Overinference from Weak Signals, Underinference from Strong Signals, and the Psychophysics of Interpreting Information

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Abstract

Numerous experiments have found that when people receive signals that would lead a Bayesian to substantially revise beliefs, they underinfer. This paper experimentally considers inference from a wider range of signal strengths and finds that subjects overinfer when signals are sufficiently weak. A model of cognitive imprecision adapted to study misperceptions about signal strength explains the data well. As the theory predicts, subjects with more experience, greater cognitive sophistication, and lower variance in answers, infer less from weak signals and infer more from strong signals. The results also relate misperceptions to demand for information and inference from multiple signals.

JEL classification: C91; D83; D91

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1 Introduction

How do people react when they receive new information? In many economic settings, people receive information that is weakly informative. For instance, a student may take a math test and update her belief about the probability that her grade point average will be high enough to obtain a job in a STEM field; a consumer may hear a new anecdote about the quality of a product and update about the overall favorability of the product; and an employer may observe the performance of one employee and update about the performance of other employees of the employee’s demographic group.

When people receive a piece of information, they may misperceive it as being stronger or weaker than a Bayesian would, leading to overinference or underinference. This paper experimentally studies how the diagnosticity (“strength”) of a signal drives the direction of this misperception and particularly focuses on how people perceive weak signals as compared to strong signals. The main treatment considers a simple environment in which people receive one binary signal about a binary state and the strength of the signal is experimentally varied. I run a within-subject experiment among 500 people using a version of a “bookbag-and-poker-chips” experimental design that is common in the literature (e.g. Phillips and Edwards 1966). Subjects are exposed to 16 different signal strengths, allowing for a sharp test of the effect of signal strength on inference.

The main result of the experiment is that people underinfer from strong signals but overinfer from weak signals.\(^1\) In the main experimental treatment block, subjects have a prior of 1/2 on a binary state (G or V) and receive a signal \(x\) that would move a Bayesian to a posterior of \(P(G|x) = p > 1/2\). Consistent with nearly all existing evidence, for \(p \geq 2/3\) I find robust evidence for underinference: subjects form posteriors that are significantly less than \(p\) (see Benjamin 2019 for a meta-analysis of the literature). For \(p \in [3/5, 2/3]\), subjects form posteriors of approximately \(p\).\(^2\) However, for \(p \in (1/2, 3/5)\), I find robust evidence for overinference: subjects form posteriors that are statistically significantly greater than \(p\), and the effect is convex in \(p\). For very weak signals, subjects act as if signals are twice as strong as they truly are.

In these types of simple settings, the literature has largely neglected weak signals. The online appendix of Benjamin (2019) discusses over 500 experimental treatment blocks across 21 papers that study inference from binary signals. In none of these papers do subjects

\(^1\)This result corresponds to the main hypothesis in my preregistration plan.

\(^2\)As discussed in Benjamin (2019), the evidence in this range is mixed, largely finding evidence for underinference (e.g. Phillips and Edwards 1966 and Edwards 1968). However, there is evidence from recent work, such as Ambuehl and S. Li (2018) and other papers with asymmetric signals, that finds overinference for \(p = 3/5\).
see signals that have a diagnosticity lower than that of a $p = 0.6$ signal. There are 21 treatments with one signal in which subjects are given symmetric priors and one symmetric signal. In two treatments in Green, Halbert, and Robinson (1965) and one in Kraemer and Weber (2004), signals have $p = 0.6$, and subjects are approximately Bayesian in each. In each of the other papers (Holt and Smith 2009, Sasaki and Kawagoe 2007, Peterson and Miller 1965, Beach, Wise, and Barclay 1970, Dave and Wolfe 2003, and other treatments of Green, Halbert, and Robinson 1965), $p \in [2/3, 5/6]$ and subjects underinfer. Meanwhile, Enke and Graeber (2021) find similar results for $p \in \{0.7, 0.9\}$, and Ambuehl and S. Li (2018) find that subjects overinfer from, but undervalue, $p = 0.6$ signals. For $p \geq 0.6$, my results are qualitatively similar to these papers. The literature tends to interpret the evidence as showing that underinference is the dominant direction of misinference (Benjamin 2019). My paper pushes back against the generality of this interpretation and is only able to do so by emphasizing weak signals ($p < 0.6$).

The second contribution of my paper is to provide a new explanation for these patterns of over- and underinference by adapting a theory of psychophysics to explain misperceptions about the strength of signals. Psychophysics, which was named and pioneered by Fechner (1860), posits that people are more sensitive to relative changes than absolute changes in magnitudes and therefore that average perceptions of a stimulus with strength $S \in \mathbb{R}_+$ are a concave function of $S$. The theory was originally used to explain stimuli such as the weight of an object and brightness of a light; it has been more recently used in economics to explain misperceptions of numbers, probabilities, and risk and ambiguity (Kaufman et al. 1949; Khaw, Z. Li, and Woodford 2021; Enke and Graeber 2021; Frydman and Jin 2020). To my knowledge, this paper is the first to use psychophysics to study information strengths. I use a meta-Bayesian model from Petzschner, Glasauer, and Stephan (2015) and Woodford (2020): Agents are cognitively imprecise about the signal strength $S = \log\left(\frac{P(x|G)}{P(x|V)}\right)$. This leads them to form an average perception of $S$ that is distributed via a power law: they perceive a signal of strength $S$ as being of strength $k \cdot S^\beta$ for $\beta \in (0, 1)$. I find that the directional predictions, as well as the functional form, fit the data remarkably well. I estimate the model, finding that $\beta$ is 0.76 and that there is a switching point of $p = 0.64$ at which people go from overinference to underinference.

There are three notable heterogeneities across subjects and rounds in the experiment: Cognitive sophistication, task experience, and lower variance of perceptions are each associated with greater sensitivity to signal strength. These heterogeneities are consistent with

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3Donnell and Charme (1975) give subjects four signals, each of which has $p = 0.55$. However, all four signals are in the same direction, so the aggregate diagnosticity is higher.

4Stevens (1946) first popularized the power function for misperceptions of physical stimuli, and Khaw, Z. Li, and Woodford (2021) use it for misperceptions of values and lotteries.
cognitive imprecision playing a role. Subjects who score higher on a cognitive reflection test (a modified version of the classic test in Frederick 2005) both infer less from weak signals and infer more from strong signals, leading their answers to be closer to Bayes’ rule. To proxy for experience, subjects repeatedly perform the main inference task without feedback; over the course of the experiment, they infer less from weak signals and more from strong ones. Subjects who have lower variance in the average weight they put on signals exhibit similar patterns. These heterogeneities provide further evidence that cognitive precision may play a role in greater sensitivity to the strength of signals, expanding upon the work by Woodford (2020) and Enke and Graeber (2021) in other domains.

This experiment also helps further clarify the relationship between misinference and commonly-studied distortions of probabilities. Probability weighting predicts that people overweight low-probability events and underweight high-probability events (Kahneman and Tversky 1979; Tversky and Kahneman 1992), and explanations for it can be preference-based or belief-based (e.g. Barberis 2013). Such models focus on distortions of final probabilities instead of inference. While final-probability distortions may be related to underinference of strong signals (such as in Enke and Graeber 2021), standard models do not predict that people overmagnify differences between 0.51 and 0.49. I am also able to distinguish between probability distortions and misinference by considering how subjects infer from asymmetric signals. A signal that happens to have a likelihood of close to 0.5 does not systematically affect inference, suggesting that it is the signal strength that is misperceived as opposed to its associated probability. The paper also considers other confounds that arise because of the particular design of the experiment (such as a general bias towards high or low numbers), but does not find evidence that these confounds drive results.

Next, I adapt the experiment to study inference from multiple signals. I find evidence that subjects infer less from three signals than from one signal. These results are broadly consistent with past literature: for instance, Griffin and Tversky (1992), Benjamin, Rabin, and Raymond (2016), and Benjamin, Moore, and Rabin (2018) find underinference from large samples. I add to this literature by showing that underinference from three signals and overinference from weak signals approximately cancel each other out.

I additionally find that biases in demand for information tend to mimic biases in inference. Subjects are asked to purchase signals of varying strengths. Compared to a payoff-maximizing benchmark, subjects purchase too many weak signals and too few strong signals. In general, these results are qualitatively consistent with those of Ambuehl and S. Li (2018),

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5Benjamin, Rabin, and Raymond (2016) (Appendix D) include a large meta-analysis that shows substantial evidence for insensitivity to sample size.

6This corresponds to the second hypothesis in my preregistration plan.
though with novel evidence for over-purchasing due to this experiment’s emphasis on weak signals.

The main results also relate to several papers that present evidence for other forms of over- and underreaction to information. Classically, Griffin and Tversky (1992) show that subjects underreact to weight relative to strength and Massey and Wu (2005) show that subjects overreact to a signal as compared to the environment that produces the signal. More recently, Gonçalves, Libgober, and Willis (2021) find underreaction to strong signals but even further underreaction to the retraction of those signals, while Bhuller and Sigstad (2021) finds overreaction to the retraction of certain types of information that may be classified as weak. This paper also relates to the use of cognitive imprecision in inference problems, such as in Enke and Graeber (2021) and Toma and Bell (2021), that finds relationships between underreaction to strong pieces of evidence and cognitive imprecision. Since other forms of decision problems can lead to overreactions, as shown in papers like Fan, Liang, and Peng (2021) and Afrouzi et al. (2020), I keep the decision problem constant.

The paper proceeds as follows. Section 2 introduces the theory; Section 3 details the experimental design; Section 4 discusses the experimental results; and Section 5 concludes. Screenshots of the pages in the experiment are in the Online Appendix.

2 Theory

Agents receive a signal \( x \) about a binary state \( \theta \) that is either Green (G) or Purple (V) and have prior \( P(G) = \pi \), which we will typically assume equals 1/2 in this paper. The signal either says \( g \) or \( v \), with \( P(G|g) > P(G|v) \). After receiving the signal, they are asked to take an action \( a(x) \). They receive utility \( 1 - (1 - a(x))^2 \) if the state is Green and \( 1 - a(x)^2 \) if the state is Violet. They maximize expected utility by taking the action corresponding to their posterior.

A Bayesian would form a posterior of logit \( P(G|x) = \logit(\pi + \log \left( \frac{P(x|G)}{P(x|V)} \right)) \). We consider agents who may over- or underinfer from information and who instead form a posterior of logit \( P(G|x) = \logit(\pi + w \log \left( \frac{P(x|G)}{P(x|V)} \right)) \).

The strength of a signal is defined by its log odds ratio: \( S \equiv \log \left( \frac{P(x|G)}{P(x|V)} \right) \in [0, \infty) \). We now consider how \( w \) depends on \( S \), positing that when agents receive a signal \( x \) of strength \( S \), they systematically distort their perception of \( S \).

Following Petzschner, Glasauer, and Stephan (2015), and Woodford (2020), agents misperceive \( S \) via a form of cognitive imprecision. First, as described by the classic Weber-
Fechner law, they interpret changes in $S$ in relative terms instead of in absolute terms (Fechner 1860). Second, they are uncertain as to what the true signal strength is.

That is, agents represent signal strengths $S$ with a value $r$, which is drawn from a normal distribution: $r \sim \mathcal{N}(\log S, \eta^2)$. They have a meta-prior about the strength of signals that is distributed log-normally: $\log S \sim \mathcal{N}(\mu_0, \sigma^2)$ and update using Bayes’ rule. When observing the signal, their perceived expected value of $S$ will be equal to:

$$
\hat{S}(r) = \mathbb{E}[S|r] = \exp \left[ \left( \frac{\sigma^2}{\sigma^2 + \eta^2} \right) \log \bar{S} + \left( \frac{\eta^2}{\sigma^2 + \eta^2} \right) r \right],
$$

where $\bar{S} \equiv \exp(\mu_0 + \sigma^2/2)$ is the meta-prior mean.

Therefore, their perception $\hat{S}$ of the true signal strength $S$ is distributed log-normally with mean equal to

$$
e(S) \equiv \mathbb{E}[\hat{S}|S] = k \cdot S^\beta,
$$

where $k \equiv \exp(\beta^2 \eta^2/2) \cdot \bar{S}^{1-\beta}$ and $\beta \equiv \sigma^2/(\sigma^2 + \eta^2) \in (0, 1)$. $e(S)$ is a power function of $S$ and $\log e(S) = k + \beta \log S$.\(^8\)

Using the mean, agents interpret a signal of strength $S$ as having strength $\hat{S} = k \cdot S^\beta$ for $\beta \in (0, 1)$. Compared to a Bayesian (who puts weight 1 on all signals), a misperceiving agent puts weight $\hat{w}(S) = k \cdot S^{-(1-\beta)}$ on the signal. There is a switching point $S^* \equiv k^{1/\beta}$ for which $\hat{w}(S) < 1$ (underinfer) for all strong signals $S > S^*$ and $\hat{w}(S) > 1$ (overinfer) for all weak signals $S < S^*$.

The top panel of Figure 1 plots $e(S)$ as a function of $S$ on a log-log scale, comparing to Bayes’ rule ($e(S) = S$) and a constant conservatism function ($e(S) = w_{\text{const}} \cdot S$ with $w_{\text{const}} < 1$).\(^9\)

Symmetric signals are signals for which $P(g|G) = P(v|V) > 1/2$. With symmetric signals, the updating process can be written as $\logit P(G|g) = \logit \pi + w(p) \logit p$ and $\logit P(G|v) = \logit \pi - w(p) \logit p$ for $p \in (1/2, 1)$, so that $S = |\logit p|$. In this case, the weighting function is:

$$
w(p) = k \cdot (\logit p)^{-(1-\beta)},
$$

\(^8\)Power perception functions were classically introduced by Stevens (1946).

\(^9\)Note that constant conservatism, which corresponds to $\beta = 1$ (and $k < 1$), is not achievable with this functional form.
and the agent’s posterior can be written as:

\[
\hat{p} = \frac{\exp(k \cdot (\text{logit } p)^{\beta})}{1 + \exp(k \cdot (\text{logit } p)^{\beta})}.
\]

The middle panel of Figure 1 plots \(\hat{p}\) as a function of \(p\) and the bottom panel plots \(w(p)\) as a function of \(p\).

Figure 1 shows some properties of the weighting function and in particular shows the agent switching from overinference to underinference as signal strength increases. Fact 1 shows that this is a general property.

**Fact 1 (Misweighting information)**

For a misperceiving agent, the weighting function \(w(p)\) from Equation (2) and the posterior \(\hat{p}\) from Equation (3) have the following properties:

1. \(w(p)\) is decreasing in \(p\).

2. There exists a switching point \(p^* \equiv \frac{k^{1-\beta}}{1+k^{1-\beta}}\) such that:
   - If the Bayesian has posterior \(p < p^*, w(p) > 1\).
   - If the Bayesian has posterior \(p > p^*, w(p) < 1\).

As signals become arbitrarily informative or uninformative, agents’ weighting function becomes arbitrarily small or large, but their posteriors converge to the Bayesian’s. For many parameters (such as the ones in Figure 1), the weighting function remains in a non-extreme range.

Increasing cognitive imprecision, as measured by \(\sigma^2\), moves agents further from Bayesian updating for both strong and weak signals. For sufficiently large \(p\), \(\frac{\partial w(p)}{\partial \sigma} < 0\), and for sufficiently small \(p\), \(\frac{\partial w(p)}{\partial \sigma} > 0\).

Agent’s instrumental value for a signal tracks signal perceptions. An agent with belief \(b\) will expect to earn utility \(b(1 - (1 - b)^2) + (1 - b)(1 - b^2) = 1 - b(1 - b)\). The agent will therefore instrumentally value a signal that moves her belief from 1/2 to \(a(x; p)\) at \(1/4 - a(x; p) \cdot (1 - a(x; p))\). Since agents start with a prior of 1/2, overinference will lead to excess demand for information and underinference will lead to too little demand, and there will be a switching point at \(p^*\).

## 3 Experiment Design

This section overviews the design and the sample, then outlines the timing and treatment blocks, and lastly discusses further details of each treatment block. The Online Appendix

\[\text{Note that both } k \text{ and } \beta \text{ are functions of } \sigma, \text{ so } p^* \text{ will also change.}\]
Figure 1: Theoretical Predictions of Over- and Underinference by Signal Strengths

Notes: Red lines correspond to Bayesian updating, gray dashed lines to conservatism ($w(S) = \alpha \cdot S$ with $\alpha = 0.8$), and black lines to the psychophysics misperception ($w(S) = k \cdot S^\beta$ with $k = 0.882$ and $\beta = 0.760$). The top panel plots signal strength perception as a function of signal strength on a log-log scale. The middle panel plots the theoretical posterior from a symmetric signal as a function of Bayesian posterior. The bottom panel plots the weight put on signals as a function of Bayesian posterior. All figures show that misperceiving agents overweight weak signals and underweight strong signals.
3.1 Overview and Data

Subjects were told that a computer has randomly selected one of two decks of cards — a Green deck or a Purple deck — and both decks are equally likely ex ante. Each deck has Diamond cards and Spade cards: the Green deck has $D_1$ Diamonds and $N - D_1$ Spades, and the Purple deck has $D_2$ Diamonds and $N - D_2$ Spades. While subjects see the numbers themselves, we will discuss results in terms of shares: Green has share $p_1$ Diamonds and $1 - p_1$ Spades, and Purple has share $p_2$ Diamonds and $1 - p_2$ Spades.

On most questions, subjects draw one (or multiple) cards from the selected deck, observe their suit, and are asked to predict the percent chance of the Green deck and Purple deck after observing the cards drawn. These probabilities are restricted to be between 0 and 100 and the sum of the percent chances is required to equal 100. One signal corresponds to a draw of one card. On other questions, they are asked to purchase cards prior to seeing their realization. This design is adapted from Green, Halbert, and Robinson (1965).

The experiment used monetary incentives to elicit subjects’ true beliefs, as incentives have been shown to improve decision-making in these settings (e.g. Grether 1992). Subjects were given a show-up fee of $3 and were told that they have a chance to win a $100 bonus or a $10 bonus based on their answers. Five subjects were chosen at random at the end of the experiment for a bonus payment; the probability of winning the high bonus was determined by the accuracy of their answers.\(^{11}\) I implemented a version of the binarized scoring rule (Hossain and Okui 2013) that is easier for subjects to comprehend: paired-uniform scoring (Vespa and Wilson 2017). In general, probability-points systems are useful in order to account for risk aversion or hedging (Azrieli, Chambers, and Healy 2018).

The experiment was conducted in March 2021. Subjects were recruited on the online platform Prolific (prolific.co). Prolific was designed by social scientists in order to attain more representative samples online; it has been shown to perform well relative to other subject pools (Gupta, Rigotti, and Wilson 2021). 552 subjects completed the experiment. Of these, 500 subjects (91 percent) passed the attention check. As preregistered, analyses are restricted to these 500 subjects.

3.2 Timing

Subjects saw the following five treatment blocks: (1) one symmetric signal, (2) one asymmetric signal, (3) three symmetric signals, (4) demand for information, (5) uncertain signals.

\(^{11}\)4 of the 5 earned an additional $100 and 1 earned an additional $10.
Details of each are in the subsequent subsections. The ordering of when subjects saw each treatment block was as follows:

| Rounds | Treatment Block                 | Frequency | Observations |
|--------|---------------------------------|-----------|--------------|
| 1-12   | One symmetric signal            | 67 percent| 4,036        |
| 1-12   | One asymmetric signal           | 33 percent| 1,964        |
| 13     | Attention check                 | 100 percent| 500          |
| 14-18  | Three symmetric signals         | 100 percent| 2,500        |
| 19-23  | Demand for information          | 100 percent| 2,500        |
| 24-25  | One uncertain signal            | 100 percent| 1,000        |

Excluding the attention check, there are 8,000 observations. The 4,036 symmetric signals include 3,964 informative and 72 completely uninformative signals. Except when noted, analyses are restricted to the 7,928 informative-signal observations.

Questions within each treatment block were randomized for each subject. The ordering of treatment blocks (besides “one symmetric” and “one asymmetric”) were fixed for ease of subject comprehension. The fixed order makes cross-treatment comparisons more difficult than within-treatment comparisons.

### 3.3 Treatment Blocks

**One Symmetric Signal**

This is the case where \( p = p_1 = 1 - p_2 \). The Bayesian posterior is equal to \( p \) or \( 1 - p \).

There were 32 possible values of \( p \) within the range \([0.047, 0.495]\) or \([0.505, 0.953]\). These values correspond to 16 possible signal strengths \( S = |\logit p| \) in the range \( S \in [0.02, 3.00] \). On each question, I randomized whether the Green deck or Purple deck had more Diamonds or Spades, which suit was chosen, and whether the deck consisted of 1665 cards or 337 cards.

To further ensure that answers are sensible, some subjects also received an uninformative signal in which they draw a Diamond or Spade when \( p \) is exactly 1/2. For instance, subjects do not see the “demand for information” treatment until they have played rounds in which they inferred from one signal and from multiple signals. Uncertain signals come after demand because they do not reflect the signals that subjects would purchase.

More specifically, I chose whole numbers of cards such that signal strengths would be closest to the following values: \( \{0.02, 0.05, 0.10, 0.15, 0.20, 0.30, 0.40, 0.50, 0.75, 1.00, 1.25, 1.50, 1.75, 2.00, 2.50, 3.00\} \).

Subjects indeed treat this signal as uninformative; 96 percent of subjects give a posterior of exactly 50 percent.
One Asymmetric Signal

This is the case where \( p_1 \neq 1 - p_2 \). The Bayesian posterior is \( \frac{p_1}{p_2} \) given a Diamond and \( \frac{1-p_1}{1-p_2} \) given a Spade.

One of the probabilities was fixed at 0.505 or 0.495 and the other probability was randomly chosen from \{0.18, 0.35, 0.65, 0.82\}. I randomized which of \( p_1 \) or \( p_2 \) corresponds to the near-0.5 probability, which deck had more Diamonds, which suit was chosen, and whether the deck consisted of 1665 or 337 cards.

Three Symmetric Signals

In this treatment block, subjects saw three simultaneous symmetric signals, each of strength \( S \), but possibly in different directions. For a given \( p \), subjects randomly saw (3 Diamonds, 0 Spades), (2 Diamonds, 1 Spade), (1 Diamond, 2 Spades), or (0 Diamonds, 3 Spades) with equal probability.

There were 14 possible values of \( p \in [0.047, 0.495] \cup [0.505, 0.953] \), which corresponded to 14 possible signal strengths. These values were chosen so there would be overlap between the posteriors for five (3,0) signals and five (2,1) signals for a Bayesian, allowing for a sharper comparison. Suit distribution and the card drawn were randomly varied as above; the deck size was fixed for this treatment block at 1665.

Demand for Information

In this treatment block, subjects were given the distribution of cards, but not given a draw of a card. Signals were (known to be) symmetric, so the expected signal strength was \( p \) regardless of the signal itself. We fix \( p < 0.75 \). Unlike before, subjects were asked to choose how many cards they would like to purchase, with costs being a convex function of the number of cards. In particular, they were given the option to:

- Draw 0 cards for a cost of $0;
- Draw 1 card for a cost of $0.50;
- Draw 2 cards for a cost of $1.50; or
- Draw 3 cards for a cost of $3.

These numbers were chosen such that purchasing 0 cards is optimal for all \( p \in [0.5, 0.57] \), purchasing 1 card is optimal for \( p \in [0.57, 0.62] \), purchasing 2 cards is optimal for \( p \in [0.62, 0.67] \), and purchasing 3 cards is optimal for \( p \in [0.67, 0.75] \).
I set five possible values of $p \in \{0.512, 0.525, 0.550, 0.622, 0.731\}$ such that optimal level for purchasing ranges from 0 to 3. Suit distribution and the card drawn were randomly varied as above and the deck size was fixed at 1665.

**Uncertain Signals**

In this treatment block, subjects saw a signal with $p$ that was either equal to $p_L$ or $p_H$ with equal probability. Subjects randomly saw one of the following sets of distributions:

\{(p_L = 0.495, p_H = 0.817), (p_L = 0.505, p_H = 0.807), (p_L = 0.495, p_H = 0.193), (p_L = 0.505, p_H = 0.183)\}. Note that a Bayesian would have the same perceived signal strength in each of these cases.

Suit distribution and the card drawn were randomly varied as above and the deck size was fixed at 1665.

4 Results

This section discusses the results for each treatment block. The first subsection presents the main results from inference from one symmetric signal and explores heterogeneity. Next, results about inference from multiple signals and demand for information are presented. After exploring potential mechanisms, and how the other treatment blocks help disentangle them, I discuss robustness exercises to probe the strength of the main results.

4.1 Main Results

First, we consider how subjects infer from one symmetric signal. As is consistent with the theory, subjects have a systematic pattern of overinference from weak signals, underinference from strong signals, and a switching point. There is clear evidence of nonlinearity in weighting as a function of signal strength and show that a power function fits the data well.

Figure 2 shows that subjects systematically overinfer from weak signals and underinfer from strong signals and shows that the data clearly reject models in which weight is not a function of the Bayesian posterior. The bottom panel additionally shows that the power-law model described in Section 2 provides a better fit of the data than a linear model. Besides the qualitative explanatory power, it predicts the levels of overinference and underinference well.

$p^*$ and $\beta$ are estimated using nonlinear least squares for signal types $s$:

\[
\text{Weight}_s = (\logit p^*)^{-(1-\beta)} \cdot |\logit p_s|^{-(1-\beta)}
\]
Figure 2: Over- and Underinference of Symmetric Signals by Signal Strength

Notes: The top panel plots signal strength perception as a function of true signal strength on a log-log scale. The middle panel plots the signal strength average answer subjects give as a function of the Bayesian posterior. The bottom panel plots the average weight subjects put on signals relative to a Bayesian. Red lines indicate Bayesian behavior. The dashed line fits the data with a power weighting function using nonlinear least squares. Both panels show that subjects overweight weak signals and underweight strong signals. Error bars indicate 95% confidence intervals, clustered at the subject level.
The estimated value for $p^*$ is 0.64 (s.e. 0.01) and for $\beta$ is 0.76 (s.e. 0.03). The value of $\beta$ is statistically significantly less than one (p-value < 0.001). These values correspond to an estimate of $k$ of 0.88 (s.e. 0.02). All standard errors are clustered at the subject level.\(^{15}\)

### 4.2 Heterogeneity

Evidence of heterogeneity in treatment effects evidence suggests that cognitive sophistication and imprecision affect misperceptions. The three-item cognitive reflection test (CRT) from Frederick (2005) provides a useful barometer for cognitive sophistication.\(^{16}\) The top panel of Figure 3 plots over/underinference by CRT score and signal strength.

Subjects who score higher on the CRT infer less from weak signals ($p < 0.6$) and more from strong signals ($p > 0.7$). Moving from a CRT score of 0/3 to 3/3 is associated with a decrease of 0.52 weight on weak signals (s.e. 0.18, p-value = 0.004). Meanwhile, this change is associated with an increase of 0.15 weight on strong signals (s.e. 0.043, p-value < 0.001).\(^{17}\)

Subjects may become more cognitively precise as they learn how to interpret more signals, so we next consider how subjects behave over the course of this part of the experiment. Results suggest that there is evidence for learning over the course of the experiment and the middle panel of Figure 3 plots over/underinference over the course of the twelve rounds. An increase in one round of the experiment is associated with a decrease of 0.074 weight on weak signals (s.e. 0.018, p-value < 0.001) and an increase of 0.008 weight on strong signals (s.e. 0.004, p-value = 0.039).\(^{18}\)

Finally, one direct proxy for cognitive precision is the variance in subjects’ answers; over the course of the experiment, subjects who have weights that have higher variance are likely less cognitively precise. The bottom panel of Figure 3 ranks subjects by the variance in their weights in the experiment and plots over/underinference by this ranking. Moving from the 75th percentile in variance to the 25th percentile in variance is associated with a decrease of 0.93 weight on weak signals (s.e. 0.11, p-value < 0.001) and an increase of 0.17 weight on strong signals (s.e. 0.03, p-value < 0.001).\(^{19}\)

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\(^{15}\)A linear Grether-style regression (Grether 1980) produces qualitatively similar predictions.

\(^{16}\)I modify the text and answers for the items in the test in case subjects have previously seen the classic version of the CRT. See the Online Appendix for the exact questions.

\(^{17}\)These regressions include controls for exogenous variation in treatments: round number, signal strength, and deck size.

\(^{18}\)This regression includes controls for signal strength and deck size.

\(^{19}\)These regressions include controls for exogenous variation in treatments: round number, signal strength, and deck size.
**Figure 3:** Heterogeneity in Inference from Weak Signals and Strong Signals

![Bar charts showing weight on signals for weak and strong signals across different conditions.](image)

**Notes:** In all three panels, the y-axis is weight subjects put on signals. Weak signals are those that lead a Bayesian to form a posterior of \((0.5, 0.6)\); strong signals lead a Bayesian to form a posterior of \((0.7, 1)\). The top panel plots weight by CRT score. The middle panel plots weight by round in the experiment. The bottom panel plots weight by how much variance the subject has in their answers. Subjects are ranked by variance in weight and split into quartiles; Quart 1 has the least variance. This figure shows that higher CRT scores, more experience, and lower variance are associated with less weight on weak signals and more weight on strong signals. Error bars indicate 95% confidence intervals.
4.3 Multiple Signals

When subjects receive multiple signals, they weight the signals less than if they receive one signal, as is consistent with past literature (as discussed in Benjamin 2019 and Benjamin, Rabin, and Raymond 2016). Figure 4 shows that subjects put less weight on multiple signals than on one signal, holding the Bayesian posterior fixed. This comparison holds both when signals are all in the same direction and when they are mixed.

Figure 4: Over- and Underinference by Number and Type of Signals

Notes: This figure plots the average weight subjects put on signals relative to a Bayesian, split by signal distribution. Grey circles correspond to one signal of strength $S$ (as in Figure 2); blue squares correspond to two signals of strength $S$ in one direction and one signal of strength $S$ in the opposing direction; green diamonds correspond to three signals of strength $S/3$ in the same the direction. This figure shows that subjects put less weight on three signals as compared to the weight they put on one signal. Error bars indicate 95% confidence intervals.

Overinference from one weak signal and underinference from multiple signals approximately cancel each other out. On average, subjects infer from three weak signals similarly to how a Bayesian would.

These results, as those in Griffin and Tversky (1992), are consistent with subjects misperceiving both the strength and the quantity of the signals. When misperceptions about quantity play a larger role than misperceptions about signal strength, there is a downward shift of the curves when agents receive multiple signals.
It is worth flagging that subjects always see the “one signal” treatment block before the “three signals” block. As such, an alternative explanation for these results is that subjects decrease inference over the course of the experiment.

4.4 Demand for Information

Patterns of overinference and underinference also lead to demand that is too high or too low relative to the optimum. Figure 5 plots the average number of signals purchased as a function of each signal strength, comparing subject behavior to the Bayesian optimum.

**Figure 5: Number of Signals Purchased**

![Number of Signals Purchased](image)

**Notes:** This figure plots the number of signals purchased as a function of signal strength. The red lines correspond to the payoff-maximizing number of signals purchased. This figure shows that subjects over-purchase weak signals and under-purchase strong signals. Error bars indicate 95% confidence intervals.

Figure 5 shows that subjects systematically over-purchase weak signals and under-purchase strong signals. The cost of a signal that leads a Bayesian to form a posterior of less than 0.57 outweighs its benefit; however, the majority of subjects purchase at least one signal when $p = 0.55$ and $p = 0.525$. Additionally, 81 percent of subjects purchase fewer than the optimal level of three signals when $p = 0.73$. On average, subjects’ answers are closest to optimal when $p = 0.62$, a level similar to the switching point from Figure 2.
It is worth noting that there are other design features that affect signal purchasing but do not affect inference. For instance, subjects may be curious to learn the card draw itself, leading them to demand information for its own sake (as in Golman et al. 2021), raising the curve. Subjects’ answers are constrained to be between 0 and 3, so they may prefer to select interior answers, flattening the curve. These effects do not seem to fully explain the results but may contribute to the extremeness. For instance, more subjects purchase zero or one signals when \( p = 0.73 \) than purchase two or three, which cannot be fully explained by curiosity or interior guesses.

4.5 Mechanisms

These results could be due to misperceptions of signal strength or due to overmagnifying probabilities that are close to 1/2.\(^{21}\) For instance, if \( p_1 = 0.505 \) and \( p_2 = 0.495 \), overinference may be due to misperceptions of weak signals or due to the fact that \( p_1 \) is only slightly greater than 1 \(- p_1 \). To disentangle these hypotheses, I compare behavior when \( p_1 = 0.505 \) and \( p_2 = p_H \) to behavior when \( p_1 = 0.495 \) and \( p_2 = p_H \), where \( p_H \gg 0.5 \).

Subjects do not systematically infer differently when \( p_1 = 0.505 \) and \( p_1 = 0.495 \). When \( p_1 = 0.505 \), the average \( \beta \) is 0.54 (s.e. 0.05). When \( p_1 = 0.495 \), the average \( \beta \) is 0.60 (s.e. 0.05). The difference is not statistically significant (-0.06, s.e. 0.07, p-value = 0.404) and the point estimate is in the opposite direction of that of the alternative model.

Next, we consider how subjects respond to signals of uncertain strength. Misperceiving subjects may apply their weighting function and signal combination in one of two ways. They may either first combine the signals and then weight the combined signal, or they may first weight the signals separately and then combine the weighted components.

Consider a signal that either leads a Bayesian to a posterior of \( p_L \geq 1/2 \) or \( p_H > \max\{p_L, 1 - p_L\} > 1/2 \), each with probability 1/2. Denoting by \( \tilde{p} \) the agent’s posterior, the “combined signals” model predicts \( \logit(\tilde{p}) = K \cdot (\logit([(p_L + p_H)/2])^\beta \). The “separate signals” model predicts \( \logit(\tilde{p}) = 1/2 \cdot \left[k \cdot \logit((p_L/2))^\beta + K \cdot \logit((p_H/2))^\beta\right] \) when \( p_L > 1/2 \) and \( \logit(\tilde{p}) = 1/2 \cdot \left[-k \cdot \logit((1-p_L)/2))^\beta + k \cdot \logit(p_H/2))^\beta\right] \) when \( p_L < 1/2 \). These models make noticeably different predictions when \( p_L \) is close to 1/2. The combined signals model predicts smooth behavior and a higher \( \tilde{p} \), while the separate signals model predicts a kink at \( p_L = 1/2 \) and a lower \( \tilde{p} \).

In the experiment, subjects receive \((p_L = 0.505, p_H = 0.807)\) or \((p_L = 0.495, p_H = 0.817)\).

\(^{20}\)A preference for stating interior answers would cause the average inference to move closer to 0.5 and in particular would not lead to overinference from weak signals.

\(^{21}\)Results may also be due to misperceiving the difference between priors and posteriors, which would produce similar results to signal misperceptions.
The Bayesian model predicts posteriors of 0.656. Using the estimated parameters as before ($\beta = 0.760$ and $k = 0.882$), the combined signals model predicts near-Bayesian posteriors of 0.653 in each case. Meanwhile, the separate signals model predicts underinference and asymmetry, with a posterior of 0.636 when the signals are both larger than 0.5 and 0.628 when they are in opposite directions.

Empirically, the separate signals model fits the data best. The fit is better for both levels and differences. Subjects’ posteriors are 0.620 (s.e. 0.057) when the signal directions are aligned and 0.609 (s.e. 0.054) when they are misaligned. In fact, subjects underinfer slightly more than the separate signals model predicts (see Liang 2021 for one possible explanation). Underinference is suggestively more severe when the directions are misaligned (p-value = 0.106) and the point estimate for this difference is similar to that of the theoretical prediction.

### 4.6 Robustness

This section considers three alternative hypotheses for these results that are unrelated to over- or underinference.

First, it is possible that subjects dislike stating “50 percent” even when signals are very uninformative. There is no systematic evidence for this. Among the 72 subjects who see a completely uninformative signal (where the decks each have 832 Diamonds and 832 Spades), 69 of them (96 percent) give an answer of exactly 50 percent.

Second, it is possible that subjects are systematically more inclined to prefer Green over Purple, or attend more to Diamonds over Spades, or vice versa. If this were the case, then subjects may overinfer in one direction and underinfer in the opposite direction by a different amount, leading to average misinference. However, there is no evidence of color asymmetry; subjects’ average estimate of $P(\text{Green})$ is 0.503 (s.e. 0.002). There is also no evidence for suit asymmetry; on average, subjects’ signal weight is 1.156 (s.e. 0.031) when they see a Diamond and 1.134 (s.e. 0.035) when they see a Spade.

Third, it is possible that something about the particular number of cards in the deck leads subjects to misperceive signal strength. For instance, they may have a left-digit bias (Thomas and Morwitz 2005). Recall that for the one-signal questions, the deck size was randomly either 1,665 or 337. The deck size leads to a statistically-significant shift in the estimated switching point $p^*$ but not in the sensitivity $\beta$: $p^*$ for the larger deck is 0.68 (s.e. 0.02) and $\beta$ is 0.75 (s.e. 0.03); $p^*$ for the smaller deck is 0.61 (s.e. 0.01) and $\beta$ is 0.77 (s.e. 0.03).

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22On the screen, subjects always are asked for $P(\text{Green})$ before $P(\text{Purple})$, so this also indicates little question-location asymmetry.
0.04). With each deck size, $\beta$ is statistically significantly less than 1 (p-values $< 0.001$).\textsuperscript{23}

It is possible that these factors have modest quantitative effects on the main estimates but they cannot entirely explain the results.

5 Conclusion

The results in this paper have shown robust evidence for overinference from weak signals and underinference from strong signals. They have also shown why it is critical to study inference from weak signals in order to draw general patterns about how people process new information. Data and heterogeneities fit theories of cognitive imprecision that predict that people noisily misperceive weak signals as being too strong and strong signals as being too weak. These misperceptions can also help explain how people demand information, make inferences from multiple signals, and make inferences from uncertain signals.

Further work can relate these patterns of misinference to more applied forms of news consumption and to better understand how to correct these biases. For instance, does overinference from weak signals predict greater susceptibility to the representativeness heuristic and stereotyping (e.g. Grether 1980; Bordalo et al. 2016) at an individual level? Are people with a high $\beta$ better at distinguishing the quality of informed versus uninformed advisors?

Lastly, results also suggest that increasing cognitive precision (as in Enke and Graeber 2021) may both decrease perceptions of weak signals and increase perceptions of strong signals. As such, feedback interventions may be a promising way to move people’s inference processes towards Bayes’ rule, leading demand for information to be more sensitive to the quality of the information.

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A Online Appendix: Study Materials

Overview and Bonus Payment

On the following pages, you will be asked to make a series of choices that can impact your bonus payment.

After all Workers complete the study, 3 Workers will be chosen at random to receive a bonus payment of up to $100 based on their choices. The high bonus is because it is important for us that you take this study seriously.

There are between 20-30 questions, most of which are similarly styled. There will be an "attention check" question in the study. The answer to this question will be obvious to anyone paying attention. Workers who do not answer the attention check question correctly will still receive their show-up payment, but will not be eligible for a bonus payment.

Instructions for the study are on the following page.
Instructions

On the following several pages, you will be asked to predict which jar a randomly-chosen ball comes from.

For instance, you will see questions like the following:

You draw a card from one of two modified decks of cards; a Green deck or a Purple deck.

The Green deck has 15 Diamonds (♦) and 10 Spades (♠).
The Purple deck has 10 Diamonds (♦) and 15 Spades (♠).

The card you draw is a Diamond (♦).

What do you think is the percent chance that your Diamond (♦) came from the Green deck vs. the Purple deck?

Please answer between 0 and 100 for each question and have your answers sum up to 100, where higher numbers mean you think that deck is more likely. Your answer may include decimals.

Percent chance that your Diamond (♦) came from the Green deck:

______ percent

Percent chance that your Diamond (♦) came from the Purple deck:

______ percent
We have carefully chosen the payment rule so that you will earn the most bonus payment on average if you give a guess that you think is the true likelihood. If you are interested, further details on the payment rule are below.

Payment for your prediction:

If you are selected to receive a bonus payment, to determine your payment the computer will randomly choose a question and then randomly draw two numbers. For each draw, all numbers between 0 and 100 (including decimal numbers) are equally likely to be selected. Draws are independent in the sense that the outcome of the first draw in no way affects the outcome of the second draw.

If the selected Jar is Jar 1 and the number you picked is larger than either of the two draws, you will get a bonus payment of $100.

If the selected Jar is Jar 2 and the number you picked is smaller than either of the two draws, you will get a bonus payment of $100.

Otherwise, you will get a bonus payment of $10.
You are on Question 1 of 15 in this section.

You draw a card from one of two modified decks of cards; a Green deck or a Purple deck.

The Green deck has 853 Diamonds (♦️) and 812 Spades (♠️).
The Purple deck has 812 Diamonds (♦️) and 853 Spades (♠️).

The card you draw is a Spade (♠️).

What do you think is the percent chance that your Spade (♠️) came from the Green deck vs. the Purple deck?

Please answer between 0 and 100 for each question and have your answers sum up to 100, where higher numbers mean you think that deck is more likely. Your answer may include decimals.

Percent chance that your Spade (♠️) came from the Green deck

Percent chance that your Spade (♠️) came from the Purple deck

Total
You draw a card from one of two modified decks of cards; a Green deck or a Purple deck.

The Green deck has 867 Diamonds (♦) and 5309 Spades (♠).
The Purple deck has 5309 Diamonds (♦) and 867 Spades (♠).

The card you draw is a Spade (♠).

This question is not like the previous ones. It is a check to make sure you are paying attention. Instead of answering the question normally, please answer 3 for the first question and 14 for the second one. You will not be eligible for a bonus payment if you get this question incorrect.

| Percent chance that your Spade (♠) came from the Green deck | 0 percent |
| Percent chance that your Spade (♠) came from the Purple deck | 0 percent |
| Total | 0 percent |
You draw a card from one of two modified decks of cards; a **Green** deck or a **Purple** deck.

This time, you do not know the composition of the two decks for sure.

The **Green** deck *either* has:

- **841 Diamonds** (♦) and **824 Spades** (♠)

  OR

- **448 Diamonds** (♦) and **1217 Spades** (♠).

The **Purple** deck *either* has:

- **824 Diamonds** (♦) and **841 Spades** (♠)

  OR

- **1217 Diamonds** (♦) and **448 Spades** (♠).

Both compositions are equally likely.

*The card you draw is a **Diamond** (♦).*

What do you think is the percent chance that your **Diamond** (♦) came from the **Green** deck vs. the **Purple** deck?

Please answer between 0 and 100 for each question and have your answers sum up to 100, where higher numbers mean you think that deck is more likely. Your answer may include decimals.

| Percent chance that your **Diamond** (♦) came from the **Green** deck | 0 percent |
| Percent chance that your **Diamond** (♦) came from the **Purple** deck | 0 percent |
| **Total** | 0 percent |
You are on Question 1 of 5 in this section.

On the previous questions, you were given a card and asked to predict what deck it came from.

On this question, you will choose how many cards to draw in order to help you with your predictions. Every card is drawn with replacement.

You may draw up to 3 cards at a cost. If you are selected for the bonus and this round is chosen for payment, you can win up to $100. The first card costs $1, the second card costs an additional $2 ($3 total), and the third card costs an additional $3 ($6 total).

- $1 roughly corresponds to moving from being 50% sure that you know the deck to being 60% sure;
- $3 corresponds to moving from being 50% sure that you know the deck to being 67% sure;
- $6 corresponds to moving from being 50% sure that you know the deck to being 74% sure.

If you think the cards are helpful in distinguishing the Green and Purple decks, you should draw more cards. If you think the cards are unhelpful in distinguishing the Green and Purple decks, you should not draw cards.

The Green deck has 853 Diamonds (♦️) and 812 Spades (♠️). The Purple deck has 812 Diamonds (♦️) and 853 Spades (♠️).

You can now choose how many cards to draw from the deck.

- Do not draw any cards
- Draw 1 card (Total cost: 1 point)
- Draw 2 cards (Total cost: 3 points)
- Draw 3 cards (Total cost: 6 points)
The **Green** deck has **853 Diamonds (♦)** and **812 Spades (♠)**.
The **Purple** deck has **812 Diamonds (♦)** and **853 Spades (♠)**.

You chose to draw 2 cards.

What do you think the percent chance (between 0 and 100) is that the card is from the **Green** deck if the cards drawn are:

- [ ] 0 2 Spades (♠)
- [ ] 0 2 Diamonds (♦)
- [ ] 0 1 Diamond (♦) and 1 Spade (♠)
What is your age?

|   |

What is your gender?

|   |
|---|
| Female |
| Male |
| Other / Prefer not to answer |

In politics today, do you consider yourself a Republican, a Democrat, or an Independent?

|   |
|---|
| Democrat |
| Republican |
| Independent |

What is your highest level of education?

|   |
|---|
| Did not graduate high school |
| High school graduate, diploma, or equivalent (such as GED) |
| Began college, no degree |
| Associate's degree |
| Bachelor's degree |
| Postgraduate or professional degree |
What is your race/ethnicity?

- American Indian
- White
- Asian
- Black or African American
- Hispanic or Latino
- Two or more of these
- Other / Prefer not to answer
Quiz 1

A bat and a ball cost $10.50 in total. The bat costs $10.00 more than the ball.

How much does the ball cost?

- $0.50
- $10.00
- $10.25
- $0.25

Quiz 2

If it takes 7 machines 7 minutes to make 7 widgets, how long would it take 70 machines to make 70 widgets?

- 0.1 minutes
- 490 minutes
- 70 minutes
- 7 minutes
Quiz 3

In a community, there is a rapidly-spreading virus. Every day, the virus infects twice as many people. If it takes 42 days for the virus to infect the entire community, how long would it take the virus to infect half the community?

|   |   |
|---|---|
| ○ | 21 days |
| ○ | 42 days |
| ○ | 2 days |
| ○ | 41 days |