

# Overconfidence, Strategic Failures, and Experience: An Experiment on Persistent Speculative Trade

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## Abstract

Individual investors are known to lower their portfolio returns by trading speculatively, thus incurring transaction fees. In this paper, I use a laboratory experiment to uncover why they do so persistently. In particular, I use experience as a criterion to compare two behavioral channels that may incentivize speculative trading: overconfidence and strategic naivete. Subjects in the experiment observe private information and then decide whether to swap Arrow securities with a partner. A no-trade theorem applies to the setting so that under rational expectations, trade should never be realized. I show that experience can reduce speculation by reducing overconfidence, but fails to correct strategic naivete: experienced subjects continue to ignore the adverse selection implied by their partners' willingness to trade. This result is most salient for subjects with high-quality information, who trade more frequently after learning their information reliably predicts the state of the world but do not choose to trade less when learning their partners' information is similarly high-quality. After revealing their partners' private information about the state of the world—thus removing the role of strategic naivete—I find subjects are less willing to trade and are more responsive to their partners' information quality. My results suggest individual investors lose from trading because they fail to consider the information driving others' trading decisions and repeated experience does not fully correct this bias.

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# 1 Introduction

Individual investors often speculate in financial markets| trading according to information they may have about future prices (Hong and Stein 2007). Typically, such trades are unprofitable after accounting for transaction fees, and, on average, individual investors have been found to under-perform the market (Barber and Odean 2000). While losses from speculative trading are consistent with no-trade theorems (e.g. Milgrom and Stokey 1982) | which rule out equilibrium incentives for speculative trade| the existence of speculative trading poses a challenge for economists, as it suggests disagreement. Investors on opposite sides of a transaction must have opposing beliefs about the future value of the asset being traded, but such opposing beliefs cannot exist under standard common knowledge assumptions.<sup>1</sup> As Hong and Stein (2007) note, while mechanical explanations of disagreement exist | information may spread gradually or investors may hold heterogeneous priors| a shared subtlety of these explanations is that investors must under-appreciate the information contained in their counterpart's willingness to trade.<sup>2</sup>

Two separate views have emerged to explain why investors may under-appreciate others' information, causing them to trade at a loss. The first, overconfidence, emphasizes incorrect beliefs investors may hold about information quality: if an investor is overconfident about the quality of her information relative to others, she may trade despite understanding her counter-party has opposing information. The second, strategic naivete, suggests that investors may fail to account for others' information altogether. For instance, investors who buy a company's shares on the basis of good news about the company may not recognize that those selling shares are likely motivated by bad news about the company. While overconfidence has proven influential in behavioral finance, findings from behavioral and experimental economics suggest that strategic naivete may also play an important role in generating speculative trade.<sup>3</sup> In fact, an experiment by Magnani and Oprea (2017) studying inexperienced investors in a no-trade setting finds that overconfidence and strategic naivete are equally important and act as substitutes; when one or both is present, they find, inexperienced subjects commit no-trade violations at the same rate.

Can individual investors learn to better appreciate others' information with experience? While past experiments have shown that experience may alleviate behavioral biases, observational studies of individual investors suggest that trading losses cannot be traced to inexperience alone.<sup>4</sup> As Coval et al. (2005) and Barber et al. (2014) show, the returns of individual investors exhibit correlation over time, meaning those who earned lower returns in the past are more likely to earn lower returns in

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<sup>1</sup>See Aumann (1976).

<sup>2</sup>See Hong and Stein (1999) and Kandel and Pearson (1995), respectively, for examples of work that study gradual information flow and heterogeneous priors.

<sup>3</sup>For instance, Odean (1999) argues individual investors engage in speculative trading at a loss because they are overconfident, while Eyster et al. (2019) argues speculative trading may arise because investors ignore the correlation between others' actions and others' information.

<sup>4</sup>Both Armantier (2004) and Kagel and Richard (2001) find evidence that, with sufficient experience, subjects can learn to lower bids in common-value settings and avoid the winner's curse.

the future. Given that the majority of individual investors fail to "beat the market" (after adjusting for transaction fees), these findings suggest that individual investors regularly fail to fully appreciate others' information despite experience they accumulate. In this paper, I use a laboratory experiment to understand why. In particular, I design an experiment that allows subjects to gain experience and then use experience as a criterion to assess whether overconfidence or strategic naivete better explains speculative trading.

My experimental design adapts the Arrow-security trading (AST) game developed in [Magnani and Oprea \(2017\)](#) to create a setting in which overconfidence and strategic naivete can exist and interact with experience. Subjects are sorted into pairs, and each subject in a pair is endowed with an asset which pays out a low or high reward depending on which of two equally likely states is realized. Assets are assigned such that there is no aggregate uncertainty within a pair: if one subject's asset pays out the high reward, then her counterpart's asset pays out the low reward and vice versa. After receiving a signal about the more likely state, a subject may pay a transaction fee to trade assets with her partner, and assets are traded when both subjects in a pair choose to. The zero-sum nature of trade in this setting implies that in any symmetric equilibrium, neither subject in a pair should ever be willing to trade regardless of the signal she receives. However, a subject may be willing to trade when (1) she believes her signal is more accurate than her partner's (overconfidence) or (2) she fails to account for adverse selection in her partner's willingness to trade (strategic naivete). My experiment addresses which of these two channels proves more robust as subjects gain experience.

In order to study how subjects trade with experience, my design features a large number of rounds (40) and feedback after each round. Additionally, I introduce new design elements to separate the roles of overconfidence and strategic naivete. Subjects' signal accuracies are determined before they participate in the AST game, via a real-effort task, and subjects who successfully complete the task are endowed with a more accurate signal. Assigning accuracies beforehand facilitates a treatment condition studying whether subjects become less strategically naive over time: before making trading decisions, subjects are told their own signal accuracies and those of their partners, so that overconfidence cannot be the cause of unprofitable trading. That is, a subject's willingness to trade with a partner known to receive an equally accurate signal may be attributed to naive beliefs she holds about her partner's strategy.

Similarly, in order to clarify the role of overconfidence, I implement a treatment condition in which subjects also observe their partners' signal realizations (in addition to their own) before they make their trading decisions. That is, a subject observes two signal realizations | one generated by her own signal and one generated by her partner's signal. Thus, in the scenario that a subject chooses to trade when encouraged to do so by her own signal and discouraged to do so by her partner's, we may understand

her decision to be driven by overconfidence. The experiment's four treatments are implemented between-session and toggle these two levers (showing subjects signal accuracies, showing subjects partners' signal realizations) to understand how experience interacts with overconfidence and strategic naivete. In the baseline treatment **SN** (show nothing), neither accuracies nor partners' signal realizations are revealed. In treatment **SA** (show accuracies), each subject observes her own signal accuracy and her partner's signal accuracy. In treatment **SS** (show signals), each subject observes her own signal realization and her partner's signal realization. In treatment **SAS** (show accuracies and signals), subjects observe both types of information.

The data exhibit two important aggregate patterns. First, in the baseline treatment **SN**, subjects choose to trade *more* often as they gain experience; when their signals indicate their partners' assets are more likely to yield the high-reward, subjects choose to trade close to 60% of the time by the end of the experiment, compared to around 50% of the time at the beginning of the experiment. Second, subjects' perceptions of their own signal accuracies (whether from experience or revealed through the experimental interface) heavily influence their decisions to trade; in all treatments, there is a substantial and persistent gap between the rates at which subjects with low-accuracy and high-accuracy signals choose to trade.

The role of signal accuracy is especially evident in the baseline treatment, in which the trend of increasing willingness to trade is driven entirely by subjects with high-accuracy signals, who trade more as they receive more correct signal realizations. On the other hand, subjects with low-accuracy signals choose to trade moderately less in later rounds. Strikingly, by the end of the experiment, behavior in the baseline treatment resembles that in the accuracy revelation treatment **SA**, in which subjects with high-accuracy signals persistently choose to trade far more often than those with low-accuracy signals (roughly 70% and 30% of the time, respectively). The parallel between these two treatments suggests that strategic naivete is the more important channel in generating persistent speculative trade: subjects are adept at understanding their own accuracies in the baseline treatment, and subjects with high-accuracy signals finish each treatment choosing to trade at a high rate.

To better understand the interaction of experience with subjects' willingness to trade, I study how subjects respond to feedback they receive | focusing on proxies for their accuracies, the accuracies of their partners, and the adverse selection induced by partners' strategies. Consistent with the aggregate analysis, subjects in the baseline treatment **SN** are highly responsive to feedback about their own signal accuracy but under-react to feedback about others' signal qualities and selection bias. However, comparison with the auxiliary treatments **SA** and **SS** indicates that high-accuracy subjects' under-reaction to information about others' information quality is a consequence of their failure to internalize the adverse selection implied by trade | in other words, their inability to learn about others' strategies.

In particular, when signal accuracies are revealed in treatment **SA**, subjects receiving high-accuracy signals persistently choose to trade at the same rate| regardless of their partners' signal accuracy and despite the fact they accumulate enough feedback to account for adverse selection. On the other hand, when subjects observe their partners' signal realizations in treatment **SS**, even those who learn they receive high-accuracy signals trade less when their feedback indicates their partners are likely to have highly accurate signals.

I additionally analyze the ex-ante profitability of trading and find that subjects with high-accuracy signals persistently choose to trade when doing so is unprofitable. Using feedback subjects receive as proxies for beliefs, I calculate subjects' expected gains from choosing to trade and find that by the end of the experiment, high-accuracy subjects are just as likely to choose to trade when the expected gain from doing so is negative as when it is positive. This pattern is consistent across treatments, except when subjects are shown their partners' signal realizations in treatment **SS**. I conclude that persistent no-trade violations| those in which individual investors are expected to lose from trading| are primarily driven by investors' struggle to internalize the adverse selection implied by trade and that this effect becomes more pronounced for investors who have access to higher quality information.

The data exhibit an additional nuance: high-accuracy subjects choose to trade most frequently in treatment **SAS**, in which both overconfidence and strategic naivete are removed. This result, while surprising, is consistent with the finding that strategic naivete interacts with subjects' perception of their signal accuracies. I speculate that inexperienced subjects have primitive heuristics of when they should trade, and in particular, these heuristics emphasize the accuracy of their own signals. When told they possess high-accuracy signals at the start of the experiment, such subjects may ignore other elements of the experimental design| in particular, the signal realizations of their partners| intended to remove strategic naivete. On the other hand, in the treatment in which only their partners' signal realizations are shown, subjects may pay closer attention to their partners' signal accuracies (revealed through feedback), as they are less sure of their own signal accuracy. A similar pattern, in which people learn better when given less information, is documented in [Esponda et al. \(2020\)](#), who find that subjects become more adept at Bayesian updating when they are not presented with the likelihood function directly.

## 1.1 Related Literature

My work adds to a nascent experimental literature studying speculative trade. Earlier work in this vein include [Carrillo and Palfrey \(2011\)](#), whose design and results emphasize the role of trading mechanisms in generating no-trade violations, and [Angrisani et al. \(2011\)](#), who find that no-trade violations may diminish over time when subjects receive precise feedback. My results contrast with the latter's finding, as I document that subjects may actually be *more* willing to trade as they learn their information is high

quality.

Most similar to my paper, [Magnani and Oprea \(2017\)](#) examine the roles of both overconfidence and cursed reasoning (a specific form of strategic naivete) for inexperienced subjects and conclude that the two behavioral forces act as substitutes. In their experiment, subjects act as though their partners trade at random (not based on the signals they receive) and as if their partners' signals are essentially noise. My work contributes several new insights. I find that with experience, strategic naivete plays the more important role in generating speculative trade, as subjects are more capable of learning about others' information quality than others' strategies. Furthermore, I find that the prominence of strategic naivete is apparent even among inexperienced subjects in the experiment, as subjects choose to trade less after being told others' signals than after being told others' accuracies.<sup>5</sup> Finally, my results suggest overconfidence and strategic sophistication may actually be complementary, as subjects receiving high-accuracy signals are less responsive to information about their partners than those receiving low-accuracy signals.

I also contribute to a large behavioral finance literature supporting the link between overconfidence and trading. Notable examples of theoretical work in this vein include [Odean \(1998\)](#), [Scheinkman and Xiong \(2003\)](#), [Gervais and Odean \(2001\)](#); interested readers should reference [Barber and Odean \(2013\)](#) for a comprehensive survey. Observational studies typically rely on survey data and generally support the hypothesis that individual investors with higher assessments about their abilities trade more. Besides [Magnani and Oprea \(2017\)](#), experiments studying the link between overconfidence and trading include [Deaves et al. \(2008\)](#) and [Bregu \(2020\)](#), with both emphasizing overconfidence as a driver of trading. My findings add the following insight: investors may actually have accurate perceptions of their own information quality, but those with high information quality are also more likely to be strategically naive and ignore adverse selection.

The body of the paper is organized as follows. In Section 2, I outline the theory and design of the experiment. In Section 3, I highlight general features of the aggregate data, and in Section 4, I analyze how subjects' experience interacts with overconfidence and strategic naivete. In Section 5, I discuss the role of realized earnings, and Section 6 concludes the paper.

## 2 The Experiment

Each session of the experiment proceeds in two phases. To study how trading changes with experience, I implement a version of the Arrow Security Trading (AST) game developed in [Magnani and Oprea](#)

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<sup>5</sup>I speculate the reason for this contrast is likely related to how strategic naivete is removed from the experimental setting. My design directly shows subjects their signals, whereas [Magnani and Oprea \(2017\)](#) show subjects their partners' strategies, so that subjects must still recognize the association between trade occurring and their partners' signal. As emphasized by [Esponda and Vespa \(2014\)](#), people generally struggle exactly with this type of thinking.

(2017), which takes place during the second phase. In brief, subjects must decide whether to trade with a partner on the basis of a private signal they receive. A no-trade theorem applies to the setting, so that under rational expectations, trade should never occur with positive probability. Subjects play 40 repetitions of the AST game, receiving feedback after each round, so that they have the opportunities and information to learn from experience.

My treatment design investigates the effect of experience on two widely cited causes of no-trade violations: overconfidence in one's signal accuracy and strategic naivete (not accounting for the relationship between others' actions and others' information). In order to create a setting in which overconfidence is plausible, subjects' signal accuracies are determined via a guessing task implemented during the first phase of the experiment; subjects who submit correct responses are assigned higher accuracy signals in the AST phase of the experiment. In the baseline treatment **SN** (show nothing), subjects are not informed about their signal accuracies, but they have the opportunity to infer it through experience. To disentangle this type of learning from increasing strategic sophistication, treatment **SA** shows subjects their signal accuracies and their partners' signal accuracies; if subjects trade less with experience, we may then attribute the change to subjects' strategic sophistication. Similarly, to account for changes in subjects' strategic sophistication, treatment **SS** (show signals) shows subjects the realizations of their partners' signals| in addition to their own| so that subjects' abilities to infer their partners' private information from trade is irrelevant. Thus, subjects' willingness to trade may be better attributed to their beliefs about signal accuracies. The final treatment **SAS** (show accuracies and signals) applies both treatment variations, showing subjects the signal accuracies and signal realizations of both subjects in a pairing.

I outline the experimental design as follows. In Section 2.1, I detail the AST game and the guessing task preceding it. In Section 2.2, I illustrate how overconfidence and strategic naivete may generate trade and explain the treatments design, highlighting how it controls for these different channels in the experimental data. Finally, I discuss further implementation details in Section 2.5.

## 2.1 The AST Game

The AST game is a simultaneous two-player game with private information and two assets, a blue ticket ( $B$ ) and a green ticket ( $G$ ). Each player starts with a different colored ticket  $t \in \{B, G\}$ , so that, for instance, if subject  $i$  starts with the green ticket ( $t_i = G$ ), her partner  $j$  starts with the blue ticket ( $t_j = B$ ).<sup>6</sup> At the end of the game, one ticket pays out a high-reward of \$14 while the other pays out a low-reward of \$4; ex-ante, each ticket is equally likely to pay out the high-reward of \$14. After observing realizations of a binary private signal  $s \in \{B, G\}$ , each subject then decides whether to keep her assigned

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<sup>6</sup>For the remainder of the paper, I will use the pronouns she/her for subject  $i$  and he/his/him for subject  $j$ . When a subject index is not specified, I will use she/her.

ticket ( $a = T$ ) or to swap tickets with her partner ( $a = K$ ). Trade costs each subject a transaction fee of \$2 and occurs only if both subjects choose to trade.

Let the state of the world  $\omega \in \{B, G\}$  be represented by the ticket which pays the high-reward at the end of the game. Subjects' signal realizations are independent, conditional on the state of the world and indicate which state is likelier, such that the conditional likelihood the state matches a given signal realization  $s^i$  is  $\alpha = \Pr[\omega = s^i | S = s^i]$ . In the design of the experiment, the signal accuracy  $\alpha_i$  of a given subject  $i$  is either 50% or 80% and is determined by  $i$ 's performance in the guessing task preceding the AST game.<sup>7</sup> In the baseline treatment, **SN**, subjects are not told their accuracies.

Proposition 1 establishes the benchmark prediction for the experiment: trade should never be observed in the data.<sup>8</sup> Note that while we have not discussed subjects' beliefs about the distribution of signal accuracies, the proposition holds for any common-knowledge distribution of accuracies. Additionally, observe that the proposition rules out *realized trades*; there are equilibria in which subjects may coordinate such that subject  $i$  chooses to trade with positive probability but subject  $j$  never trades. Restricting attention to symmetric equilibria implies that neither subject should ever choose to trade.

**Proposition 1 (No Trade)** *There is no Bayesian Nash Equilibrium in which trade occurs with positive probability.*

The intuition of Proposition 1 may be illustrated by considering subject  $i$ 's expected gain from trading (over keeping) when her signal realization indicates her partner  $j$ 's ticket is likelier to pay out the high-reward ( $s_i = t_j$ ).<sup>9</sup> Before proceeding, note that when  $j$  chooses to keep ticket  $t_j$ ,  $i$ 's choice does not affect her expected payoffs, and so  $i$ 's overall incentives to trade depend on only her expected payoffs when  $j$  chooses to trade. Now, represent subject  $i$ 's conditional expected gain from trading under these assumptions ( $s_i = t_j, a_j = T$ ) as  $\Delta_i = E[x_j - x_i | s_i = t_j, a_j = T]$ , where  $x_j, x_i$  are random variables for the respective rewards paid out by tickets  $t_j, t_i$ .

For the sake of illustration, assume further that both subjects  $i$  and  $j$  have high-accuracy signals ( $\alpha_i = \alpha_j = 80\%$ ) and this fact is common-knowledge.<sup>10</sup> Conditional on  $j$  choosing to trade, subject  $i$  must consider her gains from trading under two cases: subject  $j$ 's signal realization matches  $i$ 's ticket ( $s_j = t_i$ ) and subject  $j$ 's signal realization matches  $j$ 's ticket ( $s_j = t_j$ ). Let  $\beta_j = \Pr[s_j = t_i | a_j = T, s_i = j]$  represent the probability of the former case and observe that it indicates the extent of adverse selection implied by trade: as  $\beta_j$  increases, there is a greater probability that  $j$ 's willingness to trade indicates that  $i$ 's ticket is likely to pay out the high-reward, decreasing  $i$ 's expected gain from trading  $\Delta_i$ . To

<sup>7</sup>Signals are described as "clues" in the language of the experiment.

<sup>8</sup>For all proofs, we refer interested readers to Magnani and Oprea (2017).

<sup>9</sup>Observe that trading when  $s_i = t_i$  is a weakly dominated strategy, regardless of signal accuracy.

<sup>10</sup>Observe that when each subject knows his/her signal accuracy, we may arrive at this common knowledge assumption by noting that trading after any signal realization is weakly dominated when a subject's signal is low-accuracy ( $\alpha = 50\%$ ).



observe this formally, consider the following decomposition of  $J_i^j$ .

$$\begin{aligned}
J_i^j &= E[x_j - x_i - 2js_i = t_j, a_j = T] \\
&= \beta_j E[x_j - x_i - 2js_i = t_j, s_j = t_i] + (1 - \beta_j) E[x_j - x_i - 2js_i = t_j, s_j = t_j] \\
&= \beta_j \underbrace{\frac{8\alpha_i(1 - \alpha_j) - 12(1 - \alpha_i)\alpha_j}{\alpha_i(1 - \alpha_j) + (1 - \alpha_i)\alpha_j}}_{s_j = t_i} + (1 - \beta_j) \underbrace{\frac{8\alpha_i\alpha_j - 12(1 - \alpha_i)(1 - \alpha_j)}{\alpha_i\alpha_j + (1 - \alpha_i)(1 - \alpha_j)}}_{s_j = t_j} \tag{1}
\end{aligned}$$

As  $\alpha_i = \alpha_j = 80\%$  by assumption, the expected gains from trade are negative when  $s_j = t_i$  and positive when  $s_j = t_j$ . Therefore,  $J_i^j$  is negative for  $\beta_j$  close to 1 and positive for  $\beta_j$  close to 0. What remains to be considered is the possibility of trade in equilibrium, given alternative levels of  $\beta_j$ . First, observe that if  $\beta_j$  is not well-defined, then  $j$  never chooses to trade, implying the probability of trade is zero by construction. Second, notice that  $\beta_j < 1$  implies that  $j$  sometimes chooses to trade when  $s_j = t_j$ , which is not a best response for  $j$  if subject  $i$  ever chooses to trade with positive probability | shutting off this possibility of trade occurring in equilibrium. This leaves the case that  $\beta_j = 1$ , which implies that  $J_i^j$  is negative, and so the optimal choice for  $i$  is to keep her own ticket | in spite of receiving the signal realization  $s_i = t_j$ , which suggests  $j$ 's ticket is highly likely to pay out the high-reward.

*You own a Green Ticket: Submit a trading choice for each clue*

Clue	Your Choice	
Green	Trade for Blue Ticket	Keep my Green Ticket
Blue	Trade for Blue Ticket	Keep my Green Ticket

Figure 1: AST Choice Interface

**Implementation of AST Game** The AST game takes place during the second phase of our experiment, after four rounds of the guessing task in phase 1. Subjects play 40 rounds of the AST game, with random re-matching and fixed roles (subjects always start with the same ticket color). Subjects' signal accuracies are fixed across all rounds and are determined by their responses in the final round of the guessing task: subjects who respond correctly (incorrectly) receive a signal that matches the high reward ticket with 80% (50%) probability. We employ the strategy method, asking subjects to submit a trading decision for each possible signal realization. After each round, subjects receive the following information: **(1)** their signals and their partners' signals; **(2)** their trading decisions and their partners' trading decisions; **(3)** whether trade occurred; **(4)** the state of the world (i.e. which ticket paid out the high amount); and **(5)** their earnings.

**The Guessing Task** Prior to playing the AST game, subjects complete a guessing task in order to determine signal accuracies. Subjects are shown a grid of 400 green and blue dots and are then asked to report whether green or blue is the more common color.<sup>11</sup> Subjects complete three practice rounds before completing a fourth, incentivized round; those who respond correctly (incorrectly) in the fourth round earn \$10 (\$5) and are assigned a signal that is 80% (50%) likely to match the high-reward ticket in the AST game.<sup>12</sup>

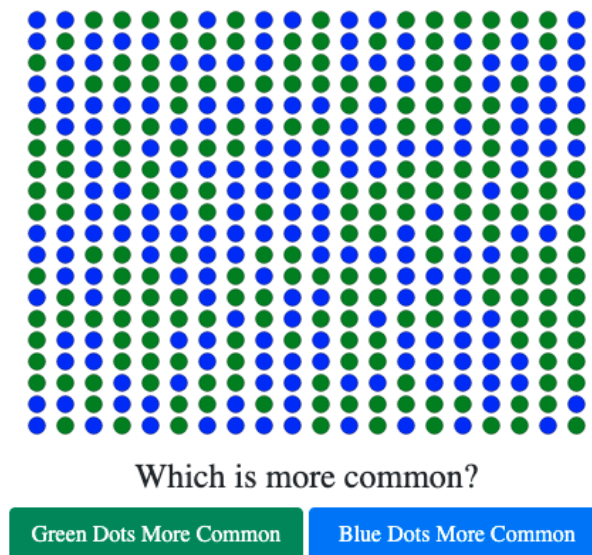


Figure 2: Guessing Task Interface

## 2.2 Channels for Trade

In addition to studying the role of experience on trading, my experiment focuses on understanding how experience interacts with two leading explanations for over-trading: overconfidence and strategic naivete. In this Section, I discuss the theoretical role each explanation could play in the AST game.

### 2.2.1 Overconfidence

Overconfidence is commonly cited in the behavioral finance literature as a primary reason why individual investors trade so much—and at a loss. As [Moore and Healy \(2008\)](#) and [Barber and Odean \(2013\)](#) discuss, the term “overconfidence” encompasses three distinct beliefs people may hold about their abilities: **(1)** believing one’s ability is higher than it actually is | *over-estimation*; **(2)** believing one’s ability is higher than the average person’s | *over-placement*; and **(3)** believing one knows more about her own ability

<sup>11</sup>[Magnani and Oprea \(2017\)](#) use the same real-effort task to determine signals. However, in their design, the color of the high-reward ticket (asset in their experiment) is exactly the more common color. Subjects first submit strategies mapping signals to trading decisions and then complete the real-effort task, so that the color they report as more common is the signal that determines their actions. We use the real-effort task to assign accuracies so that we may reveal signal accuracies as a treatment condition.

<sup>12</sup>Instructions for the AST game are dispersed *after* subjects complete the guessing task. In the instructions for the guessing task, we only inform subjects that responding correctly in the fourth round will lead to higher earnings.

than she actually does | *over-precision*.<sup>13</sup> In this paper, I focus specifically on the roles over-estimation and over-placement and how they change with experience.

Propositions 2 and 3 establish, respectively, that subjects may be incentivized to trade when they (1) believe their signal is accurate enough and (2) believe their signal is sufficiently better than their partners'. First, recall the definition of *trading-on-signal*. A subject trades-with-signal when she trades if and only if her signal indicates her partner's asset is more likely to yield the high reward; in other words, the subject naively trades according to the information she receives. Proposition 2 provides scope for trading via overestimation: trading-on-signal is optimal for a subject, given naive behavior from her partner, when she believes her signal is sufficiently accurate. Likewise, Proposition 3 establishes that trading-on-signal can be optimal for a subject when she believes her signal accuracy is sufficiently better than her partner's. In summary, subjects have an incentive to trade if they believe their signals are sufficiently accurate | in the absolute sense and relative to others | but may incur losses through trade if these beliefs are overly optimistic.

**Proposition 2** *Let  $\hat{\alpha}_i$  be subject  $i$ 's expectation of her signal's accuracy. When  $\hat{\alpha}_i < \frac{3}{5}$ , never trading is a dominant strategy, and when  $\hat{\alpha}_i \geq \frac{3}{5}$ , trading-on-signal is a best-response to any constant strategy from her partner.*

**Proposition 3** *Let  $\alpha_j$  be subject  $i$ 's expectation of her partner's signal accuracy, and let  $\hat{\alpha}_i = \frac{\alpha_i}{1-\alpha_i}$  and  $\hat{\alpha}_j = \frac{\alpha_j}{1-\alpha_j}$  be the signal-to-noise ratios of subject  $i$  and her partner, respectively. Trading-on-signal is a best response to any strategy from her partner if  $\frac{\hat{\alpha}_i}{\hat{\alpha}_j} \geq \frac{3}{2}$ .*

### 2.2.2 Strategic Naivete

A different view of trading emphasizes failures of strategic reasoning as a source of overtrading. As Eyster et al. (2019) highlights, markets may exhibit higher trading volume when investors fail to invert the mapping from others' signals to prices. More generally, evidence from past experiments suggest people struggle to behave optimally in settings with private information. For instance, subjects in both winner's curse and Acquire-a-Company experiments consistently overbid for common value assets | see Charness and Levin (2009) and Ball et al. (1991) respectively.

The idea that agents fail to appreciate the link between others' information and others' actions, formalized as *cursedness* by Eyster and Rabin (2005), has proven particularly influential for understanding strategic shortcomings in settings with private information. Building their model with cursed agents, Eyster et al. (2019) demonstrates that cursedness can be a source of excessive trading, alternative to

<sup>13</sup>Moore and Healy (2008) provide the following illustration of over-precision. Consider a person who is asked to provide intervals to 10 numerical questions | e.g. what is the length of the Nile River | such that the correct answer is contained in the interval 90% of the time. An individual exhibits over-precision when fewer than 9 of her intervals contain the correct answer.

assumptions about overconfidence. In the lab, cursedness has also proven to be useful for understanding why people violate no-trade theorems; both Carrillo and Palfrey (2011) and Magnani and Oprea (2017) find support for cursedness in their data. Below, I formalize cursedness in the AST game and show that it allows for trade in equilibrium.

**Definition 1** Let  $\sigma_i : \mathcal{F}B, Gg \rightarrow [0, 1]$  describe subject  $i$ 's strategy, such that after receiving signal  $s_i \in \mathcal{F}B, Gg$ , subject  $i$  trades ( $T$ ) with probability  $\sigma_i(s_i)$ . Additionally, let  $\bar{\sigma}_i(s_i)$  describe subject  $i$ 's average strategy when subject  $i$  receives signal  $s_i$ , such that the probability of trading is given by

$$\bar{\sigma}_i(s_i) = \sum_{s_{-i} \in \mathcal{F}B, Gg} p_i(s_{-i}|s_i) \sigma_i(s_{-i}),$$

where  $p_i(s_{-i}|s_i)$  is the subject  $i$ 's subjective probability, conditional on observing signal  $s_i$ , that subject  $i$  receives signal  $s_{-i}$ . A subject  $i$  is  $\chi$ -cursed if she best responds to the mixture  $\chi(s_i)$ , where

$$\chi(s_i) = \sum_{s_{-i} \in \mathcal{F}B, Gg} p_i(s_{-i}|s_i) [\chi \bar{\sigma}_i(s_i) + (1 - \chi) \sigma_i(s_{-i})].$$

In words, a cursed subject confuses the average distribution of actions her partner chooses with the distribution of actions her partner chooses after receiving a particular signal realization. When  $\chi$  is 0, subjects are fully rational, and when  $\chi$  is 1, subjects are fully cursed, behaving as if their partner's always play the same mixed strategy given every signal realization. In a  $\chi$ -cursed equilibrium, each subject best responds to  $\chi(s_i)$ . Proposition 4 establishes that trading-with-signal may occur in equilibrium (there are always trivial no-trade equilibria) if subjects are sufficiently cursed. The intuition is that cursed subjects ignore the adverse selection implied by trade. From the perspective of fully cursed subjects, their partners choose to trade 50% of the time at random; they fail to understand that the 50% of the time their partners choose to trade coincide exactly with the instances in which their partners' signals disagree with their own.

**Proposition 4** There exists  $m \in (0, 1)$  such that for  $\chi > m$ , there exists a cursed equilibrium in which subjects trade-on-signal.

Note that alternative behavioral concepts | such as limited depth of reasoning (e.g. Camerer et al. 2004) | may be applied to explain why people struggle in strategic settings with private information. Additionally, recent work on contingent reasoning (see Esponda and Vespa 2014) suggests that people's difficulty in such settings may actually be deeper, rooted in their struggle to process hypothetical scenarios, rather than simply overlooking correlations. As such, although cursedness has been applied in the past to study no-trade violations, I refer to failures of strategic reasoning as simply strategic naivete.

## 2.3 Treatments

I run four treatments to fully examine the following two questions: (1) how does experience affect trading behavior and (2) how does experience interact with overconfidence and naivete? In the baseline treatment **SN** (show nothing), the AST game is implemented as described in 2.1. After each round, subjects are told their partners' actions, their partners' signals, the state of the world, and their payoffs, but do not receive any additional information to mitigate the roles of overconfidence or naivete.

*You own a Green Ticket: Submit a trading choice for each clue pair*

Your Clue Partner's Clue		Your Choice	
Green	Green	Trade for Blue Ticket	Keep Green Ticket
Green	Blue	Trade for Blue Ticket	Keep Green Ticket
Blue	Green	Trade for Blue Ticket	Keep Green Ticket
Blue	Blue	Trade for Blue Ticket	Keep Green Ticket

Figure 3: Choice Interface for Treatment **SS**

In order to disentangle these two behavioral traits, I implement additional treatments between-sessions. The approach is to "help" subjects by showing them information (about signal accuracies or about signal realizations) they might otherwise have to deduce via introspection or updating through feedback. Treatment **SA** (show accuracies) focuses on the role of strategic naivete by informing subjects of their signal accuracies and their partners' signal accuracies. That is, each round, subjects are told their own signal accuracy and their partners' signal accuracies. In the analysis, I focus in particular on cases in which two subjects with high-accuracy signals are paired together, as willingness to trade can no longer be rationalized via overplacement. Analogously, in treatment **SS** (show signals), subjects are shown both their own signals and their partners' signals, in order to understand the role of overplacement. Trade is still implemented via the strategy method, so that in the experiment's choice interface, subjects must choose whether to trade for each combination of signal realizations | see Figure 3. Trading may no longer be attributed to strategic naivete, as subjects no longer need to link hypothetical signal combinations to the contingency of trade. Specifically, in my analysis, I focus on the case in which each subject in a pair receives the signal matching the other's ticket (third row in Figure 3). In this scenario, each subject understands that her partner's signal contradicts her own, and thus willingness to trade suggests a subject believes her signal to be more accurate than her partner's. In the final treatment **SAS** (show accuracies and signals), subjects are shown both types of information (signal accuracies, their partners' signals), so neither overplacement nor strategic naivete should motivate subjects to trade. Thus, any residual willingness to trade may serve as a benchmark by which to compare willingness to trade in other treatments.

Treatment	Signal Accuracy		Signal Realization	
	Own	Partner's	Own	Partners'
SN	Not Shown	Not Shown	Shown	Not Shown
SA	Shown	Shown	Shown	Not Shown
SS	Not Shown	Not Shown	Shown	Shown
SAS	Shown	Shown	Shown	Shown

## 2.4 Eliciting Beliefs

I elicit subjects' beliefs about signal accuracies in order to evaluate initial overconfidence and to study how overconfidence changes as subjects experience feedback. Beliefs are elicited twice: once after the guessing task but before the AST game and second after the AST game. In each round of elicitation, each subject chooses a number  $b^{self}$  between 0 to 100 on a slider to rate how likely they were to have submitted a correct report in the final round of the guessing task | i.e. a subject would choose 100 to indicate 100% likelihood of a correct report.<sup>14</sup> Subjects then choose a second number  $b^{others}$  between 0 and 100 to rate the percentage of other subjects in the session who reported correctly in the final round of the guessing task. For treatments **SA** and **SAS**, only beliefs about others are elicited after the AST game, as subjects are directly told their own signal accuracies during the AST game.

Subjects are incentivized to report correct beliefs via the quadratic scoring rule.<sup>15</sup> For each subject  $i$ , let  $g_i = 100$  if the subject's reported correctly in the guessing task and 0 otherwise, and let  $\rho_i$  be the percentage of other subjects who reported correctly | i.e.  $\rho_i = 100$  if 100% of other subjects reported correctly. For each round of elicitation,  $q \in \{self, others\}$  is chosen at random, and subjects are paid according to the quadratic distance between  $b^q$  and  $c(q)$ , where  $c(self) = g_i$  and  $c(others) = \rho_j$ . Specifically, subjects receive  $s(q)$  dollars, such that

$$s(q) = 4 \frac{(b^q - c(q))^2}{5000}.$$

## 2.5 Implementation Details

The experiment is conducted over Zoom with 160 subjects recruited from NYU's undergraduate population.<sup>16</sup> There are four sessions of each treatment, with sessions consisting of between 8 to 12 subjects. In addition to their earnings from the other tasks (the guessing task and the two belief elicitation tasks), subjects are paid for one randomly chosen round of the AST game. Payment information is revealed only after the experiment concludes, and subjects earn \$22.82 on average.

Instructions for the experiment are distributed in sequence, so that subjects do not receive

<sup>14</sup>I elicit beliefs about guessing task performance instead of directly about signals in order to elicit beliefs before introducing the AST game.

<sup>15</sup>See Schotter and Trevino (2014).

<sup>16</sup>The software for the experiment was written in oTree (Chen et al., 2016), and subjects were recruited via hroot (Bock et al., 2014).

instructions for a task until all preceding tasks have been completed. Instructions are first shared via Zoom's screen-sharing function and then read aloud. Additionally, to ensure subjects have access to the instructions during the experiment, they are provided a Dropbox link that enables viewing of the instructions during the course of the experiment.<sup>17</sup> While instructions are being presented, questions are asked (and repeated if necessary) and answered aloud so that all subjects can hear.

### 3 Findings

I structure the experiments' main findings as follows. To facilitate subsequent analysis of the data, Section 3.1 organizes the types of choices subjects face. Section 3.2 motivates the plausibility of overconfidence and strategic naivete as biases that may generate trade. Section 3.3 describes how experience affects trading decisions in aggregate.

#### 3.1 Organizing the Data

In the experiment, subjects make trading decisions in response to up to four different signal configurations. A subject's signal realization may be green or blue | indicating whether her ticket or her partner's ticket is likelier to pay out the high reward of \$14 | and likewise, a subject's partner's signal realization may be green or blue. In treatments **SS** and **SAS**, in which subjects also observe their partners' realizations, subjects thus make four different choices each round (as they submit full strategies). This richness of data provides various avenues of analysis. In order to focus on the roles of overconfidence and strategic naivete as causes of trade, I limit analysis to a subset of signal configurations I will describe as *crossing*. In this section, I provide a taxonomy that classifies different signal configurations and then motivate the focus on *crossing* signal configurations.

**A Taxonomy of Trading Choices** Consider a subject  $i$  and her partner  $j$  and again note that four configurations of signal realizations are possible. For treatments **SS** and **SAS**, in which subjects must make a choice for each of these configurations, I provide the following classification (from the perspective of subject  $i$ ).

1. *Same-Own (SS, SAS)*:  $s_i = s_j = t_j$ . Subject  $i$ 's and subject  $j$ 's signal-realizations match subject  $i$ 's initial ticket.
2. *Crossing (SS, SAS)*:  $s_i = t_j$  and  $s_j = t_i$ . Subject  $i$ 's signal realization matches subject  $j$ 's signal, and subject  $j$ 's signal realization matches subject  $i$ 's initial ticket | signals \cross."

---

<sup>17</sup>Downloads are disabled, so that the instructions cannot be dispersed outside the experiment.

3. *Reverse-Crossing (SS, SAS)*: Subject  $i$ 's signal realization matches subject  $i$ 's signal, and subject  $j$ 's signal realization matches subject  $j$ 's initial ticket.
4. *Same-Partner (SS, SAS)*:  $s_i = s_j = t_j$ . Subject  $i$  and subject  $j$ 's signal realizations match subject  $j$ 's initial ticket.

In treatments **SN** and **SA**, subjects do not make responses to the full set of signal realizations, as they observe only their own realizations. For these treatments, the definition of *crossing* is broadened to mean all cases in which a subject's signal matches her partner's ticket. Likewise, when a subject's signal does not match her partner's ticket, the situation is described as *non-crossing*.

1. *Crossing (SN, SA)*:  $s_i = t_j$ . Subject  $i$ 's signal realization matches subject  $j$ 's initial ticket.
2. *No Crossing (SN, SA)*:  $s_i = t_i$ . Subject  $i$ 's signal realization matches her own initial ticket.

$s_i$	$s_j$	<b>SN</b>	<b>SA</b>	<b>SS</b>	<b>SAS</b>
$t_i$	$t_i$	No Crossing	No Crossing	Same-Own	Same-Own
$t_i$	$t_j$	No Crossing	No Crossing	Reverse-Crossing	Reverse-Crossing
$t_j$	$t_i$	Crossing	Crossing	Crossing	Crossing
$t_j$	$t_j$	Crossing	Crossing	Same-Partner	Same-Partner

Table 1: Taxonomy of Signal Realizations (for Subject  $i$ )

*Crossing* is defined differently across treatments to facilitate study of (1) whether subjects trade when their own signal realizations indicate they should trade and (2) whether observing partners' signal realizations affects this decision. That is, to what extent do subjects trade according to their signals because they undervalue the possibility that their partners receive the opposite signals? A treatment-dependent definition of *crossing* eases analysis of this question: we may compare rates at which subjects choose to trade when they receive a signal realization matching their partners' assets (**SN** and **SA**) and the narrower situation in which they also learn that their partners receive the opposite signal realizations (**SS** and **SAS**).

Table 2 decomposes the frequency with which subjects *choose* to trade | that is, willingness to trade | across these different categories of situations. In treatments **SN** and **SA**, subjects rarely trade "against" their own signals, as the frequency of trade in *no crossing* situations is low and decreases over the course of the experiment | suggesting subjects understand the relationship between signals and ticket payouts. In a similar vein, frequency of trade is low in *same-own* situations and high in *same-partner* situations: a subject in treatment **SS** or **SAS** is unlikely (likely) to trade when both signals match her (partner's) ticket. Additionally, the data show subjects are moderately willing to trade in *reverse crossing* situations; this is primarily driven by low-accuracy subjects who are matched with higher accuracy partners and thus trade according to their partners' signals. Finally, notice that by



the end of the experiment, (1) trading rates in *crossing* situations are lower in treatments **SS** and **SAS** than in **SN** and **SA** and (2) in treatments **SS** and **SAS**, trading rates in *same-partner* configurations are higher than those in *crossing* configurations. These observations suggest that strategic naivete plays an important role in generating trade. Subjects are less likely to trade when they learn their partners' signal realizations are opposite theirs and are much likelier to trade when they learn their partners hold the same signal realizations; when the distinction is not made for them via the experimental interface (in treatments **SN** and **SA**), subjects choose to trade at higher rates.

Treatment	Crossing	Non-Crossing	Reverse-Crossing	Same-Own	Same-Partner
SN	0.52 (0.03)	0.17 (0.02)			
SA	0.58 (0.02)	0.16 (0.02)			
SS	0.47 (0.02)		0.21 (0.02)	0.11 (0.02)	0.65 (0.02)
SAS	0.57 (0.03)		0.26 (0.02)	0.10 (0.02)	0.76 (0.02)

(a) First 10 Rounds

Treatment	Crossing	Non-Crossing	Reverse-Crossing	Same-Own	Same-Partner
SN	0.59 (0.03)	0.09 (0.01)			
SA	0.51 (0.02)	0.14 (0.02)			
SS	0.46 (0.02)		0.25 (0.02)	0.07 (0.01)	0.73 (0.02)
SAS	0.48 (0.03)		0.31 (0.02)	0.05 (0.01)	0.75 (0.02)

(b) Last 10 Rounds

Table 2: Trade Frequencies by Situation

**Choice of Data** Note that in treatments **SN** and **SA**, choosing to trade in *non-crossing* situations is weakly dominated, as subjects' signals are at least 50% likely to match the high-reward ticket, and so the main question of interest is whether subjects trade in *crossing* situations. That is, do subjects trade when their own signals suggest that they should? While subjects' behavior in other situations is of interest | for instance, whether they choose to trade in *non-crossing* situations indicates their level of rationality | the insights from such choices are auxiliary to the main question. For this reason, I limit further analysis of the data to subjects' choices in *crossing* situations (unless otherwise specified).

Note furthermore that in the baseline treatment **SN**, a subject may choose to trade in *crossing* situations if (1) she is overconfident about the relative accuracy of her signal or (2) she is strategically naive and ignores the adverse selection implied by trade. The purpose of treatment **SA**, in which signal accuracies are made common knowledge, is to rule out the first explanation, so that willingness to trade may be attributed to strategic naivete. However, in treatments **SA** and **SAS**, choosing to trade is always weakly dominant for high-accuracy subjects when paired with low-accuracy subjects and thus does not indicate strategic naivete. Thus, for treatments **SA** and **SAS**, I drop observations in which the accuracy of subject  $i$ 's signal is greater than that of her partner's.

## 3.2 Plausibility of Behavioral Channels

Before discussing how experience affects trading behavior, I first present evidence suggesting that overconfidence and strategic naivete may play a role in the data.

### 3.2.1 Overconfidence

Figure 4 presents subjects' elicited beliefs about their performances in the guessing task. For each treatment, it computes the average probability subjects report about whether they successfully completed the guessing task (*Self*) and the average probability subjects report about whether *other* subjects successfully completed the guessing task (*Others*). In each treatment, the average subject believes she was more likely to have completed the guessing task than other subjects in her session, and, additionally, the true frequency of successful completion is lower than the average likelihood subjects report for themselves. Put differently, subjects are overconfident about their chances of having guessed correctly compared to the true probability (around 60%), and underrate the chances other subjects guessed correctly. Given subjects understand the mapping from success in the guessing task to signal accuracies in the AST game, then the average subject is overconfident about her relative signal accuracy. As such, we may plausibly attribute willingness to trade in treatments **SN** and **SS** to overconfidence; recall that in treatments **SA** and **SAS**, subjects observe both their own and their partners' signal accuracies.

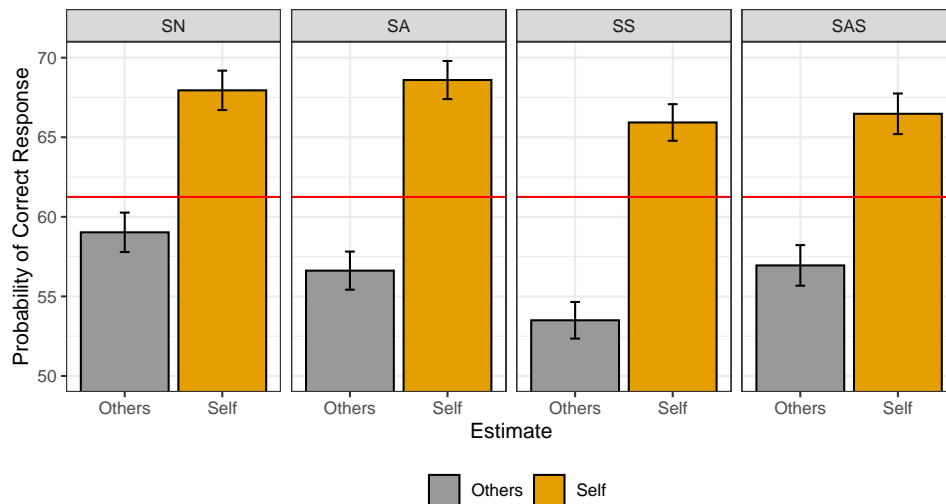


Figure 4: Elicited Beliefs about Guessing Task Performance

### 3.2.2 Strategic Naivete

In order to understand whether subjects commit no-trade violations because they are strategically naive, it is important to understand the extent to which adverse selection exists in the data at all. That is, conditional on subject  $i$  receiving the signal realization matching subject  $j$ 's ticket ( $s_i = t_j$ ) and given

that subject  $j$  chooses to trade, how likely is it that subject  $j$ 's signal matches  $i$ 's ticket ( $s_j = t_i$ )? If this likelihood ( $\beta_j$ ) is low | for instance, subject  $j$  may behave irrationally and always choose to trade | then subject  $i$  may in fact be behaving optimally by choosing to trade with  $j$ .

Figure 5 plots the level of adverse selection  $\beta_j$  subjects face as the experiment progresses.  $\beta_j$  is calculated directly using the strategies subjects submit each round. For instance, suppose that subject  $j$  chooses to trade if and only if  $s_j = t_i$ ; then,  $j$ 's partner  $i$  faces adverse selection of  $\beta_j = 1$ . The red series *Mean* reports the average level of adverse selection induced by subjects' strategies, while the other two series report the adverse selection induced by subjects with low and high-accuracy signals. To illustrate, by the end of treatment **SA**, if subject  $i$ 's partner  $j$  has a high-accuracy signal, then conditional on  $j$  being willing to trade, there is close to probability 1 that  $j$ 's signal realization matches  $i$ 's ticket. On the other hand, if subject  $i$ 's partner  $j$  has a low-accuracy signal, the conditional probability  $j$ 's signal realization matches  $i$ 's ticket is less than 60%.

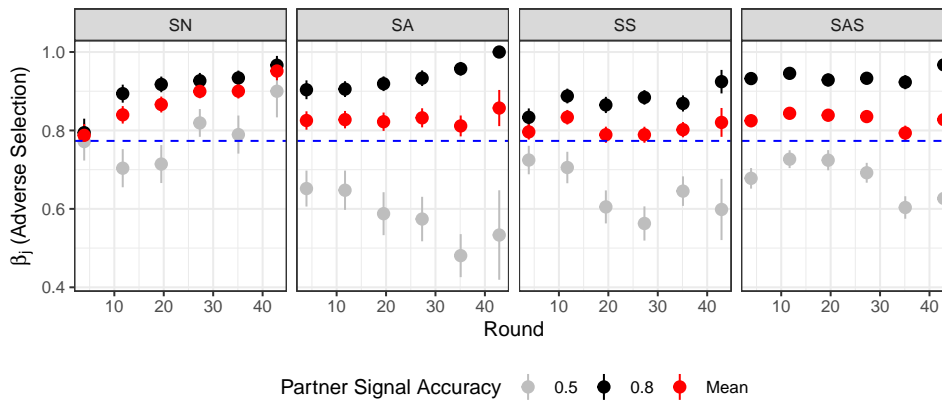


Figure 5: Adverse Selection

The dashed blue line (set around 77%) in Figure 5 indicates the maximum level of adverse selection at which trading in crossing situations is pro table for subject  $i$ , given that both subjects  $i$  and  $j$  have high-accuracy signals. Note that in all treatments, the mean level of adverse selection exceeds this maximum level, implying that trading in crossing situations is not pro table for subjects who face partners with equally accurate signals.<sup>18</sup> In particular, subjects in **SA** with high-accuracy signals should not trade when their partner's signal is also high accuracy.

### 3.3 Evolution of Trade

I now evaluate the two main questions of the experiment. First, do subjects trade less with experience? Second, which behavioral channel | overcon dence or strategic naivete | is more robust to experience?

<sup>18</sup>The maximum level of adverse selection at which it is pro table for a subject with signal accuracy  $\alpha_i$  to be trading with a partner with equal signal accuracy is increasing in  $\alpha_i$ .

To address these questions, I focus on subjects' *willingness to trade* in crossing situations.<sup>19</sup> That is, how often do subjects choose to trade when encouraged to do so by their own signal realizations (and, in treatments **SS** and **SAS**, discouraged to do so by their partners')? The findings from Section 3.2 suggest that both overconfidence and strategic naivete may motivate inexperienced subjects to choose to trade at an expected loss. In treatments **SN** and **SS**, inexperienced subjects may choose to trade at an expected loss because they overestimate the relative accuracy of their signals. Similarly, in treatments **SN** and **SA**, inexperienced subjects may choose to trade at an expected loss because they are strategically naive and ignore the high levels of adverse selection implied by their partners' strategies.

Figure 6 studies how willingness to trade evolves in aggregate: for each treatment, it plots subjects' average willingness to trade over the course of the experiment.<sup>20</sup> Surprisingly, in the baseline treatment (**SN**), subjects on average become *more* willing to trade after gaining experience: the rate at which they choose to trade increases from 50% at the beginning of the experiment to 60% by the end of the experiment. However, this trend disappears when either treatment is applied. In treatment **SA**, in which subjects observe signal accuracies, subjects initially choose to trade around 55% of the time, but this rate decreases to around 45% by the end of the experiment. In treatment **SS**, in which both signal realizations are common knowledge, subjects consistently choose to trade between 45% and 50% of the time throughout the experiment. When both treatment variations are present, in treatment **SAS**, subjects steadily choose to trade less over time, choosing to trade less than 40% of the time by the end of the experiment.

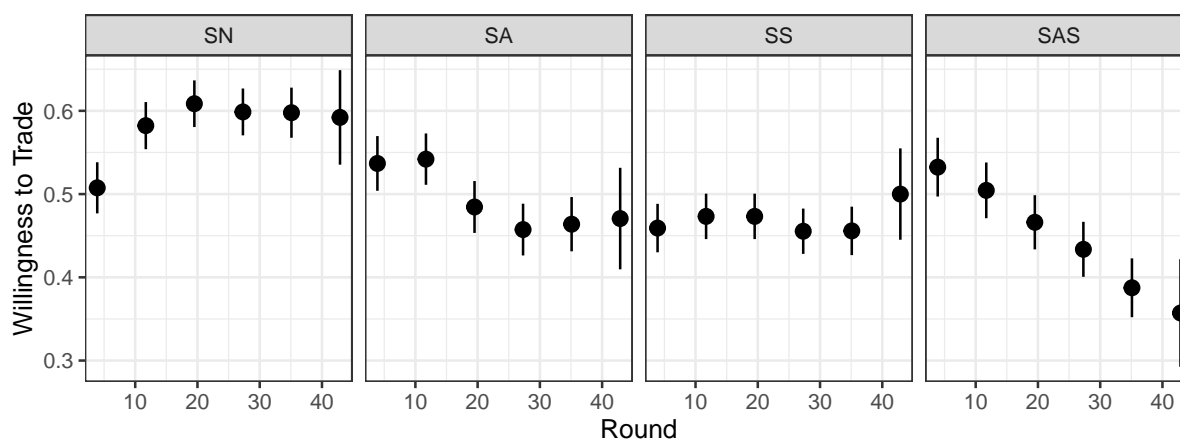


Figure 6: Effect of Experience on Trade Rate

Overall, the findings from Figure 6 show that experience alone may not be enough to reduce speculative trading. In fact, experience causes subjects in treatment **SN** to become *more* speculative.

<sup>19</sup>Figure 14 in the Appendix provides additional evidence that subjects' behavior evolves with experience in alternative situations. In particular, it plots the frequency with which subjects choose weakly dominated strategies in each treatment, and shows that the frequency with which subjects choose these strategies declines substantially throughout the course of the experiment.

<sup>20</sup>Observations are binned across rounds, and the vertical lines represent standard errors.

Comparing aggregate willingness to trade across treatments is suggestive yet inconclusive. By the end of the experiment, willingness to trade is highest in treatment **SN** and lowest in treatment **SAS**, suggesting that both overconfidence and strategic naivete may be somewhat persistent to experience. However, high willingness to trade persists for longer in treatment **SA** than in **SS**, which indicates that subjects may be slower to overcome strategic naivete than overconfidence.

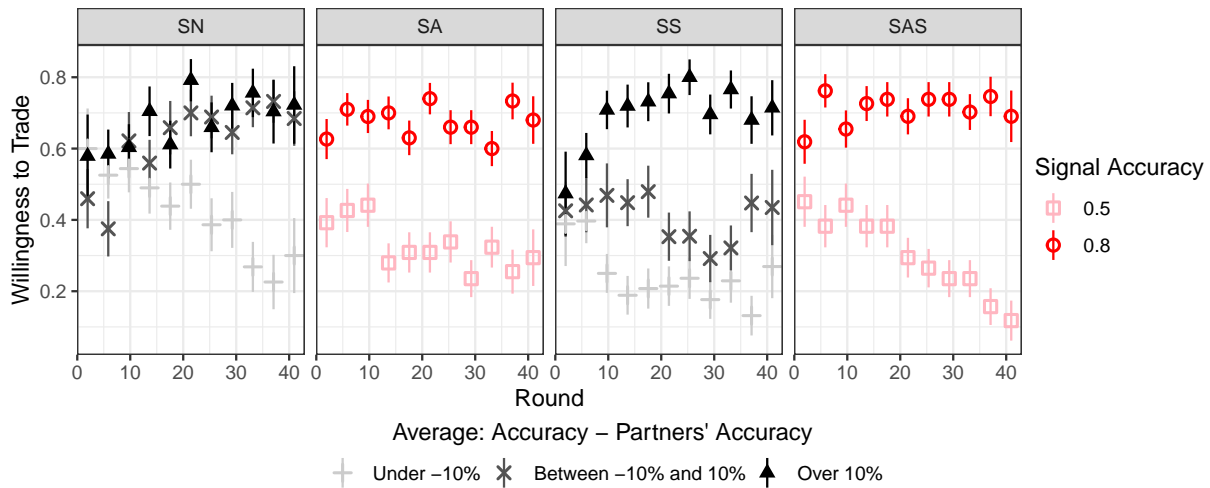


Figure 7: Effect of Experience on Trade Rate (by Signal Accuracy)

Figure 7 reveals that the effect of experience on willingness to trade depends on subjects' perceptions of their signal accuracies. For treatments **SA** and **SAS**, in which subjects are told their signal accuracies, the behavior of low and high-accuracy signals is strikingly dichotomous. Subjects with low-accuracy signals steadily choose to trade less with experience| choosing to trade only 10% of the time by the end of treatment **SAS**| while subjects with high-accuracy signals persistently choose to trade at high rates throughout the duration of both treatments. The latter pattern is especially striking because in treatments **SA** and **SAS**, willingness to trade for high-accuracy subjects is defined as the rate at which high-accuracy subjects choose to trade with *each other*.<sup>21</sup> That is, high-accuracy subjects in **SA** and **SAS** are persistently willing to trade with other high-accuracy subjects.

In treatments **SN** and **SS**, subjects do not directly observe their signal accuracies, but may infer it using the feedback they observe. Figure 7 therefore organizes subjects in these treatments according to their experienced accuracy differentials.<sup>22</sup> Subjects whose signals realizations matched the high-reward ticket 10% more often than their past partners' realizations are grouped together (*Over 10%*), and subjects whose realizations matched the high-reward ticket 10% less often than the realizations of their past partners are similarly grouped together (*Under -10%*). Finally, subjects who experience roughly equal signal accuracies as their past partners (*Between -10% and 10%*) are grouped together.

<sup>21</sup>For high-accuracy subjects in **SA** and **SAS**, observations with low-accuracy partners are dropped. Including these observations does not affect qualitative findings, as the willingness to trade of high-accuracy subjects in **SA** and **SAS** is not sensitive to partner signal accuracy.

<sup>22</sup>Recall that, after the AST game, subjects observe both their own and their partners' signal realizations.

Figure 7 reveals that in both treatments **SN** and **SS**, subjects who experience high accuracy differentials (*Over 10%*) choose to trade more with experience, and similarly, subjects who experience low accuracy differentials (*Under -10%*) choose to trade less with experience. However, subjects who experience moderate accuracy differentials (*Between -10% and 10%*) behave differently in treatments **SS** and **SN**. In treatment **SN**, they choose to trade more with experience, behaving almost identically to the group of subjects who experience high accuracy differentials; in treatment **SS**, on the other hand, these subjects learn to trade less with experience, behaving more similarly to the group of subjects who experience low accuracy differentials.

The results from Figure 7 shed further light on the findings from Figure 6, which shows that by the end of the experiment, average willingness to trade is similar in treatments **SA** and **SS**. In particular, the decline in average willingness to trade in treatment **SA** is entirely driven by subjects with low-accuracy signals, who learn to trade less over time. Subjects with high-accuracy signals, on the other hand, consistently choose to trade at high rates with high-accuracy partners, indicating that they do not internalize the adverse selection they experience over the course of the experiment. In other words, high-accuracy subjects appear to be persistently strategically naive. Similar to treatment **SA**, willingness to trade is also driven by accuracy grouping in treatments **SS** and **SN**. Initially, all accuracy groups choose to trade at similar rates| around 50% in treatment **SN** and 40% in treatment **SS**. With experience, willingness to trade diverges, so that in both treatments, subjects who experience accuracy differentials in excess of 10% choose to trade more frequently, and those who experience accuracy differentials below -10% choose to trade less frequently. That willingness to trade is sensitive to experienced accuracy differentials suggests that overconfidence may be overcome with experience: as subjects learn their signals are less accurate than those of their potential partners, they choose to trade less frequently.

## 4 Role of Experience

To better understand the main findings discussed in Section 3.3, I now investigate the role of experience on subjects' trading behavior in more detail. In particular, I examine whether subjects are more or less willing to trade as they learn more about (1) their own signal accuracies, (2) others' signal accuracies, and (3) others' strategies. I first establish theoretical predictions in Section 4.1, highlighting how fully rational subjects should respond to information that is provided through feedback. Next, in Section 4.2, I test these predictions against the data| finding that subjects in the baseline treatment **SN** under-respond to data about other subjects' strategies and signals. In Section 4.3, I evaluate the optimality of subjects' trading behavior, given past feedback, finding that while subjects respond optimally to feedback in aggregate, high-accuracy subjects generally over-trade as a consequence of ignoring other subjects' strategies.

## 4.1 Theoretical Predictions

In this section, I formalize subjects' incentives in *crossing* situations with the aim of understanding how feedback should affect willingness to trade. Let  $\varphi_i$  represent the gain in payoffs subject  $i$  expects in a crossing situation, conditional on her partner  $j$  choosing to trade.  $\varphi_i$  may be expressed as follows.

$$\varphi_i = \beta_j \frac{8\alpha_i(1 - \alpha_j) - 12(1 - \alpha_i)\alpha_j}{\alpha_i(1 - \alpha_j) + (1 - \alpha_i)\alpha_j} + (1 - \beta_j) \frac{8\alpha_i\alpha_j - 12(1 - \alpha_i)(1 - \alpha_j)}{\alpha_i\alpha_j + (1 - \alpha_i)(1 - \alpha_j)} \quad (\text{GT})$$

Note that in this parameterization of the AST game, the gain from trading for  $i$  is weakly decreasing in  $\beta_j$ , as signal accuracies are always at least  $\frac{1}{2}$ . Additionally, observe that while the incentive for  $i$  to trade is increasing in her own signal accuracy  $\alpha_i$ , it may be decreasing or increasing in the conditional signal accuracy of her partner  $\alpha_j$ . Recall that in the treatments featuring the augmented AST game (**SS** and **SAS**), in which subjects observe their partners' signals, *crossing* situations imply that both subjects receive signals matching the other's ticket, and so  $\beta_j = 1$  by construction. Thus, in treatments **SS** and **SAS**,  $\varphi_i$  is increasing in  $\alpha_i$  and decreasing in  $\alpha_j$ .

**Proposition 5** *Suppose that subject  $i$  is in a crossing situation. Conditional on subject  $j$  being willing to trade, subject  $i$ 's expected gain  $\varphi_i$  from trading for  $j$ 's ticket in treatments **SN** and **SA** is*

- increasing in  $\alpha_i$ , her own signal accuracy;
- weakly decreasing in the conditional likelihood that  $i$  holds the opposite signal,  $\beta_j$ ;
- decreasing in the signal accuracy of  $i$ ,  $\mu_i$ , when  $\beta_j > \frac{1}{2}$ , and increasing in  $\mu_i$ , when  $\beta_j < \frac{1}{2}$ .

In treatments **SS** and **SAS**,  $\varphi_i$  is increasing in  $\alpha_i$  and decreasing in  $\mu_i$ .

## 4.2 Empirical Responses to Feedback

I now assess whether the comparative statics outlined in Section 4.1 are reflected in the data. I pursue the following approach to test the predictions of Proposition 5. For each round and each subject, I construct proxies  $(\bar{\alpha}_i, \bar{\alpha}_j, \bar{\beta}_j)$  for  $(\alpha_i, \mu_i, \beta_j)$  by computing empirical averages.  $\bar{\alpha}_i$  is defined to be the frequency with which subject  $i$ 's signal realizations have matched the high-reward ticket in all past rounds, and similarly,  $\bar{\alpha}_j$  is the frequency with which the signal realizations of subject  $i$ 's past partners have matched the high-reward ticket, conditional on the partner being willing to trade.<sup>23</sup> Finally,  $\bar{\beta}_j$  is defined to be the frequency with which subject  $i$ 's past partners have held the signal matching  $i$ 's ticket, conditional on subject  $i$ 's partner being willing to trade.

<sup>23</sup>Note that empirical accuracy levels may actually be higher or lower than 80% or 50%, respectively. However, I simply use empirical averages as it bypasses the need for estimating priors and accuracy averages quickly converge to subjects' true accuracies | see Appendix.

Table 3 reports a linear regression of subjects' willingness to trade on  $(\bar{\alpha}_i, \bar{\alpha}_j, \bar{\beta}_j)$ .<sup>24</sup> That is, for each round, I regress a subject's choice of whether to trade in a *crossing* situation on the proxies constructed for that round.<sup>25</sup> The results in Table 3 lead us to conclude that subjects not only suffer from strategic naivete but are also unable to become more strategically sophisticated through experience. Notably, subjects in treatments **SN** do not trade less as adverse selection ( $\bar{\beta}_j$ ) increases and those in **SA** trade *more*. On the other hand, subjects do seem to respond to information about signal accuracies in the predicted direction: subjects in treatments **SN** and **SS** are more willing to trade if their past signal accuracies are higher and are less willing to trade when their past partners have had more accurate signals. Interestingly, strategic sophistication appears to interact with subjects' responses to others' accuracies: subjects in treatment **SN** are less responsive to others' accuracies than in treatment **SS**, in which adverse selection is artificially "revealed" to subjects.

Table 3: Effect of Feedback on Willingness to Trade

	SN	SA	SS	SAS
	(1)	(2)	(3)	(4)
$\bar{\alpha}_i$	0.58 (0.22)	0.71 (0.13)	0.76 (0.03)	0.87 (0.22)
$\bar{\alpha}_j$	0.34 (0.11)	0.23 (0.16)	0.52 (0.22)	0.14 (0.23)
$\bar{\beta}_j$	0.10 (0.36)	0.29 (0.13)	0.06 (0.16)	0.02 (0.16)
Constant	0.34 (0.44)	0.03 (0.14)	0.26 (0.10)	0.004 (0.30)
Observations	1,396	1,217	1,577	1,068

*Note:* p<0.1; p<0.05; p<0.01  
Standard errors clustered at session level

In Table 4, I investigate further how subjects respond to information about others' accuracies by running separate regressions for subjects with low and high-accuracy signals and find further evidence that subjects' perceptions of their own accuracies affect the manner in which they respond to feedback.<sup>26</sup> Specifically, in treatment **SN**, subjects with low-accuracy signals trade less when their feedback suggests others are likely to have high-accuracy signals, but those with high-accuracy signals do not respond to feedback about others' signals.

<sup>24</sup>I include results for treatment **SAS** for completeness. As expected, subjects do not respond to information about past rounds, as they are told both signal accuracies and their partners' signals. In a similar vein, subjects in **SA** do not respond to information about signal accuracies of past partners ( $\bar{\alpha}_{-i}$ ) and those in **SS** do not respond to information about adverse selection ( $\bar{\beta}_j$ )

<sup>25</sup>I do not include controls for subject fixed-effects or true signal accuracies, as both are heavily correlated with measures of empirical signal accuracy  $\bar{\alpha}_i$ .

<sup>26</sup>I present regressions featuring only  $\bar{\alpha}_j$  as a dependent variable for the sake of presentation, but results do not change when including  $\bar{\alpha}_i$  and  $\bar{\beta}_j$  | see Appendix.



Table 4: Effect of Others' Accuracies on Willingness to Trade

	SN: 0.5	SS: 0.5	SN: 0.8	SS: 0.8
	(1)	(2)	(3)	(4)
$\bar{\alpha}_j$	0.66 (0.14)	0.55 (0.20)	0.10 (0.19)	0.59 (0.32)
Constant	0.81 (0.12)	0.71 (0.13)	0.76 (0.14)	0.97 (0.29)
Signal Accuracy	50%	50%	80%	80%
Observations	509	527	887	1,050

Note:  $p < 0.1$ ;  $p < 0.05$ ;  $p < 0.01$   
Standard errors clustered at session level

The dichotomous response of **SN** subjects to information about others' signals accuracy strongly resembles the aggregate behavior of subjects in treatment **SA**. When told both their own and their partners' signal accuracies, subjects with high-accuracy signals not only choose to trade more frequently than those with low-accuracy signals, but also do not discriminate based on the signal accuracies of their partners. That is, high-accuracy subjects in treatment **SA** choose to trade just as often when paired with a high-accuracy partner as when paired with a low-accuracy partner. In keeping with the dichotomy noted for **SN**, however, low-accuracy subjects learn to trade less when paired with a high-accuracy partner. Thus, in both treatments **SN** and **SA**, a subject's own signal accuracy plays an important role in whether subjects adjust for accuracy information about others (feedback in **SN**, presented outright in **SA**).

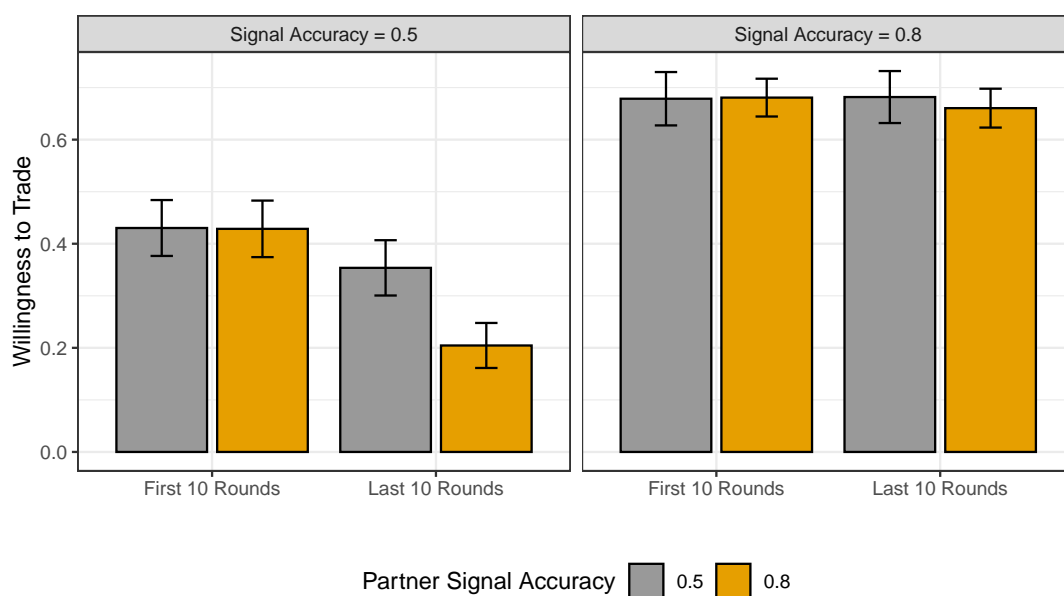
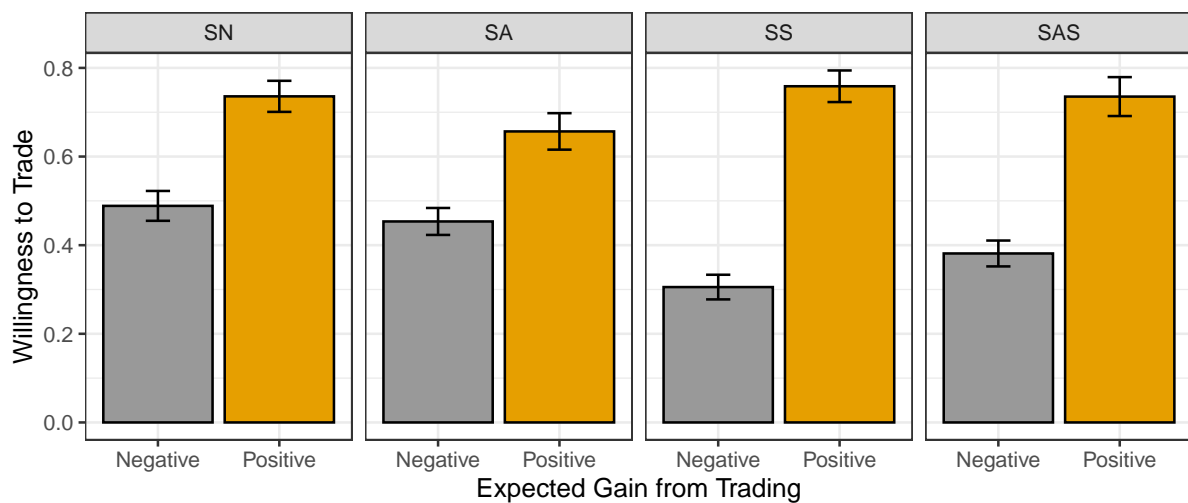


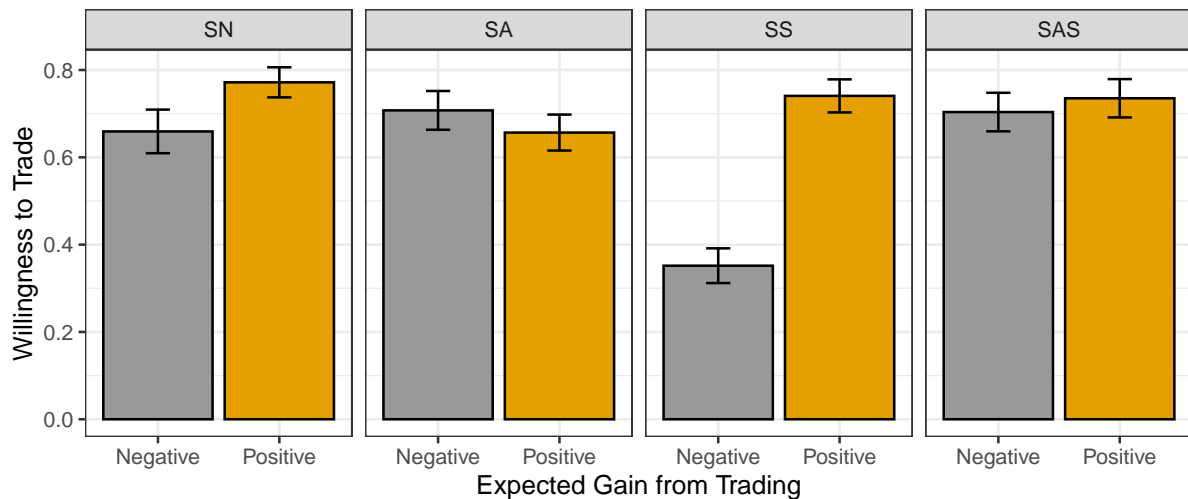
Figure 8: Willingness to Trade by Partner Accuracy (Treatment **SA**)

### 4.3 Optimality of Behavior

In this Section, I evaluate whether subjects behave sub-optimally as a consequence of the patterns documented in Section 4.2. Substituting proxies for accuracies  $(\bar{\alpha}_i, \bar{\alpha}_j, \bar{\beta}_j)$  into equation GT, I compute subjects' expected gain from trading over keeping ( $\bar{g}$ ). For treatments **SA**, **SA**, and **SAS**, I substitute values known to subjects when possible. That is, for treatments **SA** and **SAS**, I use subjects' true accuracies (shown to them) in place of their proxies  $(\bar{\alpha}_i, \bar{\alpha}_j)$ , and for treatment **SS** and **SAS**, I set  $\beta = 1$ . Figure 9 examines the rate at which subjects trade in *crossing* situations, decomposed by whether  $\bar{g}$  is positive or negative.



(a) All Subjects



(b) Subjects with High-accuracy Signals

Figure 9: Willingness to Trade by Pro tability (Last 10 Rounds)

In aggregate, I find that subjects generally trade for their partners' tickets when the gain from trading is positive (around 70% of the time) and keep their own tickets when the gain is negative (roughly 60% of the time). However, upon closer examination, high-accuracy subjects| except those in

**SS** | choose to trade almost as often when expected gain from trading is negative as when it is positive. In other words, high-accuracy subjects' trading decisions are generally not responsive to expected payoffs, given observables.

The pattern evident in panel 9b persists when profitability of trade is approximated via the average profitability of trading in past rounds. That is, I construct an alternative measure of profitability by averaging the ex-post profit to trading in *crossing* situations (controlling for the accuracy of subjects' partners in treatments **SA** and **SAS**) and examine the rate at which subjects choose to trade. Figure 10 displays the result of this exercise for subjects with high-accuracy signals; again, subjects choose to trade just as often (if not more often) when the expected gains to trading are negative as when they are positive. Only in treatment **SS** are subjects less willing to trade when the expected gains are negative.

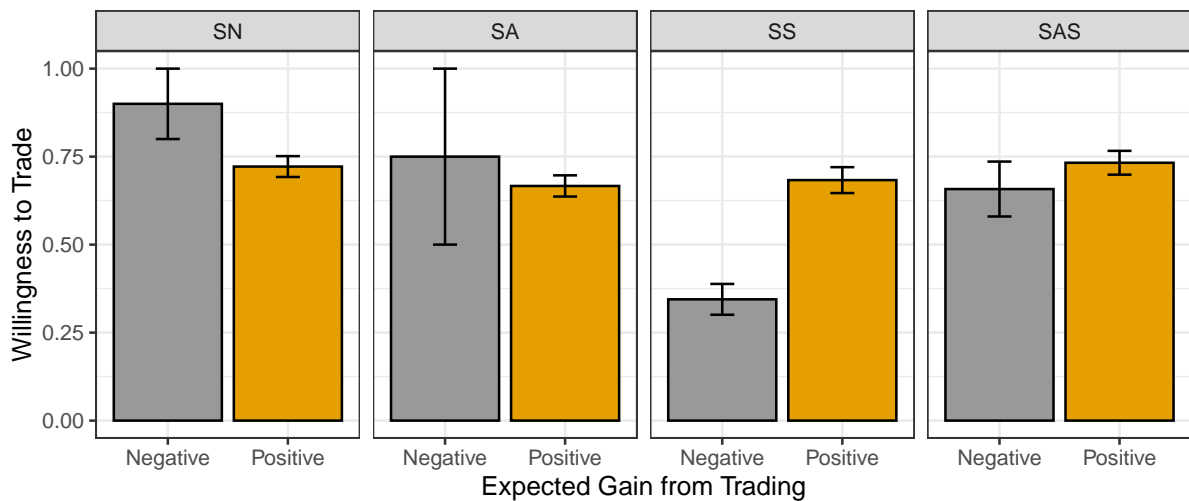


Figure 10: Willingness to Trade by Profitability (Ex-Post Method, Last 10 Rounds, High-Accuracy)

## 5 Realized Trade and Earnings

In the previous section, we observe that subjects in the experiment respond more to information about their signal accuracies than to information about others' strategies. However, the evolution of subjects' behavior is not purely determined by the information they accumulate through feedback. In general, changes in subjects' trading behavior occur most often after subjects *realize* trade with their partners. Figure 11 illustrates this point: it shows the probability a subject's willingness to trade changes from round to the next, depending on whether trade was realized in the previous round and whether they received a low or high reward in the previous round. The figure reveals that subjects are far more likely to change their strategies (1) after receiving a low-reward in the previous round and (2) after trade is realized in the previous round. For example, high-accuracy subjects in treatment **SN** rarely change their strategies if trade did not occur in the previous round, but they are twice as likely to change their

strategies and keep their tickets if trade was realized in the previous round and they earned a low-reward.

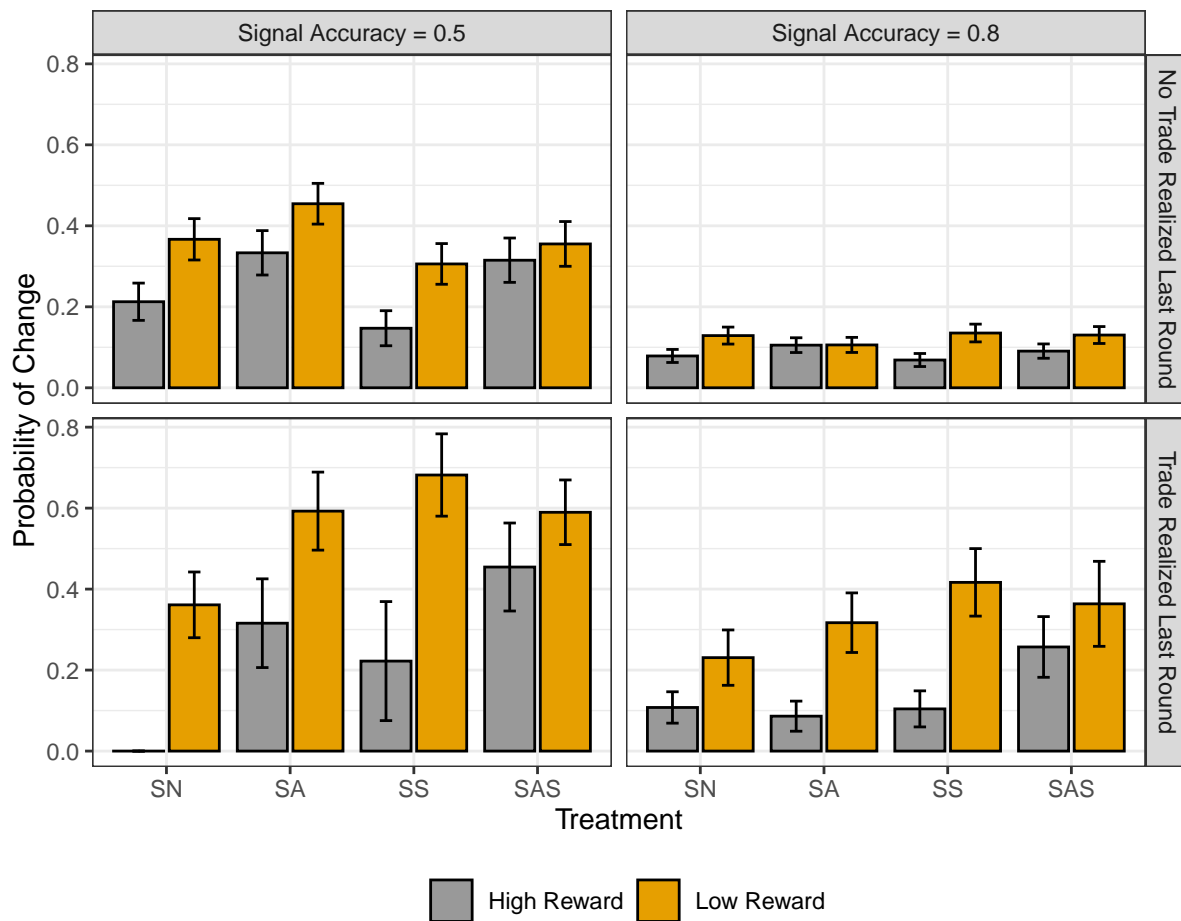


Figure 11: Probability of Change in Willingness to Trade

The patterns of behavior revealed in Figure 11 indicate that subjects are more likely to trade less after realizing losses from trade | in other words, receiving the low-reward ticket from trade. This suggests that learning to trade less may take especially long for subjects with high-accuracy signals for two reasons. First, subjects with high-accuracy signals profit from trading with low-accuracy subjects | thus encouraging them to trade. Second, trade is rarely realized when high-accuracy subjects are paired together. Even if both high-accuracy subjects choose to trade according to their signals, the fact that both possess highly accurate signals implies that their signals are unlikely to disagree, and hence trade is unlikely to be realized. Thus, while high-accuracy subjects should expect to suffer losses from trading with each other | discouraging them from trading | their expected losses are rarely realized as trade is rarely realized. These observations are helpful in explaining why high-accuracy subjects **SAS** are persistently willing to trade with each other. In treatment **SAS**, willingness to trade cannot be explained by either overconfidence or strategic naivete by design, but subjects with high-accuracy signals may still choose to trade with each other because such trade are rarely realized. Indeed Figure 12 shows that high-accuracy subjects in treatment **SAS** experience the *fewest* realized trades on average (below 3.5 out of 40 rounds)

and comparatively high earnings when trade *is* realized.

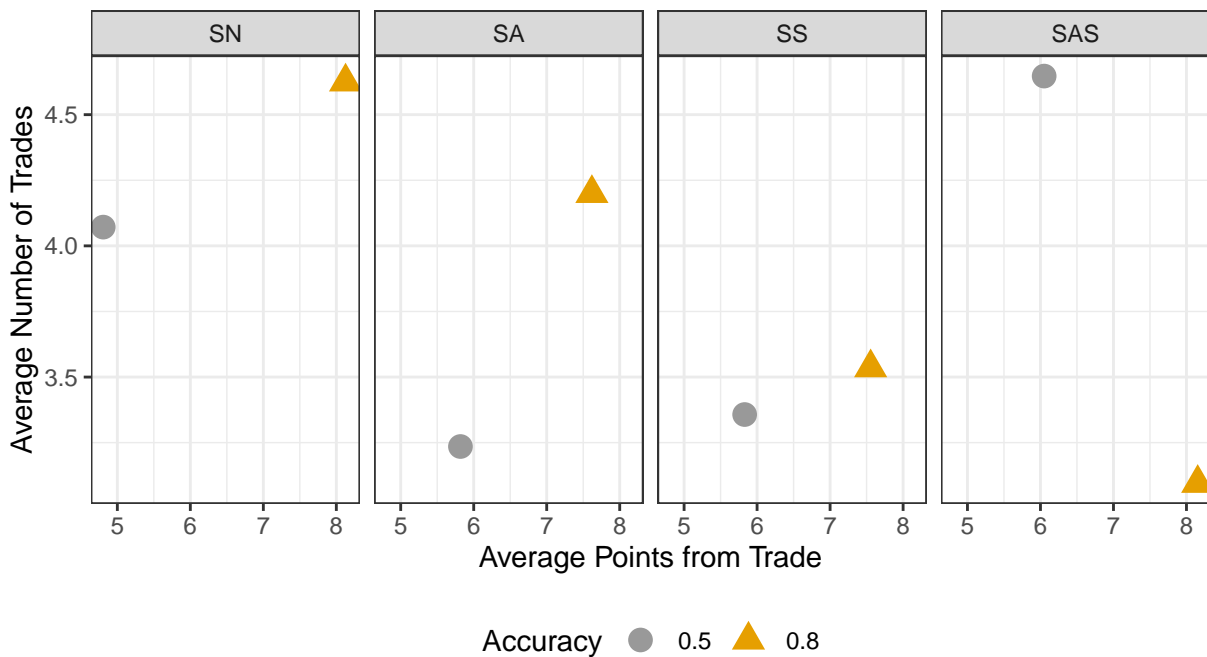


Figure 12: Earnings and Frequency of Trade

## 6 Conclusion

Evidence from the field shows that, in general, individual investors lose money by engaging in speculative trade. I study the persistence of this phenomenon by analyzing the effect of experience on experimental subjects participating in a simple no-trade game. My design focuses on two leading explanations for speculative trading| overconfidence and strategic naivete| by revealing subjects' information quality and the information of their trading partners.

I find that strategic naivete is the more important behavioral hurdle investors face. When signal qualities are revealed, subjects receiving high-accuracy signals continue to trade with partners receiving equally accurate signals; on the other hand, their partners' signal realizations are revealed, subjects choose to trade less if their perception of their partners' signal quality improves. Additionally, my analysis reveals an important interaction between information quality and strategic sophistication. Subjects with higher information quality are less sensitive to the information quality of their partners, appearing more strategically naive when they have more accurate signals. This effect appears to be so strong that it can override the experimental features in place to alleviate strategic naivete. In treatment **SAS**, in which both signal realizations and signal accuracies are revealed, subjects who are told they receive high-accuracy signals consistently choose to trade with partners who also receive high-accuracy signals. I find that, as a result of their strategic naivete, subjects frequently choose to trade when the

expected payoff from keeping their assigned tickets is greater than that of trading for their partners' ticket. Only in treatment **SS**, which alleviates strategic mistakes due to adverse selection, do subjects' trading decisions correlate with their expected gains from trading.

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# Appendices

## A Figures

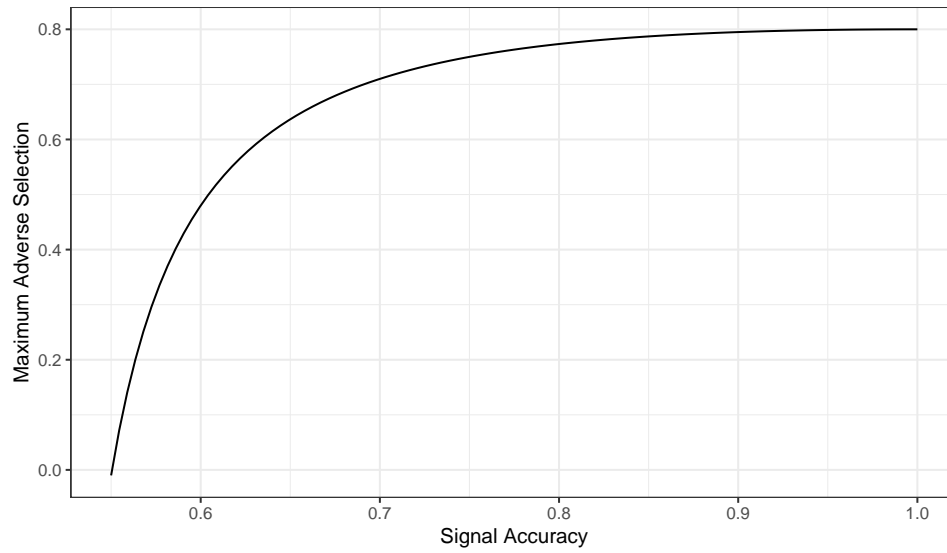


Figure 13: Maximum Adverse Selection as a Function of Signal Accuracy

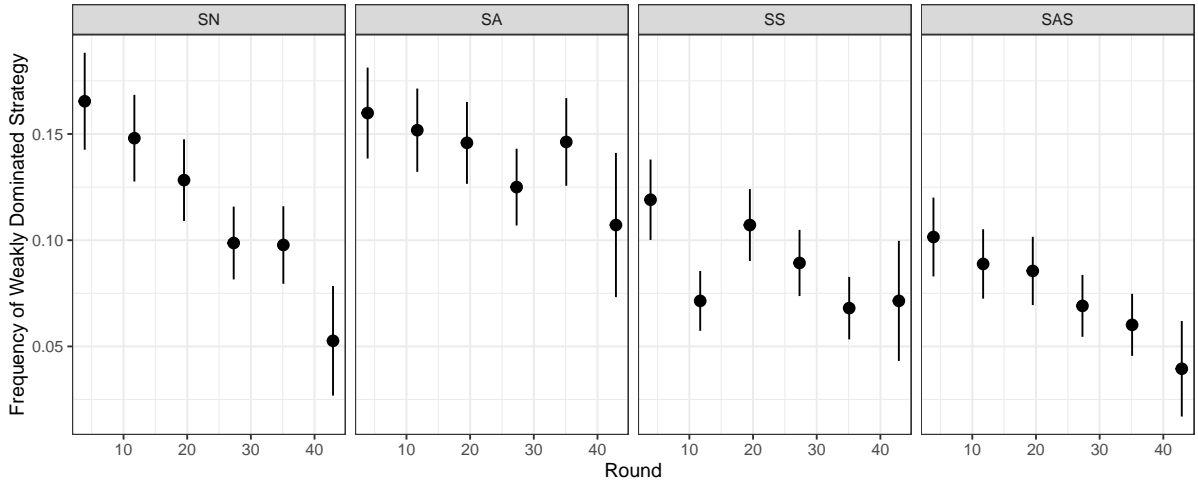


Figure 14: Frequency of Weakly Dominated Strategies

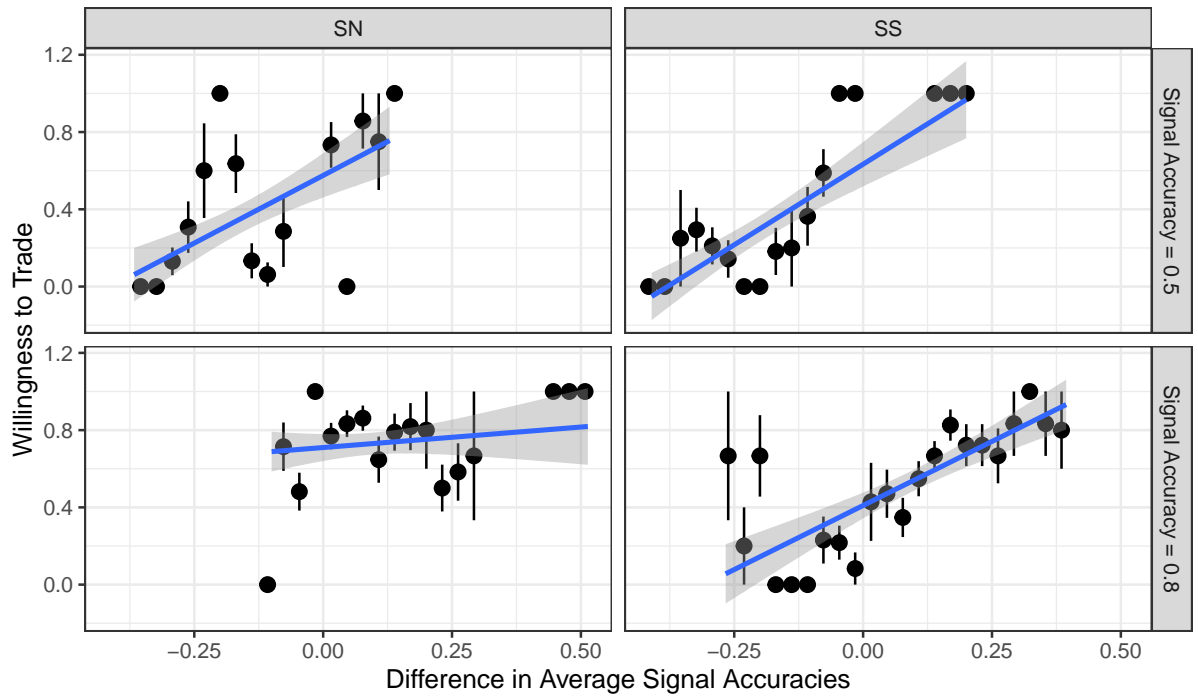


Figure 15: Effect of Experienced Accuracy

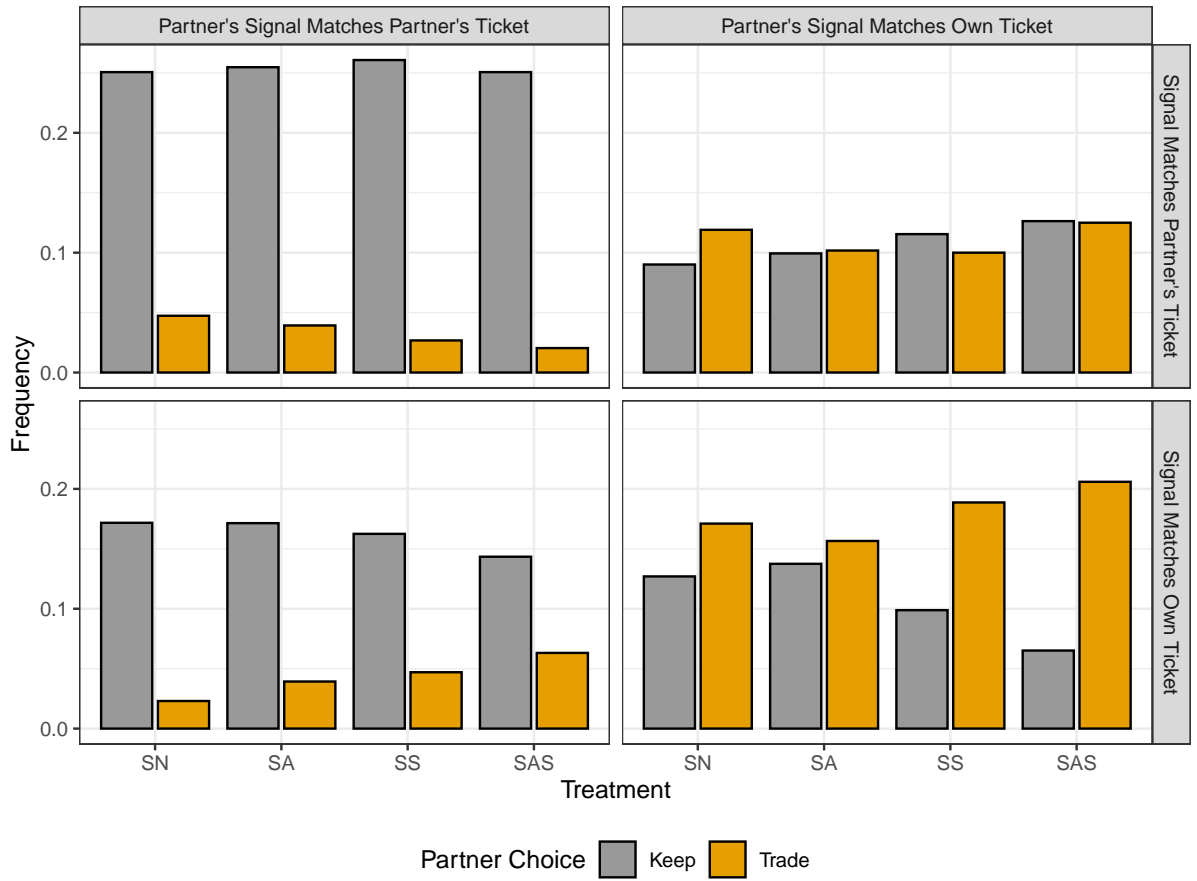


Figure 16: Frequency of Outcomes

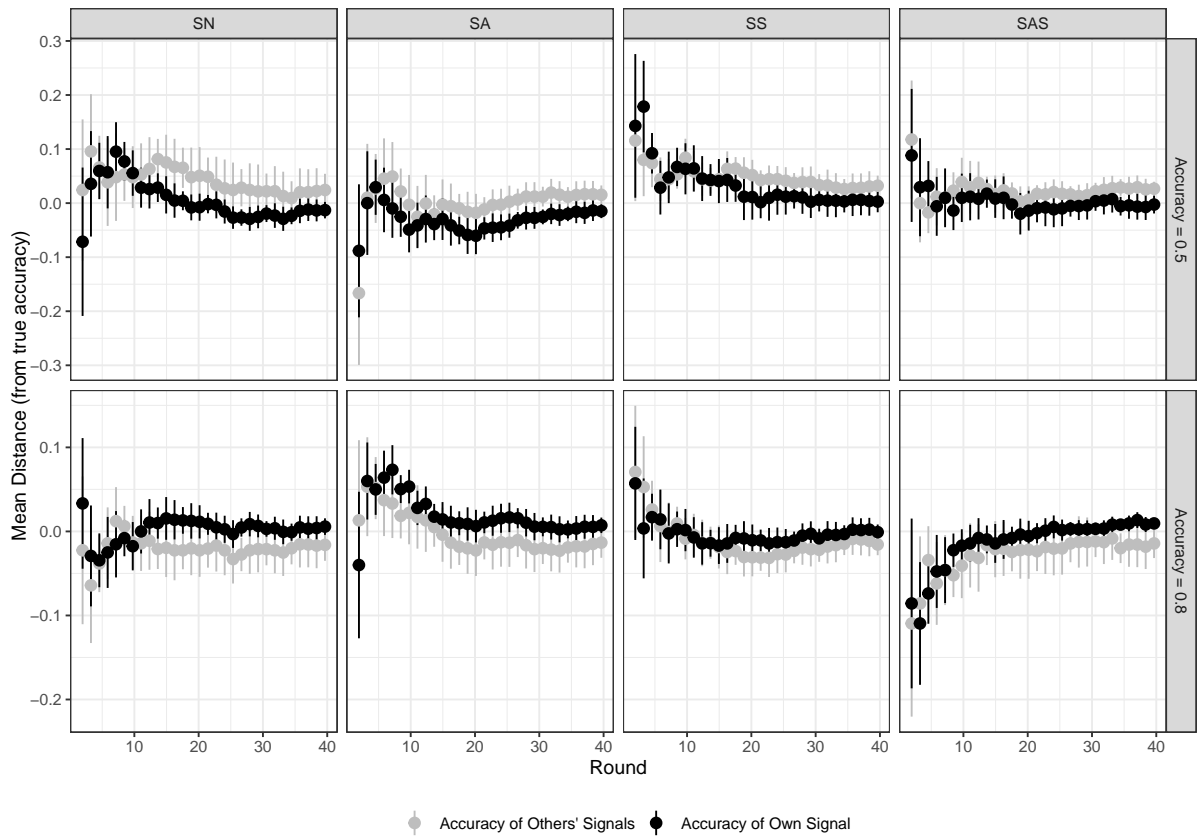


Figure 17: Evolution of Average Accuracy

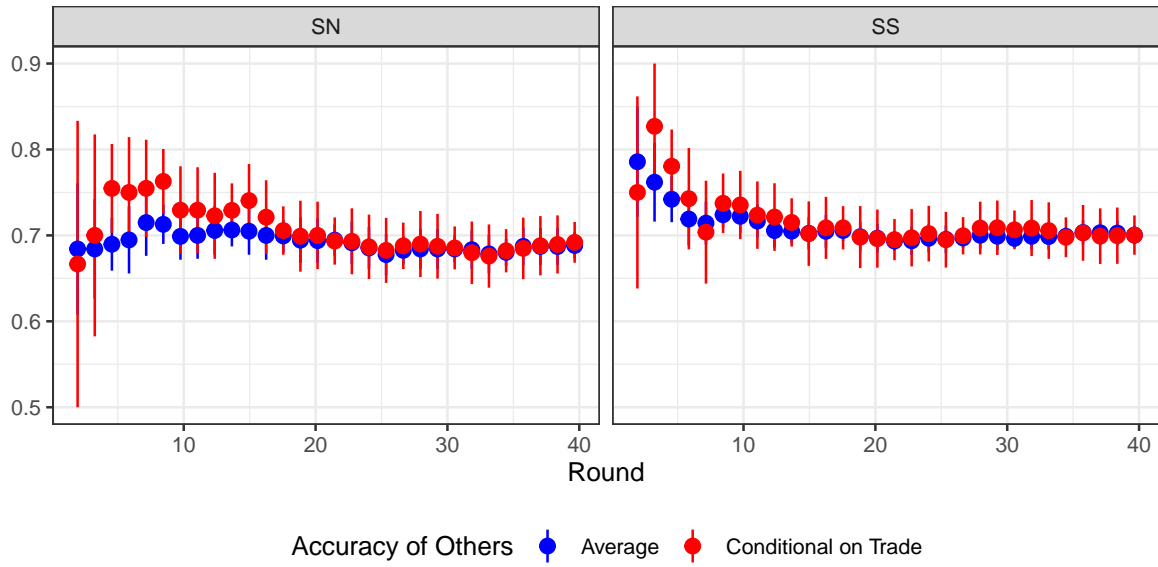


Figure 18: Adverse Selection in Accuracy

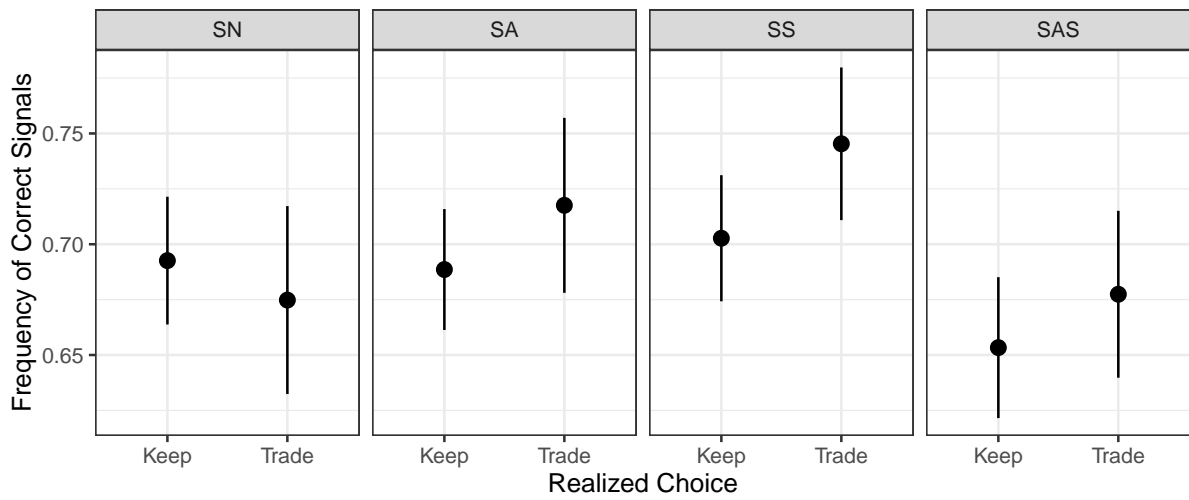


Figure 19: Signal Accuracy Conditional on Choice (Last 10 Rounds)

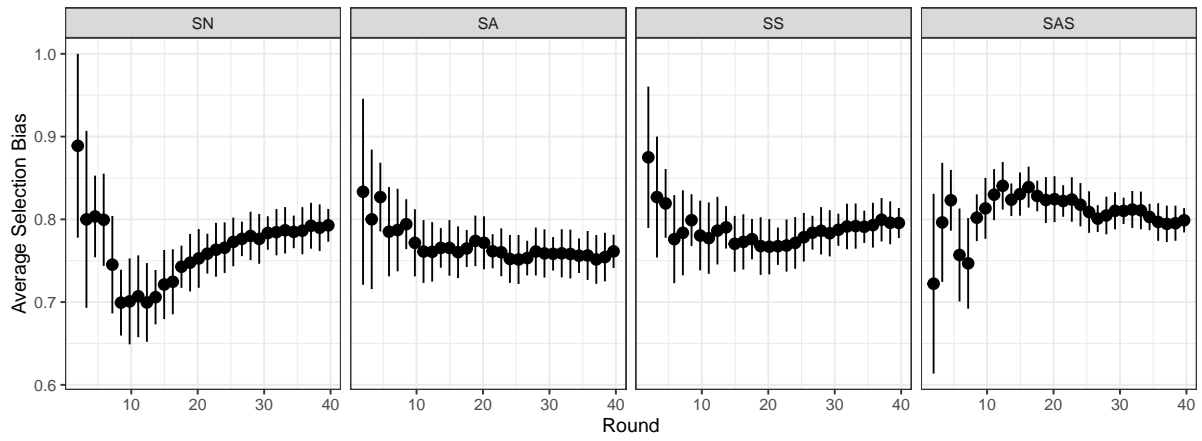


Figure 20: Evolution of Adverse Selection ( $\bar{\beta}_j$ )

## B Instructions

Instructions are made available both through a no-download Dropbox link and via the experimenter's Zoom interface. After distribution, instructions are read aloud, and subjects ask questions aloud, so that all other subjects could hear them, and likewise, questions are answered for all subjects to hear.

In the following pages, I include the instructions used for the baseline treatment **SN**. Instructions for the remaining treatments are similar (with minor variations). Instructions are distributed in parts, so that after completing a task, subjects receive instructions for the next task. The correspondence of parts to task is detailed below.

- **Part 1** explains the color-guessing task.
- **Part 2** explains the belief elicitation task (occurring before the AST game).
- **Part 3** explains the AST game.
- **Part 4** re-explains the belief elicitation task (occurring after the AST game).

# INSTRUCTIONS

1. You are about to participate in an experiment on decision-making. What you earn depends partly on your decisions, partly on the decisions of others, and partly on chance. Please turn off cell phones and close any unrelated software or tabs on your computer.
2. Please do not talk or in any way try to communicate with other participants.
3. We will start with a brief instruction period. If you have any questions during this period, please ask and your question will be answered so everyone can hear.
4. This experiment has four parts.



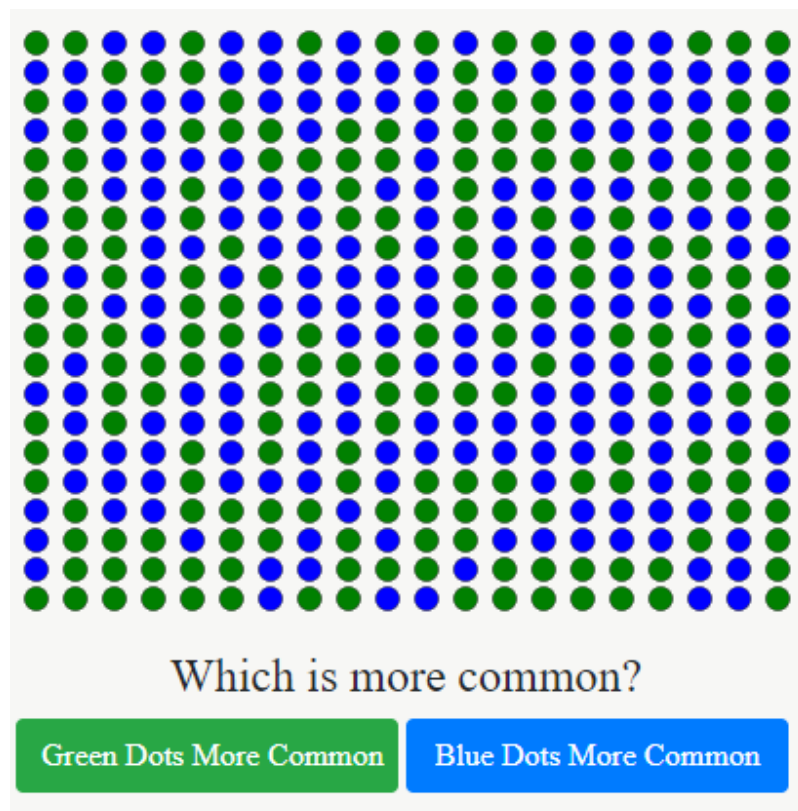
## Part 1

*These instructions are for the first part. Once this part is over, instructions for the next part will be given to you.*

---

This part will consist of four rounds. The first three rounds will be for practice; **you will be paid for your response in the fourth and final round.**

In each round, you will be shown an image of 400 green and blue dots—similar to the one below. You will be asked which color is more common. **In the payment round,** you will earn \$10 if you are correct, and \$5 if you are incorrect.



You will have ten seconds to respond. If you fail to do so, your response will automatically be counted as incorrect.

## Part 2

*These instructions are for the second part. Once this part is over, instructions for the next part will be given to you.*

---

In this part, you will estimate (1) the likelihood that your final response in the *payment* round of the **Part 1** was correct and (2) the percentage of others' final responses that were correct. Note that everyone was shown the exact same arrangement of green and blue dots.

For each estimate, you will select a number between 0% and 100% on each of the sliders, as shown below.

The image shows two identical horizontal sliders. The top slider is titled "How likely do you think your *final response* is to be correct?". The bottom slider is titled "What percent of others' *final responses* do you think are correct?". Both sliders have a scale from 0 to 100 with major tick marks at 0, 25, 50, 75, and 100. A small box labeled "0%" is positioned at the 0 mark of each slider. The sliders are currently set to 0%.

One of these estimates will be randomly chosen for payment, which is calculated in the following way.

$$\text{Payment} = \$4 - \frac{(\text{Your Estimate} - \text{Correct Answer})^2}{5000}$$

**In words, your payment for the chosen estimate will be higher when it is closer to the correct answer.** The correct answer for the first question is 100% if your final response was correct and 0% if your final response was incorrect. For the second question, the correct answer is the percentage of other subjects whose final responses were correct.

## Part 3

In this part of the experiment, you will make trading decisions over 40 rounds. In each round, you will be paired with a random trading partner. You will start every round with a colored ticket (Green or Blue), and your trading partner will start with the other colored ticket. After each round, one ticket will pay out a reward of \$14, and the other ticket will pay out a reward \$4. Therefore, either:

- The Green ticket pays \$14, and the Blue ticket pays \$4, or
- The Green ticket pays \$4, and the Blue ticket pays \$14.

*Note: you will start with the same ticket color in all rounds.*

---

### Trading

During a round, you choose to either (1) keep your assigned ticket or (2) trade for your partner's ticket. Trading costs a fee of \$2 and only occurs if both you and your partner agree to trade for each other's tickets. That is:

- If you choose to trade tickets and your partner chooses to keep his/her ticket, you each keep your tickets.
- If your partner chooses to trade tickets and you choose to keep your ticket, you each keep your tickets.
- If both you and your partner choose to trade tickets, you will trade tickets, and a fee of \$2 will be subtracted from each of your rewards.

### Clues

Before you trade (or not), you will receive a clue—either Green or Blue—as to which ticket pays out the high reward. You and your partner may receive different clues. The likelihood *your* clue matches the high-reward ticket is determined by your final response from Part 1.

- If your final response was correct, your clue will match the high-reward ticket 80% of the time.
- If your final response was incorrect, your clue will match the high-reward ticket 50% of the time.

## Submitting a Trading Decision

Your clue will be automatically generated by the software. Before the clue is revealed, you will submit a trading plan to specify how you would like to trade depending on the clue you receive. That is, you choose (1) whether you'd like to trade if your clue is Green and (2) whether you'd like to trade if your clue is Blue. After you submit these two choices, the software will reveal your clue and will implement a trading decision based on your clue and your trading plan.

The two examples below illustrate how submit a trading plan. In the first example, you start with a Green ticket, and in the second example, you start with a Blue ticket. In both examples, if your clue is Green, your trading decision will be determined by your choice in the "Green clue" row, and if your clue is Blue, your trading decision will be determined by your choice in the "Blue clue" row. To submit your trading plan, simply click on the choice you'd like to take for each clue.

*You own a **Green Ticket**: Submit a trading choice for each clue*

Clue	Your Choice	
<b>Green</b>	Trade for Blue Ticket	Keep my Green Ticket
<b>Blue</b>	Trade for Blue Ticket	Keep my Green Ticket

*You own a **Blue Ticket**: Submit a trading choice for each clue*

Clue	Your Choice	
<b>Green</b>	Trade for Green Ticket	Keep my Blue Ticket
<b>Blue</b>	Trade for Green Ticket	Keep my Blue Ticket

## Interface

You submit your choices on the left side of the interface shown below.

1. After you submit your trading plan, you will be shown your clue and trading decision.
2. Clicking next will reveal your partner's clue, trading decision, and the trading outcome.
3. The final page in a round will reveal the high-reward ticket and your earnings.

*You own a **Green Ticket**: Submit a trading choice for each clue*

Clue	Your Choice	
Green	Trade for Blue Ticket	Keep my Green Ticket
Blue	Trade for Blue Ticket	Keep my Green Ticket

**Reminders**

- Your clue matches the high-reward ticket 80% of the time if your response in the **payment round** of Part 1 was correct and 50% of the time if your response was incorrect.
- Trade occurs if both you and your partner choose to trade.
- You and your partner may receive different clues.
- Completed trades cost a fee of \$2

Round	Trade	Your Clue	Your Choice	Partner's Clue	Partner's Choice	High Reward	Your Earnings
1							

At the bottom of the interface, you will see a history table. Each column displays the following information:

- The first column “Round” of a row displays the round the data is drawn from;
- The second column “Trade” indicates if you and your partner traded;
- The third column “Your Clue” shows your clue;
- The fourth column “Your Choice” shows whether you decided to trade or keep;
- The fifth column “Partner’s Clue” shows your partner’s clue;
- The sixth column “Partner’s Choice” shows whether your partner decided to trade or keep;
- The seventh column “High Reward” shows which ticket paid out the high reward of \$14;
- The final column “Your Earnings” shows your earnings from the round.

## Payment

Your earnings from a round will equal the reward from the ticket you hold at the end of the round, minus the \$2 trading fee if you and your partner traded. One round will be randomly selected for payment at the end of the experiment.

## **Summary**

- Either your ticket or your partner's ticket will pay out a high reward of \$14, and the other ticket will pay out \$4;
- Both you and your partner will receive potentially different clues that are more likely to match the high-reward ticket if your final responses from Part 1 were correct;
- Your decision for each round is whether or not to trade tickets with your partner, depending on the clue you receive;
- If you and partner both choose to trade tickets, you will each pay a trading fee of \$2;
- You will be randomly rematched to a partner each round.

## Part 3

In this part of the experiment, you will make trading decisions over 40 rounds. In each round, you will be paired with a random trading partner. You will start every round with a colored ticket (Green or Blue), and your trading partner will start with the other colored ticket. After each round, one ticket will pay out a reward of \$14, and the other ticket will pay out a reward \$4. Therefore, either:

- The Green ticket pays \$14, and the Blue ticket pays \$4, or
- The Green ticket pays \$4, and the Blue ticket pays \$14.

*Note: you will start each round with the same ticket color.*

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### Trading

During a round, you choose to either (1) keep your assigned ticket or (2) trade for your partner's ticket. Trading costs a fee of \$2 and only occurs if both you and your partner agree to trade for each other's tickets. That is:

- If you choose to trade tickets and your partner chooses to keep his/her ticket, you each keep your tickets.
- If your partner chooses to trade tickets and you choose to keep your ticket, you each keep your tickets.
- If both you and your partner choose to trade tickets, you will trade tickets and will each pay a fee of \$2.

### Clues

Before you trade (or not), you will receive a clue—either Green or Blue—as to which ticket pays out the high reward. You and your partner may receive different clues. The likelihood *your* clue matches the high-reward ticket is determined by your final response from part 1.

- If your final response was correct, your clue will match the high-reward ticket 80% of the time.
- If your final response was incorrect, your clue will match the high-reward ticket 50% of the time.

## Part 4

*These instructions are for the last part of the experiment.*

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In this part, you will again estimate (1) the likelihood that your final response in the *payment* round of the **Part 1** was correct and (2) the percentage of others' final responses that were correct. Note that everyone was shown the exact same arrangement of green and blue dots.

For each estimate, you will select a number between 0% and 100% on each of the sliders, as shown below.

The image shows two identical slider interfaces. The top slider is titled "How likely do you think your *final response* is to be correct?" and the bottom slider is titled "What percent of others' *final responses* do you think are correct?". Both sliders have a horizontal track from 0 to 100 with major tick marks at 0, 25, 50, 75, and 100. A small box labeled "0%" is positioned at the 0 mark. A vertical slider handle is currently positioned at the 100 mark on both tracks.

One of these estimates will be randomly chosen for payment, which is calculated in the following way.

$$\text{Payment} = \$4 - \frac{(\text{Your Estimate} - \text{Correct Answer})^2}{5000}$$

**In words, your payment for the chosen estimate will be higher when it is closer to the correct answer.** The correct answer for the first question is 100% if your final response was correct and 0% if your final response was incorrect. For the second question, the correct answer is the percentage of other subjects whose final responses were correct.