kappa_1^* \beta_i^* \left(\boldsymbol{\tau}^*\right)\right)^2}{2\tau_i^{*2}} - C'\left(\tau_i^*\right) = 0 \tag{24}$$

for each $i \in \{1, 2\}$, $j \neq i$.

Using the above observations, we now show that our two-stage game has a unique equilibrium in which both agents choose the same precision level.

Proposition 1 *The unique equilibrium precision choice for agent* i, $i = 1, 2$, *is* τ^*, *where* τ^* *is the unique solution to*

$$\tau^* = \sqrt{\frac{1}{2} \frac{|U_{aa}| \kappa_1^{*2}}{C'\left(\tau^*\right)}} - \frac{1}{1-\alpha^*}\tau_z \tag{25}$$

Proof. We first show that there exists a unique symmetric equilibrium. Let $\tau_i = \tau_j = \tau^*$ and $\boldsymbol{\tau}^* = \{\tau^*, \tau^*\}$. Then

$$\beta^*(\boldsymbol{\tau}^*) \equiv \frac{(1-\delta^*)(1-\alpha^*)}{1-\alpha^*(1-\delta^*)} \tag{26}$$

and $\delta^* = \tau_z / (\tau^* + \tau_z)$. Hence, the symmetric equilibrium precision choice has to satisfy

$$\frac{|U_{aa}|(\kappa_1^* \beta^*(\boldsymbol{\tau}^*))^2}{2\tau^{*2}} - C'(\tau^*) = 0 \tag{27}$$

Using the definition of $\beta^*(\boldsymbol{\tau}^*)$ in the above equation and simplifying the resulting expression we obtain

$$\tau^* = \sqrt{\frac{|U_{aa}|\kappa_1^{*2}}{2C'(\tau^*)}} - \frac{\tau_z}{1-\alpha^*}, \tag{28}$$

It is straightforward to see that Equation (28) has a unique solution, which implies that our model features a unique symmetric equilibrium.

To show that there exist no asymmetric equilibria we use iterative deletion of strictly dominated strategies. Let, $\overline{\tau}$ be the unique solution to

$$\lim_{\tau_i, \tau_j \to \infty} F(\widehat{\boldsymbol{\tau}}) = 0$$

Since $\widehat{\tau}(\boldsymbol{\tau})$ is increasing in τ_i and τ_j (Lemma 5), we know that for all τ_i,$\tau_j \in \mathbb{R}_+$

$$\widehat{\tau}(\boldsymbol{\tau}) < \overline{\tau}$$

Since agents are symmetric, it follows then no agent will ever choose precision larger than $\overline{\tau}$. Let $\overline{\tau}_0 = \overline{\tau}$ and suppose that agents are prescribed to choose $\overline{\boldsymbol{\tau}}_0 = \{\overline{\tau}_0, \overline{\tau}_0\}$. Since $\widehat{\tau}(\boldsymbol{\tau})$ is increasing in both τ_i and τ_j, it follows that $\overline{\tau}_1 = \widehat{\tau}(\overline{\boldsymbol{\tau}}_0) < \overline{\tau}_0$. Since agents are symmetric, it follows that no agent will find it ever optimal to choose precision larger than $\overline{\tau}_1$. Iterating in this fashion, we obtain a decreasing sequence $\{\overline{\tau}_k\}_{k=0}^{\infty}$ bounded from below by 0. Therefore, this sequence converges and we denote its limit by $\overline{\tau}_\infty$. Note that $\overline{\tau}_\infty$ has to satisfy

$$\frac{|U_{aa}|(\kappa_1^* \beta^*(\overline{\boldsymbol{\tau}}_\infty))^2}{2\overline{\tau}_\infty^2} - C'(\overline{\tau}_\infty) = 0, \tag{29}$$

where $\overline{\boldsymbol{\tau}}_\infty = \{\overline{\tau}_\infty, \overline{\tau}_\infty\}$, as otherwise we would be able to iterate further.

We then follow an analogous approach from "below" starting with $\underline{\tau}_0 = 0$ and

$\underline{\boldsymbol{\tau}}_0 = \{\underline{\tau}_0, \underline{\tau}_0\}$. Following this approach we obtain an increasing sequence $\{\underline{\tau}_k\}_{k=0}^{\infty}$ bounded from above by $\overline{\tau}_\infty$. Therefore, this sequence converges and we denote its limit by $\underline{\tau}_\infty$. Note that $\overline{\tau}_\infty$ has to satisfy

$$\frac{|U_{aa}| \left(\kappa_1^* \beta^* \left(\underline{\boldsymbol{\tau}}_\infty\right)\right)^2}{2\underline{\tau}_\infty^2} - C' \left(\underline{\tau}_\infty\right) = 0, \tag{30}$$

where $\underline{\boldsymbol{\tau}}_\infty = \{\underline{\tau}_\infty, \underline{\tau}_\infty\}$. Comparing Equations (29) and (30) we see that $\overline{\tau}_\infty$ and $\underline{\tau}_\infty$ satisfy the same equation which, as we argued above, has a unique solution. Therefore, $\underline{\tau}_\infty = \overline{\tau}_\infty = \tau^*$, where τ^* is the unique symmetric equilibrium choice. It follows that there are no asymmetric equilibria. ■

Proposition 1 implies that in the unique equilibrium agents choose the same precision, τ^*, and follow symmetric strategies in the coordination game. Therefore, in what follows we drop subscript i (j) when referring to agent i's (agent j's) choices.

Lemma 6 *Consider the equilibrium precision choice τ^*.*

1. *The equilibrium precision choice τ^* is decreasing in the precision of public information τ_z, that is $\partial\tau^*/\partial\tau_z < 0$.*
2. *The equilibrium precision choice τ^* is decreasing in the degree of strategic complementarities α, that is $\partial\tau^*/\partial\alpha < 0$.*

Proof. Immediate from the Equation (25). ■

A.4 Derivation of Equation (11)

In this section, we derive Equation (11) and discuss the assumptions regarding agent i's perception of the relations between signals and signals that one needs to impose to arrive at this equation.

Recall that the ex-ante utility of agent i is given by

$$E\left[U\left(\tau_i\right)\right] = -E\left[\left(1-\alpha\right)\left(a_i - \theta\right)^2 + \alpha\left(a_i - a_j\right)^2\right],$$

Assume that agent i uses a linear strategy given by $a_i = \widehat{\gamma}_i z + (1 - \widehat{\gamma}_i)\, x_i$, where $\widehat{\gamma}_i \in [0,1]$ is the weight (potentially non-optimal) that player i assigns to public signal. Furthermore, assume that player i believes that player j also follows a linear strategy given by $a_j = \widehat{\gamma}_j z + \left(1 - \widehat{\gamma}_j\right) x_j$, where $\widehat{\gamma}_j \in [0,1]$ is the weight that player i

believes that player j assigns to public signal. We can now wrote ex-ante utility as

$$\begin{aligned} E\left[U\left(\tau_i\right)\right] &= -E\left[(1-\alpha)\left(\widehat{\gamma}_i\left(z-\theta\right)+\left(1-\widehat{\gamma}_i\right)\left(x_i-\theta\right)\right)^2\right. \\ &\quad \left. +\,\alpha\left(\widehat{\gamma}_i\left(z-\theta\right)+\left(1-\widehat{\gamma}_i\right)\left(x_i-\theta\right)-\widehat{\gamma}_j\left(z-\theta\right)+\left(1-\widehat{\gamma}_j\right)\left(x_j-\theta\right)\right)^2\right] \end{aligned}$$

Up to this point, we only imposed linearity of strategies. If we further assume that agents understand that signals are unbiased (which we emphasized to subjects in instructions), that is, $E\left[x_i-\theta\right]=E\left[x_j-\theta\right]=E\left[z-\theta\right]=0$, then we can simplify ex-ante utility to

$$\begin{aligned} E\left[U\left(\tau_i\right)\right] &= -\widehat{\gamma}_i Var^i\left(z-\theta\right)-\left(1-\widehat{\gamma}_i\right)Var^i\left(x_i-\theta\right)-2\widehat{\gamma}_i\left(1-\widehat{\gamma}_i\right)Cov^i\left(z-\theta,x_i-\theta\right) \quad (31) \\ &\quad -\alpha\left\{\widehat{\gamma}_j Var^i\left(z-\theta\right)-\left(1-\widehat{\gamma}_j\right)Var^i\left(x_j-\theta\right)-2\widehat{\gamma}_j\left(1-\widehat{\gamma}_j\right)Cov^i\left(z-\theta,x_j-\theta\right)\right\} \\ &\quad +\alpha\left\{2\widehat{\gamma}_i\widehat{\gamma}_j Var^i\left(z-\theta\right)+2\widehat{\gamma}_i\left(1-\widehat{\gamma}_j\right)Cov^i\left(z-\theta,x_j-\theta\right)\right. \\ &\quad \left.+\,2\left(1-\widehat{\gamma}_i\right)\widehat{\gamma}_j Cov^i\left(x_i-\theta,z-\theta\right)+2\left(1-\widehat{\gamma}_i\right)\left(1-\widehat{\gamma}_j\right)Cov^i\left(x_i-\theta,x_j-\theta\right)\right\}, \end{aligned}$$

where $Var^i\left(\cdot\right)$ and $Cov^i\left(\cdot\right)$ capture agent i's subjective beliefs about of the variances and covariances of relevant random variables. If we further assume that agents understand that

$$E\left[\left(z-\theta\right)\left(x_i-\theta\right)\right]=E\left[\left(z-\theta\right)\left(x_j-\theta\right)\right]=E\left[\left(x_i-\theta\right)\left(x_j-\theta\right)\right]=0$$

then Equation (31) can be further simplified to

$$\begin{aligned} E\left[U\left(\tau_i\right)\right] &= -\widehat{\gamma}_i Var^i\left(z-\theta\right)-\left(1-\widehat{\gamma}_i\right)Var^i\left(x_i-\theta\right) \quad (32) \\ &\quad -\alpha\left\{\widehat{\gamma}_j Var^i\left(z-\theta\right)-\left(1-\widehat{\gamma}_j\right)Var^i\left(x_j-\theta\right)-2\widehat{\gamma}_i\widehat{\gamma}_j Var^i\left(z-\theta\right)\right\}, \end{aligned}$$

which is Equation (11) in the text.

A.5 Comparison with Morris and Shin (2002)

The model used in the experiment is a natural simplification of the framework introduced by Morris and Shin (2002). Nevertheless, this simplification does have implications for some predictions of the model. In particular, in the unique equilibrium of our model, agents underuse public information while in Morris and Shin (2002) they overuse it. The reason for this difference is easiest to highlight in the context of a model with a continuum of players.

Recall that in Morris and Shin (2002), agents' utility function is given by

$$U^{MS}(\mathbf{a},\theta) = -(1-\alpha)(a_i-\theta)^2 - \alpha\left(L_i - \bar{L}\right), \tag{33}$$

where $L_i = \int_0^1 (a_i - a_j)^2 dj$ is the average mean-squared difference between agent i and other agents' actions, and $\bar{L} = \int_0^1 L_j dj$ is the average of the mean squared differences across all agents. Thus, in Morris and Shin (2002) agents care about how far their mean-squared difference is from the average mean-squared difference. Since the average $L_i - \bar{L}$ across agents is zero, from a social perspective one should not care about the coordination motive. However, from the individual perspective, coordination motive matters and, thus, from the social perspective agents use public information too much. Therefore, equilibrium degree of coordination exceeds the efficient degree of coordination.

In contrast, suppose that the utility function was given by

$$U(\mathbf{a},\theta) = -(1-\alpha)(a_i-\theta)^2 - \alpha L_i \tag{34}$$

In this case, miscoordination of action is also important from social perspective. However, agents do not take into account the effect that their actions have on the ability of other agents to match their actions. As such, they underuse information. In our 2-player model, utility function is given by $U(\mathbf{a},\theta) = -(1-\alpha)(a_i-\theta)^2 - \alpha(a_i-a_j)^2$ and, thus, it captures inefficiencies arising from the utility function in Equation (34) rather than the one in Equation (33).

B Discussion of Alternative Models

B.1 Level-k model

Models with limited depth of strategic reasoning such as level-k and cognitive hierarchy models (see Nagel (1995) or Costa-Gomes and Crawford (2006)). In the context of beauty contest models to explain observed behavior in experiments (see, for example, Cornand and Heinemann (2014) or Shapiro et al. (2014)).

The main challenge when using Level-k or cognitive hierarchy models is choosing the appropriate rule for Level 0 ($L0$) types, that is, the non-strategic, anchoring types. In what follows we assume that agents of type $L0$ follow a linear strategy in the coordination stage given by $a = \pi z + (1-\pi)x_i$, where π is an integrable random variable with support on $[0,1]$. This specification is very flexible.[2] In all cases, we assume that $L0$ randomizes uniformly between all choices of information. Given that type $L0$ follows a linear strategy at the coordination stage, all types of level k (Lk), $k \geq 1$ also use linear strategies.

We first argue that the level-k model cannot explain overuse of information. Let τ_{Lk} be the precision of the private signal that type Lk chooses in the information acquisition stage. Given τ_{Lk}, let $\delta(\tau_{Lk})$ be the weight assigned to public information in the Bayesian posterior belief about θ. Finally, denote by γ_{Lk} the weight that type Lk assigns to public information when choosing his optimal action in the coordination stage.

Lemma 7 *Consider $k \geq 1$. Then for any $\tau_{Lk} \geq 0$, we have $\gamma_{Lk} \geq \delta(\tau_{Lk})$.*

Applied to our particular experimental setup, Lemma 7 implies that level-k agents would never assign a weight on private information higher than 0.2 if they chose precision level 2, or 0.01 if they chose precision level 4. Since in our experiment we see subjects using weights much higher than that, we conclude that the level-k model cannot explain the overuse of private information that we document.

Proof of Lemma 7. Consider the problem of type Lk player at the coordination stage who chose precision τ_{Lk} and who believes that type $Lk-1$ player assigns the weight γ_{Lk-1} to public information, where γ_{Lk-1} is an integrable random variable (independent of x_j and θ) with mean $\overline{\gamma}_{Lk-1} \in [0,1]$.[3] Then, type Lk player chooses action a_i to solve

$$\min_{a_i} E\left[-(1-\alpha)(a_i-\theta)^2 - \alpha(a_i-a_j)^2 \,|x_i, y\right]$$

where $a_j = \gamma_{Lk-1}z + \left(1-\gamma_{Lk-1}\right)x_j$ and the expectations are taken over $\left\{\theta, x_j, \gamma_{Lk-1}\right\}$. Taking F.O.C. and rearranging, we obtain

$$a_i = E\left[(1-\alpha)\theta + \alpha\left(\gamma_{Lk-1}z + \left(1-\gamma_{Lk-1}\right)x_j\right)|x_i, y\right]$$

[2] We follow Crawford and Iriberri (2007) by considering non-strategic L0 types and reserving more sophisticated thinking for higher level types. Our specification includes as special cases the specification where L0 ignores strategic considerations and simply minimizes the distance between their actions and fundamentals, as in Cornand and Heinemann (2014). It also includes "random types" that always assign weight of one-half to private and public signals, as in Shaprio et al. (2014).

[3] The randomness in γ_{LK-1} captures the possibility that level $Lk-1$ agent may randomize his precision choices. From type Lk's perspective randomization over precision choice translates then into randomness in γ_{LK-1}.

Since γ_{Lk-1} is independent of x_j and θ, and since $E[x_j|x_i, y] = \delta(\tau_{Lk}) z + (1-\delta(\tau_{Lk})) x_i$ we have

$$\begin{aligned} a_i &= \left[(1-\alpha)\delta(\tau_{Lk}) + \alpha\overline{\gamma}_{Lk-1} + \alpha\delta(\tau_{Lk})\left(1-\overline{\gamma}_{Lk-1}\right)\right] z \\ &+ \left[(1-\alpha)\theta(1-\delta(\tau_{Lk})) + \alpha\left(1-\overline{\gamma}_{Lk-1}\right)(1-\delta(\tau_{Lk}))\right] x_i \end{aligned}$$

Therefore, the weight that player of type Lk assigns to public signal is given by

$$\gamma_{Lk} = \delta(\tau_{Lk}) + \alpha\overline{\gamma}_{Lk-1}(1-\delta(\tau_{Lk}))$$

It follows that $\gamma_{Lk} \geq \delta(\tau_{Lk})$ with equality if and only if $\overline{\gamma}_{Lk-1} = 0$. ■

Lemma 7 does not depend on the specific assumptions made in our experimental setup. In contrast, the proof of Lemma 8 makes use of specific assumptions and parameter values chosen in our experimental setup.

We next argue that the level-k model cannot explain the overacquisition of information we observe in our experiment.

Lemma 8 *Applied to our experimental setup, for all $\alpha \in (0,1)$ the Level-k model predicts that all types Lk, $k \geq 1$, choose to acquire precision level* 4*.*

Proof of Lemma 8. Let p_n be the probability that agent of type $Lk-1$ chooses precision level n, $n \in \{1,2,3,4\}$, $\gamma_{Lk-1}(\tau_n)$ be the weight he assigns to public information if he chose precision level n, and $\overline{\gamma}_{Lk-1} = \sum_{n=1}^{4} p_n \gamma_{Lk-1}(\tau_n)$. Denote by τ_m precision level chosen by type Lk agent. From Lemma 7 we know that if agent of type Lk chose precision τ_n then his optimal action at the coordination stage is

$$a^*_{Lk}(\tau_m) = \gamma_{Lk}(\tau_m) z + (1-\gamma_{Lk}(\tau_m)) x_i,$$

where $\gamma_{Lk}(\tau_m) = \delta(\tau_m) + \alpha\overline{\gamma}_{Lk-1}(1-\delta(\tau_m))$ and $\delta(\tau_n) = \tau_z/(\tau_z+\tau_m)$. Given these observations and suppressing the dependence of weights on precision choices for notational convenience, the expected utility of agent of type Lk who chooses precision τ_m at the information stage is given by

$$U_{Lk}(\tau_k) = -\left[\gamma_{Lk}^2 \tau_z^{-1} + (1-\gamma_{Lk})^2 \tau_k^{-1}\right] - 2\alpha \sum_{n=1}^{4} p_n \gamma_{Lk}\gamma_{Lk-1}\tau_z^{-1} - \Delta,$$

where

$$\Delta \equiv \alpha \sum_{n=1}^{4} p_n \left[\gamma_{Lk-1}^2 \tau_z^{-1} + \left(1-\gamma_{Lk-1}\right)^2 \tau_n^{-1}\right]$$

captures the terms that do not depend type Lk agent's precision choice.

We now show that $U_{Lk}(\tau_4) - U_{Lk}(\tau_m) > 0$ for $m \in \{1,2,3\}$. First, we note that

$$\gamma_{Lk}^2(\tau_4)\,\tau_z^{-1} + (1-\gamma_{Lk}(\tau_4))^2\,\tau_4^{-1} < 1$$

since by Lemma 7 we have $\gamma_{Lk}(\tau_4) \geq \delta(\tau_4) \equiv \tau_z/(\tau_z+\tau_4)$ and $\gamma_{Lk}^2(\tau_4)\,\tau_z^{-1} + (1-\gamma_{Lk}(\tau_4))^2\,\tau_4^{-1}$ is a convex in γ_{Lk} and achieves its minimum at $\gamma_{Lk} = \delta(\tau_4)$. Next, we note that given that $\tau_z = 1$, we have

$$\gamma_{Lk}^2(\tau_m)\,\tau_z^{-1} + (1-\gamma_{Lk}(\tau_m))^2\,\tau_k^{-1} > \delta^2(\tau_m)$$

Therefore, for any $m \in \{1,2,3\}$, we have

$$\begin{aligned} U_{Lk}(\tau_4) - U_{Lk}(\tau_m) &> C(\tau_m) - C(\tau_4) - \left(1-\delta^2(\tau_m)\right) \\ &\quad +2\alpha\sum_{n=1}^{4} p_n\left[\gamma_{Lk}(\tau_4) - \gamma_{Lk}(\tau_m)\right]\gamma_{Lk-1}\tau_z^{-1} \\ &> C(\tau_k) - C(\tau_4) - 1 \end{aligned}$$

where the last inequality follows by observing that $\gamma_{Lk}(\tau_4) - \gamma_{Lk}(\tau_m) > 0$ and $\delta^2(\tau_m) > 0$. Since $C(\tau_k) - C(\tau_4) > 1$ for all $m \in \{1,2,3\}$ (see Table 1), we conclude that for all $m \in \{1,2,3\}$ we have $U_{Lk}(\tau_4) - U_{Lk}(\tau_m) > 0$. Since the above argument does not depend on the level of reasoning (except that agent must best respond to the agent of lower level of reasoning), we conclude that all types of level k, $k \geq 1$, find it optimal to choose precision 4. ■

Together, Lemmas 7 and 8 establish that despite the very flexible formulation of the level-k model that we consider, this model is unable to rationalize the biases in the choice and use of information that we identify in the experiment.

B.2 Anticipated regret

It has been suggested that anticipated regret minimization can help explain both departures from equilibrium strategies (see Filiz-Ozbay and Ozbay (2007)) and excessive information acquisition (see Gretschko and Rajko (2015)) in auctions.

To model regret, we assume that agents can feel regret about mismatching the state and about miscoordinating with the other agent. The regret function is quadratic and $r_\theta, r_a \geq 0$ are the weights that an agent assigns to regret from mismatching the state and miscoordinating with the other, respectively. As above, let $\delta(\tau_i)$ denote the weight assigned to public information in the posterior belief about θ of a Bayesian player who observes a private signal with precision τ_i.

Lemma 9 *Let $\boldsymbol{\tau} = \{\tau_i, \tau_j\}$. For any $r_a, r_\theta \geq 0$ and any precision choices, we have $\gamma_i(\boldsymbol{\tau}) \geq \delta(\tau_i)$.*

Lemma 9 establishes that the weight on public information assigned by an agent that anticipates regret is always larger than $\delta(\tau_i)$. Since in our experiment, for each level of precision, we find that subjects assign weights to public signal much smaller than $\delta(\tau_i)$, we conclude that regret minimization cannot explain the observed overuse of information.

We denote an agent's regret by R, where $R : \mathbb{R}^2 \to \mathbb{R}$ and R maps $(\theta - a_i)$ and $(a_j - \alpha_i)$ into a real number. We assume that R is a quadratic function given by

$$R(\theta - a_i, a_j - \alpha_i) = -r_\theta(\theta - a_i)^2 - r_a(a_j - \alpha_i)^2, \tag{35}$$

where $r_a, r_\theta \geq 0$, so that in the model with regret, agents maximize utility

$$U^R = U + R,$$

where U is the underlying utility function (Equation (1)). This choice of regret function is natural given our payoff function. Moreover, R has also an intuitive property that agent i feels only a small amount of regret if his losses from mismatching θ and a_j are small, but strongly regrets his choices when his losses are large.[4]

Note that if r_θ is large relative to r_a then agents regret more mismatching the state. This should make them use public information less in equilibrium than in the benchmark model since in this case they value less the coordinating effect of the public signal. Similarly, high values of r_θ and r_a may increase the value of information since agents have stronger incentives to avoid large losses.

Proof of Lemma 9. We have

$$U^R(a_i, a_j, \theta) = 100 - (1 - \alpha + r_\theta)(\theta - a_i)^2 - (\alpha + r_a)(a_j - \alpha_i)^2$$

Therefore, the above utility function fits into the general setup described in Section A.1 of this appendix, with $U_{aa} = 2(1 + r_\theta + r_a)$, $U_{aa'} = 2(\alpha + r_a)$, $U_{a\theta} =$

[4] Filiz-Ozbay and Ozbay (2007) and Gretschko and Rajko (2015) consider piecewise-linear regret functions. However, since in our setting choosing a_i smaller or larger than θ or a_j leads to symmetrical utility losses, we choose a symmetric regret function.

$2(1-\alpha+r_\theta)$, $U_{a'a'=}(\alpha+r_a)$, $U_{a'\theta}=0$, and $U_{\theta\theta}=0$. Therefore, from Lemma 2 in this appendix, we know that the equilibrium weight on public information is given by

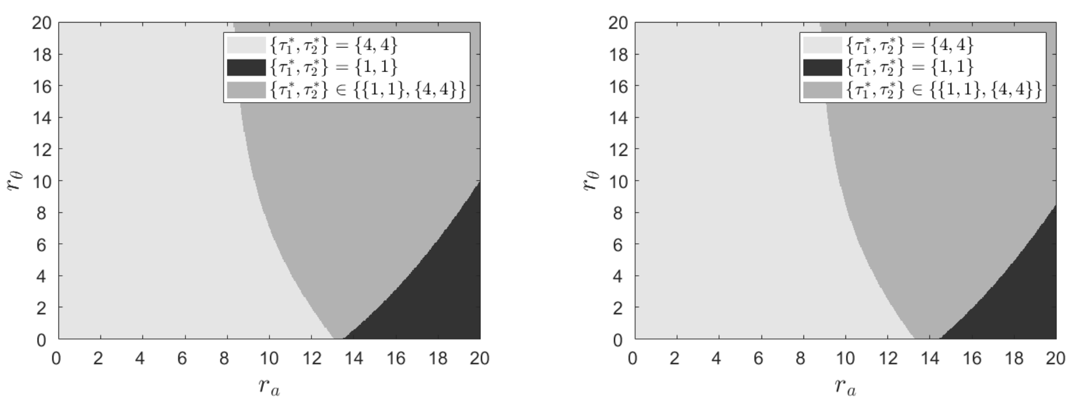
$$\gamma^*=\frac{\delta_i+\alpha^*\delta_j(1-\delta_i)}{1-\alpha^{*2}(1-\delta_i)(1-\delta_j)},$$

where $\alpha^*=-U_{aa'}/U_{aa}=\frac{\alpha+r_a}{1+r_\theta+r_a}\in(0,1)$. Since $\gamma^*=\delta_i$ if $\alpha^*=0$ and $\partial\gamma^*/\partial\alpha^*>0$ if follows that

$$\gamma^*\geq\delta_i$$

Finally, from the expression for α^*, we see that this bound is achieved only as $r_\theta\to\infty$. ■

We also find that in our particular setup, regret minimization cannot induce information overacquisition unless the weight on anticipated regret from mismatching the action, r_a, is two orders of magnitude larger than the weight on actual payoff loss, α. Moreover, if regret minimization does lead to information overacquisition, then it induces the choice of the most precise information (see Figure 1). Given this, it seems unlikely that anticipated regret minimization can be driving our findings.



(a) $\alpha=0.25$ (b) $\alpha=075$

Figure 1: Equilibrium precision choices for different combinations of r_θ and r_a

B.3 Quantal Response Equilibrium

Quantal response equilibrium (QRE) is another popular model that has been successful in explaining deviations from equilibrium in many experimental settings (see e.g., McKelvey and Palfrey (1995) and Goree et al. (2016)). In the context of incomplete information games, QRE assumes that agents have correct beliefs about strategies used by other agents and they do not exhibit any biases in information processing.

However, QRE relaxes the assumption that agents best respond to their beliefs by allowing them to make mistakes when choosing actions, with mistakes that are more costly being less likely to occur.

To investigate whether QRE can explain our experimental findings, we consider the popular symmetric logit QRE with logit parameter λ and apply it to the coordination stage (we focus only on the coordination stage for computational simplicity). Given the lack of closed-form solutions (a common feature of QRE), we compute the logit QRE of the coordination stage numerically for a wide range of λ's, where $\lambda = 0$ corresponds to random behavior, while $\lambda \to \infty$ corresponds to behavior that converges to Nash equilibrium.[5] For each λ, we simulate agents' behavior a large number of times using computed numerically QRE best-response functions and the signals observed in our experiment. Finally, using data from each simulation separately, we estimate the weight on private signals the same way as we did using our experimental data. Thus, for each λ we obtain a large number of estimated signal weights.

Figure 2 depicts the average weight on the private signal estimated using simulated data when both agents choose precision level 2 (overacquisition, left panel) and when both agents choose precision level 4 (equilibrium precision, right panel) in the information acquisition stage. The shaded areas represent two standard deviation bounds for estimated weights on private signals with 95% of estimated QRE weights on the private signal lying within these bounds.

Both panels show that average weights on the private signal implied by QRE are very close to the equilibrium weights. Moreover, for all values of λ and in all simulations, the estimated weight on private information lies below the weight estimated using our experimental data. Based on these results, we conclude that QRE is unlikely to explain our experimental results.

B.3.1 Implementation

In this section, we describe in detail how we implemented quantal response equilibrium in our setting. Note that QRE is typically applied in the context of finite-action models with complete information (see Goree et al. (2016) and references therein). Even in those relatively simple settings, QRE often has to be solved numerically. In contrast, our model features a continuum of actions and incomplete information. With a continuum of actions the so-called statistical reaction functions (which play

[5] QRE is typically used in the context of complete information, finite-action games and is not easily adaptable to environments with infinite action spaces and incomplete information. Therefore, to compute QRE we discretize our setup considering fine but finite grids on both signals and actions.

the role of best-response functions in QRE) may not be well-defined. In addition, due to incomplete information, even if statistical reaction functions are well-defined they will be complex functionals that map any pair of signals $\{x_i, y\} \in \mathbb{R}^2$ into a probability distribution over $\mathbb{R}$. This makes implementation of QRE in our setting challenging.

We focus on the so-called logistic QRE (see McKelvey and Palfrey (1995)) where agents' choices are subject to errors that follow type I extreme value distribution. To compute logistic QRE, we discretize the model, that is we consider an approximation to our model where actions and signals take values on fine but finite grids. Discretizing action space allows us to circumvent the issue that statistical response functions may be not well-defined. Discretizing signal space implies that statistical response functions will take the form of matrices rather than functions. Finally, to further decrease computational difficulty, we focus on the coordination stage assuming that both agents chose the same precision level and they have correct beliefs about the precision choice of the other agents.[6]

Computing QRE Denote the common private precision choice by τ_x. All other parameters of the model are the same as in the experiment. The algorithm to solve for QRE consists of two parts: discretization of the model and computation of statistical response functions in the discretized model.

Discretization of the model To discretize the model perform the following steps.

1. Fix a realization of public signal, y (and, hence a realization of z).

2. Restrict action choices to belong to interval $[-100, 100]$ and choose an equally spaced grid on this interval consisting of n_A points. Denote by $a(i)$ the i^{th} element of the gird over possible actions.

3. Restrict private signals to belong to interval $[-100, 100]$ and choose an equally spaced grid on this interval consisting of n_x points.[7] Denote by $x(i)$ the i^{th} element of the gird over possible signals.

[6] Our implementation of QRE allows us to extend it to the case of asymmetric precision choices but at a cost of an additional computational burden.

[7] In our experimental data all signals belong to the interval $[-60, 60]$. Thus, the chosen interval includes all observed signals. Moreover, given the parameters used in experiment, conditional on observing the highest (lowest) signal, the probability attached by agent i to either θ or x_j exceeding 100 (or being lower than -100) is negligible.

4. Let $P_x(m,n) = \Pr(x_j = x(m) | x_i = x(n), z)$ so that P_x is a matrix whose $\{m,n\}^{th}$ element is the probability that agent i who observed private signal $x(n)$ assigns to agent j observing private signal $x(m)$. To compute P_x we adapt Tauchen method for discretizing AR(1) processes (Tauchen (1986)) to our setting as follows.

   (a) Recall that $x_j|x_i \sim N\left(\delta z + (1-\delta) x_i, (\tau_x + \tau_z)^{-1} + \tau_x^{-1}\right)$, where $\delta = \frac{\tau_z}{\tau_z + \tau_x}$.

   (b) Denote by $x(1)$ is the smallest signal on the grid over signals. Then, we set
$$P_x(1,n) = \Phi\left(\frac{x(1) - \delta z + (1-\delta) x(n)}{\sqrt{(\tau_x + \tau_z)^{-1} + \tau_x^{-1}}}\right)$$
   for each $n \in \{1, ..., n_x\}$.

   (c) Denote by $x(n_x)$ is the largest signal on the grid over signals. Then, we set
$$P_x(n_x,n) = 1 - \Phi\left(\frac{x(n_x) - \delta z + (1-\delta) x(n)}{\sqrt{(\tau_x + \tau_z)^{-1} + \tau_x^{-1}}}\right)$$
   for each $n \in \{1, ..., n_x\}$.

   (d) For all $m \in \{2, ..., n_x - 1\}$ and all $n \in \{1, ..., n_x\}$ we set
$$P_x(m,n) = \Phi\left(\frac{x(m) - \delta z + (1-\delta) x(n)}{\sqrt{(\tau_x + \tau_z)^{-1} + \tau_x^{-1}}}\right) - \Phi\left(\frac{x(m-1) - \delta z + (1-\delta) x(n)}{\sqrt{(\tau_x + \tau_z)^{-1} + \tau_x^{-1}}}\right)$$

This concludes the discretization step. At this point we have a grid over actions, a grid over signal, and a matrix that captures each agents' beliefs about the private signal observed by the other agent. In our numerical analysis we set $n_a = n_x = 1001$ so that P_x is a 1001-by-1001 matrix.

Computing QRE We next describe how we compute logistic QRE in our discretized model. For a given z, our goal here is to find matrix P_a where $\{m,n\}^{th}$ element of this matrix, is the probability that each agent i plays action $a(m)$ conditional on observing private signal $x(n)$ given that he believes that the other agents chooses his actions according to P_a.

1. Fix $\lambda \geq 0$, the logistic parameter.

2. Keep z fixed at the same value as in the discretization step.

3. Guess P_a, the matrix of probabilities with which agents play actions on the grid for each private signal on the grid.

4. Compute the probability that agent i who observed private signal $x(n)$ assigns to player j taking action $a(l)$, and denote this probability by $P_{a_j|x}(l,n)$. This probability is given by

$$P_{a_j|x}(l,n) = \Pr(a_j = a(l) | x_i = x(n), z) = \sum_{m=1}^{n_a} P_a(l,m) P_x(m,n)$$

Repeat this for each action $a(l)$ and each private signal $x(n)$ on the grids to obtain $P_{a_j|x}$.

5. Let $\overline{U}$ be a matrix whose $\{k,n\}^{th}$ element is agent's expected utility from taking action k conditional on observing signals $x(n)$ and z and given $P_{a_j|x}$. Compute $\overline{U}(k,n)$, agent's expected utility from taking action $a(k)$ conditional on observing signal $x(n)$, according to

$$\overline{U}(k,n) = -(1-\alpha) E\left[(\theta - a(k))^2\right] - \alpha \sum_{l=1}^{n_a} P_{a_j}(l,n)(a(l) - a(k))^2,$$

which can be simplified to

$$\begin{aligned}\overline{U}(k,n) &= -(1-\alpha)(\tau_x + \tau_z)^{-1} + (\delta_z z + (1-\delta) x_i - a(k))^2 \\ &\quad -\alpha \sum_{l=1}^{n_a} P_{a_j}(l,n)(a(l) - a(k))^2\end{aligned}$$

Repeat this for each action and each private signal on the grid.

6. Let $\widehat{P}_a$ be a matrix whose $\{k,n\}^{th}$ element is the probability with which an agent chooses action $a(k)$ conditional on observing private signal $x(n)$. To compute $\widehat{P}_a(k,n)$ apply the logistic choice function so that

$$\widehat{P}_a(k,n) = \frac{e^{\lambda \overline{U}(k,n)}}{\sum_{\ell=1}^{n_a} e^{\lambda \overline{U}(\ell,n)}}$$

Compute the above probability for each action and each signal on the grid.

7. Set $P_a = \widehat{P}_a$ and repeat Steps $1-5$

8. Iterate till $\max\left(\left|P_a - \widehat{P}_a\right|\right) < \varepsilon$, where the max operator is taken over all elements of $\left|P_a - \widehat{P}_a\right|$ matrix and where ε is the chosen tolerance level.

The above procedure computes the statistical response functions, P_a, that constitutes a QRE. In our implementation of the above algorithm, we set $\varepsilon = 10^{-7}$ and set initial guess to a uniform distribution over all actions for each possible value of private signal.

B.3.2 Simulate Data

Having solved numerically for QRE, the final step is to simulate agents behavior using signals observed in the experimental data. That is, our goal is to obtain simulated actions for each pair of private and public signals observed in our experiment. In what follows we consider only the observations in which subject chose precision k and believed that the pair member also chose precision level $k \in \{2, 4\}$, as these were the most commonly chosen precision levels.

Let S_k be a matrix such that its first column contains to all private signals observed by subjects who chose precision k and believed that other subject also chose precision k while the second columns contains corresponding public signals that were observed by these subjects. Thus, n^{th} row of S_k is the n^{th} pair of signals $\{x_i, y\}$ observed by a subject who chose precision k and believed that other agent also chose precision k in the experimental data.

To simulate actions follow the steps outlined below.

1. Fix the logistic parameter $\lambda \geq 0$.

2. Consider the first pair $\{x_i, y\}$ that belong to $\mathcal{S}_k$.

3. Compute z and solve for P_a associated with z using the algorithm described above.

4. Find a signal on the gridpoint that is closest to x_i. Let n denote the index of that gridpoint.

5. Use a random number generator to draw a random number, call it ξ, from a continuous uniform distribution on $[0, 1]$ and find the smallest index k such that

$$\xi < \sum_{l=1}^{k} P_a(l, n)$$

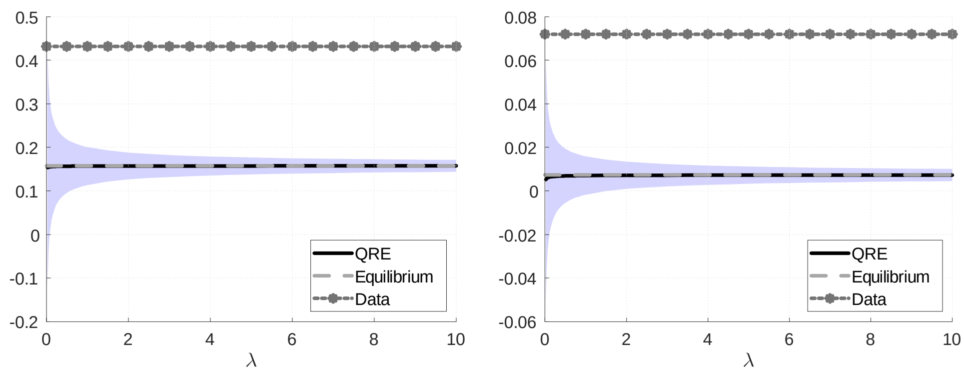
Then set $a(k)$ as the simulated action of an agent who observed signal $\{x_i, y\}$. Store this action as the first entry in a column vector A_k.

6. Continue in this fashion for each pair of signals that belong to S_k.

7. Regress A_k on S_k to estimate the implied weights by agents to private and public signals.

8. Repeat this N times, $N \in \mathbb{N}$.

In our simulations we set $N = 1000$ and repeat the above simulation for 60 different values of λ in the interval $[0, 10]$. Thus, we obtain 1000 estimates of weights on private and public signals implied by logistic QRE with a given parameter λ. Figure 2 is generated using this data.



(a) Precision level 2 (b) Precision level 4

Figure 2: Comparison of estimated weights using QRE for different values of λ with the theoretical and estimated weights.

B.4 Overconfidence

We investigate whether our results can be explained by overconfidence which leads to subjects erroneously treating private signals as more precise than they objectively are. Formally, overconfidence would imply that each subject i acts as if the private signal he observes is distributed according to $N\left(\theta, (\xi_i \tau_i)^{-1}\right)$, where τ_i is subject i's precision choice at the information acquisition stage and $\xi_i \geq 1$ is the extent of overconfidence that subject i exhibits. Therefore, $\xi_i \tau_i$ is the perceived precision of the private signal by subject i.[8] This form of overconfidence (often referred to as overprecision) has

[8] As in Odean (1998), we assume that subjects exhibit overconfidence only with respect to their own signal.

been documented extensively in the literature (see Moore and Healy (2008) and the references therein) and has been studied in the context of financial markets (Odean (1998)), firm investment (Gervais et al. (2011)), or corporate culture (Bolton et al. (2013)).

Overconfidence can potentially rationalize the overuse of information. However, there are several issues with this explanation. First, the required level of overconfidence varies greatly across treatments and across precision choices. In particular, as Table 1 in the Appendix shows, the degree of overconfidence needed to rationalize the weights estimated with our data varies from 1.34 when $\alpha = 0$ and subjects choose precision level 2 (column P 2) to 22.99 when $\alpha = 0.75$ and subjects choose the equilibrium precision and believe that their pair member does the same (column P $\{4, 4\}$). Moreover, there is no level of overconfidence that can rationalize the estimated weight observed for subjects who choose precision level 2 and believe that their pair member chooses the same precision when $\alpha = 0.75$.

Furthermore, overconfidence is unable to explain overacquisition of information. In the Online Appendix we argue that when $\tau_y = 1$, regardless of the value of ξ, the theory predicts that an overconfident subject will always choose the equilibrium precision level 4. Taken together, these observations imply that overconfidence is unlikely to explain our results.

We model overconfidence as in Odean (1998). That is, we assume that each agent i, $i \in \{1, 2\}$, believes erroneously that the acquired precision of his signal is $\xi_i \tau_i$, with $\xi_i \geq 1$. When $\xi_i = 1$ then agent does not exhibit overconfidence and perceives precision of his signal correctly. In addition, we assume that agents perceive precision of other agents correctly.[9]

Lemma B.1 *Suppose that agent i chose precision τ_i and believes that subject j chose precision τ_j. Then for any $\widehat{\beta} \in \left[\beta^*, \overline{\beta}\right]$, where $\overline{\beta} = (1-\alpha)\frac{1+\alpha(1-\delta_j)}{1-\alpha^2(1-\delta_j)}$, there exists ξ_i such that optimal weight assigned by agent i to private signal is $\widehat{\beta}$.*

Proof. Following the same steps as in the proof of Lemma 2 one can show that the optimal weight assigned by the agent i to private signal when his overconfidence level

[9] Odean (1998), motivated by the behavioral literature, assumes that agent i actually underestimates the precision of others' signal. This allows the model to capture another type of overconfidence, referred to as overplacement (overconfidence about one's performance relative to others). This additional source of overconfidence would only strengthen the case against overconfidence as a driver of our results as it would lead to shrinking of set of weight on private signal that overconfidence could justify.

is ξ is given by

$$\beta^*(\xi_i) = (1-\alpha)(1-\delta_i(\xi)) \frac{1+\alpha(1-\delta_j)}{1-\alpha^2(1-\delta_i(\xi))(1-\delta_j)},$$

where $\delta_i(\xi) = \tau_z/(\tau_z + \xi\tau_i)$ and $\delta_j = \tau_z/(\tau_z + \tau_j)$. Note that if $\xi_i = 1$ then the above weight corresponds to the optimal weight in the baseline model. Furthermore, we have

$$\frac{\partial \beta^*(\xi_i)}{\partial \xi} = (1-\alpha) \frac{1+\alpha(1-\delta_j)}{[1-\alpha^2(1-\delta_i(\xi))(1-\delta_j)]^2} \frac{\tau_z \tau_i}{(\tau_i + \tau_z)} > 0$$

Finally,

$$\lim_{\xi_i \to \infty} \beta^*(\xi_i) = (1-\alpha) \frac{1+\alpha(1-\delta_j)}{1-\alpha^2(1-\delta_j)}$$

Setting $\overline{\beta} = (1-\alpha)\frac{1+\alpha(1-\delta_j)}{1-\alpha^2(1-\delta_j)}$ establishes the claim. ■

Constructing Table 1 To compute levels of overconfidence needed to rationalize the estimated weights using our experimental data we first check whether the estimated weight is smaller than $\overline{\beta}$. If $\alpha = 0.75$ and agent i chose precision level 2 and believes that agent j also chose precision 2 then the estimated weight exceeds $\overline{\beta}$ and, hence, there exists no value of $\xi_i \geq 1$ that can rationalize estimated weight. In all other cases, the level of overconfidence needed to rationalize particular estimated weight can be found by solving

$$\beta^*(\xi_i) = \widehat{\beta}$$

By Lemma B.1 this equation has unique solution. Table 1 reports ξ_i that solves the above equations across treatments and precision choices.

Overacquisition The next Lemma considers our specific experimental setting with public signal having standard deviation of $\sigma_y = 1$ and agents facing only four precision choices as specified in Table 1.

Lemma B.2 *Suppose that $\alpha = 0$. Then for any $\xi_i \geq 1$, agent i finds it optimal to acquire the lowest level precision.*

Proof. Using the properties of Gaussian distribution, it is straightforward to show that the perceived ex-ante utility of an overconfident agent as a function of precision choice τ_i is given by

$$\mathbb{E}\left[U\left(\tau_i\right)\right] = -\left(1-\delta_i\left(\xi\right)\right)^2\left(\xi\tau_i\right)^{-1} - \delta_i^2\left(\xi\right)\tau_z^{-1} - C\left(\tau_i\right),$$

where $\delta_i = \tau_z / \left(\tau_z + \xi\tau_i\right)$ is the weight assigned by an overconfident agent to public signal in his posterior about θ belief. Simplifying the above expression we obtain

$$\mathbb{E}\left[U\left(\tau_i\right)\right] = -\frac{1}{\tau_z + \xi\tau_i} - C\left(\tau_i\right),$$

It follows that for all $\xi \geq 1$ and all τ_i and $\tau_{i'}$ such that $\tau_i < \tau_{i'}$ we have

$$\mathbb{E}\left[U\left(\tau_i\right)\right] - \mathbb{E}\left[U\left(\tau_{i'}\right)\right] > -\frac{1}{\tau_z + \xi\tau_i} + \left[C\left(\tau_{i'}\right) - C\left(\tau_i\right)\right] \geq -\frac{1}{\tau_z + \tau_i} + \left[C\left(\tau_{i'}\right) - C\left(\tau_i\right)\right],$$

where the last inequality follows from the fact that $\xi \geq 1$.

Given the parameters of our model chosen for the experiment, we have $\frac{1}{\tau_z + \xi\tau_4} > 0.987$ and $C\left(\tau_3\right) - C\left(\tau_4\right) = 1.5$, $C\left(\tau_2\right) - C\left(\tau_4\right) = 5$, and $C\left(\tau_1\right) - C\left(\tau_4\right) = 11$. Thus, it follows that $\mathbb{E}\left[U\left(\tau_4\right)\right] > \mathbb{E}\left[U\left(\tau_i\right)\right]$ for all $i \in \{1, 2, 3\}$. That is precision choice four, τ_4, leads to the highest ex-ante utility for any level of overconfidence. ■

To investigate whether overconfidence can explain information overacquisition when $\alpha > 0$ we solve our model numerically. In particular, we consider a grid over possible overconfidence levels of both agents. For each agent we then choose level of overconfidence from this grid and solve the model with overconfident agents numerically. Figure 3 plots equilibrium precision choices for each of these simulations, where each equilibrium precision choice pair is denoted with different color.[10] As can be readily observed, for all pairs of $\left\{\xi_i, \xi_j\right\}$ in equilibrium agents choose to acquire signals of the lowest precision (precision level 4). Thus, Figure 3 indicates that overconfidence cannot explain overacquisition of information.

[10] While the legend only shows symmetric equilibrium, we also checked for non-symmetric equilibria, too. We found no asymmetric equilibria for any values of ξ_i and ξ_j we considered.

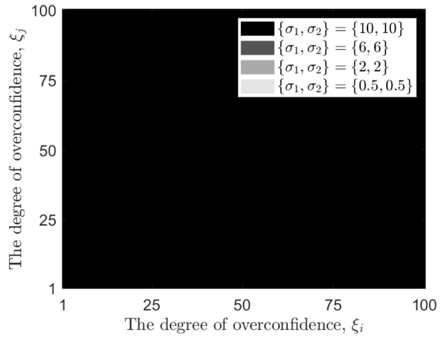


Figure 3: Equilibrium precision choices as players' degree of overconfidence varies between 1 and 100.

$\alpha = 0$		$\alpha = 0.25$		$\alpha = 0.75$	
P 2	P 4	P $\{2, 2\}$	P $\{4, 4\}$	P $\{2, 2\}$	P $\{4, 4\}$
1.34	7.32	4.80	10.62	N/A	22.99

Table 1: The degree of overconfidence implied by estimated weights across treatments for different precision choices. P k refers to precision choice by an agent when $\alpha = 0$; P $\{k, k\}$ refers to the individual precision choice and the belief about opponent's precision choice when $\alpha > 0$.

References

[1] Angeletos, G.M. and Pavan, A., 2007. Efficient use of information and social value of information. *Econometrica*, 75(4), pp.1103-1142.

[2] Colombo, L., Femminis, G. and Pavan, A., 2014. Information acquisition and welfare. *Review of Economic Studies*, 81(4), pp.1438-1483.

[3] Cornand, C. and Heinemann, F., (2014). Measuring agents' reaction to private and public information in games with strategic complementarities. *Experimental Economics*, 17(1), pp.61-77.

[4] Costa-Gomes, M. A., and Crawford, V. P. (2006). Cognition and behavior in two-person guessing games: An experimental study. American economic review, 96(5), 1737-1768.

[5] Crawford, V. P., and Iriberri, N. (2007). Level-k auctions: Can a nonequilibrium model of strategic thinking explain the winner's curse and overbidding in private-value auctions?. *Econometrica*, 75(6), 1721-1770.

[6] Filiz-Ozbay, E. and Ozbay, E. Y., 2007. Auctions with Anticipated Regret: Theory and Experiment. *American Economic Review*, 97(4), 1407–1418.

[7] Gervais, S., Heaton, J. B., and Odean, T. (2011). Overconfidence, compensation contracts, and capital budgeting. *Journal of Finance*, 66(5), 1735-1777.

[8] Goree, J., C. Holt, and T. Palfrey (2016). Quantal Response Equilibrium: A Stochastic Theory of Games. Princeton University Press.

[9] Gretschko, V., and Rajko, A. 2015. Excess information acquisition in auctions. *Experimental Economics*, 18(3).

[10] McKelvey, R. D., and Palfrey, T. R. (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior*, 10(1), 6-38.

[11] Moore, D.A. and Healy, P.J., (2008). The trouble with overconfidence. Psychological review, 115(2), p.502.

[12] Morris, S. and Shin, H.S., 2002. Social value of public information. *American Economic Review*, 92(5), pp.1521-1534.

[13] Nagel, R. 1995. Unraveling in Guessing Games: An Experimental Study. *American Economic Review*, 85(5), 1313–1326.

[14] Odean, T. (1998). Volume, volatility, price, and profit when all traders are above average. *Journal of Finance*, 53(6), 1887-1934.

[15] Shapiro, D., Shi, X., and Zillante, A. (2014). Level-k reasoning in a generalized beauty contest. *Games and Economic Behavior*, 86, 308-329.

[16] Ui, T. and Yoshizawa, Y., 2015. Characterizing social value of information. *Journal of Economic Theory*, 158, pp.507-535.