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Essays on Influence of Information and Technology in Decision Making

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ESSAYS ON INFLUENCE OF INFORMATION AND TECHNOLOGY IN DECISION MAKING

A dissertation submitted in partial satisfaction of the requirements for the degree of

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by

Liwei Liu

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Abstract

Essays on Influence of Information and Technology in Decision Making

by

Liwei Liu

This dissertation presents three studies with an emphasis on the influence of information and technology in people's behavior. The first chapter focuses on theoretical and experimental evaluation of the information revelation strategies in a persuasion game. The second and third chapters focus on how advanced technology such as ridehail and social media apps can change people's access to information and their behavior.

In Chapter 1, we design a persuasion game in which two players compete for limited resources under asymmetric information and conflicting interests to study whether verifiable but vague messages can improve information transmission. The predictions are derived using two theoretical solution concepts, Perfect Bayesian Equilibrium (PBE) and Iterative Admissibility (IAS), both restricted to pure strategies. In a laboratory experiment, we observe behavior to be consistent with the highest reasoning level under IAS. Our evidence shows that the senders' pure strategies which are PBE and satisfy the highest-level IAS are the most commonly chosen strategies. When vague messages can be sent, senders reveal more information using vague messages, and receivers have more accurate beliefs about the true state.

In Chapter 2, we analyze what ridehail drivers do when searching for paid fares. We use a dataset of 5.3 million trips in San Francisco and partition each search

trip into cruising, repositioning, and parking segments. We find that repositioning accounts for nearly two-thirds (63%) of the time between trips, with cruising and parking accounting for 23% and 14% respectively (these figures exclude short trips). Our regression models suggest that drivers tend to make reasonable choices between repositioning and parking, heading to high-demand locations based on the time of day. However, we also find suggestive evidence of racial bias, supporting previous studies of both taxis and ridehailing that indicate that drivers tend to avoid neighborhoods with high proportions of residents of color.

The final chapter investigates personalization in online social networks, which has been constantly criticized for intensifying opinion polarization. Yet polarization can result from confounding effects. We build a model which combines an endogenous network formation process and endogenous probability of observing agents. By separating the influences of different factors on polarization, the model is able to evaluate the pure effects of personalization and shows that stronger polarization occurs under personalization when agents are easier to be persuaded by others. We further conduct a novel lab experiment, and the results confirm our theoretical predictions. Additionally, the experiment results indicate that without personalization, a transitionary polarization occurred under a low disconnection threshold environment.

To my loving family.

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Chapter 1

Information Revelation under Vague Messages

1.1 Introduction

In many economic situations, it is common to observe two parties competing for limited resources and holding asymmetric information. For example, two people applying for the same job position may have different knowledge about the company; an incumbent company in an industry often has more information than a potential new entrant; in an oil tract auction, an experienced bidder can have a more accurate estimate of the value than an inexperienced bidder. In all these cases, the two parties have conflicting interests, and the informed party is not willing to reveal the whole truth.

However, in many of these contexts, the informed parties might have incentive to reveal part of their information, seeking to change their opponent's behavior. For the two people applying to the same position, if Person A already got interviewed, they may reveal and exaggerate the difficulty of the position to Person B in the hope that Person B will give up applying to it. For the incumbent company and the new entrant, the former may only share bad news as a signal (such as lack of supplies or high costs) to affect the potential new entrant's decision to enter the market. In an oil tract auction, the experienced bidder may have the incentive to convince the inexperienced bidder that the value of the oil tract is low, thus lowering the bid of their opponent and getting a higher chance to win.

The strategic information transmission described in these cases can be achieved by sending a vague message, which discloses a subset of the state space containing the true state but not the exact truth. For example, in the oil tract auction case, the experienced bidder can tell the inexperienced bidder "The value is not higher than 100" while the true value is 100. Then the inexperienced bidder may bid lower, thus decreasing their chance to win. In this situation, vague messages are designed to manipulate the uninformed party's beliefs. As stated in Deversi et al. (2018), vague messages are not thorough lies, which may cause legal concerns or strong skepticism from the uninformed party, but merely inflate the truth to the direction benefiting the informed party.

In this paper, we investigate theoretically and experimentally whether vague messages can induce more information transmission in a context of conflicting interests and asymmetric information. We used a persuasion game with a specific payoff structure to replicate a simplified oil tract common value auction with two bidders. In the persuasion game, the sender is the experienced bidder who has private information about the realized state, the value of the item, as given by finite numbers. The experienced bidder's bids are fixed given the realization of the item value. When the item value is higher, the bid is also higher. The receiver in the game is the inexperienced bidder who only knows the distribution of the item values and needs to submit a bid. When the receiver's bid is higher or equal to the sender's bid, the receiver wins, and their payoff depends on both the value of the item and their bid: a higher item value leads to a higher payoff, and a higher bid leads to a lower payoff. If the receiver's bid is higher than the value of the item, they suffer from the winner's curse, and the payoff will be negative. When the receiver's bid is lower than the sender's bid, the sender wins, and their payoff is higher when the item value is higher. If a bidder loses, their payoff would be 0. To further simplify the game, we limit the receiver's bid options to a menu with finite numbers. The sender would prefer the receiver to bid lower than themselves while the receiver prefers to have the same bid as the sender. Before the auction starts, the sender can choose a message to send to the receiver.

In our environment, we study two conditions (henceforth message rules) that provide a menu from which the sender can select messages. In the first condition (Message Rule 1), the message menu consists of two options: telling the precise truth (reveal the true state), or give no information (a message that is the state space). In the second condition (Message Rule 2), the message menu consists of all subsets of the state space that contain the true state. Unlike Message Rule 1, in Message Rule 2, the sender may send vague messages (any interval which is a proper subset of the state space and contains the true state).[1]

Theoretically, persuasion games have been solved using Perfect Bayesian Equilibrium (PBE) or a sequential equilibrium (Milgrom and Roberts, 1986), which specify both a strategy and a belief for each player following sequential rationality and consistency. Yet, an analog of iterative admissibility for extensive-form games (IAS), or prudent rationalizability (Heifetz et al., 2011), has been used to solve these games more transparently level-by-level in a similar fashion to a level-k approach (e.g. Stahl and Wilson, 1994). Stemming from the rationalizability concept, IAS eliminates obviously dominated strategies repeatedly, which does not require contingent thinking or Bayesian updating by the players (Hagenbach and Perez-Richet, 2018). In games with multiple equilibria, IAS is able to provide clear predictions for every finite level of mutual cautious belief in rationality (Li and Schipper, 2020). We study and derive the pure strategy solutions of this game using both PBE and IAS. A theoretical comparison of the two conditions indicate that both PBE and IAS notions predict more information disclosure through sending vague messages in the second condition.

Our experiment uses a within-subject design. In each round, a sender and a receiver are randomly matched. In the main sessions, the item has three possible values. We apply Message Rule 1 as the first treatment for the first 14 rounds, which is the benchmark game with only precise messages and no information in the message menu. Then we apply Message Rule 2 as the second treatment for another 19 rounds, where vague messages are also allowed. In the last round of each treatment, the subjects' beliefs

[1] We focus on voluntary disclosure by allowing the sender to choose no information; thus, we are able to investigate whether senders have incentives to reveal information.

on the sender and receiver's strategies are elicited to evaluate the receiver's information gains and whether subjects' behaviors are the best response to their beliefs. We also add two strategy method rounds to each treatment for four sessions to collect more data in case some states have never been reached. Finally, as a robustness test, two additional sessions are conducted with a similar game with 4 possible item values to examine whether the results are consistent across different state space and complexity of strategy space.

Our empirical analysis has two parts. In the first part, we compare the experimental results with the theoretical predictions and compare the predictions of pure strategy combinations elicited from PBE and IAS solutions. In the second part, we compare the information transmission level, subjects' reasoning level, and welfare level before and after vague messages are added to the message menu. The key findings are as follows. First, we found the subjects' strategies are essentially aligned with the IAS predictions. By looking at the sender's pure strategies, IAS solutions predict the subjects' behavior more accurately under Message Rule 1, which refines the PBE solutions. Under Message Rule 2, the intersection of PBE and IAS solutions predict most of the subjects' behavior and can be a refinement of both IAS and PBE solutions. Second, to evaluate the information transmission level, we examined the information disclosure level from the sender and information gains of the receiver. We found that under Message Rule 2 relative to Message Rule 1, more disclosure has been achieved by the sender choosing vague messages, and the receiver had more accurate beliefs of the true state, especially for states where the sender and receiver's interests are not aligned. For the reasoning level, while most subjects reached the highest level under Message Rule 1, a smaller fraction of subjects were able to reach the highest level under Message Rule 2. Finally, by examining the average payoff of the sender and receiver, we found no obvious welfare improvements for either side.

Our work adds to experimental work on persuasion games under verifiable information. While most experimental work tests the information unraveling in persuasion games, few have paid attention to the effects of vagueness on disclosure. Furthermore, with a payoff structure replicating a common value auction, our research provides a bridge between the literature of persuasion games and the literature of information revelation in auctions. In our environment, two parties compete for limited resources, and the optimal strategy for the sender is no revelation under the benchmark treatment where only precise messages are allowed. Our results show that the information revelation is improved after adding vague messages, which provides implications for the possibilities of information disclosure in auctions. Finally, by showing that the intersection of IAS and PBE predicts the subjects' behaviors more accurately than PBE, this paper adds evidence to literature discussing IAS as an equilibrium selection criterion.

The rest of the paper is organized as follows. Section 1.2 reviews the related literature. Section 1.3 presents the theoretical models and solutions to the game. Section 1.4 describes the experiment design and hypotheses. Section 1.5 discusses the experimental results. Finally, Section 1.6 concludes. The 4-state game and associated solutions, proofs of IAS solutions, strategy consistency, robustness tests, and other results can be found in the Appendix.

1.2 Related Literature

Our paper is closely related to the literature studying persuasion games under verifiable information. In a persuasion game, players have asymmetric information, and communication is restricted to verifiable disclosure. Milgrom and Roberts (1986) solve the sequential equilibrium of a persuasion game with a seller and a buyer and show information unraveling. Following their study, several experimental works (e.g. Forsythe et al., 1989; Jin et al., 2015; Li and Schipper, 2020) have documented the unraveling of information in persuasion games. While studies on verifiable disclosure in persuasion games mainly examine the information unraveling, there is only one experimental work by Deversi et al. (2018) comparing the different effects of a precise language regime and a flexible language regime on disclosure in a standard persuasion game. Their paper studies voluntary disclosure under precise versus vague message rules and concludes that information transmission is improved by imposing precision.

The message design of our paper is similar to Deversi et al. (2018). However, with a different payoff structure representing two parties competing for limited resources (e.g., two bidders in a common value auction), we find that vague messages can induce more disclosure and information gains for the uninformed party compared to precise messages. This is opposite to the findings in Deversi et al. (2018). The reason is that under the environment of our paper, the sender's preference is cyclic, which means that some sender types have incentive to masquerade another type and their masquerade path forms a cycle (Hagenbach and Perez-Richet, 2018). In our paper, all types of senders can masquerade another type without reducing their payoff, so disguising their true state will enable them to earn a payoff at least as high as truth-telling; thus, no information is preferred when only precise messages are allowed. However, Deversi et al. (2018) designed a seller-buyer game where all the sellers would like to masquerade the type with the highest quality to achieve more sales, but the highest-quality sellers have no incentive to masquerade as other types. The senders' preference in this environment is not cyclic, and the highest-quality seller benefits from revealing their true type to the buyer. Therefore, when only precise messages and no information are allowed, the highest-quality sellers would prefer the precise message. There would then be a cascade of other sellers revealing their exact truth as well. This is consistent with findings of research studying the conditions for unraveling in persuasion games (e.g. Hagenbach and Perez-Richet, 2018; Miura, 2018): full disclosure is achieved in games with acyclic sender preference, while it is not necessary in games with cyclic sender preference. After vague messages are allowed, both papers find that senders turn to use vague messages more frequently. Since the sender's disclosure strategy with only precise messages is opposite in the two papers, the impacts of vague messages on information transmission are also different.

Our paper is also related to the literature on strategic information transmission based on a model raised by Crawford and Sobel (1982), which analyzed unverifiable information revelation strategies with conflicts of interest between the two parties. The model proved that partition equilibria exist under strictly concave utility. Our work is related to a growing literature in this area examining the role of vague language as a tool to enhance efficient communication (e.g. Serra-Garcia et al., 2011; Agranov and Schotter, 2012; Wood, 2016; Sun and Chen, 2020). In this body of research, deception is typically allowed. This makes it difficult to answer whether vague messages can enhance information transmission because deception adds noise and confounding factors when studying the impact of vague messages. For example, Wood (2016) finds that the sender lies less and the receiver trusts the sender more when vague messages are used. The study focuses on the impacts of vagueness on trust-building between the sender and receiver rather than information transmission. While our paper's message design is built similarly to those studies, the difference is that we do not allow the informed party to use deception. This enables us to evaluate the pure effects of vague messages on information transmission.

In strategic communication research, there is also a growing body of literature focusing on Bayesian persuasion and information design (e.g. Kamenica and Gentzkow, 2011; Bergemann and Morris, 2019). Similar to work on persuasion games, this type of research also examines strategic information transmission from the sender to the receiver. However, contrary to the settings in a persuasion game, the sender commits to a decision rule before the realization of the state rather than choosing a message after observing the true state.

To solve the game in our paper, we use an extensive-form analog to iterative admissibility (IAS) based on the notion of prudent rationalizability (PR) introduced by Li and Schipper (2020), in which for each elimination level, players have full-support beliefs of the opponents' surviving strategies from the one-step lower level. Most experimental studies on persuasion games have used sequential equilibrium as the solution concept (e.g. Jin et al., 2015; Dickhaut et al., 2003). Pearce (1984) characterized a different solution concept called rationalizability, which iteratively eliminates strictly dominated strategies in a normal form game and suggested that extensive-form rationalizability (EFR) may be used to refine the notion of sequential equilibrium. Heifetz et al. (2011) further defined PR and proved that PR weakly refines the path induced by EFR. Li and Schipper (2020) was the first to apply PR to solve the standard persuasion game between a seller and a buyer. They show that the solution of iterative admissibility refines the sequential equilibrium solutions and is consistent with the experiment results. In our paper, we compare the solution concepts of IAS and PBE. With the game solutions containing multiple strategies, we show that the intersection of the two solution concepts is a better prediction of subjects' behavior in a lab experiment. This result is consistent with previous work and provides empirical evidence to research discussing IAS as an equilibrium selection criterion (e.g. Hagenbach and Perez-Richet, 2018; Miura, 2018).

Two other experiment work has used the solution concepts of IAS so far up to my knowledge. Hagenbach and Perez-Richet (2018) applied IAS to solve different types of disclosure games. They study multiple sender-receiver games where the sender's incentives differ based on the payoff structures. By comparing the solutions of IAS to experiment results, they conclude that senders, whose interests are aligned with receivers, would fully disclose. For other types of senders, vague messages are used. This is consistent with our results, and we further investigate the role of vague messages in information transmission by comparing different disclosure rules. Schipper and Woo (2018) use IAS to solve a political model to examine to what extent the electoral campaigns can reveal information about the candidate's political position and improve the awareness of the voters.

Because the procedure of IAS is to eliminate weakly dominated strategies repeatedly, the games are solved level by level under IAS, which is similar to level-k reasoning (Stahl and Wilson, 1994, 1995; Nagel, 1995). The level-k model requires assumptions on the level-0 types' behavior, and each level k type responds optimally, treating the opponents as level k-1. Under IAS, with full-support beliefs of the opponent's rational strategies, all available strategies are level-0 rationalizable naturally. Therefore, assumptions on the level-0 types' behavior are unnecessary.

Discussion about vague messages also arises in the literature studying political platform competition. A part of the research in this field has focused on strategic ambiguity in the electoral competition (e.g. Aragones and Neeman, 2000; Meirowitz, 2005a; Bräuninger and Giger, 2018). They show that the purpose of ambiguity in the political competition is to remain uncommitted to policies. Meirowitz (2005b) forwards a different explanation of candidate ambiguity: the candidate has incentives to avoid the opponent learning their private information. This is close to the conclusion of our paper: when the two parties are in a contest of limited resources, the informed party tends to send vague messages to the uninformed party.

Finally, the results of our paper may provide implications to information revelation among bidders in auctions since the competition between bidders is closest to the game setup in our paper. Among the literature studying verifiable disclosure between bidders, both theoretical and experimental work have consistent conclusions that there is no incentive for the bidders to reveal information in pure value auctions (e.g. Milgrom and Weber, 1982; Benoit and Dubra, 2006; Tan, 2016). However, these studies focus on the situation of precisely revealing the true signal or not. While vague message revelation is rarely discussed in this field, the game design in our research replicates the payoffs of a common value auction and offers a window to observe information revelation under more flexible communication rules.

1.3 Theory

1.3.1 The Persuasion Game

We use a persuasion game to replicate a simplified oil tract common value auction with two bidders. The value of the item can take three different levels (low, medium, high) with equal probability.[2] The first player is the experienced bidder who has private information about the true value. Their bid is determined by the item value. When the value is low, they bid 1; when the value is medium, they bid 2; when the value is high, they bid 3. Therefore, their bids are a mapping from the true state.[3] This bidder needs to send a message to the other bidder.[4] The second player is the inexperienced bidder who only knows the distribution of the item value and the associated bid of the

[2]We focus on a uniform distribution of the true state to ensure the sender's preference is cyclic.

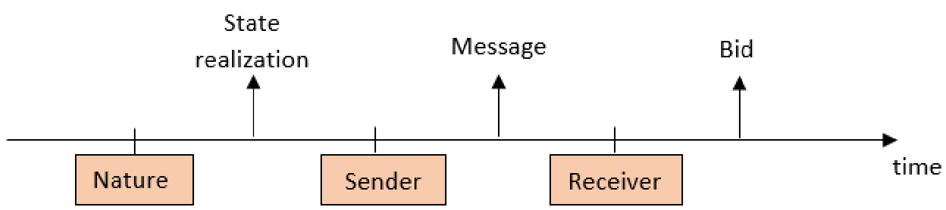
[3]Based on the optimal strategies of bidders with asymmetric information in a common value auction from Milgrom and Weber (1982)

[4]Since we want to study the messaging and information sharing behavior, we have fixed the first mover's bidding function to track the true state perfectly.

experienced bidder but cannot observe the true state or their opponent's bid. They receive the message from the first player and need to choose their bid from a menu with three integers: 1, 2, and 3. We call the experienced bidder the sender and the inexperienced bidder the receiver.

Formally, the sender observes the state and chooses a message m from a menu to send to the receiver. Then the receiver sees the message and submits a bid selected from the menu. Figure 1.1 depicts this timeline.

Figure 1.1: Timeline



The payoff matrix of the sender and the receiver are shown in Table 1.1 and Table 1.2. Each column of the table is the true state and the associated sender's bid. Each row is the receiver's bid choice. In Table 1.1, when the sender's bid is higher than the receiver's bid, the sender wins and earns a positive payoff. The payoff is higher when the true state and the associated sender's bid are higher. When the sender's bid is lower or equal to the receiver's bid, the sender loses and earns 0. In Table 1.2, when the receiver's bid is higher or equal to the sender's bid, the receiver wins. Their payoff depends on both the true state and their own bid. When the true state is low (sender's bid is 1), if the receiver wins by bidding 2 or 3, the bid is higher than the true value, and the receiver's payoff is negative. The higher the bid is, the more loss is incurred. This represents the winner's curse. When the true state is medium (sender's bid is 2), the receiver wins by bidding 2 or 3. With the item value fixed, the payoff of a higher bid of 3 is lower than a bid of 2. When the true state is high (sender's bid is 3), the receiver wins only when they bid 3 and earns the highest payoff of 10. The receiver loses and earns 0 when their bid is lower than the sender's bid. Therefore, the sender can get the highest payoff when they win, while the receiver can get the highest payoff when they submit the same bid as the sender. Under this situation, the receiver's bid that benefits the sender the most would deviate from the receiver's own optimal choice when the state is medium or high. The sender and receiver's interests are not aligned for these two states.

Since there is a mapping between item values and the sender's bids, we will use the sender's bid as the true state for the rest of the paper. We study two different message spaces (also referred to as message rules). Under Message Rule 1, the sender can either reveal the true state exactly or "keep silent". In particular, if the realized state is s, the only two possible messages are $m \in \{\{s\}, S\}$, where $S = \{1, 2, 3\}$ is the state space. We define the message revealing the true state exactly ($m = \{s\}$) as precise message. Keeping silent is sending a message that is the state space ($m = S$), and we call this no information.

Table 1.1: Payoff matrix for the sender

		True Value (Sender's Bid)		
		low (1)	medium (2)	high (3)
Receiver's Bid	1	0	5	10
	2	0	0	10
	3	0	0	0

Table 1.2: Payoff matrix for the receiver

		True Value (Sender's Bid)		
		low (1)	medium (2)	high (3)
Receiver's Bid	1	0	0	0
	2	-5	5	0
	3	-10	0	10

Under Message Rule 2, the message options available to the sender are the union of all subsets of the state space S containing the true state s. Same as Message Rule 1, when the sender keeps silent ($m = S$), we call this no information and call $m = \{s\}$ the precise message. For the rest of the situations when the message is a non-singleton proper subset of S which contains s ($m \subset S$, $m \neq \{s\}$, and $s \in m$), we define it as a vague message. Table 1.3 shows the message menu for each state under Message Rule 1 and Message Rule 2.

We also consider a version of the game with a different state space. In this version, the true state is uniformly distributed between four integers: 1, 2, 3, and 4. By solving this 4-state game and comparing the results to the 3-state game, we are able to examine whether the results are consistent across state space and complexity of strategy space. The payoff matrix, solution of the 4-state game can be found in the Appendix.

Table 1.3: Message Menu

State	Message Options	
	Message Rule 1	Message Rule 2
1	{1},{1,2,3}	{1},{1,2},{1,3},{1,2,3}
2	{2},{1,2,3}	{2},{1,2},{2,3},{1,2,3}
3	{3},{1,2,3}	{3},{1,3},{2,3},{1,2,3}

1.3.2 Solution Concept

1.3.2.1 Perfect Bayesian Equilibrium

Perfect Bayesian Equilibrium (PBE) is commonly used to solve dynamic games with incomplete information. Based on PBE, the sender is mapping from the true state to messages, and the rational receiver updates their posterior belief on the true state under each message. Both players respond optimally to the opponent. Let the sender's strategy be $M_i \in M(s)$, , where $M(s)$ is the set of available messages under s. Let the receiver's strategy be $a \in A$, where A is the action space, and the receiver's belief of the state s under m be $\beta_m(t)$. Then the PBE $(m^*(s), a^*(m), \beta_m(t))$ can be shown below.

$$\beta_m(t) = P(t|m) = \frac{P(t,m)}{P(m)} = \frac{P(m|t)P(t)}{\sum_{t' \in m} P(m|t')}$$

$$a^*(m) \in arg \max_{a \in S} \sum_{t \in m} u_r(a,t)\beta_m(t)$$

$$m^*(s) \in arg \max_{M_i \in M(s)} u_s(a^*(M_i), s)$$

We focus on pure strategy PBEs to avoid loss of generality[5] and find that

[5]We also checked the sequential equilibrium of our game since it is widely used to solve persuasion

for both message rules, there are multiple PBEs. However, in a one-shot game with multiple equilibria, the game is complicated, and it is hard to get a clue on how PBEs can predict people's behaviors.

1.3.2.2 Iterative Admissibility

We use an extensive-form analog to iterated admissibility (IAS), based on Li and Schipper (2020) as well as Hagenbach and Perez-Richet (2018). The basic idea is the iterated elimination of obviously dominated strategies. All strategies are available initially, and the worst strategy is eliminated for each level of reasoning until a steady situation is reached. The reasoning procedures of this approach are similar to a level-k analysis, where each more sophisticated player believes that other players have bounded rationality and act non-strategically. The advantage over the level-k method is that it is unnecessary to fix an assumption on the level-0 behavior, thus avoiding discussion on the benchmark (Li and Schipper, 2020). There is also proof of the existence of IAS solutions for finite extensive-form games (Heifetz et al., 2011).

Consider a persuasion game where the true state s is drawn from a finite set S. For the sender, the possible strategies $M(s)$ are contingent on the true state. For the receiver, their interpretation of a message M_i given the message space M is $I(M_i|M) = \{s \in S : \exists m \in M, m(s) = M_i\}$ (e.g., If the possible strategy for the sender is to send {1,2} under state 2 and {2,3} under state 3, then the interpretation of message {2,3} would be {3}.). u_s, u_r are the utility of the sender and receiver respectively.

games. The results are similar to the PBEs. Only the posterior beliefs on the out-of-equilibrium messages are refined, and receivers only guess 3 for message {2,3}.

Definition 1 (Obviously dominated strategy for the receiver)**.** A receiver's strategy a_h is obviously dominated by a_l given a subset M of sender strategies, denoted by $a_l \triangleright_M a_h$, if for every $M_i \in M$ such that $a_h \neq a_l$,

$$\min_{t \in I(M_i|M)} \{u_r(a_l(M_i), t)\} \geq \max_{t \in I(M_i|M)} \{u_r(a_h(M_i), t)\},$$

and when equality holds, either $\{u_r(a_l(M_i), t) : t \in I(M_i|M)\}$ or $\{u_r(a_h(M_i), t) : t \in I(M_i|M)\}$ is not a singleton.

To understand the obviously dominated strategy for receivers, let us consider a situation where a message {1,2,3} is received. Suppose the interpretation of this message is {2,3}, which means the sender only sends {1,2,3} when the state is 2 or 3. If the receiver bids 1, the payoff would be 0 for certain. If the receiver bids 2, the payoff will be either 0 or 5. Therefore, the minimum payoff from biding 2 is larger or equal to the maximum payoff of biding 1; thus, biding 1 is obviously dominated by biding 2 under message {1,2,3}.

Definition 2 (Obviously dominated strategy for the sender)**.** A sender's strategy m_i is obviously dominated by m_j given a subset A of the receiver's strategies, denoted by $m_j \triangleright_A m_i$, if for every $s \in S$ such that $m_i(s) \neq m_j(s)$,

$$\min_{a \in A}\{u_s(a(m_i(s)), s)\} \geq \max_{a \in A}\{u_s(a(m_j(s)), s)\},$$

and when equality holds, either $\{u_s(a(m_i(s)), s) : a \in A\}$ or $\{u_s(a(m_j(s)), s) : a \in A\}$ is not a singleton.

Similarly, to understand the obviously dominated strategy for the sender, consider a situation where the true state is 2, and the sender believes the receiver would choose from the numbers contained in the message. Then if message {2} is sent, the receiver bids 2. For this case, the sender's payoff is 0 for certain. If message {1,2,3} is sent, the receiver will choose bids among 1, 2, and 3. Then the sender's payoff is either 0 or 5. Because the minimum payoff by sending message {1,2,3} is larger or equal to the maximum payoff by sending message {2}, sending {2} is obviously dominated by sending {1,2,3}[6].

The iterative elimination procedure can be described as follows:

1. At level $k = 0$, for both senders and receivers, all strategies are available.

2. Starting from level 1 receivers, for each level k, receivers update their interpretation of each message given the strategies of level $k-1$ senders. They then eliminate the obviously dominated actions from the surviving action set of level $k-1$ receivers:

$$A^k = \{a \in A^{k-1} : \forall a' \in A^{k-1}, a' \not\succ_{A^{k-1}} a\}$$

3. Level k senders consider all level $k-1$ receivers' actions under each message, and then eliminate the obviously dominated messages from the surviving message set of level $k-1$ senders:

$$M^k = \{m \in M^{k-1} : \forall m' \in M^{k-1}, m' \not\succ_{M^{k-1}} m\}$$

4. Iterate until there is no more updating.

[6]In our game, obviously dominated strategies are equivalent to weakly dominated strategies for both the sender and receiver

Table 1.4: Message Rule 1: sender reasoning

Level of reasoning	State	Message			
		{1}	{2}	{3}	{1,2,3}
0 and 1	1	✓			✓
	2		✓		✓
	3			✓	✓
2 and higher	1	✓			✓
	2				✓
	3				✓

In each row, the check marks show the messages that are not obviously dominated and thus not eliminated for each state. The strategies with ✓ are eliminated in the higher reasoning level.

Table 1.5: Message Rule 1: receiver reasoning

Level of reasoning	Message received			
	{1}	{2}	{3}	{1,2,3}
0	1,2,3	1,2,3	1,2,3	1,2,3
1 and higher	1	2	3	1,2,3

In each cell, the numbers show the receiver's bids that are not obviously dominated, thus not eliminated for each message. The receiver's bids marked as red are eliminated in the higher reasoning level.

Table 1.4 and Table 1.5 show how this procedure operates for Message Rule 1. In Table 1.4, the first column is the reasoning level of the sender. The second column is three states under each reasoning level. Each of the remaining columns represents a message option of the sender. For each row, the check marks show all the message options available to the sender, which are not eliminated under the corresponding state and reasoning level. For example, in the row where the level of reasoning is 2 and the state is 2, the available messages which are not eliminated are only {1,2,3}. The red check marks show messages that survived but will be eliminated in the next reasoning level, such as {2} for state 2 and {3} for state 3, which are eliminated by level-2 senders. In Table 1.5, the first column is the reasoning level of the receiver. Each of the remaining columns shows the receiver's choices which are not eliminated under each message. For example, the column of {1} reflects that level-0 receivers would choose bids among 1,2, and 3 after receiving message {1}, while level-1 receivers would only bid 1. Similarly, the choices marked with red are eliminated in the next reasoning level.

The level-0 senders and receivers choose all possible strategies. For the receiver, there is one level of reasoning. At level 1, when a precise message is received, the receiver learns the true state because the sender cannot lie. Then the bids which do not match the true state are obviously dominated and eliminated. For the sender, there are two levels of reasoning, and the strategies are only refined in level 2. After receiving a precise message, the level-1 receiver would choose the bid that matches the sender's bid and lead to a 0 payoff for the sender. Therefore, for the level-2 senders, precise messages are obviously dominated and eliminated when the true state is 2 or 3. The detailed proof can be found in the Appendix.

Proposition 1. If the sender is only allowed to send precise messages or reveal no information (Message Rule 1), the highest level senders will choose no revelation except when the state is 1. The highest level receivers will choose all bids that match the states contained in the message received.

Table 1.6: Message Rule 2: sender reasoning

Level of reasoning	State	Message						
		{1}	{2}	{3}	{1,2}	{1,3}	{2,3}	{1,2,3}
0 and 1	1	✓			✓	✓		✓
	2		✓		✓		✓	✓
	3			✓		✓	✓	✓
2 and 3	1	✓			✓	✓		✓
	2				✓			✓
	3					✓	✓	✓
4 and higher	1	✓			✓	✓		✓
	2				✓			✓
	3					✓		✓

In each row, the check marks show the messages that are not obviously dominated and thus not eliminated for each state. The strategies with ✓ are eliminated in the higher reasoning level.

Table 1.7: Message Rule 2: receiver reasoning

Level of reasoning	Message received						
	{1}	{2}	{3}	{1,2}	{1,3}	{2,3}	{1,2,3}
0	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
1 and 2	1	2	3	1,2	1,3	2,3	1,2,3
3 and higher	1	2	3	1,2	1,3	3	1,2,3

In each cell, the numbers show the receiver's bids that are not obviously dominated, thus not eliminated for each message. The receiver's bids marked as red are eliminated in the higher reasoning level.

Table 1.6 and Table 1.7 show the iterative elimination procedures for Message Rule 2. Table 1.6 is structured similarly to Table 1.4. The check marks show all messages available to the sender which are not eliminated. The messages with red check marks are eliminated in the next reasoning level. Table 1.7 shows the receiver's bid choices that are not eliminated, and those of red color are eliminated in the next reasoning level.

Similarly, level-0 subjects start by choosing all available strategies. Because the sender starts to refine their strategies at level 2, the strategies of every two levels are the same for both the sender and receiver. For level-2 and level-3 senders, when the state is 2, message {2,3} is eliminated because it provides a 0 payoff, which is obviously dominated by {1,2,3} and {1,2}. Then for level-3 receivers, by responding to level-2 senders with updated beliefs, their interpretation of message {2,3} would change to {3} and thus to only bid 3, while the interpretation of other messages remains the same. The detailed proof of each reasoning level is provided in the Appendix.

Compared to Message Rule 1, the message options are more complicated under Message Rule 2; thus, more reasoning levels are required. Regarding the sender disclosure, the sender with a level higher or equal to 2 chooses no revelation under Message Rule 1. After vague messages are allowed under Message Rule 2, even for the sender of the highest level, it is still possible for them to reveal information. Therefore, the sender has more incentive of disclosure under Message Rule 2. The only precise message which is not eliminated under Message Rule 2 is {1}.

Proposition 2. If precise messages, vague messages, and no information are all allowed (Message Rule 2), the strategies which are not eliminated for the highest level senders are all messages that contain state 1. For the highest level receivers, if the received message contains state 1, their bids will match the numbers in this message; if the received message does not contain state 1, their bid will be the same as the largest number in this message[7].

The two propositions from the IAS solutions show clear patterns which can be compared with the experiment results. Relative to Message Rule 1, the highest level senders choose vague messages more often instead of keeping silent all the time under Message Rule 2.

1.3.2.3 Comparison between IAS and PBE

The critical differences between PBE and IAS stem from the differences between equilibrium and rationalizability concepts. The former assumes mutual belief of actions between players, in which each strategy is the best response to the actions of other players, reaching a situation without action deviation. As a type of Nash equilibrium, PBE specifies players' strategies and beliefs about which node in the information set is reached. It requires sequential rationality and belief consistency. The solution concept of rationalizability was first defined by Pearce (1984). Players are assumed to be rational and eliminate the dominated strategies regardless of the strategies of other players. In both Nash equilibrium and rationalizability, players respond optimally to some beliefs about their opponents' strategies. However, rationalizability has weaker constraints and does not require the beliefs to be correct. On the track of rationalizability, IAS or prudent rationalizability further requires prudent beliefs. In the strategy elimination procedure, a strategy only survives if it is the best response to a full-support

[7] Proposition 1 and 2 also hold for the 4-state game. The game design and IAS solutions can be found in the Appendix

belief rather than some belief over the opponent's surviving strategies.

Our game can reflect the differences between PBE and IAS clearly. For example, one PBE under Message Rule 1 is that the sender selects message $\{s\}$ for each state s; the receiver chooses the bid $a = s$ under the message $\{s\}$. The condition for this equilibrium is that the sender believes the receiver would only bid 3 after receiving message {1,2,3}. However, if the sender is prudent and assumes all bids are possible for the receiver, for state 2 and 3, the precise messages are obviously dominated by no information. Therefore, this PBE is not a reasonable solution under IAS. Actually, all PBE equilibria with direct disclosure of the true state 2 and 3 are excluded in the IAS solutions for both Message Rule 1 and Message Rule 2.

Table 1.8: Sender's Pure Strategy Categories: Message Rule 1

Pure Strategy			PBE	IAS
State 1	State 2	State 3		
{1}	{2}	{3}	●	
{1}	{2}	{1,2,3}	●	
{1}	{1,2,3}	{1,2,3}	●	●
{1,2,3}	{2}	{1,2,3}	●	
{1,2,3}	{1,2,3}	{1,2,3}	●	●

Each row shows a pure strategy combination. ● in the PBE column means the strategy is PBE; ● in the IAS column means the strategy is IAS.

Another example is an IAS pure strategy for Message Rule 2 where the sender chooses no information (send message {1,2,3}) under state 1 and 2, and send message {1,3} under state 3. This case is not an equilibrium because sending {1,3} under state

3 cannot achieve the optimal expected payoff. The sender would deviate to choose message {1,2,3}, thus benefiting from the receiver bidding 1 or 2.

Table 1.9: Sender's Pure Strategy Categories: Message Rule 2

Pure Strategy			PBE	IAS	Pure Strategy			PBE	IAS
State 1	State 2	State 3			State 1	State 2	State 3		
{1}	{2}	{3}	●		{1,2}	{1,2}	{1,2,3}	●	●
{1}	{2}	{1,3}	●		{1,2}	{1,2,3}	{1,3}		●
{1}	{2}	{2,3}	●		{1,2}	{1,2,3}	{1,2,3}		●
{1}	{2}	{1,2,3}	●		{1,3}	{2}	{1,3}	●	
{1}	{1,2}	{3}	●		{1,3}	{1,2}	{1,3}	●	●
{1}	{1,2}	{1,3}	●	●	{1,3}	{1,2}	{1,2,3}		●
{1}	{1,2}	{2,3}	●		{1,3}	{2,3}	{1,3}	●	
{1}	{1,2}	{1,2,3}	●	●	{1,3}	{1,2,3}	{1,3}	●	●
{1}	{2,3}	{2,3}	●		{1,3}	{1,2,3}	{1,2,3}		●
{1}	{1,2,3}	{1,3}		●	{1,2,3}	{2}	{1,2,3}	●	
{1}	{1,2,3}	{1,2,3}	●	●	{1,2,3}	{1,2}	{1,3}		●
{1,2}	{1,2}	{3}	●		{1,2,3}	{1,2}	{1,2,3}	●	●
{1,2}	{1,2}	{1,3}	●	●	{1,2,3}	{1,2,3}	{1,3}		●
{1,2}	{1,2}	{2,3}	●		{1,2,3}	{1,2,3}	{1,2,3}	●	●

Each row shows a pure strategy combination. ● in the PBE column means the strategy is PBE; ● in the IAS column means the strategy is IAS.

From both the PBE and IAS solutions, we can elicit the sender's pure strategies and categorize them into four types: Only PBE, Both PBE and IAS[8], Only IAS, Neither PBE nor IAS. Table 1.8 and Table 1.9 show the pure strategies of the first three types for Message Rule 1 and Message Rule 2 (the last type contains all of the possible pure strategy combinations not listed).

[8]Here we mean the highest level IAS strategies

For Message Rule 1, all IAS pure strategies are PBE, so there is no strategy falling into Only IAS category. In Only PBE category for both Message Rule 1 and Message Rule 2, almost all strategies contain precise message revelation under state 2 or 3, which is not an option under IAS. For the IAS pure strategy combinations under Message Rule 2, when the state is 2 or 3, the strategies are either vague messages or no information, and message $\{2,3\}$ is eliminated. In section 1.5, we will show the prediction results of each category.

There are also other PBE refinement approaches, and we have checked sequential equilibrium as well as payoff dominance PBE. For our game, sequential equilibrium cannot further refine the pure strategy PBE for senders. The payoff dominance PBE eliminates strategies that are frequently chosen, which cannot provide more accurate predictions.

1.4 Experiment

1.4.1 Design

We deploy the same game described in Section 1.3.1. To make the game easier to understand, we phrased it as a guessing number game, which is a one-shot two-player sequential game in the experiment. The number is uniformly distributed between three integers: 1, 2, and 3. The state space S is $\{1,2,3\}$. In each round, Player 1 (sender) observes the true state and chooses a message from a menu to send to Player 2 (receiver) in Stage 1. Then in Stage 2, Player 2 receives the message and guesses what the true number is. Our benchmark treatment applied Message rule 1, and the main treatment applied Message Rule 2. In each session, both treatments are applied using a within-subject design.

At the beginning of each session, half of the subjects were randomly assigned as Player 1 and the rest as Player 2. The roles are fixed. For each round, a Player 1 and a Player 2 were randomly matched. After half of the rounds of each treatment, subjects switched to the opposite role. The purpose of switching roles once is to accelerate the learning procedure in a complicated signaling game like ours.[9] At the end of each round, the information of the true state, the message sent by Player 1, Player 2's guess, and each player's own payoff were provided on the computer screen of each subject. The last round of each treatment was a belief elicitation round where each subject stated their beliefs on both Player 1 and Player 2's strategies. Bonus points were earned depending on the accuracy of the subject's beliefs compared to the empirical frequency. A quadratic scoring rule same as the one in Hagenbach and Perez-Richet (2018) was used.

We also conducted 4 sessions with a strategy method in case some states were never reached[10]. We changed the rounds before subjects switched roles and before belief elicitation to use the strategy method. In this way, we can collect more data and observe strategies for each possible state or message. The results of the direct-response rounds in both the main sessions and strategy method sessions are compared with the strategy

[9]This setup is different from many other experimental work on sender-receiver games where the role is randomly drawn for each round. We did not apply this approach because changing roles too frequently may confuse the subjects and cause opposite effects.

[10]Strategy method is used to elicit participants' decisions for all possible situations

method rounds, and will be shown in Section 1.5.

To further check whether our results are robust to the state space, we conducted two more sessions with a similar 4-state game which is explained in the Appendix.

1.4.2 Hypotheses

In Section 1.3, IAS solutions showed clear strategy options for both senders and receivers level by level. We expect to see that the behavior of most subjects in the experiment matches the highest-level player. The details can be summarized in the following two hypotheses.

Hypothesis 1. In line with Proposition 1, under Message Rule 1, we expect senders to choose no information with the highest frequency for state 2 and 3, and receivers' guesses match the states contained in the message most of the time.

Hypothesis 2. In line with Proposition 2, under Message Rule 2, we expect senders to choose messages which contain number 1 with the highest frequency. For receivers, when the message contains number 1, the guesses match the numbers in the message most of the time; otherwise, receivers guess the highest number in the message most of the time.

Since there are multiple equilibria for the one-shot sender-receiver game under PBE, it might be hard for the players to have accurate beliefs on their opponents' strategies. While IAS does not require accurate beliefs on the opponents' strategies, it might work as an equilibrium selection criterion. Therefore, we have the next hypothesis to test whether IAS can be a refinement of PBE.

Hypothesis 3. We expect that among the four categories of pure strategies (Both PBE and IAS, Only PBE, Only IAS, Neither PBE nor IAS), the intersection of PBE and IAS is a better prediction of the subjects' behavior.

Our primary research question is whether information transmission can be enhanced by allowing vague messages. The theory predicts that, when allowed, vague messages can be a strategic option for the sender. This necessarily implies that more information might be revealed since vague messages always contain the true state. Also, since information transmission is improved, we expect the receiver to have more accurate beliefs as well as guesses of the true number. These are reflected in the next two hypotheses.

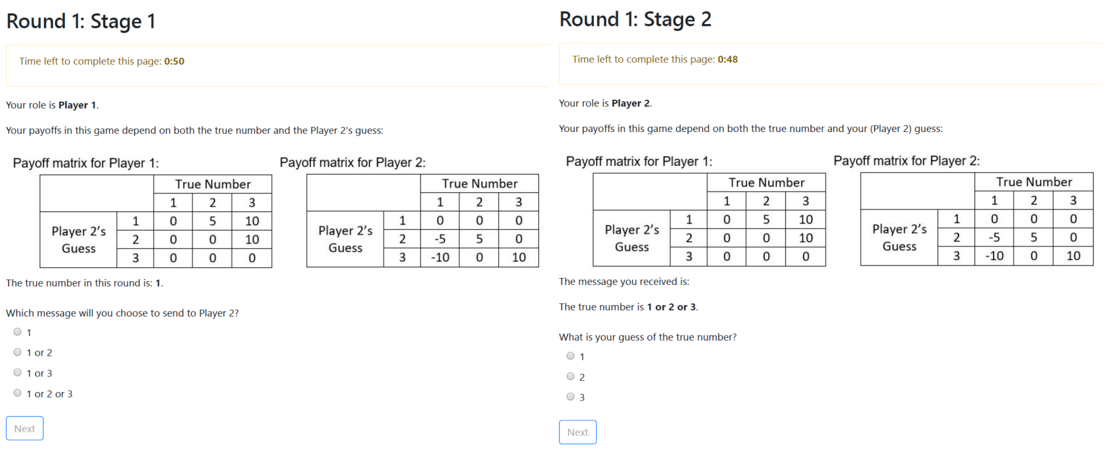
Hypothesis 4. According to the IAS solutions, relative to Message Rule 1, the rate of information disclosure (sending something different than $\{1, 2, 3\}$) would be higher under Message Rule 2. Additional information will be disclosed through vague messages.

Hypothesis 5. Receivers have more accurate beliefs and correct guesses of the true state when vague messages are allowed (Message Rule 2) relative to when those are not allowed (Message Rule 1).

1.4.3 Procedures

The game was programmed in oTree (Chen et al., 2016). In each session, subjects read a paper-based instruction of the experiment first, and then the experimenter explained the games one more time. Before the game started, subjects needed to do a quiz with 4 questions to make sure they understand the game well. After the game was completed, subjects needed to fill out a paper-based questionnaire which is the same as the one in Li and Schipper (2020), for feedback and demographic information. The whole session takes around 1.5 hours. At the time of the experiment, all participants were undergraduate students at UC Santa Cruz and were recruited using an online recruiting system ORSEE from the LEEPS lab.

Figure 1.2: Game Interface



(a) Sender Page (b) Receiver Page

In the main sessions and the strategy-method sessions, subjects played the game with Message Rule 1 for 14 rounds and then Message Rule 2 for 19 rounds. The first two rounds of Message Rule 1 and the first round of Message Rule 2 were practice rounds, as well as the first round after the player switched roles. Figure 1.2 shows a screenshot of the game interface for the sender and receiver.

For the 4-state game, the recruited subjects are experienced players who have participated in the experiment before since this game is more complicated than the 3-state game. Subjects played under Message Rule 1 for 19 rounds and then Message Rule 2 for 24 rounds. The practice rounds were the same as the main sessions, but the strategy method and belief elicitation were not applied. Table 1.10 shows the session summaries.

Table 1.10: Summary of Sessions

Session	Participant	Rounds		Beliefs
		Message Rule 1	Message Rule 2	
Main	50	14	19	Yes
Strategy Method	32	14	19	Yes
4-state Game	24	19	24	No

At the end of each session, participants' payment was calculated. The payment depends on the total points earned, which has two parts. The first part is an endowment given to each subject at the beginning of the game, 200 points. The second part is the payoff earned from each paying round. Then the points are converted to US dollars with an exchange rate equal to 2 cents for each point. The payment each subject finally earns is a US$ 7 show-up fee plus the total payoff from the game, which is rounded to the nearest quarter dollar.

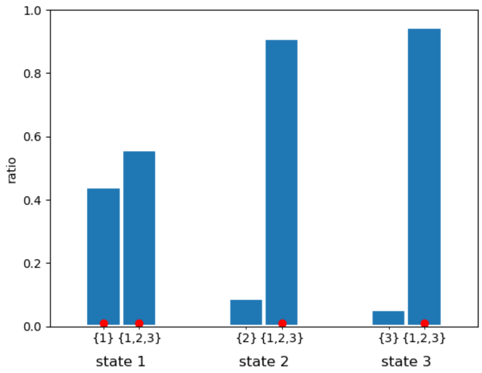
1.5 Results

1.5.1 Strategies

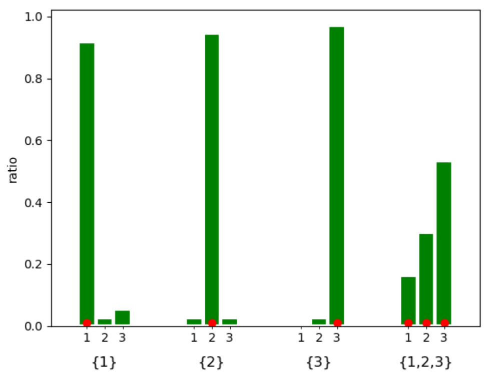
We combined the data from both the direct-response rounds and strategy method rounds, and computed the frequency of strategies.

1.5.1.1 Message Rule 1

Figure 1.3: Strategies: Message Rule 1



(a) Sender



(b) Receiver

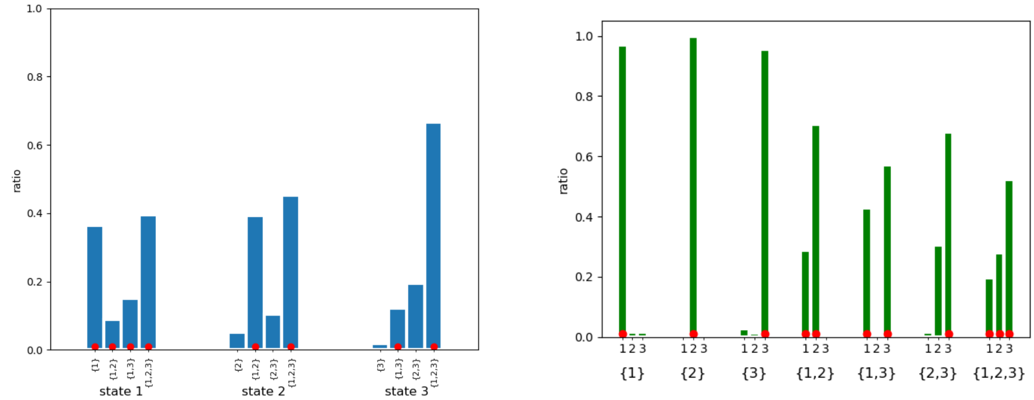
The messages (guesses) with a red dot below are the surviving strategies of the highest level senders (receivers) under the IAS solution.

Figure 1.3a shows the frequency of the sender's strategy under Message Rule 1. When the state is 2 and 3, more than 90% of the messages sent are {1,2,3}. For state 1, about 44% of messages sent are {1} and 56% are {1,2,3}. The precise messages are essentially eliminated under Message Rule 1. Most of the time, the sender chooses to keep silent when their interests are not aligned with the receiver under state 2 and 3. Under state 1, since the sender's payoff is not influenced by the receiver's choice, the sender would like to reveal the true state to the receiver almost half of the time.

Figure 1.3b is the frequency of the receiver's strategy under Message Rule 1. After receiving precise messages, the receiver's guesses match the number contained in the message most of the time, which is reasonable since they know the sender cannot lie. When the sender keeps silent, message {1,2,3} is received, and all three numbers are guessed frequently. The patterns show that receivers tend to guess 3 more often (around 53% of the time). On the contrary, number 1 is guessed with the least frequency (around 16% of the time). Since the sender sends {1,2,3} more often under state 2 and 3, the posterior probability of the state to be 2 or 3 should be higher than the posterior probability of the state to be 1 under message {1,2,3}. Therefore, the patterns of the receiver's strategy for message {1,2,3} are logical and may suggest that the receivers can update their beliefs in the correct direction. Both of the sender and receiver's strategies are consistent with the highest level IAS solutions.

1.5.1.2 Message Rule 2

Figure 1.4: Strategies: Message Rule 2



(a) Sender

(b) Receiver

The messages (guesses) with a red dot below are the surviving strategies of the highest level senders (receivers) under the IAS solution.

Figure 1.4 shows the sender's strategy frequency under Message Rule 2. When the state is 1, the highest level IAS predicts that no messages are eliminated. We can observe that messages {1} and {1,2,3} are sent most frequently, with a ratio around 36% and 40% respectively. Compared to Message Rule 1, both ratios decrease since there are more message options under Message Rule 2: the sender chooses message {1,3} 16% of the time and {1,2} 9% of the time. When the state is 2, IAS predicts that the message {2} and {2,3} would be eliminated by the level 2 and 3 senders. The results also show that the sender tends to send message {1,2} and {1,2,3} more often (39% and 45% respectively), which is consistent with the highest level IAS. When the state is 3, even though message {1,2,3} is sent with the highest frequency (67%), compared to Message Rule 1, the ratio has dropped about 30 percentage points. With the ratio of sending message {3} still low, the sender choose vague message {1,3} and {2,3} 32% of the time. The experiment results show a relatively high ratio of message {2,3} being sent, which is still consistent with the IAS solution since only the highest level senders are able to eliminate message {2,3}. In comparison, others can keep sending {2,3}.

Figure 1.4b is the receiver's strategy frequency under Message Rule 2. When precise messages are received, the receivers guess the number matching the message most of the time. When the message {1,2,3} is received, all three numbers are guessed frequently, with the highest ratio guessing 3 (52%) and the lowest ratio guessing 1 (20%). These two features are similar to the patterns in Message Rule 1. The slightly higher ratio of guessing 3 under message {1,2,3} is also consistent with the posterior probability of each state conditional on the sender's strategy frequency. When the vague messages are received, the receiver essentially guesses both the numbers contained in the message frequently. For message {1,2}, the ratio of guessing 2 is 70%, which is much higher than guessing 1. Since message {1,2} is sent more frequently under state 2 than state 1, this result is reasonable. For message {2,3}, IAS predicts the highest level receiver would only guess 3. The experimental results reflect that the receiver would still guess 2 around 30% of the time. It suggests that subjects may not be rational enough to eliminate guessing 2.

In general, both senders' and receivers' strategies are consistent with the highest reasoning level of the IAS solutions. This also holds for the 4-state game. We have also compared the strategy frequency by periods and by decision elicitation methods. The results show that there are no significant learning effects and behavioral differences between the two methods. The details can be found in the Appendix.

1.5.2 Model Predictions Comparison

In Section 1.3.2, we categorize the sender's pure strategies into four types: Only PBE, Both PBE and IAS, Only IAS, and Neither PBE nor IAS. In this part, we evaluate the prediction accuracy by computing the proportion of the senders from our experiment data falling into each category[11]. Since the state is randomly drawn for each round, some states may never be reached for some subjects. Therefore, we also check the data from the strategy method rounds. By collecting each subject's choices for each possible state or message stated in the strategy method round, we can further see whether the prediction results are consistent.

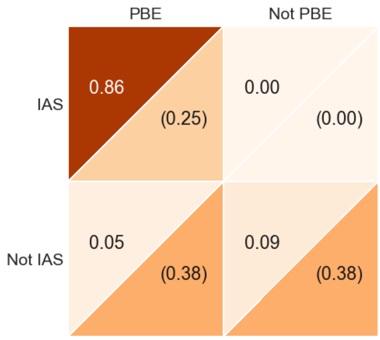
Figure 1.5a and 1.5b show the model predictions for Message Rule 1. In Section 1.3.2, we showed that under Message Rule 1, all IAS pure strategies are PBE, no strategies are categorized as IAS only. Therefore, the number in the top-right cell of both Figure 1.5a and 1.5b are 0. Among all possible pure strategy combinations of the sender, 38% are only PBE, which is the majority. 37% of the strategy combinations are neither PBE nor IAS. The remaining 25% are both PBE and IAS, which is the minority. Suppose the sender picks a pure strategy combination randomly. In that case, we expect

[11] For the direct-response method rounds, we calculate the frequency of each message sent under each state for a subject, and regard the message with the highest frequency as the pure strategy of that subject. If there is a tie of two messages, we count both as the subject's pure strategies and assign 0.5 weight to each pure strategy. If there are more than 2 messages in a tie or more than two ties, we regard this subject as playing randomly and exclude them from the sample.

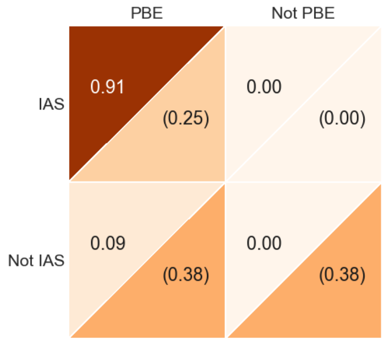
to observe the largest number of senders falling into the category Only PBE, and the fewest senders falling into the category Both PBE and IAS. What we instead observe in the experiment results show that most senders' strategies are both PBE and IAS (86% in the direct-response method rounds and 91% in the strategy method rounds), while less than 10% of the senders' strategies are only PBE. Additionally, less than 10% of the senders' strategies are neither PBE nor IAS. Therefore, for Message Rule 1, IAS solutions refine the PBE solutions and predict the subject's behavior more accurately.

Figure 1.5c and 1.5d show the model predictions for Message Rule 2. Among all possible pure strategy combinations of the sender, more than 50% are neither PBE nor IAS, which is the majority. For the other three categories, similar to Message Rule 1, the number of combinations that are only PBE (17%) is higher than those which are both PBE and IAS (14%). The remaining 11% are only IAS. However, in the experiment results, most senders are in the category Both PBE and IAS (54% in the direct-response method rounds and 56% in the strategy method rounds). Less than 25% of senders fall into Neither PBE nor IAS and no more than 20% fall into Only IAS. The fewest senders (no more than 15%) are in the category Only PBE. Therefore, under Message Rule 2, PBE that also satisfies IAS predicts the sender behavior most accurately, which are a refinement of PBE.

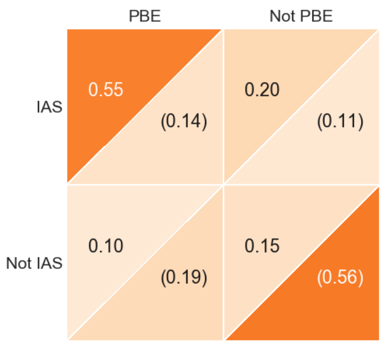
Figure 1.5: Model Prediction



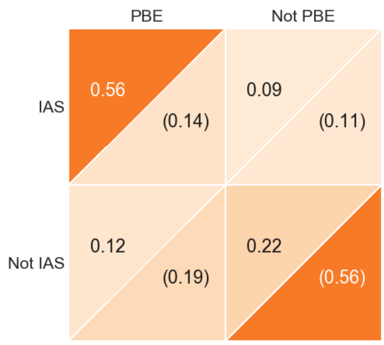
(a) Message Rule 1: DR Method



(b) Message Rule 1: Strategy Method



(c) Message Rule 2: DR Method



(d) Message Rule 2: Strategy Method

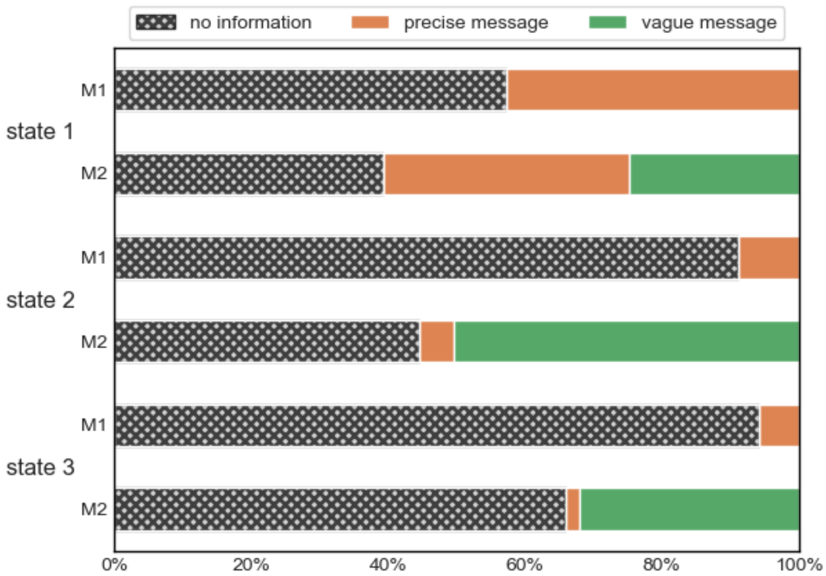
The numbers in each cell are the ratio of subjects falling into each category. The numbers in parentheses are the ratio of the pure strategy combinations in each category to all possible pure strategy combinations.

1.5.3 Sender Disclosure

To evaluate whether information transmission has been improved under Message Rule 2, we compare the sender's disclosure level for both message rules directly.

Similar to the strategy frequency, we computed the rate of disclosure using data of both direct-response rounds and strategy method rounds. The results are shown in Figure 1.6.

Figure 1.6: Sender Disclosure



The graph shows clearly that more disclosure is achieved under Message rule 2. For all three states, the disclosure rate is higher relative to Message Rule 1, especially for state 2 and 3, where the disclosure rate increases around 45 and 30 percentage points respectively. There is also clear evidence that the additional disclosure under Message Rule 2 is mainly achieved through vague messages. When the state is 2, 50.4 percentage points of the disclosure rate are contributed by vague messages. When the state is 3, vague messages contribute to 32 percentage points of the disclosure rate. Additionally, both the disclosure rate and the frequency of vague messages being sent are higher under state 2 than state 3. This is consistent with the results in Section 1.5.1. Since the chance for the sender to win is lower under state 2 than state 3 without communication, the sender may have more incentive to disclose under state 2 when there is a lower probability to win.

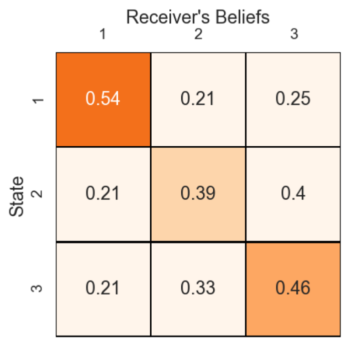
1.5.4 Receiver's Information Gain

The strategy summaries in Section 1.5.1 suggest that senders disclose more through vague messages under Message Rule 2, and receivers' actions are consistent with the posterior probability of the sate conditional on the message. To further evaluate whether there are information gains for the receiver due to more disclosure from the sender, we use data from the direct-response method rounds to compare the receivers' average beliefs (actions) under each state between Message Rule 2 and Message Rule 1. The results are showed in Figure 1.7.

Figure 1.7a and 1.7b reflect the receiver's average beliefs under each state for Message Rule 1 and Message Rule 2. The diagonal of 1.7a and 1.7b reflects the average ratio of the receiver's beliefs matching the true state (belief accuracy), which can be used to measure the receiver's information gains. When the true state is 1, the belief accuracy is 0.54 for both Message Rule 1 and Message Rule 2. Instead, relative to Message Rule 1, the receiver's belief accuracy increases from 0.39 to 0.5 for state 2 and from 0.46 to 0.54 for state 3 under Message Rule 2. There is an obvious increase in the belief accuracy for state 2 and 3. We further run a linear regression of the belief accuracy on the message rules to test the difference between Message Rule 1 and Message Rule

2, and the results are significant.

Figure 1.7: Receivers' Information Gain



(a) Message Rule 1: Belief

(b) Message Rule 2: Belief

(c) Message Rule 1: Action

(d) Message Rule 2: Action

The numbers in each cell show the ratio of beliefs (actions) conditional on each state. The numbers on the diagonal of each table, which are marked as orange, reflect the ratio of beliefs or actions matching the state. The darker color reflects the higher number.

Figure 1.7c and 1.7d use an alternative way to examine the receiver's information gains, which is reflected by the ratio of guesses (actions) matching the true state. Relative to Message Rule 1, when the state is 1, the frequency of the receiver guessing the state correctly increases from 0.49 to 0.55; for state 2, the ratio increases from 0.39 to 0.45 and from 0.58 to 0.61 for state 3. The receiver's guess accuracy is improved for all three states. Similarly, we run a regression of the guessing accuracy on message rules, and the results are significant. Therefore, both measures suggest that there is more information transmission to the receiver under Message Rule 2.

1.5.5 Reasoning

Because IAS applies an iterative elimination procedure to solve the game level-by-level, it provides a window to partially observe the strategic reasoning of players. Table 1.11 summarizes the players' reasoning. The numbers show the ratio of subjects who failed to pass each level. For example, under Message Rule 2, 32% of senders failed Level 2 and 3; 28% of senders passed Level 2 and 3 but failed Level 4; the remaining 40% passed all reasoning levels.

Table 1.11: Ratios of subjects for each reasoning level

	Sender		Receiver	
Message Rule 1	Fail L2	0.17	Fail L1	0.07
	Pass IAS	0.83	Pass IAS	0.93
Message Rule 2	Fail L2/3	0.32	Fail L1/2	0.07
	Fail L4	0.28	Fail L3	0.24
	Pass IAS	0.40	Pass IAS	0.69

For Message Rule 1, the highest level senders are Level 2; the highest level receivers are Level 1. For Message Rule 2, the highest level senders are Level 4; the highest level receivers are Level 3.

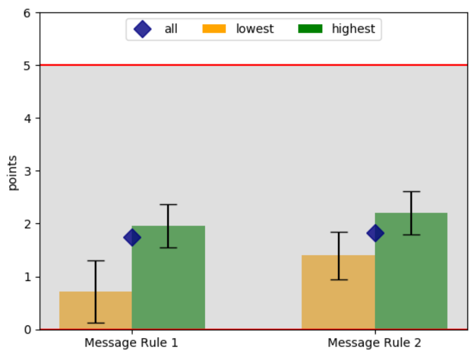
For Message Rule 1, most subjects passed IAS. Only 17% of senders failed level 2 reasoning due to sending precise messages. Even fewer receivers (7%) failed the level 1 reasoning because they guessed the number incorrectly after receiving a precise message. In general, most subjects passed the highest level IAS under Message Rule 1. For Message Rule 2, more receivers passed the highest level IAS than senders. While 69% of receivers passed IAS, only 40% of senders passed IAS. This is reasonable because, under Message Rule 2, there are more message options for the sender, which increases the difficulty for the sender to figure out the best strategy. The complexity is also reflected in the number of reasoning levels. For the senders under Message Rule 2, there are 4 reasoning levels, which is more than the receivers. The senders who did not pass IAS under Message Rule 2 mainly failed to eliminate the message {2,3}. However, since the strategies for each level overlap, different reasoning levels are not distinguishable. For example, a subject sending message {1} for state 1, message {1,2} for state 2 and message {1,2,3} for state 3 can fall into any reasoning level. Therefore, these results are just suggestive.

1.5.6 Welfare Analysis

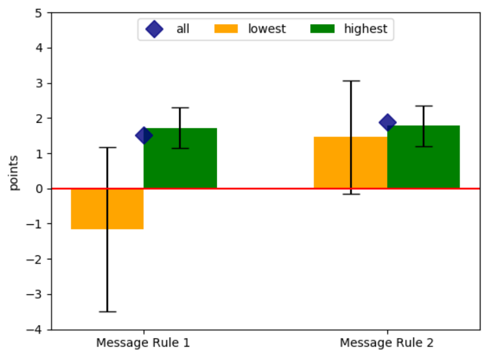
Our results indicate that the sender has more incentive to disclose through vague messages and that the receiver benefits from the information gained. In this section, we examine how the disclosure under Message Rule 2 influences the welfare of the sender and receiver.

Figure 1.8a shows the average payoff for the sender. The grey area is the range of expected payoff where the sender can reach without communication, which is between 0 and 5 points. The average payoff of the sender for both Message Rule 1 and Message Rule 2 falls into this range, reflecting no information gains for the sender. While the overall average payoff under Message Rule 1 is 1.74, the sender's payoff under Message Rule 2 is a little higher at 1.82. The difference is not significant based on the t-test. Since disclosure may affect subjects of different rationality levels differently, we further compare the average payoffs of subjects passing only the lowest IAS reasoning level (naive sender) and subjects passing the highest IAS reasoning level (sophisticated sender). The results show greater improvements of payoffs for naive senders, but the t-test still shows the changes are insignificant.

Figure 1.8: Average Payoffs



(a) Sender



(b) Receiver

The orange bars are average payoffs of the subjects only passing the lowest IAS reasoning level; green bars are average payoffs of the subjects passing the highest IAS reasoning level. Blue diamonds show the overall average payoffs. Red lines are upper and lower bounds of expected payoffs without communication.

Figure 1.8b is the receiver's average payoff. Compared to the 0 expected payoff without communication, the receiver earns a positive overall average payoff under both message rules. Therefore, both message rules are better than no communication to the receiver. The overall average payoff earned in Message Rule 2 (1.88 points) is slightly higher than the payoff in Message Rule 1 (1.51 points), but the t-test shows the difference is not significant. Like the sender's payoffs, we divide subjects into different rationality groups and evaluate the effects of disclosure on each subgroup. For the receivers of the lowest IAS reasoning level (naive receivers), there are relatively larger payoff gains under Message Rule 2 (from -1.17 to 1.46 points). One reason for this is that naive receivers tend to guess smaller numbers after receiving the message {1} and {1,2,3} under Message Rule 2 relative to Message Rule 1, which leads to less loss under state 1. Another reason is that, when the state is 2 or 3, the average payoff of naive receivers are higher when vague messages are received compared to other messages. For the receivers passing the highest IAS reasoning level (sophisticated receivers), their payoffs have no notable difference (from 1.72 to 1.77 points). Despite the payoff improvements, the t-test results are not significant for either naive receivers or sophisticated receivers. In summary, the payoff improvements are merely suggestive as they have no statistical significance.

1.6 Conclusions

We propose an experiment design replicating a simplified common value auction, where two players are competing for limited resources in the context of asymmetric information and conflicting interests. Our results suggest that information transmission can be improved by using vague messages. On one hand, senders choose to send vague messages rather than no disclosure after vague messages are allowed. On the other hand, by receiving messages with better qualities, receivers are able to have more accurate beliefs on the true state. These can provide implications to real case scenarios. For example, intuitively, we would expect an incumbent company not to share its complete private information with its opponent, a new entrant. However, our results suggest that it would still prefer to share vague information, which improves the information transmission. Therefore, a regulator can allow a flexible disclosure between competitors such as an incumbent company and a new entrant to incentivize voluntary information revelation and weaken the information asymmetry.

Our welfare analysis provides weak evidence that for both senders and receivers, the average payoff increases mainly for those of the lowest reasoning level, especially receivers. This can reflect that with information transmission improved, naïve players benefit the most, and the total welfare increases. However, since the payoff changes are not significant, this conclusion is only suggestive.

Additionally, the results suggest that the sender has more incentive to disclose under the states where the chance to gain benefits without communication is low. One explanation is that by convincing the receiver to change their actions through disclosure, the sender benefits from a higher possibility to win. It is consistent with the situation of “insider’s curse” in auctions (Hernando-Veciana and Tröge, 2011), which indicates that the informed bidder (insider) has more incentive to disclose when facing sufficiently intense competition from the uninformed bidder (outsider). These patterns also hold when the state space is larger.

By comparing the pure strategies of PBE and IAS solutions of the game, our results also support the prediction that the strategies of most subjects fall into the intersection of the two solutions. It suggests that when there are multiple equilibria, it might be difficult for players to have accurate beliefs of their opponent’s action, and they tend to have cautious beliefs. Therefore, IAS can be used as an equilibrium selection criterion. A more interesting observation is that despite there being more pure strategy combinations that are only PBE than both PBE and IAS, the experiment results show that most senders’ strategies are both PBE and IAS. This provides a direction for future research to examine the differences between PBEs which satisfy IAS and the remaining PBEs in a game with multiple equilibria.

Chapter 2

Where Ridehail Drivers Go between Trips[1]

2.1 Introduction

App-based ridehailing services, often known as Transportation Network Companies (TNCs), have revolutionized the customer experience in urban centers in recent years. TNC firms such as Uber and Lyft often provide more abundant, reliable, and cheaper service than taxis, their closest competitor (Brown and LaValle, 2021), leading to rapid growth in ridership. Within San Francisco, for example, ridehailing accounted for 15 percent of intra-city vehicle trips in 2016 (Castiglione et al., 2016).

A large number of studies have analyzed the consequences of ridehailing for travel behavior and congestion. The most common finding is that ridehailing induces

[1]The second chapter is a joint work with Adam Millard-Ball, Whitney Hansen, Drew Cooper, and Joe Casstiglione. It's based on an article accepted for publication in Transportation.

users to make more trips, and that it shifts trips away from private cars, walking, and public transit (Rayle et al., 2016; Hampshire et al., 2017; Clewlow and Mishra, 2017; Gehrke et al., 2019; Babar and Burtch, 2020; Bradley et al., 2021). In San Francisco, ridehailing has been the largest contributor to increased congestion in recent years (Erhardt et al., 2019). However, ridehailing can improve mobility, particularly in neighborhoods where car ownership is low (Brown, 2019a) and for older adults (Leistner and Steiner, 2017). In some cases, ridehailing can also complement transit use by filling gaps in the reach of scheduled bus and rail services (Hall et al., 2018), although the modes can compete with as much as complement each other (Barajas and Brown, 2021; Dong, 2020; Jin et al., 2019; King et al., 2020).

Less attention, however, has been paid to the strategies of ridehailing drivers, and in particular what they do between paid rides. Most analyses focus on the paid, with-passenger portion of a ridehail trip, but deadheading — such as driving to the next pick-up location and cruising while waiting for a trip request — may have major consequences for the environment and congestion (Ward et al., 2021). Driver choices regarding whether and where to park while waiting for the next trip also affect curbspace and parking availability. Thus, understanding deadheading behavior is important for developing municipal policies for regulating and pricing ridehail services, such as congestion surcharges, and for allocating and pricing curbspace (Strong, 2015; Li et al., 2019; Marsden et al., 2020).

In this report, we quantify the choices that ridehail drivers make between paid trips. We focus on the period of time when the driver is available (the app is turned on, but the driver has not yet accepted a trip request), which we call search travel or search time, and is sometimes referred to as Period 1 or P1. We do not quantify other types of deadheading, which we define as any period when the ridehail vehicle is not occupied by a passenger.

We develop a method to partition search travel into cruising, repositioning, and parking segments, and apply it to a dataset of 5.3 million trips in San Francisco. We find that while almost all trips involve repositioning (traveling to another location where demand is expected to be higher), a surprising portion (29 percent) entail at least some cruising. We develop a regression model to quantify the factors associated with driver choices, and find that ridehail drivers appear to reposition to neighborhoods where ridehail demand is high, but the model also suggests that drivers may avoid neighborhoods with high proportions of residents of color. A key limitation of our analysis is that we have no way to assess a driver's intent or reasoning; we are limited to examining their paths of travel.

The rapid growth of ridehailing mean that our findings are relevant to policymakers dealing with present-day transportation challenges. However, our results also provide a preview of what might be expected in a future with autonomous vehicles, whose transportation and environmental consequences may bear many parallels to those of ridehailing.

2.2 Driver behavior: comparing taxis and ridehail

Taxi drivers in large cities often cruise along busy streets in search of a street hail, or reposition to major trip generators such as airports and hotels. In New York City, for example, cruising and repositioning account for 44 percent of miles driven by taxicabs, with an average of 2.9 miles of deadheading between trips (Abrams et al., 2007). Driving around rather than waiting at a taxi stand may be rational from the taxi driver's perspective, as it makes the vacant taxicab visible to prospective passengers, but its impacts from a social welfare perspective are mixed. On the one hand, a ready supply of available taxis reduces wait times for passengers, but cruising taxis are highly visible contributors to congestion. Thus, limiting cruising has often been a key goal of taxicab regulators and a justification for limits on the number of taxicabs (Shreiber, 1975; Yang et al., 2005; Abrams et al., 2007).

Another long-standing regulatory challenge has been to ensure the availability of taxis in low-income neighborhoods and communities of color, which typically experience longer wait times. Drivers often decline to accept calls for service to such neighborhoods, and also tend to reposition away from them after dropping off a passenger due to perceptions of lower demand, fears for their personal safety, and racial profiling (Davis, 2002; Ingram, 2003; Brown, 2019b). Regulatory responses have included enforcement "stings," but also programs such as New York City's "green cabs," which can only pick up passengers outside of the high-demand areas of Lower Manhattan and the airports (King and Saldarriaga, 2017).

To what extent do these findings translate from taxis to ridehailing? Both sets of drivers should seek to maximize the expected net revenue from their next paid trip, and minimize search time and travel. The options open to taxi and ridehail drivers are also similar. They can park (or equivalently, wait at a taxi stand), cruise around while remaining in the same general neighborhood, or reposition to a different neighborhood where they expect demand to be higher. Cruising and repositioning are often conflated in the literature (e.g. Henao and Marshall, 2019; Nair et al., 2020), but conceptually the two categories of search behavior (cruising and repositioning) are distinct.

While the options of taxi and ridehail drivers may be similar, their optimal strategies are likely to be considerably different because their costs and sources of information differ in four main respects. First, while taxi drivers must normally be conspicuous to passengers hailing a taxi on the street[2], most cities prohibit ridehail drivers from accepting street hails, and in any case the app-based system used by ridehail firms renders such visibility unnecessary. Second, a first-in, first-out rule typically applies at taxi stands at hotels, airports, and other major trip generators. In contrast, ridehail drivers are subject to the opaque methods that ridehail firms use to match drivers with passengers, and the incentives that the firms use to encourage drivers to head to specific locations and to start or extend their shifts. Third, while taxi drivers might rely on heuristics or experience to identify high-demand locations, ridehail drivers have access to real-time information on demand patterns through their smartphone app. Fourth, taxi drivers may have lower costs for repositioning if, as in cities such as San Francisco,

[2]This discussion focuses on street hail taxis, rather than telephone dispatch systems which are more similar to ridehailing in the incentive structures that they provide to drivers.

they have access to bus lanes or dedicated taxi stands.

As a result, one would expect ridehail drivers to cruise less frequently than taxi drivers. While cruising may be rational for taxi drivers, it is less reasonable for ridehail drivers unless parking is limited or expensive. For a ridehail driver, parking is likely to provide similar prospects to cruising in terms of obtaining the next paid ride, without the costs of fuel and vehicle wear and tear. Since drivers can easily move if and when an enforcement officer arrives, they have little need to pay for parking either. Indeed, many online guides and fora for ridehail drivers (such as Reddit's r/uberdrivers) exhort drivers to save money by parking rather than driving around in circles. However, the online fora also provide examples of drivers who are unsure of the optimum strategy, or who prefer to cruise. One Reddit user says: "I keep moving...I have loops I drive. I would probably park if I wasn't getting 40 mpg."[3]

The relative advantages of repositioning for taxis and ridehailing, in contrast to those for cruising, are not intuitively clear, but one might expect shifts in the destinations and times of repositioning. Given the dynamic information available to ridehail drivers, they might be expected to reposition to a broader range of destinations, not just the hotels and airports that are obvious sources of demand for taxis (Dempsey, 1996; Schaller, 2007).

Little empirical work, however, exists to support or refute these hypotheses. Data sharing by ridehail firms such as Uber and Lyft has been extremely limited, meaning that most researchers have focused on the paid portion of the trip which is easier to

[3] www.reddit.com/r/uberdrivers/comments/jz1eu4/wanted_to_get_drivers_viewpoints_on_this_is_it/, last accessed December 5, 2021

observe through field or household surveys (e.g. Grahn et al., 2020; Brown and LaValle, 2021). Deadheading behavior is harder to identify, and often, the distance driven while searching for rides is simply assumed (e.g. Tirachini and Gomez-Lobo, 2020) or simulated based on assumptions of rational driver behavior (e.g. Komanduri et al., 2018; Gurumurthy et al., 2020). In almost all travel demand models, the vehicle dematerializes after dropping off a passenger, only to reappear on the network at the start of the next paid trip.

Among the exceptions, Henao and Marshall (2019) find that deadheading accounts for 41 percent of the miles driven by ridehail drivers, but this estimate is based on data from a single driver — the first author. Several studies use a dataset released by RideAustin to impute deadheading based on pick-up and drop-off locations. While the actual paths taken by drivers are uncertain, the data indicate that 37 to 45 percent of total miles driven were by deadheading vehicles (Komanduri et al., 2018; Wenzel et al., 2019). In California as a whole, analysis of data provided by ridehail firms (under a legal requirement) indicates that deadheading accounts for 39.5 percent of miles driven (California Air Resources Board, 2019). In Manhattan, a similar analysis puts the proportion at 40% (Schaller, 2021). Geographically, the broadest estimates are made by Cramer and Krueger (2016) using proprietary data provided by Uber; they find that deadheading accounts for 39 percent of miles by Uber drivers across five major cities. Proprietary data from Uber and Lyft are also used by Martin et al. (2021), who find that search travel (a subset of deadheading) accounts for an average of 34 percent of total miles in three regions — San Francisco, Los Angeles, and Washington, DC. Finally, a study commissioned by Uber and Lyft puts the proportion of deadheading at 38-46 percent in a set of six metropolitan regions (Balding et al., 2019). Their breakdown indicates that 28-37 percent of the distance is driven while waiting for a ride request (i.e., search travel), and 9-10 percent while driving to the pick-up location after accepting a request. These estimates are remarkably consistent. They suggest that deadheading by ridehail vehicles is substantial at about 40 percent of the total distance driven. This consistency comes in spite of different methodologies, data sources, and scopes — for example, whether they consider travel between a driver's home and the first activation of the ridehail app, or whether they consider cruising or assume shortest-path travel distances. Surprisingly, estimates of deadheading for ridehail services are not much less than those for taxis, in spite of the information advantages held by the former.

Studies of racial equity, meanwhile, suggest that discrimination still exists in the ridehail market, although perhaps to a lesser extent than with conventional taxis. At the individual level, field audits that requested rides in Boston and Washington, DC found that cancellations doubled when using an African American-sounding name rather than a white-sounding name (Ge et al., 2020; Mejia and Parker, 2021). Studies of wait time are mixed: aggregate wait times for ridehailing requests in Austin are longer in neighborhoods with a higher proportion of people of color, after controlling for residential and employment densities and average income (Yang et al., 2021), but a study in Seattle found no such effect (Hughes and MacKenzie, 2016).

2.3 Research Approach

2.3.1 Ridehail Data

We used a unique dataset of 5.3 million ridehail trips in San Francisco from November 12, 2016 through December 21, 2016, compiled by researchers at Northeastern University by querying the Uber and Lyft Application Programming Interfaces (APIs) which give access to vehicle locations. The data returned by the servers includes a unique identifier, vehicle type, and a vector of timestamped latitude and longitude coordinates that reflects each vehicle's recent path. When a vehicle driver has accepted a ride and is no longer available, or has ended their shift, the vehicle no longer appears in the information returned by the servers. Similarly, when a vehicle driver drops off a passenger and becomes available again, or when a driver starts a shift, the vehicle appears in the information from the server. An important distinguishing difference between the data revealed by Uber and Lyft is that while Uber appears to assign a new unique identifier to every vehicle after it has completed a trip, Lyft allows the vehicle identifiers to persist across the entire sampling period[4].

Further details of data acquisition, processing, and validation are elaborated in Cooper et al. (2018), and a summary is given in the Appendix. The dataset has been used in several empirical analyses, most notably an assessment of the congestion impacts of ridehailing in San Francisco (Erhardt et al., 2019), and a profile of TNC activity in San Francisco (Castiglione et al., 2016). However, those analyses focus on

[4]This discussion is based on Cooper et al. (2018).

the occupied (paid) portions of the rides, rather than the search portions on which we focus here.

Each trip in the dataset consists of a sequence of points with geographic coordinates and a timestamp. On average, the points are 3.0 seconds apart. We cleaned the dataset to drop points with invalid coordinates, restricted the dataset to trips within the city of San Francisco, and excluded shared (e.g., Lyft Line) and delivery (e.g., UberEats) trips. Note that the dataset only includes points when the ridehail app is turned on and the driver is available to accept a ride, which we call search trips (so-called "P1" miles in California regulatory parlance). Our data does not capture travel between ride acceptance and passenger pick-up ("P2" miles).

We map-matched each trip to the OpenStreetMap road network in order to provide more accurate estimates of driving distances that are not affected by irregularities in the GPS trace. We used a three-stage process: (i) matching GPS points to OpenStreetMap (OSM) links using Mapillary's publicly available map-matching algorithm[5], (ii) dropping links where the preceding and succeeding links directly connect, in order to eliminate out-and-back detours down side streets, and (iii) interpolating gaps in the link sequence using the turn-restricted shortest path function in the pgRouting software package.

[5]Code is available at https://github.com/caomw/map_matching

2.3.2 Classification of Behavior

We classified each point[6] as short, parking, cruising, or repositioning as follows:

Short points are those on trips where either (i) there are fewer than six GPS points or (ii) the trip duration is less than two minutes. For these trips, it was not possible to determine the driver's intent. Except where indicated, short trips are excluded from the subsequent analysis.

Parking points are defined as a cluster of points within any three-minute interval where at least 90 percent of the points are within 7.5 meters of each other. After identifying these clusters, each point within the cluster was classified as parking, and the parking location was defined as the closest point to the centroid of the cluster. To avoid classifying vehicles stuck in congested traffic as parked, we created exceptions where time- and location-specific traffic speeds (obtained from INRIX) were less than three mph, or where the GPS point was on a freeway. In these instances, the parking classification was not applied.

Cruising points are those that involve circling or backtracking. We first identified cruising at the trip level using the definition in Weinberger et al. (2020) — where the actual (map-matched) distance is at least 200 meters longer than the shortest-path network distance. Within each cruising trip, however, the driver may not be cruising the entire time. Therefore, we identified the cruising portion of each trip as a function of the path of the squared displacement — the squared (Euclidean) distance from each

[6]We did not classify the first point in each GPS trace, because the classification of each point is based on the driver's behavior between that point and the previous point.

point to the origin. This metric is often used in movement ecology studies to distinguish the movements of individual animals, such as deer collared with a GPS tracker, and can distinguish between migratory, non-migratory, and dispersing behavior (Killeen et al., 2014; Singh et al., 2016).

Specifically, if we plot the squared displacement over time, a positive slope indicates that the driver is moving away from the origin. A negative slope shows that the driver is returning towards their origin (i.e., the start of the search trip). After smoothing the standardized slope[7], consecutive points with a slope of +1 form a positive segment, and consecutive points with a slope of -1 form a negative segment. We therefore classified a point as cruising if the trip involves cruising per the definition above and either (i) the point is on a negative segment, or (ii) the point is on a positive segment, but its squared displacement is offset by a subsequent negative segment. Figure 2.1 provides an example.

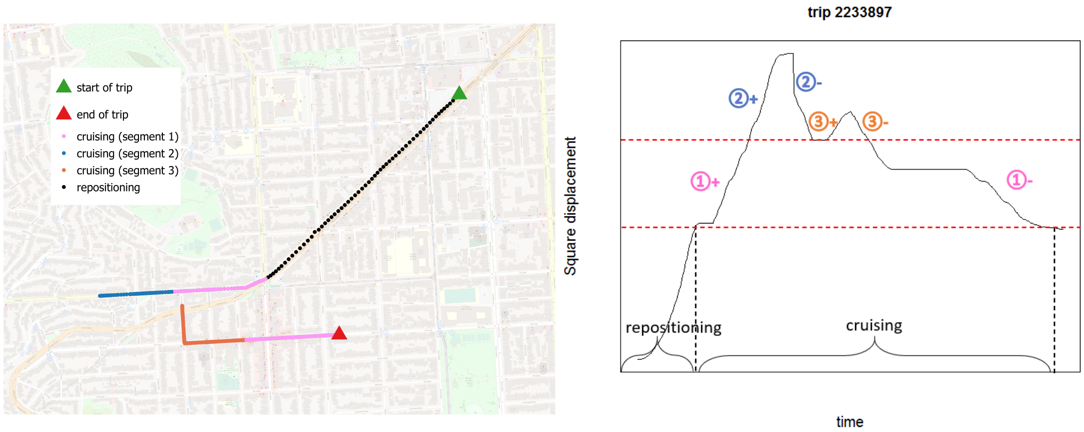
Repositioning points constitute the remainder of the data set. In other words, all other points (i.e., those that are not classified as parking, cruising, or short) were classified as repositioning.

One key limitation of our analysis, discussed further in the conclusion, is that we are unable to link these patterns of behavior to driver reasoning and specific intent. Further uncertainty is added by the scraped nature of the data; while the validation discussed in the Appendix suggests that estimated trip volumes and patterns are consistent

[7]The smoothing method considers five points before and after the current point. If these points have the same normalized slope of square displacement, and the current point is also within 30 seconds of these points, we assign the same value of the normalized slope of these 10 points to the current point.

with independent data sources on ridehail activity, we could not directly verify that our data fully reflect search travel. In addition, our classification depends on several arbitrary thresholds, in particular the 200m difference between the actual distance and the shortest path network distance, which is set to be longer than the typical 100 to 150m long San Francisco blocks. The sensitivity analysis in the Appendix, however, shows only modest effects from varying this threshold. Eliminating it altogether increases our estimate of distance cruised from 23% to 25% of search travel, while doubling the threshold to 400m reduces cruising to 20%.

Figure 2.1: Example of cruising and repositioning segments



The driver's route is shown in the left panel, with the right panel showing how squared displacement changes over the route. The first segment (marked in black) is classified as repositioning because the squared displacement keeps increasing, indicating movement away from the origin. The subsequent segments are classified as cruising because backtracking is involved. Each of the three pairs of cruising segments has a positive segment which is offset by a subsequent negative segment, as shown by the three pairs of segments labeled in the figure. For the pink cruising segment, the positive segment (1+) is offset by the negative segment (1-). Similarly, for the blue segment, (2+) is offset by (2-), and for the orange segment (3+) is offset by (3-).

2.3.3 Other Data Sources

We attached the covariates shown in Table 2.1 to each point. For most variables, we used data at the level of the Transportation Analysis Zone (TAZ), the geographical unit used in transportation analysis by the San Francisco County Transportation Authority. We produced a weighted average for each point by aggregating the values for the TAZ containing the point and neighboring TAZs where the neighboring values were weighted using a distance decay function. This smoothing algorithm avoids abrupt changes in the values of the variables at TAZ boundaries, and also reflects how drivers are likely to perceive gradual changes in neighborhood demographics and parking supply. There are 981 TAZs in San Francisco, with a mean surface area of 0.12 km2. We merged the TAZ level covariates to the point level data, and added lagged dependent variables (indicating prior driver behavior) and time of day and day of week variables for each point. For Lyft trips, we also calculated driver experience, measured as the number of trips by that particular driver observed in the dataset. (The Uber API does not provide a persistent driver identifier.)

2.3.4 Regression Analysis

We used multinomial logistic regression to estimate the effects of covariates in Table 2.1 and interaction terms on the driver's decisions to reposition, cruise, or park. We use these variables because both basic theory and previous studies (e.g. Ghaffar et al., 2020; Grahn et al., 2020; Hughes and MacKenzie, 2016) suggest their importance for ridehail demand and/or ridehail availability, in turn implying that they may affect a driver's decision to reposition, cruise, or park. We include several measures of parking supply due to their effect on both ridehail demand and a driver's ability to park.

To avoid serial correlation of the error terms, we downsampled the data to 1-minute resolution. The downsampled dataset is about 5 percent of the full dataset. For computational reasons, our regressions use a 40% subsample of this downsampled dataset. Because the distributions of most non-ratio numeric covariates are right-skewed, we applied a log transformation on the non-ratio covariates. This can further avoid serial correlation and strong effects from extreme values. Since the magnitudes of covariates have a large variation, we also normalized all numeric covariates by subtracting the mean and then dividing the value by the standard deviation of each covariate.

We also tested the robustness of our results to key modeling assumptions in two ways. First, we used a nested logistic regression to model a process where drivers first choose between repositioning and remaining in the same area, and if the latter, choosing between cruising and parking. The hypothesis is that with low demand, drivers would prefer to reposition to another place, while with high demand the driver would choose between parking and cruising. Second, we aggregated the point level data to the TAZ level with different times of day and days of week, and then ran a fractional multinomial logistic regression of the ratio of points for each behavior on the covariates. Fractional logistic models are designed for aggregate data where the dependent variable is a proportion, rather than a binary or categorical outcome.

Table 2.1: Descriptive Statistics

Covariate	Description	Mean	Standard Deviation	Data Source
TAZ-level variables				
hh_density	**Household density**, calculated by the number of households divided by TAZ area (acres)	26.827	20.276	SFCTA
ratio_age62	Share of the population age 62 or over	0.180	0.068	SFCTA
work_age	Fraction of population of working age (aged 20-64)	0.678	0.151	SFCTA
emp_dens	**Total employment density**, calculated as the total employment divided by TAZ area (acres)	99.428	175.733	SFCTA
service_dens	**Service and visitor employment density**, calculated as the sum of service and visitor employment divided by TAZ area (acres)	20.802	31.453	SFCTA
high_inc	**Fraction of high-income households**, calculated as the fraction of households in the highest and second highest income quantiles	0.391	0.137	SFCTA
onstreet_capacity	On-street parking capacity (number of spaces)	238.156	138.104	SFCTA
offstreet_capacity	Off-street public parking capacity (number of spaces)	115.835	144.410	SFCTA
parking_est	Off-street private parking capacity (estimated number of spaces)	338.821	194.098	SFCTA
frc_latino	Fraction of population that is Hispanic / Latino	0.123	0.098	US Census
frc_african_american	Fraction of population that is African American	0.059	0.062	US Census
frc_white	Fraction of population that is white	0.536	0.172	US Census
Other variables				
driver_exp	**Driver experience**, calculated by counting the number of trips for each driver [only available for the Lyft subsample]	212.283	139.593	Calculated
weekend	**Day of week**, a categorical variable: "weekday" for Monday to Thursday, "fri" for Friday, "weekend" for Saturday and Sunday	-	-	Calculated
timeperiod	**Time of day**, binary variables indicating 6 periods: "ea" for 3-6 am, "am" for 6-9 am, "md" for 9 am-3:30 pm, "pm" for 3:30-6:30 pm, "ev" for 6:30 pm-0:00 am, "night" for 0-3 am	-	-	Calculated
lag_cruise_mnt	**Lag cruising**. Dummy variable that is 1 if the previous point is classified as cruising (only for point level regression)	-	-	Calculated
lag_park_mnt_mnt	**Lag parking**. Dummy variable that is 1 if the previous point is classified as parking (only for point level regression)	-	-	Calculated

2.4 Results

2.4.1 Classification of driver behavior

We begin by presenting the broad patterns of driver behavior in terms of the choices between parking, cruising, and repositioning. Table 2.2 and Figure 2.2 show the percentage of time and distance driven in each of the categories. Repositioning accounts for the majority of search time and distance traveled, and almost all trips involve at least a small amount of repositioning. Perhaps surprisingly given the fuel and wear-and-tear costs of cruising, more time is spent cruising than parking, and the average search trip cruises for nearly half a kilometer.

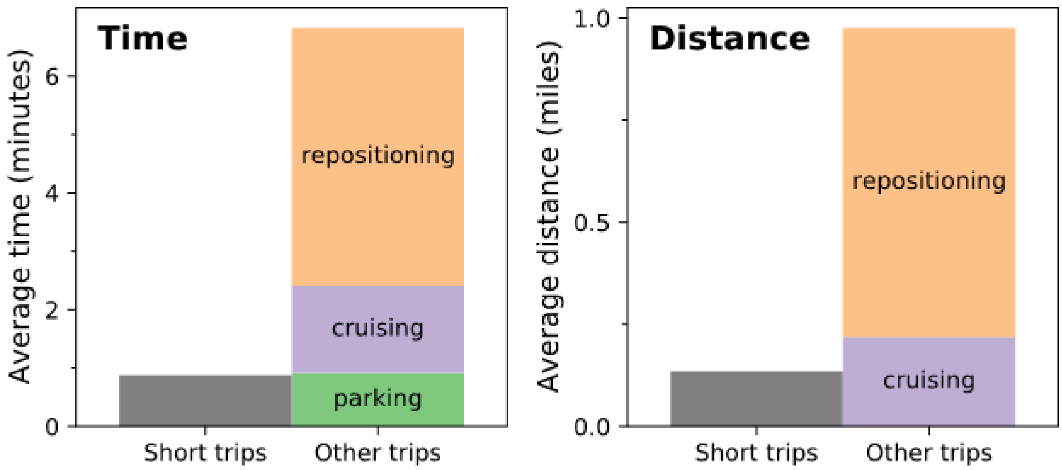
Table 2.2: Classification of driver search behavior

	% of trips	Mean time per trip	Mean distance per trip
Excluding short trips			
Parking	10%*	0.9 mins (14%)	N/A
Cruising	29%*	1.5 mins (23%)	0.35 km (22%)
Repositioning	86%*	4.1 mins (63%)	1.22 km (78%)
All trips	100%	6.6 mins	1.57 km
Including short trips			
Short	44%	0.9 mins	0.22 km
Not short	56%	6.6 mins	1.57 km
All trips	100%	4.1 mins	0.98 km

* Trips may include multiple behaviors. This column counts trips that have at least one point in a given behavior.

As shown in Table 2.2, the average search distance traveled is 0.98 km (0.6 miles). The average paid ride is 4.2 km (2.6 miles), based on a previous analysis of the same dataset (Castiglione et al., 2016). Therefore, the search portion accounts for 19 percent of ridehail vehicle travel. Note that this estimate excludes travel before the driver activates the app, and between accepting a ride request and picking up the passenger.

Figure 2.2: Driver behavior when searching for rides

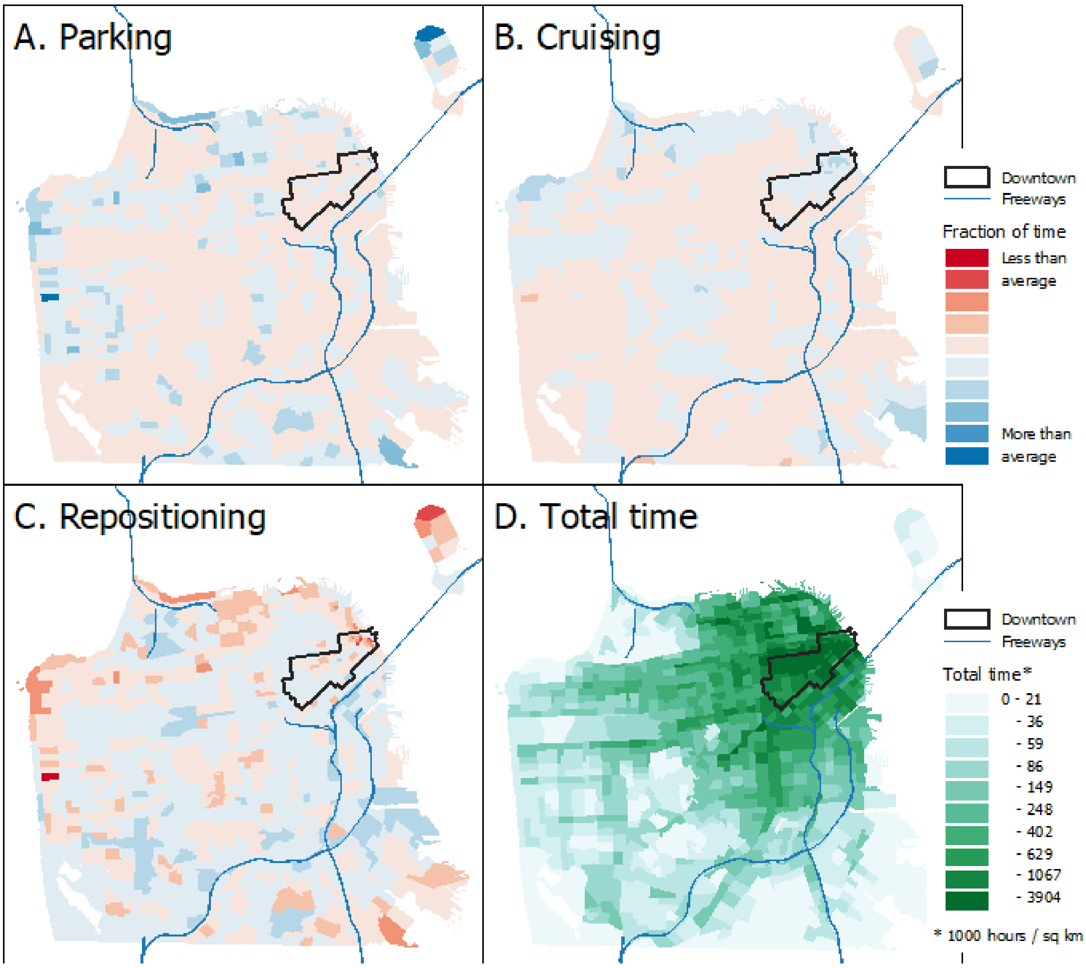


Short trips (defined as fewer than six GPS points or lasting less than two minutes) are not further categorized, as we have insufficient data to classify the drivers' behavior.

Drivers for the two ridehail firms operating in San Francisco — Uber and Lyft — spend almost identical proportions of their time across the three categories of parking, cruising, and repositioning. However, search trips are longer for Lyft drivers (5.5 minutes and 1.35 km, compared to 3.6 minutes and 0.86 km for Uber drivers). Lyft drivers also have a smaller proportion of short search trips (36 percent compared to 46 percent for Uber). Since Uber accounts for three-quarters of the trips in our sample, it is possible that economies of scale lead to their drivers obtaining a paid fare more quickly, reducing the amount of search travel required.

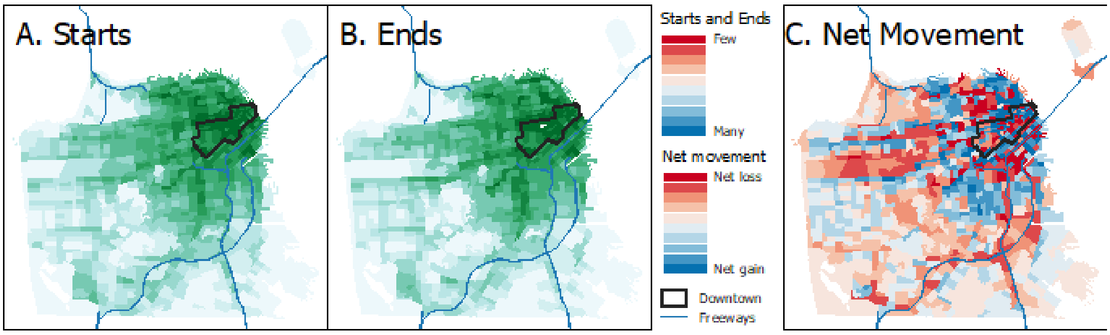
There is surprisingly little geographic variation in the three behaviors across the city (Figure 2.3). Drivers finding themselves in the ring of dense residential neighborhoods around the downtown core are more inclined to park rather than reposition or cruise, but the effects are not strong. Northeastern San Francisco — the densest part of the city — accounts for the largest share of search time (Figure 2.3) and trip starts and ends (Figure 2.4). There is a noticeable concentration of trip starts on freeway corridors, perhaps reflecting drivers turning on their app as they enter the city. Otherwise, there is no obvious geographic pattern in the number of search trip ends minus the number of trip starts (net trip flows), with Figure 2.4 showing a patchwork quilt across the city. The exception is along freeways, where for obvious reasons there is a net movement away from these facilities.

Figure 2.3: Geographic patterns in parking, cruising, parking, and repositioning



Panels A, B and C show the fraction of time within each TAZ spent parking, cruising, and repositioning respectively. Each category spans a ten percentage point range (e.g. 40-50% below average, 30-40% below, etc.) Most of the color hues are in the center of the distribution, especially for cruising, indicating that behavior is relatively uniform across the city. Panel D shows the distribution of search time across the city, normalized to land area and expressed as thousand hours per square kilometer.

Figure 2.4: Net search flows

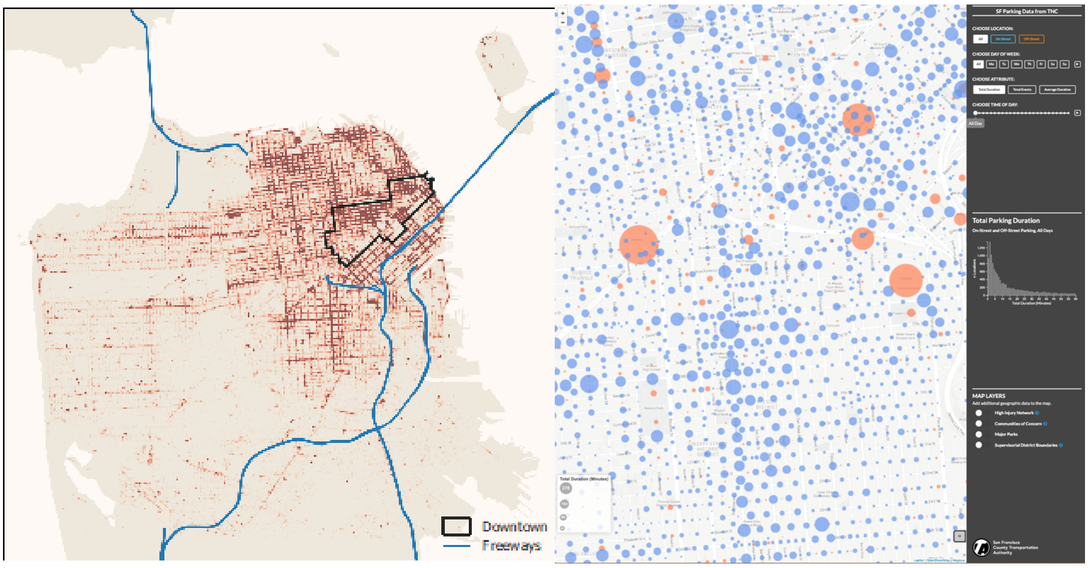


Panels A and B and C show the number of search trip starts and trip ends in each TAZ, normalized to area and express as deciles. Panel C shows the net movement, with red-shaded TAZs having more trip starts than ends (a net movement away) and blue-shaded TAZs having more trip ends than trip starts.

2.4.2 Parking

We now consider the characteristics of parking events. The map in Figure 2.5 (left panel) shows a concentration in the inner ring of dense residential neighborhoods. Within this general area, however, drivers find a range of parking options. Off-street parking is most visibly concentrated in grocery store surface parking lots, gas stations, and similar locations, where drivers may be able to linger for a short time before being moved on by security staff or parking attendants. On-street parking is spread more diffusely, but concentrations are evident along neighborhood commercial corridors. In some cases, ridehail drivers park on blocks where driveways, fire hydrants, loading zones, or other restrictions preclude parking for regular vehicles, but mean that curb space is readily usable by ridehail drivers who can quickly move if needed. These concentrations are most visible in an interactive online version of the parking map (right panel of Figure 2.5), available at https://tncparking.sfcta.org.

Figure 2.5: Concentrations of parking locations



Each location is weighted by the length of time parked. The right panel shows a screenshot from the interactive online map available at https://tncparking.sfcta.org. Blue symbols denote on-street parking, and red symbols denote off-street parking, with a gas station and surface lots at two grocery stores being readily apparent.

Overall, almost all the time spent parking (93 percent of the total duration) occurs on-street. Non-metered on-street spaces (both legal and illegal) account for the majority of ridehail parking, with the largest share (31 percent) occurring on residential streets (Table 2.3 and Figure 2.6). Parking at meters accounts for just over one-third of the aggregate time spent parked, but given that most drivers do not park at all while searching for a ride, this amounts to only 12 seconds in the average trip, of which 5 seconds are during metered hours. Thus, on a per-trip basis, the impact on parking availability is minimal, as is the revenue loss to the City (less than half a cent). However, given the 1.2 million ridehail trips per week in late 2016 (Castiglione et al., 2016), aggregate meter revenue amounts to more than \$200,000 per year, based on the typical meter rate of \$2.50 per hour. This calculation also excludes time spent while loading or unloading passengers at meters, and stays of less than three minutes (the minimum length of a parking event in our analysis).

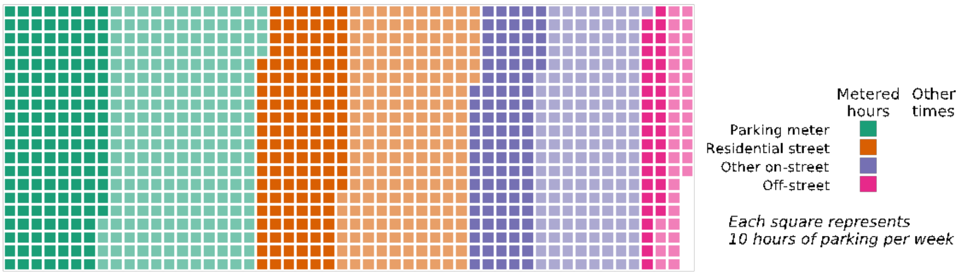
Table 2.3: Time spent parked (hours per week)

	Metered hours*	Non-metered hours
Parking meter	1,562 (37%)	2,281 (37%)
On-street: residential	1,303 (31%)	1,918 (31%)
On-street: other	992 (24%)	1,557 (25%)
Off-street	353 (8%)	368 (6%)
Total	4,209	6,124

* Typically Mon-Sat 9am-6pm. A total of 37 percent of trips in our dataset take place during metered hours. Includes trips with no parking events. Time spent parked is calculated on a per-trip basis, and scaled up to a weekly aggregate based on 1.2 million ridehail trips per week in late 2016 (Castiglione et al., 2016).

Parking meter locations are defined as those within 10 meters of a parking meter. We used OpenStreetMap (OSM) to identify residential streets and off-street parking locations (signified by a "service" classification in OSM, which typically consists of access roads or parking aisles in surface lots). We were unable to identify parking garages.

Figure 2.6: Distribution of time spent parked



2.4.3 Determinants of driver behavior

We now consider the associations between neighborhood characteristics and a driver's decision to park, cruise, or reposition, using the logistic regression models discussed in the Research Approach section. Two coefficients are attached to each variable, indicating the associated change in the probability of repositioning and cruising respectively, compared to a baseline behavior of parking. All coefficients are shown in Table 2.4 and, with the confidence intervals graphically represented, in Figure 2.7.

Table 2.4: Regression coefficients

	Reposition	Cruise		Reposition	Cruise
(Intercept)	3.822***	1.736***	Interaction: with HH density		
Demographic and neighborhood variables			Weekday	0.035***	0.003
Fraction age 62+	–0.048***	–0.037***	Friday	0.029***	0.008
HH density	0.031***	0.022***	Time period: early AM	–0.063***	–0.009
Fraction of working age	–0.013***	–0.051***	Time period: AM	–0.158***	–0.113***
Employment density	–0.184***	–0.049***	Time period: midday	–0.018***	–0.013*
Service and visitor employment density	0.044***	–0.007	Time period: PM	0.029***	0.020**
Fraction high income HHs	–0.110***	–0.086***	Time period: night	–0.075***	–0.029**
On-street parking capacity	0.018***	–0.012***	Interaction: with employment density		
Off-street parking capacity (public)	0.011***	–0.018***	Weekday	0.067***	0.071***
Off-street parking capacity (residential)	0.013**	0.014**	Friday	0.054***	0.057***
Fraction Latinx residents	0.037***	0.026***	Time period: early AM	0.358***	0.257***
Fraction African-American residents	–0.009***	–0.021***	Time period: AM	0.524***	0.392***
Fraction White residents	–0.059***	–0.005	Time period: midday	0.287***	0.183***
Driver experience (Lyft subsample only)			Time period: PM	0.073***	0.027*
Driver experience	0.035***	0.008**	Time period: night	–0.125***	–0.091***
Time and day of week variables			Interaction: with service/visitor employment density		
Time period: early AM	–0.303***	–0.097***	Weekday	–0.046***	–0.038***
Time period: AM	–0.086***	–0.119***	Friday	–0.028*	–0.036**
Time period: midday	–0.092***	–0.125***	Time period: early AM	–0.277***	–0.154***
Time period: PM	0.061***	–0.040***	Time period: AM	–0.237***	–0.151***
Time period: night	0.003	0.133***	Time period: midday	–0.143***	–0.038***
Friday	0.063***	–0.023***	Time period: PM	–0.018	0.044***
Mon-Thurs	–0.065***	–0.057***	Time period: night	0.068***	0.040*
Lagged dependent variables					
Lag cruise	–1.378***	1.769***			
Lag park	–6.892***	–5.064***			

A positive coefficient for repositioning indicates that the driver is more likely to reposition away from a TAZ than to park. Both cruising and repositioning coefficients are relative to the baseline of parking. Baseline (omitted) categories are the fraction of Asian residents, weekend days, and the evening time period.

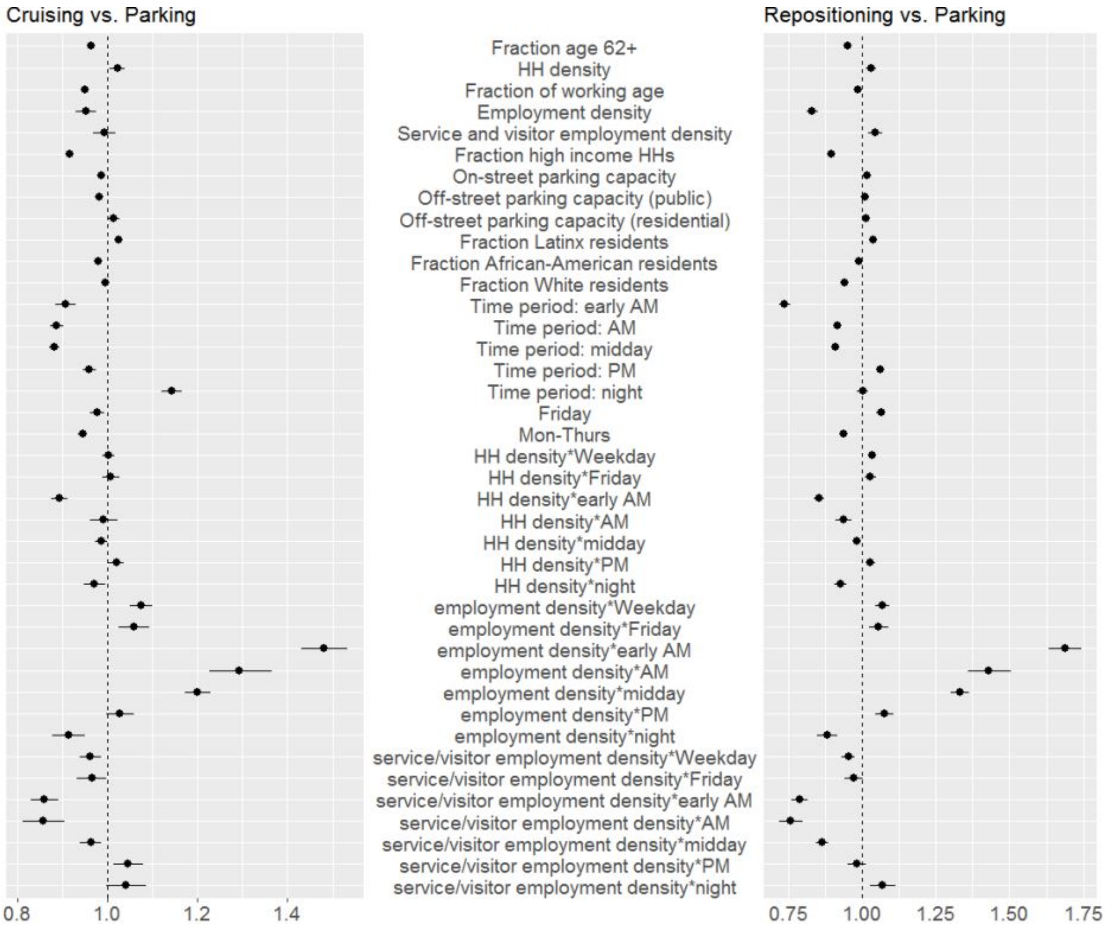
The estimates are from our preferred model (the point-level multinomial logistic regression at one-minute resolution). All coefficients are estimated from the full dataset, except that for driver experience, which is estimated from the Lyft subsample. For computational reasons, we use a random 40% subsample of the full dataset.

Residual Deviance: 6957399 on 15002084 degrees of freedom

Log-likelihood: –3478700 on 15002084 degrees of freedom

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 2.7: Confidence intervals for regression coefficients



Note that the chart omits the lag behavior coefficients, which are much larger than the other covariates.

The variables are standardized, and so each coefficient represents the effect of a one-standard deviation change. A positive sign indicates that that behavior is more likely compared to parking, and a negative sign that it is less likely. For example, drivers are less likely to reposition away from TAZs with a high proportion of White residents (coefficient of –0.059), and slightly less likely to cruise (–0.005), compared to parking.

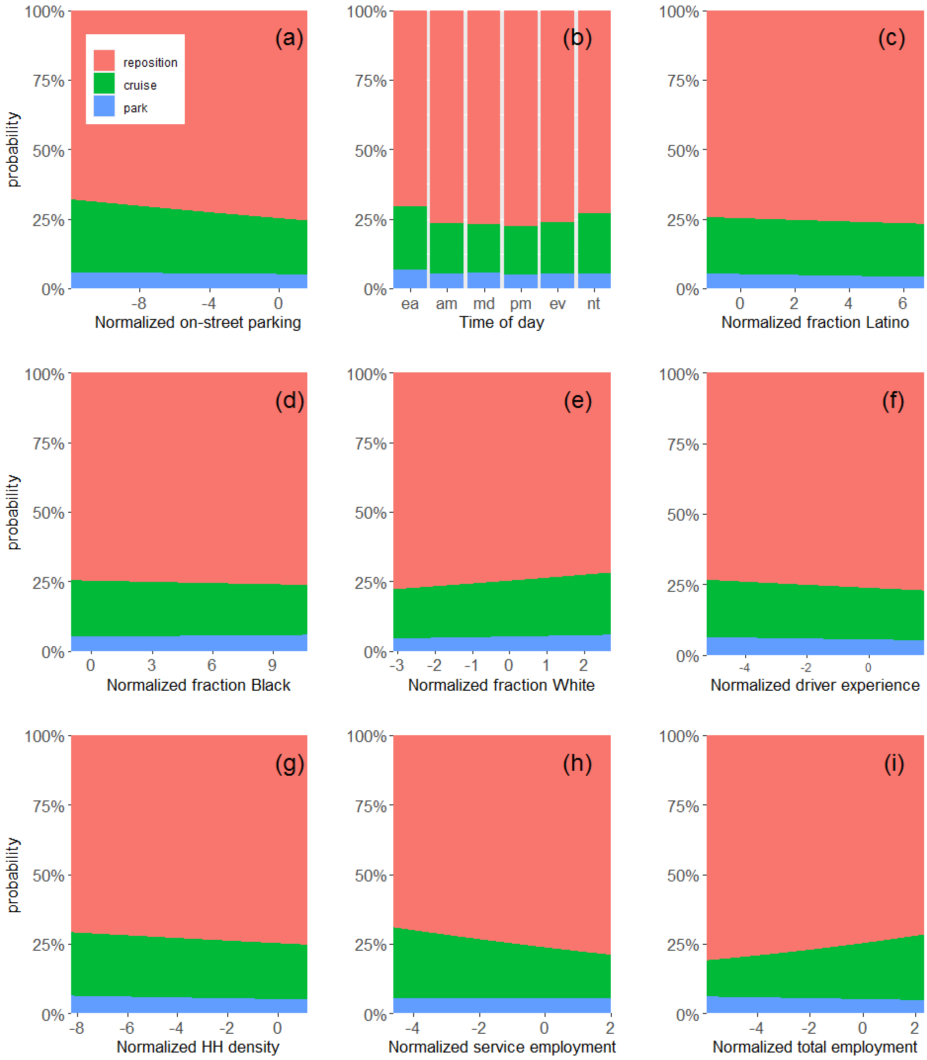
Given the large sample size, most of the coefficients are statistically significant at conventional levels. However, they are hard to interpret given that there are three separate behaviors (parking, cruising, and repositioning); and interaction terms that allow our density coefficients to vary by time of day and day of week (right columns in Table 2.4). Therefore, Figure 2.8 plots the effects of each variable in terms of the probabilities of each behavior. Several findings emerge from these analyses.

Ridehail drivers tend to reposition away from neighborhoods with more parking, especially on-street parking as shown in Figure 2.8a. This perhaps indicates that individuals might choose to drive their own cars to neighborhoods with plentiful parking, meaning less demand for ridehail services in these areas. This demand-side effect appears to outweigh the advantage to ridehail drivers of readily available parking.

Drivers also tend to reposition away from neighborhoods with a higher proportion of residents of color, and do the opposite in neighborhoods with more White residents (Figure 2.8c-e)[8]. These findings provide suggestive evidence that drivers avoid neighborhoods with more people of color, supporting the findings of the earlier research on both ridehail and taxi drivers discussed above.

[8]The baseline category in the regressions is the fraction of Asian residents. The negative coefficient for the fraction of White residents shows that drivers are less likely to reposition away from a TAZ if it has a higher fraction of White residents compared to Asian residents. While the coefficient for Black residents is also negative, it is much smaller than that for White residents. The positive coefficient for Latinx residents means that repositioning away is even more likely, again compared to the baseline of Asian residents.

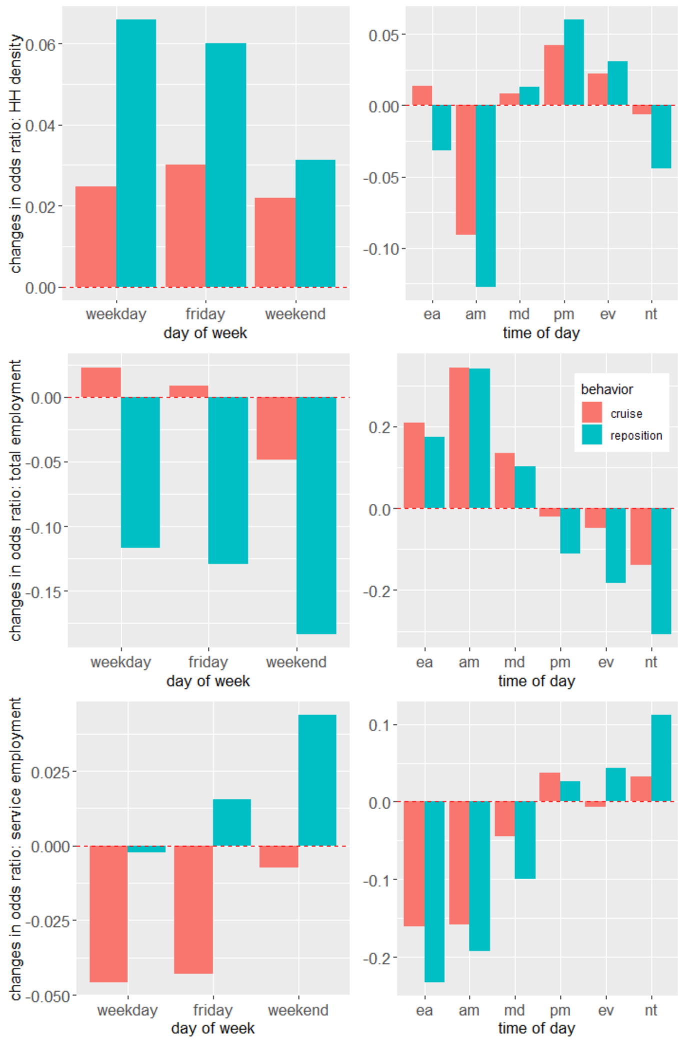
Figure 2.8: Probability of specific behaviors given change in key variables



The plots show the probability of repositioning, cruising, and parking against changes in several key independent variables, which are normalized so that the x-axis indicates standard deviations from the mean. All other variables are held at their means. For example, the upper-left plot shows that repositioning is the most common behavior, but even more so in high-residential density neighborhoods. As the prevalence of repositioning increases with density, that of cruising declines, while parking remains at similar levels.

As seen in Figure 2.8g-i, the effects of density are perhaps initially counter-intuitive. Drivers are more likely to reposition away from neighborhoods with higher residential or service employment density, even though these types of neighborhoods might be expected to generate more ridehail trips, whether due to the presence of bar and restaurant customers or the lower car ownership rates seen in dense residential neighborhoods. In contrast, drivers are less likely to reposition away from neighborhoods with a higher density of non-service employment. However, a more intuitive picture emerges when we consider how the effects of density change over the course of the day and week, through the interaction terms in the regression model. As illustrated in Figure 2.9, while there is little change in the effect of density throughout the week, there are strong time-of-day effects. Drivers are more likely to reposition away from dense residential neighborhoods in the afternoon and evening, and less likely to do so in the morning and at night, presumably when more people are at home to request ridehail trips. The opposite patterns are seen with employment density (but not service and visitor employment density), with drivers more likely to reposition away from job-rich areas in the mornings, presumably when potential customers are traveling from home to work. In addition to perceptions of demand, lack of parking and traffic congestion may also be factors that affect repositioning decisions.

Figure 2.9: Effect of density on driver behavior by day of week and time of day



The plots show how the changes in probability (measured by odds ratios) for residential, employment, and service/visitor density vary with the time of day and day of week. Positive changes mean that the probability of cruising (red bars) or repositioning (blue bars) increases more than the baseline probability of parking, and vice versa. For example, the impact of household density is similar on weekdays and weekend days (top left plot). But drivers are more likely to cruise in and reposition away from higher-density neighborhoods in the afternoon and evening, and less likely at night and in the mornings (top right plot).

Figure 2.8f also plots the effects of driver experience (estimated using the Lyft subsample only). Full-time drivers are less likely to cruise and more likely to reposition, suggesting that they are more aware of areas of high demand.

2.5 Conclusions

The choices made by ridehail drivers about where to go between trips determine the overall impacts of ridehailing on vehicle travel and associated congestion and pollution, as well as on parking availability. There is a tradeoff between the two — more time spent parked means less vehicle travel, but potentially greater impacts on the availability of space for parking, drop-offs and deliveries. More repositioning, on the other hand, decreases the pressure on curb space and off-street parking and allows the fleet to operate more intensively, but at the cost of more vehicle travel, congestion, and pollution. A certain amount of repositioning is inherent in the business model of ridehailing (and in effect differentiates ridehailing from private chauffeur-driven cars), given that demand is not perfect symmetrical throughout the day. But a smaller fleet that parks less implies more repositioning.

Such tradeoffs between parking demand and vehicle travel would also apply to future autonomous vehicles, as demonstrated by Kondor et al. (2020) in the Singapore context. For a given number of trips, the more that the deployment of autonomous vehicles lowers parking demand, the greater the distance driven by deadheading vehicles. In this report, we provide the first analysis of how ridehail drivers make these tradeoffs using a dataset of 5.3 million search trips in San Francisco.

We find that the average search segment between paid trips lasts 4.1 minutes, during which time drivers travel 1.0 km (0.6 miles). The average paid fare is 4.2 km (2.6 miles), meaning that searching for rides accounts for 19 percent of ridehail vehicle travel. Our estimated proportion of 19 percent is lower than the roughly 40 percent typically cited in the literature, but our data excludes the portion of the trip between accepting a ride request and picking up the passenger (i.e., "P2"). High demand and short distances within San Francisco may also account for our lower estimate, as previous studies have shown that deadheading tends to be lower in urban areas compared to suburbs and rural areas (e.g. Nair et al., 2020).

We classify points on each search trip as cruising, repositioning, or parking. Both repositioning and parking can represent rational behavior on the part of drivers seeking to minimize downtime and maximize revenue from their next trip. Indeed, our regression models suggest that drivers tend to make apparently reasonable choices between repositioning and parking, heading to high-demand locations based on the time of day. For example, they reposition away from dense residential neighborhoods in the afternoon and evening when demand is likely to be higher in other areas, but stay within those neighborhoods in the morning and at night. However, we also find suggestive evidence of racial disparities, supporting previous studies of both taxis and ridehailing (Ingram, 2003; Ge et al., 2020) that indicate that drivers tend to avoid neighborhoods with high proportions of people of color. These disparities are relatively small and are not necessarily due to conscious or unconscious bias on the part of drivers.

They may at least partly reflect the impact of other neighborhood characteristics that correlate with race, such as income and the presence of demand generators such as restaurants in predominantly White neighborhoods. Regardless of driver intent, though, the repositioning patterns that we identify are likely to lead to poorer availability and longer wait times in neighborhoods of color.

While cruising by traditional taxicabs makes them visible to potential passengers, it would seem to offer little advantage to a ridehail driver who can simply park instead. Therefore, perhaps our most surprising finding is that cruising accounts for 23 percent of search time and 22 percent of the search distance driven by ridehail drivers (excluding short trips). Cruising in lieu of parking means that the impacts on curb occupancy and meter revenue loss are smaller than might be expected, but those on congestion, pollution, and the other consequences of vehicle travel are greater.

Why do ridehail drivers cruise? This question is beyond our ability to answer with the present dataset, and future research might usefully probe driver decision-making processes. In some cases, a lack of available curb space or high levels of parking enforcement may be the cause. Possibly, drivers believe that they can game the trip allocation system by driving around to be closer to potential passengers, and thus being allocated a trip. Alternatively, psychological factors may be at work. More experienced drivers cruise less, suggesting that drivers learn over time that cruising is a suboptimal strategy.

More generally, our analysis is limited by the lack of information on a driver's intent. The nature of our data mean that we are limited to analyzing the paths of travel;

we do not know why drivers park, cruise, or reposition, or to what extent their chosen strategies are successful in increasing their hourly earnings. Our results highlight the opportunity for future research, possibly qualitative, to investigate further the strategies, heuristics, and reasoning that drivers employ in search of their next paid trip, and the roles of factors such as parking availability, parking enforcement, and the real-time driver information provided by ridehail firms through their apps.

A clearer understanding of motivations through further research would also inform policy responses. In broad terms, however, we suggest that cruising might partly be reduced through tweaks to driver-facing ridehail apps, prompting drivers to find a safe place to park while waiting for their next ride. It may also be possible for cities and other government agencies to regulate deadhead time. Cities, meanwhile, might consider how ridehailing can take advantage of curbspace in front of residential driveways and other curb cuts that are used only occasionally. Some ridehail drivers already park in front of driveways on an informal basis, as they can quickly move if a resident needs to access their garage.

Ultimately, however, revising fee structures to be distance- and time-based, regardless of whether a passenger is in the vehicle, may be the most effective way for cities to address the external costs of ridehailing including congestion and pollution. Ridehail firms would pay these fees, and determine whether and how to pass them on to passengers. In addition, place-based time charges might be used as a proxy for parking fees, and to encourage drivers to park in locations where they do not compete with other curbspace users. Many cities already levy ridehail fees or taxes on a per-trip or percentage basis, but these charges only apply to the paid, with-passenger portion of a trip. To more comprehensively address pollution, congestion, and other externalities caused by ridehailing, policy makers need to extend these policies to encompass what drivers do between trips.

Chapter 3

Polarization in Online Social Networks[1]

3.1 Introduction

With the rapid development of the Internet, the population using online social networks accelerates. On platforms such as Facebook and Twitter, people can easily access information through their connections. It not only shortens the time for people to exchange opinions but also expands their connections dramatically. However, since the 2016 presidential election, the influence of online social networks on opinion polarization has drawn much attention. There is constant criticism on the role that online social networks play in turning communities into homophilous cocoons (Pariser, 2011), especially through personalized recommendation.

Previous studies have shown that people prefer the information that aligns with their own opinion, which is referred to as confirmation bias (e.g. Eil and Rao, 2011; Stroud, 2008; Westerwick et al., 2017). This is reflected in online social networks as users

[1]The third chapter is a joint work with Weinan Gong.

seek content that agrees with their views. Therefore, they tend to connect to others who have similar opinions to their own. Based on this, personalized recommendation is invented and commonly applied by online social networks, fostering users to observe content similar to their own opinions. This suggests that polarization can be a result of confounding effects of both confirmation bias and personalization. However, there is a lack of research focusing on evaluating the pure effects of personalization on polarization. To achieve this, we build a theoretical model to separate the two effects and conduct a novel lab experiment to test our model predictions.

In our theoretical model, confirmation bias is reflected as agents' payoffs from interactions depend on the homophily of their own opinion concerning the opinion of others. Therefore, an agent gains a higher utility level if they build connections with subjects who have homogeneous or similar opinions to their own. We use an endogenous network formation setup (Bolletta and Pin, 2020) to model agents' selection on connections where they benefit from connecting but need to balance between two losses based on the payoff function: coordination loss and adaptation loss. Coordination loss occurs when an agent's opinion is different from their neighbors' opinions. This reflects that people dislike being different from others. Adaptation loss occurs when an agent's current opinion deviates from their original belief, which reflects people's dislike of changing their original attitudes. People usually have such dilemmas when they exchange beliefs and update opinions in the real world. To model personalization, we adopt a probability of observing other agents, which is endogenous to the similarity between opinions. When there is personalization, the possibility of observing other agents depends on the similarity between agents' own opinions and their neighbors' opinions. However, when there is no personalization, the possibility follows a uniform distribution. In the model, parameters representing how easily others can influence opinions, benefits of connection, and the degree of personalization can all affect the opinion evolution results. The polarization level is evaluated by both the number of converged groups and a polarization measurement.

Since the observation of other agents follows a random selection, we computed the average results of 100 simulations for each combination of parameters in the model to fully understand the impacts of personalization. The results show that when there is personalization, opinions converge more slowly, and the number of converged groups and polarization increase when agents are more easily convinced by others.

We further designed a novel lab experiment to test whether participants' behavior is consistent with our theoretical predictions when they have confirmation bias. Different from work like Allcott et al. (2020), which conducts experiments through Facebook directly, our design of a lab experiment can separate the effects of different factors and test them individually. Hence, we can examine the pure effects of personalization on polarization. In our experiment, subjects are assigned initial numerical positions as substitutes for their original opinions in the real world. To motivate confirmation bias, we applied a payoff function the same as the one in our theoretical model, but relaxed the assumption of agents' beliefs on other agents' opinions and elicited players' actual beliefs in the experiment to see whether it is consistent with the model. Our main treatments compare the opinion evolution process with and without personalization under selected parameter combinations based on the theoretical predictions using a between-subject design. 12 production sessions were conducted, each with 9 subjects.

The experimental results are consistent with our hypothesis and, therefore, simulation results. When agents are easily convinced by others, personalization amplifies polarization. However, we cannot observe such difference when the sufficient threshold to disconnect becomes lower, where agents are reluctant to connect with others. Furthermore, a transitionary polarization occurred in the treatment without personalization under a low disconnection threshold environment.

This research contributes to the current literature in several ways. First, this paper applies an endogenous network formation setup, which is rarely discussed in research studying social learning but more reasonable in online social networks. Second, while effects of personalization are barely evaluated in research on polarization, this paper combines it with the traditional social learning model and is able to isolate its effects from other factors. Finally, this paper is the first to test endogenous network formation with personalization in a lab experiment environment.

This paper is organized as follows. In Section 3.2 we discuss related literature. The model and simulation results are presented in Section 3.3. In Section 3.4 we demonstrate the experimental design and hypotheses. The experimental results are provided in Section 3.5 and Section 3.6 concludes.

3.2 Related Literature

This paper is closely related to the literature on learning in social networks. One stream of research focuses on Bayesian learning models where agents are fully rational. Acemoğlu et al. (2013) and Yildiz et al. (2013) study the situation with stubborn agents and minimal conditions on bounded rationality to break the convergence. Our design is related to the other stream of research based on the naive learning model raised by DeGroot (1974). The model assumes repeated linear updating of opinions within a social structure described by a weighted and directed network. With the advantage of tractability and prediction power, the DeGroot model has been investigated in many other works related to this paper. DeMarzo et al. (2003) consider the situation where agents' opinions are shaped without accounting for the repetition of information. Golub and Jackson (2010) show that opinions reach consensus when the network is strongly connected and the adjacency matrix is aperiodic. There are also studies focusing on the hearing matrix to derive the conditions for consensus (e.g. Krause et al., 2000; Hegselmann and Krause, 2005). It is assumed that agents have bounded confidence, and opinions are only considered when they are similar enough. Therefore, when the distance parameter is too close, the consensus is not reached. In our model, agents also tend to pay attention to those who have similar opinions to their own, but we make this rule a consequence of the endogenous network.

In our paper, there is a co-evolution of networks and opinions. A similar idea has been applied in previous work, but the approach is different. Zimmermann et al.

(2004) and Holme and Newman (2006) use a mechanical model without accounting for the strategic motives of agents. In Melguizo (2019), agents have initial attributes. They favor those with similar attributes to their own and assign dynamically growing weights to them. Since characteristics are binary, when opinions diverge, there can only be two groups. This is different from our setting, where more general cases with more than two groups are possible. Our paper is closest to work by Bolletta and Pin (2020). The endogenous network formation setting in our design is based on their model. However, to generalize the theory and make it more applicable to online social networks, we add the agent observation stage to capture the effects of personalization and the network growth process, which is inspired by Maes and Bischofberger (2015).

In broader literature examining belief polarization, research can be categorized by the causes of polarization. One strand of work closely related to ours studies the polarization due to heterogeneity in preferences, especially for political polarization (e.g. Dixit and Weibull, 2007; Pogorelskiy and Shum, 2019). Our main contribution to this type of literature is bringing the network formation process into consideration and combine it with different initial attitudes to lead to polarization. Another strand of work focuses on the behavioral bias (e.g. Levy and Razin, 2019; Hoffmann et al., 2019; Enke et al., 2020). The last strand of work considers polarization due to biased or multidimensional information sources (e.g. Mullainathan and Shleifer, 2005; Andreoni and Mylovanov, 2012; Perego and Yuksel, 2018). For both types of research, there is often a true state of the world, and agents are motivated to estimate the true state. Unlike this setup, agents are motivated by seeking agreements without a true state in our model. In reality, many topics do not need to have a true state, or the true state is too complicated to get, especially in online social networks where most information is biased, and people's purpose may not be finding the truth. Therefore, the setup in our paper provides a new angle to evaluate the opinion evolution process, which is more reasonable in online social networks.

Finally, our paper is also related to the literature on using communication in coordination problems (e.g. Alonso et al., 2008; Evdokimov and Garfagnini, 2019). For this type of research, the agents are motivated the same way as in our paper and seek agreements. While our design is more like a decentralized coordination problem, the main difference is that we bring network updating to the basic coordination game and apply it to online social networks. Therefore, our research builds a bridge between research on social learning in networks and coordination problems.

3.3 Theoretical Model

3.3.1 Basic Setup

Online social networks such as Twitter can be represented by a directed network where users can form single-direction links by following other users. Formally, consider a directed unweighted network G with N agents. Each agent i has different initial attitudes $\theta_i \in \Theta = [0, 1]$ towards a topic at time $t = 0$. θ_i is exogenously given and follows a uniform distribution on $[0, 1]$. At each round t, agent i can observe their neighbors' (observed other agents who i connect with) opinions at $t - 1$ and form their own opinion $x_{i,t}$.

3.3.2 Network Formation and Growth

All agents start without neighbors. At each round t, for each agent i, $k < N-1$ other agents are drawn from a distribution. Among the k chosen agents, if agent j is not i's neighbor, then j is observed by i and can be added to i's network. In other words, i can observe 0-k other agents at each round and needs to decide whether to form connections with them. In addition, i can disconnect with agents they already connected with at each round.

3.3.3 Agent Problem

Our primary assumption is that agents seek agreements to their own opinions in online social networks. This can be reflected on two aspects: 1) Agents incur an adaption loss if their opinion at t disagrees with their opinion in the previous round $t-1$. 2) Agents incur a coordination loss if their opinion differs from their neighbor j's opinion at t. Since agents can only observe past opinions, the coordination loss can only be computed based on i's belief on their neighbors opinion at t. Then the payoff of agent i given their belief on the opinion of j at round t can be represented as:

$$\pi_{i,t}(x_{i,t}, \hat{x}_{j,t}) = V - f(x_{i,t} - \hat{x}_{j,t})^2 - (1-f)(x_{i,t} - x_{i,t-1})^2$$

V is a positive constant representing the benefit of connecting to other agents, such as the useful information from other agents. When V takes a higher value, it is more beneficial for agents to form connections. f is the weight assigned to the coordination loss, which represents how easily agents are influenced by others' opinions, or flexibility. Similar to Bolletta and Pin (2020), we assume agents are naive without considering opinion updating of other agents at t, so $\hat{x}_{j,t} = x_{j,t-1}$. Let $d_{i,t}$ represents i's network at t, $n_{i,t} = |d_{i,t}|$ is the number of i's neighbors at t. Then i's total payoff from all their connections is:

$$\begin{cases} \pi_{i,t}(x_{i,t}, x_{j,t-1}) = \sum_{j \in d_{i,t}} (V - f(x_{i,t} - x_{j,t-1})^2 - (1-f)(x_{i,t} - x_{i,t-1})^2) & \text{if } n_{i,t} > 0 \\ \pi_{i,t}(x_{i,t}) = -(x_{i,t} - x_{i,t-1})^2 & \text{if } n_{i,t} = 0 \end{cases}$$

When i has no connections, their payoff only depends on the adaption loss.

The agent problem has two stages. For each agent at t, they need to: 1) Build the optimal connections among current neighbors and newly observed agents 2) Choose the opinion $x_{i,t}$ to maximize the payoff. The Nash equilibrium of this problem can be solved using backward induction. First, assume the connection is fixed, then the optimal opinion formation for i can be solved:

$$x_{i,t}(x_{j,t-1}) = \begin{cases} f\mu_{i,t} + (1-f)x_{i,t-1} & \text{if } n_{i,t} > 0 \\ x_{i,t-1} & \text{if } n_{i,t} = 0 \end{cases} \tag{3.1}$$

where $\mu_{i,t} = \frac{\sum_{j \in d_{i,t}} x_{j,t-1}}{n_{i,t}}$ represents the average opinions of i's neighbors. This opinion updating rule reflects correspondence with the Degroot model. Next, (3.1) can be used to solve the optimal network selection. The payoff in the temporary equilibrium is a function of i's connections:

$$\pi^*_{i,t} = \begin{cases} n_{i,t}(V - f(1-f)(\mu_{i,t} - x_{i,t-1})^2 - f\sigma^2_{i,t}) & \text{if } n_{i,t} > 0 \\ \\ 0 & \text{if } n_{i,t} = 0 \end{cases} \tag{3.2}$$

where $\sigma_{i,t} \equiv \frac{\sum_{j \in d_{i,t}} (x_{j,t-1} - \mu_{i,t})^2}{n_{i,t}}$ represents the variance of the opinions of i's neighbors. At each round, agent i chooses a connection that can maximize their payoff. Therefore, at round 1, i will form links if $\max \pi^*_{i,1} > 0$ after building links. In future rounds, when $f \to 1$, agents tend to form links to homogeneous groups to reduce $\sigma_{i,t}$; when $f \to 0$, they tend to update their opinion more slowly, and neighbors are less relevant. The optimal connection formation strategy for agents is making opinions both homogeneous and similar to their own. This can possibly cause agents to disconnect at some point to form polarization. We measure polarization level at t as the sum of the absolute difference of opinions between each pair of agents in network G, which is widely used in studies on polarization (e.g. Augias and Barreto, 2020):

$$Pol_t = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} |x_{i,t} - x_{j,t}| \tag{3.3}$$

3.3.4 Probability of Observation

To add personalization to the model, we applies an endogenous probability of observing other agents. At each round t, k other agents are drawn from a distribution to be observed by agent i. When there is personalization, the probability of each other agents j being observed by i depends on the similarity between i and j's opinions in the previous round. Use $s_{ij,t-1} = 1 - |x_{i,t-1} - x_{j,t-1}|$ to represent the similarity between i and j's opinions at $t-1$, then the probability of j being observed by i at t is $p_{ij,t} = \frac{s_{ij,t-1}^{h}}{\sum_{m \in N} s_{im,t-1}^{h}}$. Here $h \geq 0$ represents the degree to which the observed agents are driven by homophily. When $h = 0$, the agents being observed follow a uniform distribution. When h is larger, the agents with opinions closer to i have a higher probability of being observed. Therefore, higher h captures a stronger effect of personalization.

3.3.5 Opinion Convergence and Disconnection

In our model, equilibrium exists based on Bolletta and Pin (2020). The connection formation process is endogenous, and opinion updating depends on each agent's connections. When two agents get close enough, they will eventually build connections with each other, which will cause the opinions of the two agents to update closer to each other, thus strengthening the mutual network between them. Therefore, in equilibrium, opinions converge, and agents are fully connected within each converged group. This is summarized as Proposition 1. The full proof is in Appendix A, which follows from Proposition 1 in Golub and Jackson (2010).

Proposition 1. In equilibrium, within each closed group, agents are fully connected, and opinions converge. There are no network connections across groups.

Based on Proposition 1, there are no connections between converged groups after equilibrium is reached. When there is more than one converged group, groups are disconnected and thus polarized from each other. Therefore, we can combine the number of converged groups and the polarization measurement to evaluate the polarization level of the whole network.

For polarization to occur, agents need to disconnect. Similar to Bolletta and Pin (2020), we investigated the existence of a sufficient condition for two agents to disconnect.

Proposition 2. There is a threshold ξ, depending on f and V, such that for agent i and j, if $|x_{i,t-1} - x_{j,t-1}| > \xi$, then they will not build connection with each other at t. This threshold is $\xi = (\frac{V}{f(1-f)})^{\frac{1}{2}}$, and is increasing on V and convex on f with a minimum value when $f = 0.5$.

The threshold ξ provides a criterion for two agents to disconnect regardless of their connections with other agents. When V gets larger or when f is away from 0.5, ξ increases and makes it harder to disconnect, and vice versa. In addition, since opinions in earlier rounds can influence whether to disconnect in the later rounds, the beginning rounds take an essential role in shaping the opinion evolution results. The formal proof of Proposition 2 can also be found in Appendix A.

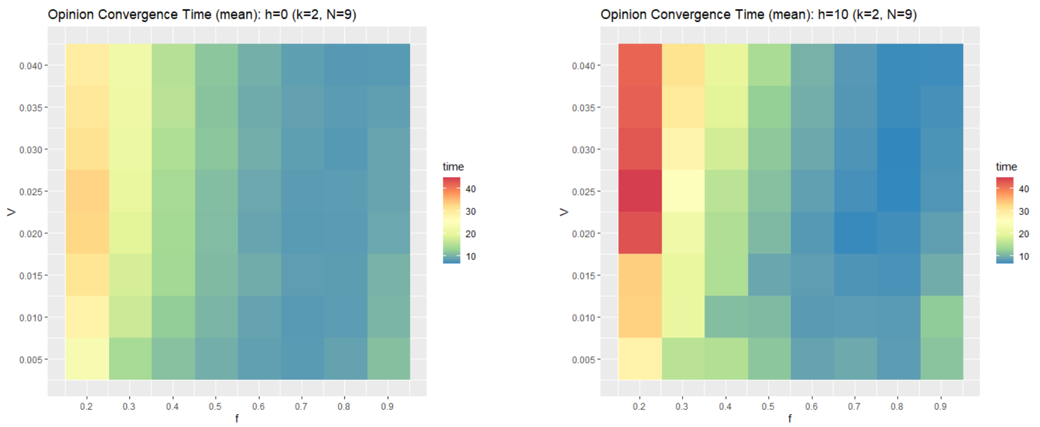
3.3.6 Impacts of Personalization

Personalization influences the distribution where other agents are selected to be observed. Since the selection is a random process, the result is intractable. Therefore, we run 100 simulations given each combination of V and f and compare the result with and without personalization. In the simulation, we set the total number of agents in the network $N = 9$. The opinions of each agent follow a uniform distribution on $[0, 1]$.

The number of other agents selected at each round, k, is set to 2. A smaller $\frac{k}{N}$ ratio can better replicate an online social network where each user only observes a minor portion of information from all other users. Therefore, the possible variation between the opinion evolution results with and without personalization is expected to be larger. We set the parameter h, the degree to which observation is driven by homophily, to 10 for personalization and 0 otherwise. The simulation results are performed as heatmaps on a 8×8 grid of parameters V and f, with warmer color representing higher value and colder color representing lower value.

Figure 3.1a and 3.1b show the results of opinion convergence time. We can observe that it takes longer for opinions to converge when personalization occurs. The reason is straightforward. With personalization, agents are more likely to observe those close to them. This decelerates the process of observation and connection to other agents. The difference is especially strengthened under smaller f and larger V where disconnection is difficult and the consensus is reached. Hence, the speed of convergence becomes slower. Another observation is that when $f \to 0$, convergence gets slower. This is because agents are more reluctant to change their own opinion with smaller f.

Figure 3.1: Convergence time



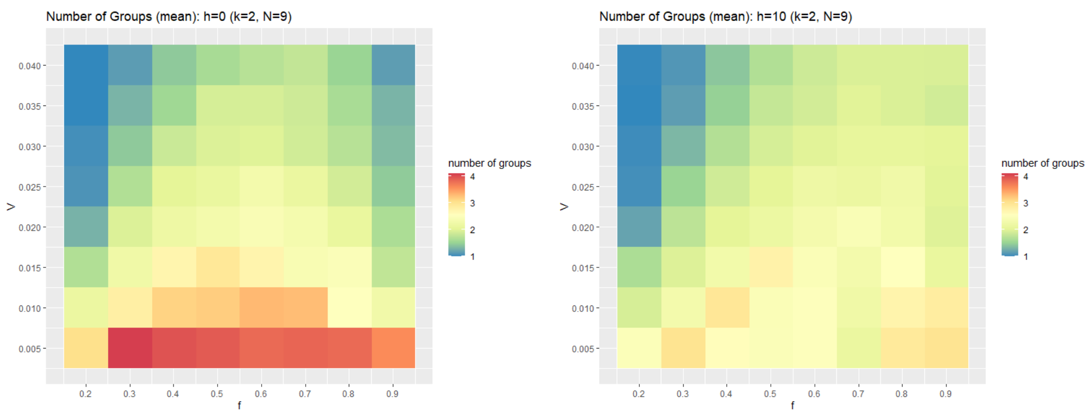
(a) $h = 0$

(b) $h = 10$

The polarization level is reflected on Figure 3.2 and 3.3. Figure 3.2 compares the number of converged groups, and Figure 3.3 compares the polarization measurement, both after equilibrium is reached. We can observe similar patterns between the two sets of plots to evaluate the polarization level. First, when $f \to 1$, polarization is stronger with personalization than without personalization. The intuition behind this is that when $f \to 1$, agent i's payoff in equilibrium $\pi^*_{i,t} \to n_{i,t}(V - \sigma^2_{i,t})$, which depends less on i's own opinion $x_{i,t-1}$. Therefore, given V, agents tend to connect to a more homogeneous group rather than connect to those close to themselves. Since the initial attitudes of agents are evenly distributed between 0 and 1, forming links in one direction (either left or right to the agent) can reach a more homogeneous group. In addition, agents are constrained to observe and form links to those closest to their own opinions first with personalization. Both effects cause links between groups to become frail and easier to be broken. When there is no personalization, the possibility of observing and connecting to agents further away is higher. Therefore, even though agents still tend to form links in one direction at the beginning when $f \to 1$, the links between groups can be reinforced. This result is strengthened when V takes a larger value, where building connections with agents further away is more accessible based on Proposition 2.

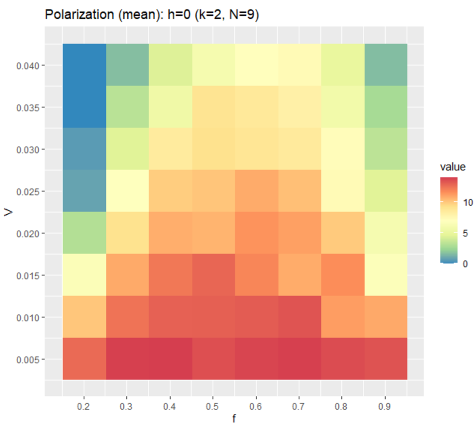
Additionally, when V decreases, polarization becomes stronger without personalization than with personalization. When V takes a small value, the distance between $x_{i,t-1}$ and $x_{j,t-1}$ sufficient to disconnect is small. Therefore, the constraint on forming links becomes tighter, and agents only build connections with closer agents. With personalization, agents are more likely to observe those close to them. This makes link formation easier than without personalization.

Figure 3.2: Number of groups

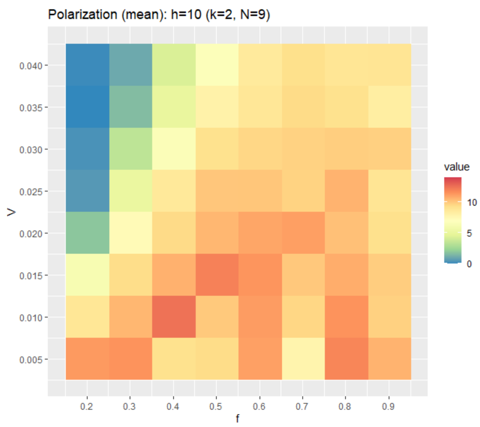


(a) $h = 0$ (b) $h = 10$

Figure 3.3: Polarization measurement



(a) $h = 0$



(b) $h = 10$

Finally, we observe that the patterns of polarization level are more consistent with Proposition 2 without personalization. That is to say, when $f \to 0.5$ or $V \to 0$ where disconnection is more likely, polarization becomes stronger. The reason is similar to the previous observation. Proposition 2 provides the sufficient condition for the distance between the opinions of two agents to disconnect from each other. When personalization is applied, agents always observe those close to them first, so restrictions on the distance between agents are less relevant. At the same time, the impact of f becomes dominant. In contrast, when there is no personalization, agents have more flexibility and a higher chance of observing those further away from themselves. Therefore, the threshold in Proposition 2 is more binding for this situation.

In summary, the simulation results indicate that personalization has the most substantial effect on amplifying polarization when building connections is easy and agents are willing to listen to others. Otherwise, the effects of personalization are trivial. To make sure the patterns are robust to a larger range of parameters, we ran simulations with a different value of the number of agents N and the number of selected other agents each round k. The simulations show similar results, which can be found in Appendix B.

3.4 Experiment

We evaluate the network formation and opinion evolution process in a lab experiment to test the model predictions. We examine behavior differences with and without personalization when subjects are motivated by the payoff function in our model.

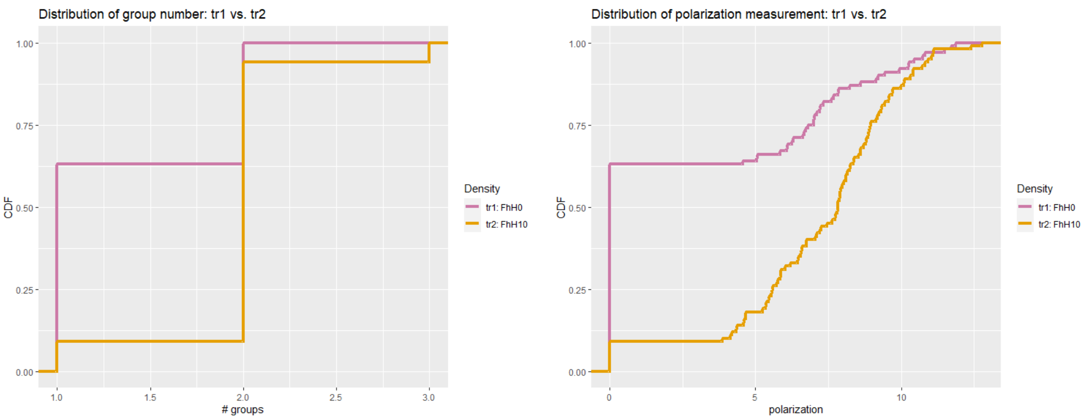
3.4.1 Treatments

Based on the simulation results, we compared the opinion evolution with and without personalization under a high value of f and a low value of V. The comparisons are summarized as four treatments in Table 3.1.

Table 3.1: Treatments

Treatment	Label	Benefit of connection V	Flexibility f	Personalization h
1	fHh0	0.015	0.9	0
2	fHh10	0.015	0.9	10
3	Vlh0	0.005	0.5	0
4	Vlh10	0.005	0.5	10

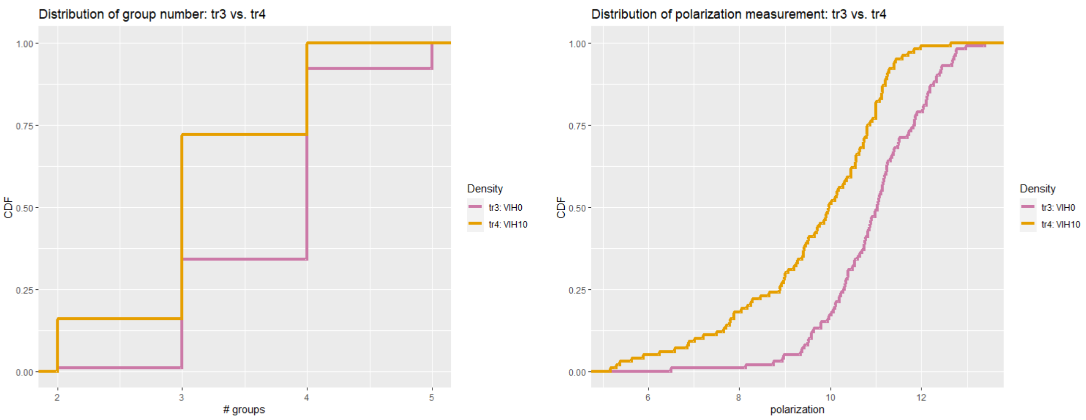
Figure 3.4: Comparison between Treatment 1 and 2 Simulation Results



We further computed the distribution of the number of converged groups and polarization measurement in equilibrium for each treatment based on the simulation results. Treatments 1 and 2 are compared with each other, and the results are in Figure 3.4. We expect to observe stronger polarization under Treatment 2 reflected by a larger number of groups and polarization measurement.

Treatments 3 and 4 both evaluate the opinion evolution process with a small V and are compared with each other. The results are in Figure 3.5 and show the number of groups under Treatment 4 is a little larger, and there are no significant deviations in the polarization measurement. Therefore, we expect to observe trivial effects on polarization under Treatment 4.

Figure 3.5: Comparison between Treatment 3 and 4 Simulation Results



3.4.2 Experiment Design and Implementation

Subjects were recruited from UC Santa Cruz undergraduate students through ORSEE. 12 sessions were conducted involving 9 subjects each between March and April 2022. Table 3.2 shows the arrangements for the production sessions. Each session included one interactive game with 20 to 25 rounds. During the session, subjects were informed to read instructions, complete a quiz[2], and play a 5-round practice game to get familiar with the whole process. At the beginning of the official game (Figure 3.6), each subject was randomly assigned an initial position from $\{0, 10, 20, 30, 40, 50, 60, 70, 80\}$[3].

[2]The quiz has 7 questions and tests the subjects' understanding of payoffs, adaptation loss, coordination loss, and basic structures of the game. Subjects will know whether they are correct or not when they click the "next" button. The accuracy of the quiz does not contribute to any extra bonus or loss for the subjects.

[3]The range of positions replicates opinions varying from 0 to 0.8. While the opinions in the theoretical model vary from 0 to 1, we change the range in the experiment for simple implementation. The simulation results are the same and can be found in Appendix B.

Table 3.2: Production sessions

Session	Treatment	Label	Round per Treatment
1-3	1	fHh0	20-25
4-6	2	fHh10	20-25
7-9	3	Vlh0	20-25
10-12	4	Vlh10	20-25

We use numerical positions to manipulate the opinions of the real world. Each round, subjects update their connection and position following the rules below:

1. Each subject observes two other players' positions in the previous round. The possibility of each player being observed depends on the similarity between the subject and other players' positions in the previous round. Since h captures the personalization level, when $h = 0$, the probability of each other player being observed is the same; when $h = 10$, the subject is more likely to observe two other players who are closer to them.

2. Each subject decides whether to connect with each observed player based on whether their payoff could be improved. The subject either chooses to connect or keep unconnected. If an observed player is already connected in previous rounds, the subject chooses to keep the connection or disconnect. Once the subject decides to connect with a player, the player becomes the subject's neighbor. However, once the subject disconnects with a player, the player is removed from the subject's neighbor set.

3. After making the connection decisions, the positions of all neighbors' from the

end of the previous round are presented on the screen. At this step, the subject makes a guess about how neighbors update their positions in the current round. Moreover, the subject has a chance to decide whether to keep connections with current neighbors based on their guess. If they decide to disconnect with one neighbor, the neighbor is removed from the subject's neighbor set.

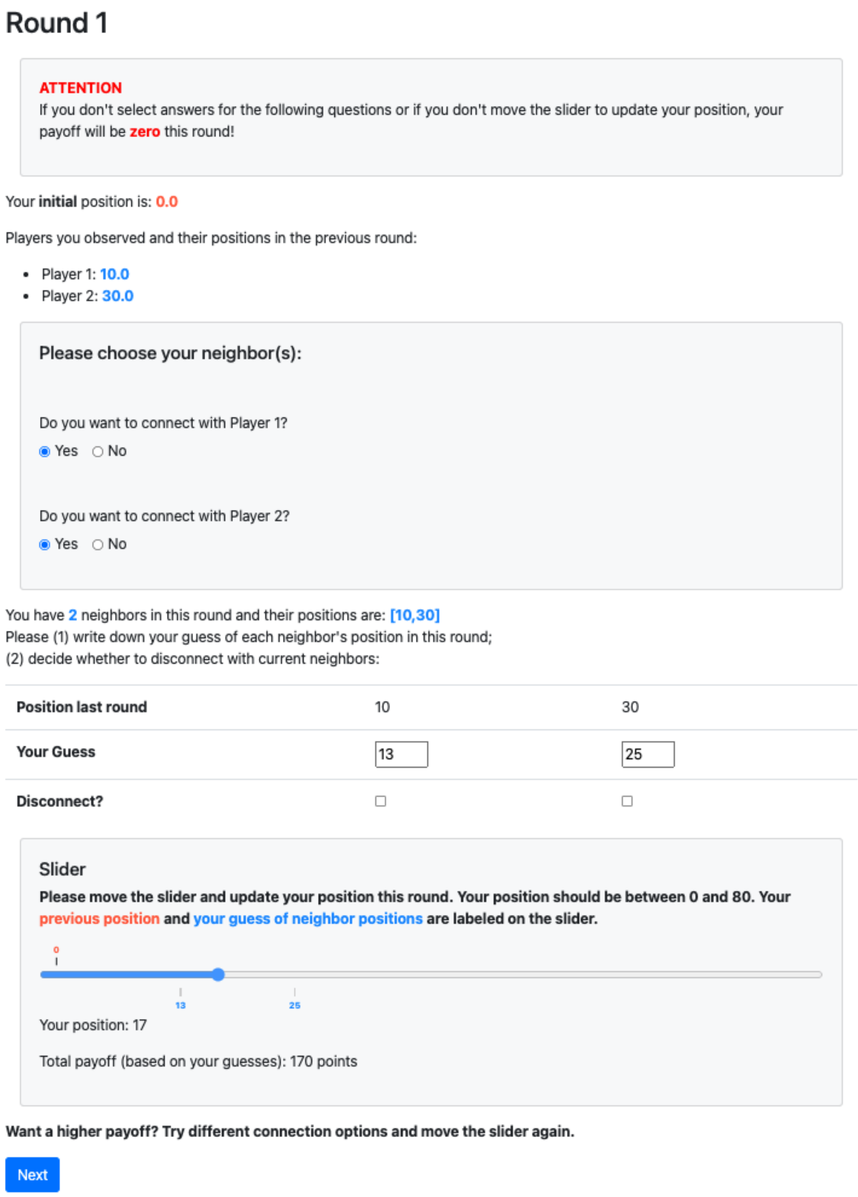
4. Finally, the subject updates their position based on the payoff formula by moving the slider.

The payoff of subject $i \in \{1, 2, ..., 9\}$ in round t is given by

$$\pi_{i,t} = \begin{cases} \sum_{j \in d_{i,t}} (V - f(x_{i,t} - \hat{x}_{j,t})^2 - (1-f)(x_{i,t} - x_{i,t-1})^2) & \text{if } n_{i,t} > 0 \\ -(x_{i,t} - x_{i,t-1})^2 & \text{if } n_{i,t} = 0 \end{cases}$$

where $x_{i,t}$ is subject i's position in round t. Here $\hat{x}_{j,t}$ represents player i's belief of neighbor j's position in round t, which is used to compute the real-time payoff under the slider for players as a reference. In the result page, subject is informed that the actual payoff is calculated based on the neighbors' actual current positions, that is $\hat{x}_{j,t} = x_{j,t}$. $n_{i,t}$ is the number of neighbors in i's network. $d_{i,t}$ is subject i's network in round t. If subject i has neighbor(s), their payoff is the sum of payoffs from all neighbors. Specifically, the first component of the payoff function captures coordination loss arising from the mismatch between $x_{i,t}$ and $\hat{x}_{j,t}$. The second component captures the adaptation loss arising from the mismatch between $x_{i,t}$ and $x_{i,t-1}$. The parameter $V \in \{50, 150\}$ captures a bonus granted per neighbor subject i has. $f \in \{0.5, 0.9\}$ measures the weight assigned to the coordination loss. However, if subject i does not have neighbors, their payoff depends solely on adaptation loss.

Figure 3.6: Experiment Interface of game fHh10



The subjects' earnings were determined as follows. Every subject was guaranteed a show-up fee of $5.00. To ensure that earnings were non-negative, we provided subjects with an endowment of $5.00 at the beginning of the official game. In addition, the payoff of one round was randomly selected, and the extra payment is calculated as $\sqrt{\text{points earned in selected round}}$[4]. Therefore, the total earnings are determined by the sum of the show-up fee, endowment, and additional payment in the official game. The subjects were anonymously paid via Venmo at the end of the experiment. The sessions lasted for around 90 minutes. The average experiment payment was 22 dollars, above the hourly minimum wage in California.

Since only one treatment is conducted each session, we can use between-subject to test the effect of personalization h under different combinations of flexibility f and connection bonus V on polarization. In addition, we control random seeds, and three different random seeds are selected for each treatment. Therefore, our experimental results could be compared with simulation results with the same random seeds.

3.4.3 Hypothesis

Our experiment design can test the following hypothesis:

Hypothesis 1. Opinion Evolution

Impact of Personalization under High f and High V - Under an environment where people are willing to connect with others, we expect to observe a larger number of groups and higher polarization measurement in the treatment with personalization (Treatment 2). Personalization plays a role in amplifying polarization.

[4]The square root form in the conversion of points helps to limit the extreme high and low payoffs. While it may raise concerns about causing players to behave more risk-averse, we compared the results to sessions with a standard linear function in points conversion. There are no apparent behavior deviations.

Impact of Personalization under Low f and Low V - Under an environment where people are reluctant to connect with others, we expect to observe a similar number of groups and polarization measurement in the two treatments. Personalization has trivial effects on polarization.

Hypothesis 2. Connection pattern

All treatments will end up with a symmetric connection pattern, consistent with Proposition 1.

3.5 Results

Twelve production sessions were conducted with nine subjects each. Therefore, three different random seeds were used for each treatment. Since we kept the same random seed both in simulation and human interactive game, we were able to compare simulation results with experimental results and investigated any deviation from human behavior.

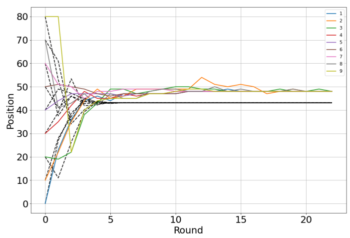
To investigate the effect of personalization on different environments, we first focus on the position evolution process and second on the polarization measurement (Sections 3.5.1 and 3.5.2). Section 3.5.3 tests the connection pattern for each treatment. Section 3.5.4 digs deeper to explain the deviation between simulation and human behavior. Finally, section 3.5.5 focuses on how subjects guess their neighbors' positions.

3.5.1 Position Evolution Process

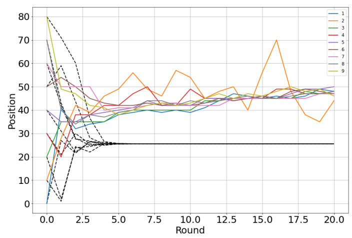
We hold parameters f (flexibility) and V(connection bonus) constant when comparing the effect of personalization.

When f is high, subjects put more weight on neighbors' positions. When V is high, subjects find it beneficial to connect more players as neighbors. Therefore, high f and high V create an environment where people are willing to connect with others and easily form agreements.

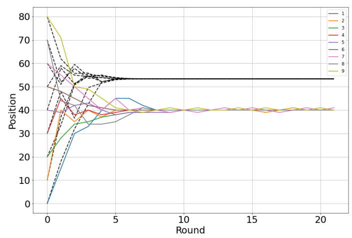
Figure 3.7: Position Evolution Under High f and High V



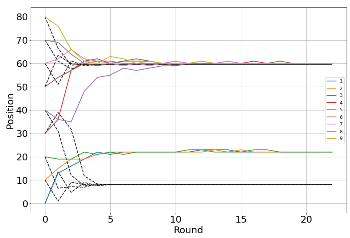
(a) fHh0(I)



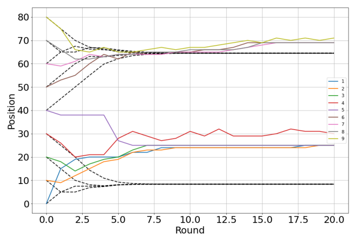
(b) fHh0(II)



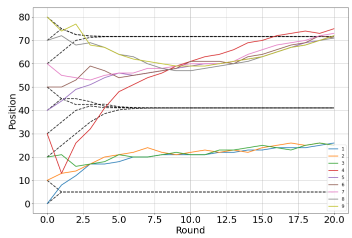
(c) fHh0(III)



(d) fHh10(I)



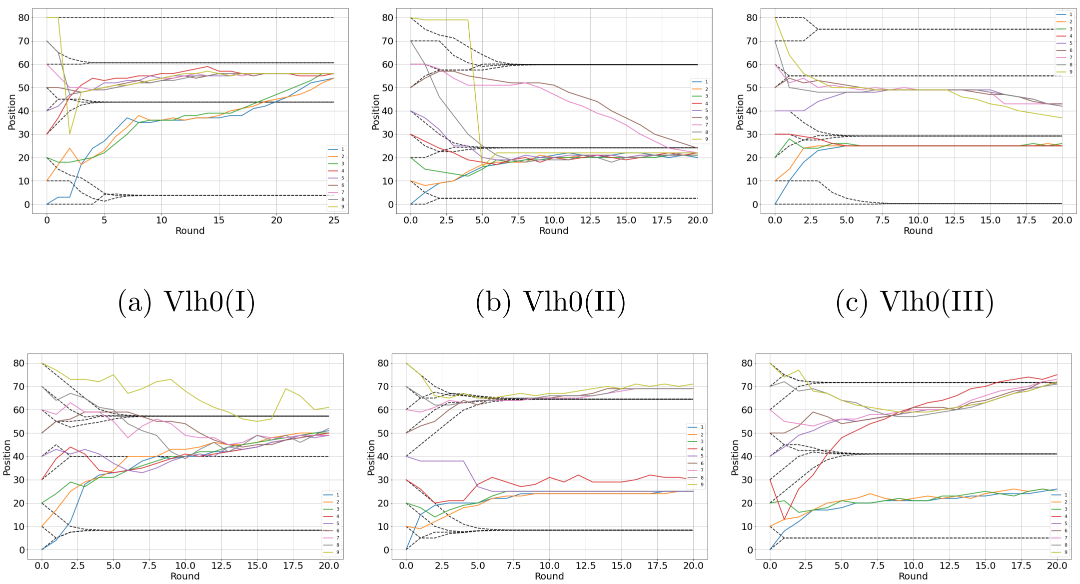
(e) fHh10(II)



(f) fHh10(III)

Figure 3.7 reflects position evolution process under high f and high V combined with simulation results. Specifically, 3.7a, 3.7b, and 3.7c show treatment without personalization, where the possibility of observing other players is independent of subject's position. 3.7d, 3.7e, and 3.7f are results for treatment with penalization, where the possibility of observing other players depends on how similarity the player's position to the subject's. The closer the position of subject to the player, the more likely that the player is observed by the subject. The solid lines plot nine subjects' positions across rounds on each figure. The dash lines are the simulation results with the same random seeds used in the session. Even though we use three different random seeds, treatment $fHh0$ (treatment 1) ends with one group, consistent with simulation results. Treatment $fHh10$ (treatment 2) ends with two subgroups as expected. However, for both treatments with and without personalization, it takes a longer round for subjects to reach consensus or form polarization.

Figure 3.8: Position Evolution Under Low f and Low V



(a) Vlh0(I)

(b) Vlh0(II)

(c) Vlh0(III)

(d) Vlh10(I)

(e) Vlh10(II)

(f) Vlh10(III)

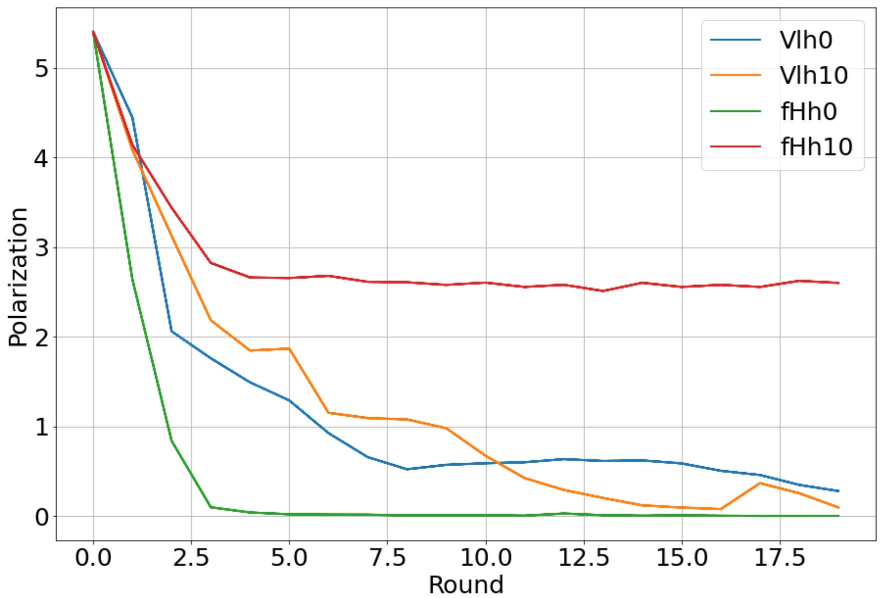
Figure 3.8 depicts position evolution process for treatments under low f and low V. Therefore, we are able to investigate the effect of personalization when subjects are reluctant to connect by comparing treatment $Vlh0$ (treatment 3) and treatment $Vlh10$ (treatment 4). The experimental results are much noisier than in Figure 3.7 because decreasing the value of V makes the connection less profitable. Unlike simulation results, subjects form fewer groups regardless of whether there is personalization under low f and low V. One reason is that subjects make too many connections at the beginning of the game at a sacrifice of benefits. It becomes more profitable in the later rounds since positions converge and players get closer to each other. Therefore, eventually, most of the sessions in Figure 3.8 reach to consensus at the end of the game.

In treatment without personalization ($Vlh0$, treatment 3), the experimental results indicate that subjects converge into two subgroups and form polarization in the short rounds. However, the polarization is not stable. Subjects will slowly converge and reach a consensus in the long run. The transition round varies in figure 3.8a, 3.8b, and 3.8c. Session 3.8a starts to transform after 16 rounds, session 3.8b starts to change after 8 rounds, and session 3.8a starts to converge after 12 rounds. We find two interesting trends for the transition: First, the transition always happens in the smaller subgroups. The smaller subgroup slowly adapts its position every round until it aligns with the larger subgroup's position. Second, the timing of transition depends on the size of smaller subgroups. The fewer the subjects in the smaller subgroup, the earlier the subgroup starts to converge. The intuition is that subjects would be more likely to observe the players in other groups when the subgroup is small. The transition timing depends on how early they observe players in other groups.

3.5.2 Polarization

Figure 3.9 depicts the average polarization measurement of the three sessions for the same treatment across rounds. Since the initial positions are always on $[0, 80]$ with an increment of 10, the polarization level is the same at the beginning of the game regardless of the sessions.

Figure 3.9: Polarization Measurement by Treatments



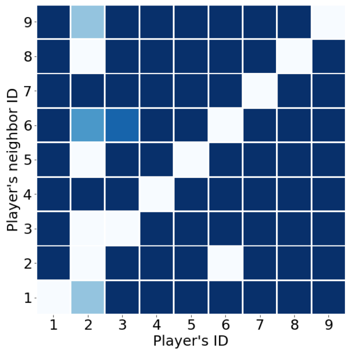
All treatments have a decreasing trend of the polarization measurement. Treatment $fHh0$ and $fHh10$ decrease in short rounds and are stable in long rounds. Specifically, since $fHh0$ ends with consensus, the polarization level becomes zero. There is a clear and stable difference in polarization measurement between $fHh0$ and $fHh10$.

Under high f and high V, the treatment with personalization ($fHh10$, treatment 2) has a higher level of polarization, consistent with Hypothesis 1. In comparison, treatments $Vlh0$ and $Vlh10$ have a very similar decreasing trend. Since players still keep updating positions at the end of the game, the polarization is not stable though. However, the current evidence shows that the polarization is similar under low f and low V, regardless of whether there is personalization. Therefore, when people are reluctant to connect with others, personalization has no obvious effects on polarization, consistent with Hypothesis 1.

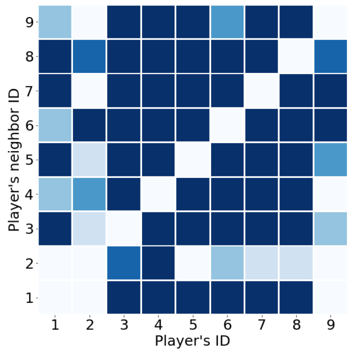
3.5.3 Connections Pattern

To justify Hypothesis 2, the heatmaps in Figure 3.10 and 3.11 display the average frequency of connections of each subject with other players in the last 5 rounds by treatments and random seeds. Under high f and high V, both treatments show a clear symmetric pattern (except 3.10b, because there is an obvious outlier in figure 3.7b). The connection is much clear and almost perfect symmetric in treatment with personalization in 3.10d, 3.10e, and 3.10f. After equilibrium is reached, there is a full connection within each subgroup and therefore, positions converge. There is no connection across groups. For example, in 3.10d, Subject 1, 2, and 3 converge as one subgroup and the rest of 6 subjects form another group. There is no cross connection in two groups. This result is consistent with Hypothesis 2. Figure 3.11 is quite noisy, and there is no clear symmetric pattern. One reason is that subjects still keep updating positions and connections at the end of the game. Therefore, they still need more rounds to reach equilibrium.

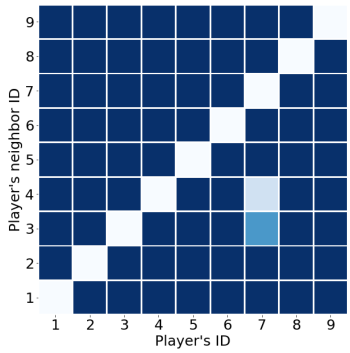
Figure 3.10: Connection Frequency Under High f and High V



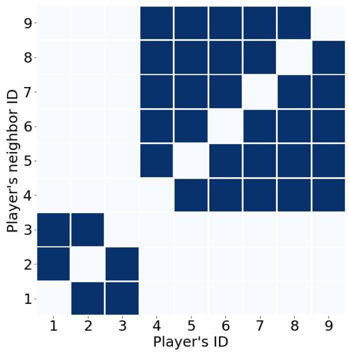
(a) fHh0(I)



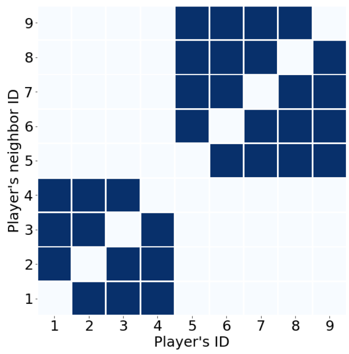
(b) fHh0(II)



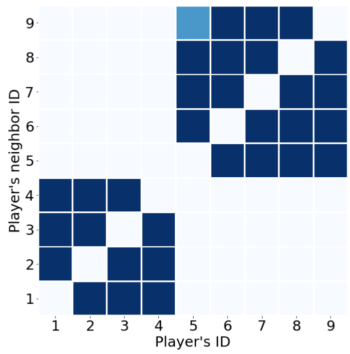
(c) fHh0(III)



(d) fHh10(I)



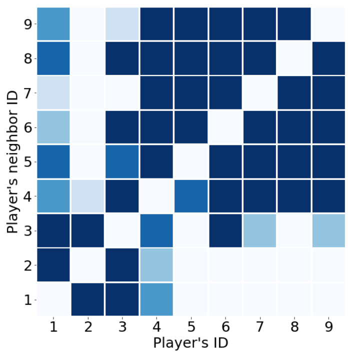
(e) fHh10(II)



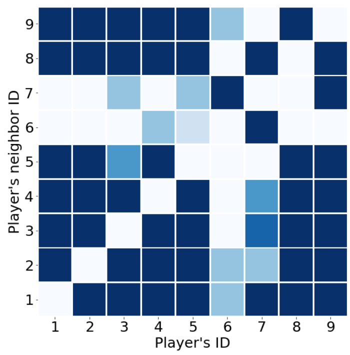
(f) fHh10(III)

The darker color of the cell represents a higher frequency.

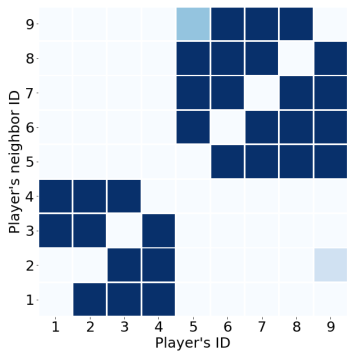
Figure 3.11: Connection Frequency Under Low f and Low V



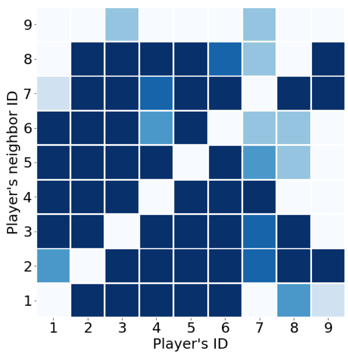
(a) Vlh0(I)



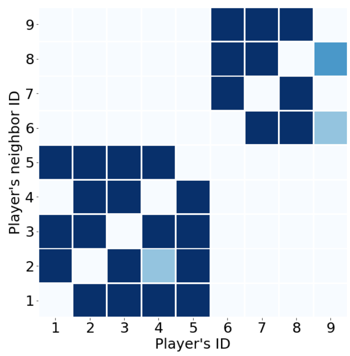
(b) Vlh0(II)



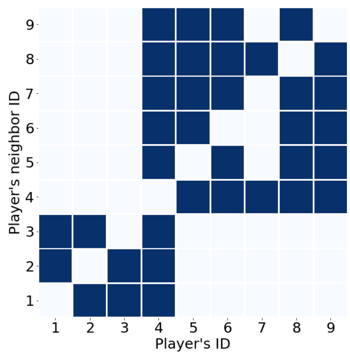
(c) Vlh0(III)



(d) Vlh10(I)



(e) Vlh10(II)



(f) Vlh10(III)

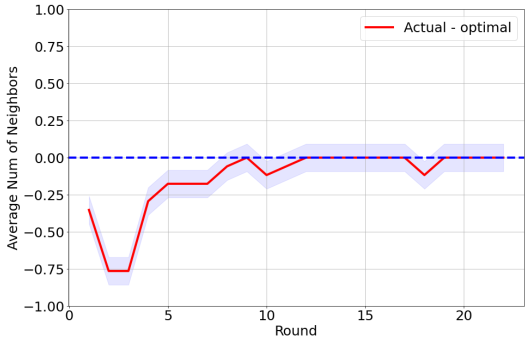
The darker color of the cell represents a higher frequency.

3.5.4 Optimal Connection

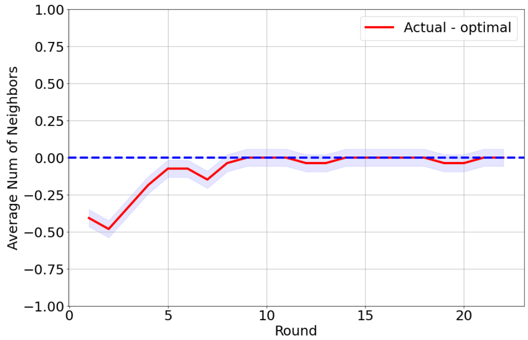
We observe deviations between experimental results and simulations in the position evolution process in section 3.5.1. First, subjects spend more time converging in all four treatments than in simulations. Some sessions have not reached equilibrium even after 20 rounds. Second, for treatments under low f and low V, the number of subgroups is lower than predictions.

To investigate the reason for the deviations, we calculate the optimal number of neighbors for each subject each round, given the subject's previous position, observations, and previous neighbors' position set. That is, if the subject is fully rational, how many neighbors they should have connected with each round. Figure 3.12 plots the difference between the actual and optimal number of neighbors with 95% confidence intervals. If the difference is negative, it suggests subjects connect with too few neighbors as expected. However, if the difference is positive, subjects connect with too many neighbors under the sacrifice of payoff each round. Figure 3.12a and 3.12b show that subjects connect with too fewer neighbors than expectation under high f and high V on average. However, the deviations decrease in later rounds. After reaching equilibrium, the actual connections are the same as optimal connections. This pattern explains why subjects spend a longer time converging than in simulation. At the beginning of the game, since subjects connect with fewer neighbors than expected, it takes longer rounds for subjects to observe and update positions. Figure 3.12c and 3.12d, in opposite, show that subjects on average connect with too many neighbors than expected under low f and low V. The deviations decline for several rounds but start increasing in the opposite direction in later rounds. The reason is that subjects are closer with each other in the first several rounds after over-connection. However, they should have connected with more neighbors when close enough, but they still keep the same connection habits. Therefore, in later rounds, they are under-connection. Since most sessions of treatments $Vlh0$ and $Vlh10$ have not reached equilibrium, the deviation persists at the end of the game.

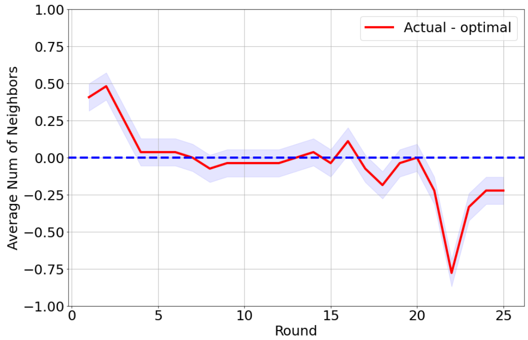
Figure 3.12: Distance Between Actual and Optimal Number of Neighbors



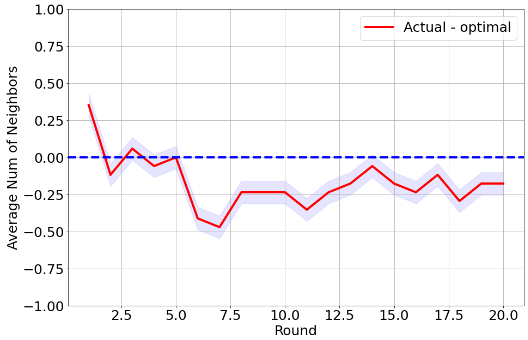
(a) fHh0



(b) fHh10



(c) Vlh0



(d) Vlh10

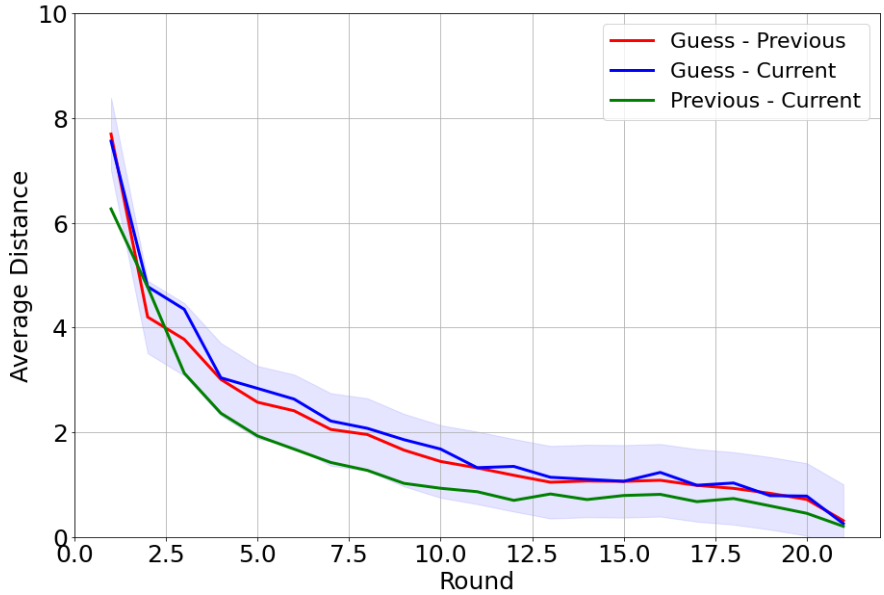
The shaded area traces confidence intervals.

3.5.5 Subject's Guess

In the model, we assume agents are naive and treat neighbors' opinions the same as in previous rounds. However, in the experiment, we relaxed this assumption. Subjects are asked to guess how their neighbors update positions. In this section, we can test whether the assumption of naive agents holds (section 3.5.5.1) and find the factors that decide the subject's guess.

3.5.5.1 Whether subjects are naive

Figure 3.13: Distance between subject's guess and previous position



The shaded area traces confidence intervals.

Figure 3.13 depicts the average distance between the subject's guess and neighbor's previous position with 95% confidence intervals (red line), the average distance between the subject's guess and neighbor's current position (blue line), and the average distance between neighbor's previous position and current position (green line). The three lines are close to each other. The red line with 95% confidence intervals tests the assumption that subjects are naive. The blue line shows the deviation from the guess to the actual neighbor's position, testing the accuracy of the guess. The green line indicates how neighbors update their positions. The three lines decrease across rounds, both due to the learning effect and position convergence. Subjects get more and more familiar with the game, and therefore, their guess is more and more accurate. The green line is slightly below the other two lines, indicating that subjects slightly overestimate the change in the neighbor's position.

3.5.5.2 Factors of subject's guess

Table 3.3: Regressions of subject's guess on key determinants

	(1)	(2)
VARIABLES	OLS	Fixed Effects
Subject previous position	0.134***	0.119***
	(0.00725)	(0.00728)
Neighbor's previous position	0.747***	0.752***
	(0.00634)	(0.00629)
Other neighbors' average previous positions	0.113***	0.124***
	(0.00773)	(0.00773)
Observations	9,097	9,097
R-squared	0.968	0.969
Treatment FE		YES
Round FE		YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 3.3 we examine the determinants of a subject's guess. We use the subject's previous position, neighbor's previous position, and the previous average positions of other neighbors as independent variables. We find that subjects' guess of one neighbor's position is mainly based on the neighbor's previous position. The subject's previous position and other neighbors' previous positions also play a role. The coefficients are still significant after controlling for treatment fixed effects and round fixed effects.

3.6 Conclusions

This paper constructs a theoretical model that combines an endogenous network formation setup and personalization to investigate the pure effect of personalization on polarization. The simulation results show that when agents are more easily convinced by others, personalization amplifies polarization and increases opinion converge time. However, when agents are reluctant to change their own opinions, personalization has no pronounced effect on polarization. In addition, the connection pattern indicates that there is no cross-connection between different subgroups after equilibrium is reached.

The paper further designs a lab experiment to test the predictions and hypotheses from simulations. The experimental results are consistent with all hypotheses. When the sufficient threshold to disconnect is high, where agents are willing to connect with others, personalization amplifies polarization. When the sufficient threshold to disconnect is low, or when agents are hard to be convinced by others, the personalization has no apparent effects. Moreover, under a low disconnection threshold, a transitionary polarization occurred in the treatment without personalization. Subjects are polarized in short rounds but reach a consensus in the long run.

Appendix A

Supplement to Chapter One

A.1 4-state Game and IAS Solutions

The 4-state game extends the original 3-state game with the state uniformly distributed between 4 integers: 1, 2, 3, and 4. The payoffs replicate a common value auction. While the payoffs for state 1-3 do not change, it keeps the feature that the sender earns the highest payoff when the receiver bids a smaller number than the true state, and the receiver earns the highest payoff when they submit the same bid as the sender. Without communication, the expected payoff for the receiver by selecting each bid is 0. The payoff matrices are showed in Table A.1 and A.2.

Same as the 3-state game, we allow two different message rules. Under Message Rule 1, precise messages and no information are allowed, while vague messages are added to the menu under Message Rule 2. The summary of the message menu for each message rule is showed in Table A.3.

Table A.1: Payoff matrix for the sender

		True State			
		1	2	3	4
Receiver's Bid	1	0	5	10	15
	2	0	0	10	15
	3	0	0	0	15
	4	0	0	0	0

Table A.2: Payoff matrix for the receiver

		True State			
		1	2	3	4
Receiver's Bid	1	0	0	0	0
	2	-5	5	0	0
	3	-10	0	10	0
	4	-15	-5	5	15

Table A.3: Message Menu

State	Message Options	
	Message Rule 1	Message Rule 2
1	{1},{1,2,3,4}	{1},{1,2},{1,3},{1,4},{1,2,3},{1,2,4},{1,3,4},{1,2,3,4}
2	{2},{1,2,3,4}	{2},{1,2},{2,3},{2,4},{1,2,3},{1,2,4},{2,3,4},{1,2,3,4}
3	{3},{1,2,3,4}	{3},{1,3},{2,3},{3,4},{1,2,3},{1,3,4},{2,3,4},{1,2,3,4}
4	{4},{1,2,3,4}	{4},{1,4},{2,4},{3,4},{1,2,4},{1,3,4},{2,3,4},{1,2,3,4}

Using the iterative elimination procedure of IAS, we can solve the game under both message rules. The solutions for Message Rule 1 are shown in Table A.4 and A.5. The highest-level sender eliminates the precise messages except for state 1, while the highest-level receiver selects bids from all the numbers contained in the message received. These features match Proposition 1 in Chapter 1 Section 3.2.

Table A.4: Message Rule 1: sender reasoning

Level of reasoning	State	Message				
		{1}	{2}	{3}	{4}	{1,2,3,4}
0 and 1	1	✓				✓
	2		✓			✓
	3			✓		✓
	4				✓	✓
2 and higher	1	✓				✓
	2					✓
	3					✓
	4					✓

In each row, the check marks show the messages that are not obviously dominated and thus not eliminated for each state. The strategies with ✓ are eliminated in the higher reasoning level.

Table A.5: Message Rule 1: receiver reasoning

Level of reasoning	Message received				
	{1}	{2}	{3}	{4}	{1,2,3,4}
0	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4
1 and higher	1	2	3	4	1,2,3,4

In each cell, the numbers show the receiver's bids that are not obviously dominated, thus not eliminated for each message. The receiver's bids marked as red are eliminated in the higher reasoning level.

Table A.6 and A.7 show the sender and receiver reasoning under Message Rule 2. For the sender, there are 6 levels of reasoning. The precise messages and the vague messages containing numbers larger than the true state are eliminated first. This is reasonable because the sender only benefits when the receiver bids a smaller number than the true state. Then the vague messages without number 1 are eliminated in the next level except for the message {2,3,4} under state 4. In the highest level, {2,3,4} is eliminated for all states. The messages which survive the highest level are those containing number 1. For the receiver, there are 5 reasoning levels. The numbers not contained in the message are eliminated first. In the next level, the smallest number in vague messages without number 1 are eliminated. In the highest level, the receiver only bids the highest number contained in the messages without number 1. The patterns for the sender and receiver match Proposition 2 in Chapter 1 Section 3.2.

Table A.6: Message Rule 2: sender reasoning

Level of reasoning	State	Message														
		{1}	{2}	{3}	{4}	{1,2}	{1,3}	{1,4}	{2,3}	{2,4}	{3,4}	{1,2,3}	{1,2,4}	{1,3,4}	{2,3,4}	{1,2,3,4}
0 and 1	1					✓	✓	✓				✓	✓	✓		✓
	2		✓			✓			✓	✓		✓	✓		✓	✓
	3			✓			✓		✓		✓	✓		✓	✓	✓
	4				✓			✓		✓	✓		✓	✓	✓	✓
2 and 3	1	✓				✓	✓	✓				✓	✓	✓		✓
	2					✓						✓	✓			✓
	3						✓		✓			✓		✓	✓	✓
	4							✓		✓	✓		✓	✓	✓	✓
4 and 5	1	✓				✓	✓	✓				✓	✓	✓		✓
	2					✓						✓	✓			✓
	3						✓					✓		✓		✓
	4							✓					✓	✓	✓	✓
6 and higher	1	✓				✓	✓	✓				✓	✓	✓		✓
	2					✓						✓	✓			✓
	3						✓					✓		✓		✓
	4							✓					✓	✓		✓

In each row, the check marks show the messages that are not obviously dominated and thus not eliminated for each state. The strategies with ✓ are eliminated in the higher reasoning level.

Table A.7: Message Rule 2: receiver reasoning

Level of reasoning	Message received														
	{1}	{2}	{3}	{4}	{1,2}	{1,3}	{1,4}	{2,3}	{2,4}	{3,4}	{1,2,3}	{1,2,4}	{1,3,4}	{2,3,4}	{1,2,3,4}
0	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4	1,2,3,4
1 and 2	1	2	3	4	1,2	1,3	1,4	2,3	2,4	3,4	1,2,3	1,2,4	1,3,4	2,3,4	1,2,3,4
3 and 4	1	2	3	4	1,2	1,3	1,4	3	4	4	1,2,3	1,2,4	1,3,4	3,4	1,2,3,4
5 and higher	1	2	3	4	1,2	1,3	1,4	3	4	4	1,2,3	1,2,4	1,3,4	4	1,2,3,4

In each cell, the numbers show the receiver's bids that are not obviously dominated, thus not eliminated for each message. The receiver's bids marked as red are eliminated in the higher reasoning level.

A.2 Proof

A.2.1 IAS Solutions of Message Rule 1

Level 0 and level 1 sender: The level 0 senders and receivers choose all possible strategies. Level 1 senders will assume the opponents are level 0 receivers who consider all bids no matter what message they receive. Therefore, the level 1 senders' optimal reaction is still randomly selecting all available messages, same as level 0 senders. By this logic, every two levels have the same behavior.

Level 1 and level 2 receiver: Level 1 and level 2 receivers will assume the senders are level 0 and level 1. When the precise message $\{t\}$ is sent, they know the true state is t; thus, the bid t dominates all other bids. When there is no revelation ({1,2,3} for the 3-state game and {1,2,3,4} for the 4-state game), based on the iterative elimination, there is no obviously dominated bid, so the receivers' strategy will be choosing from all bids.

Level 2 and level 3 sender: Level 2 and level 3 senders will assume the receivers are level 1 and level 2. If the precise message $\{t\}$ is sent, the receivers will choose to bid t for sure. Then the payoff for the senders is 0. Instead, if the senders choose no revelation, the minimum payoffs under state 2 and 3 (state 2, 3, and 4 for the 4-state game) equal to 0, which is the same as the maximum payoff under message $\{t\}$, and u_s is not a singleton. By iterative elimination, the precise messages are obviously dominated by no revelation. When state is 1, since u_s under both {1} and {1,2,3} ({1,2,3,4} for the 4-state game) are singleton, there is no dominated bid.

Higher levels: The higher level senders will behave like level 2 senders, and the higher level receivers will behave like level 1 receivers.

A.2.2 IAS Solutions of Message Rule 2

Level 0 and level 1 sender: When both precise and vague messages are allowed, the level 0 and level 1 senders have the same behavior as those under Message Rule 1. Similarly, for both senders and receivers, every two levels have the same strategies.

Level 1 and level 2 receiver: When the receivers are level 1 and 2, the logic is similar. For each message received, they will choose bids matching all states contained in the message (e.g. If the received message is {2,3}, the receivers' strategy is either bidding 2 or bidding 3). Because the message can be sent under each state t in the message, no bid is obviously dominated. For example, senders can send the message {2,3} when the true state is 2 or 3. Then for receivers in the 3-state game, the payoff of bidding 1 is 0;

the payoff of bidding 2 is either 0 or 5; the payoff of bidding 3 is either 0 or 10. Only bidding 1 is obviously dominated. The analysis is similar in the 4-state game.

Level 2 and level 3 sender: When senders assume the receivers only choose bids that match the states contained in the message, they will eliminate precise massages $\{t\}$ and messages where the true state is the smallest number (e.g. {2,3} and {2,3,4} for state 2), except for state 1. The payoffs for senders under these messages are 0 for sure, while for the remaining messages, the minimum payoff is 0 and u_s not a singleton. For state 1, the payoff for senders is always 0, so there is no obviously dominated strategy.

Level 3 and level 4 receiver: When receivers know that senders will avoid making the true state the smallest number in the message, they will avoid the bid that matches the smallest number in a message (unless state 1 is included) because the payoff will be 0 for sure. Then these bids are obviously dominated. For example, receivers know the senders would only send message {2,3} when the true state is 3, and send message {2,3,4} when the true state is 3 or 4. Then bidding 2 is dominated under both messages and is eliminated.

Level 4 and level 5 sender: Now senders consider that receivers will not choose bids that match the smallest number in a message (except for state 1). Then if $1 < t_1 < t_2$, a message $\{t_1, t_2\}$ would be interpreted as message $\{t_2\}$ by receivers. Therefore, senders will avoid sending messages {2,3}, {3,4} and {2,4} since they are dominated with payoff 0. By the same logic, message {2,3,4} will be interpreted as {3,4}, and the sender will stop sending message {2,3,4} when the true state is 3.

Level 5 and level 6 receiver: Among the messages sent by level 4 and 5 senders, {2,3,4} is sent only under state 4 while other messages are possible to be sent under all states in the message. Therefore, receivers will only choose to bid 4 under {2,3,4}. The bids under other messages are the same as level 3 and 4 receivers.

Level 6 and level 7 sender: Since receivers only choose to bid 4 under message {2,3,4}, this message is obviously dominated under state 4. The senders will only choose to send messages that contain state 1.

Higher levels: For the 3-state game, the higher level senders will behave like level-4 sender, and the higher level receivers will behave like level-3 receivers. For the 4-state game, the higher level senders will behave like level-6 senders, and the higher level receivers will behave like level-5 receivers.

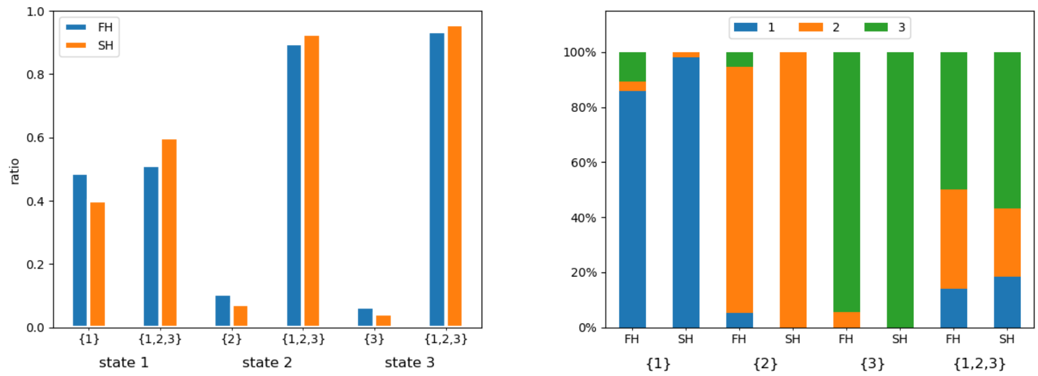
A.3 Strategies Consistency

We have combined the data from both the direct-response method rounds and strategy method rounds to evaluate the subjects' strategies across all periods. In case that there are learning effects or different patterns between the direct-response method and strategy method, we further check the strategy consistency across periods and decision elicitation methods.

A.3.1 Strategies by Periods

Figure A.1 compares the strategy frequency of the first half of the rounds and the second half of the rounds in each session under Message Rule 1. The differences can reflect learning effects on some level[1]. A.1a shows the sender's strategies. We can see there is no big difference between the first half and second half of the rounds. Only for state 1, the sender tends to send message {1,2,3} more in the second half of the rounds, but the changes are not obvious. A.1b shows the receiver's strategies. Similarly, no big difference can be observed. Only when message {1,2,3} is sent, receivers tend to guess 3 and 1 a little more frequently. In general, there are no obvious learning effects under Message Rule 1.

Figure A.1: Strategies by periods: Message Rule 1



(a) Sender (b) Receiver

[1]In our experiment design, subjects switch roles after half of the rounds. Therefore, the comparison between the first and second half of the rounds is a between-subjects comparison, which may not reflect pure learning effects.

Figure A.2 is the sender's strategies by periods under Message Rule 2. There is essentially no significant change of strategies in the second half of the rounds. For state 2 and 3, senders disclose more and send the message {2,3} less over time, which may reflect some learning effects, but not obvious.

Figure A.2: Sender strategy by periods: Message Rule 2

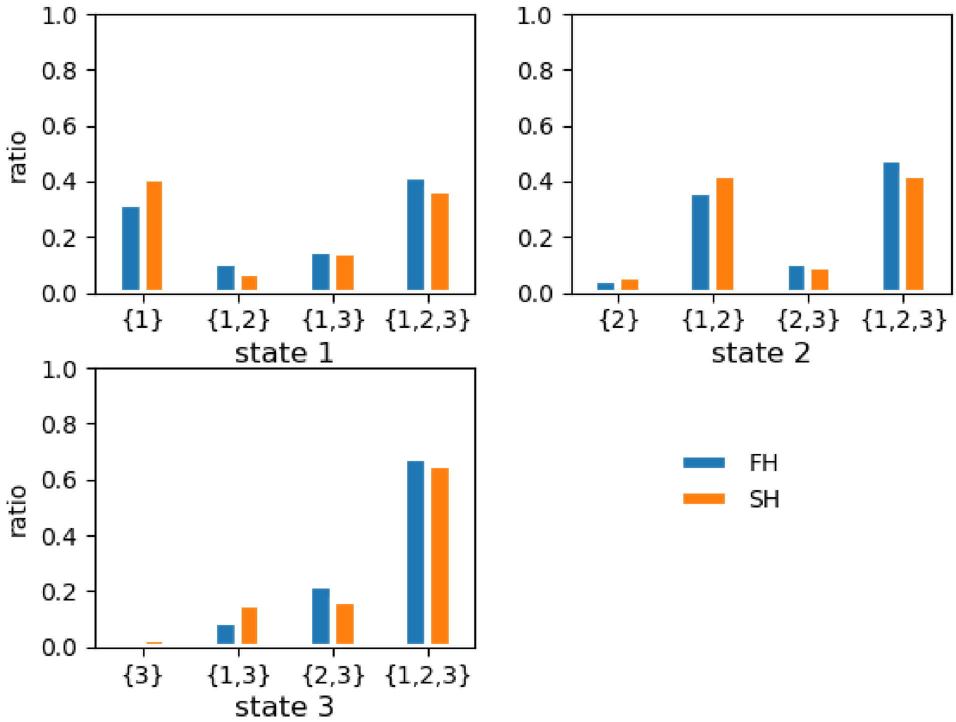
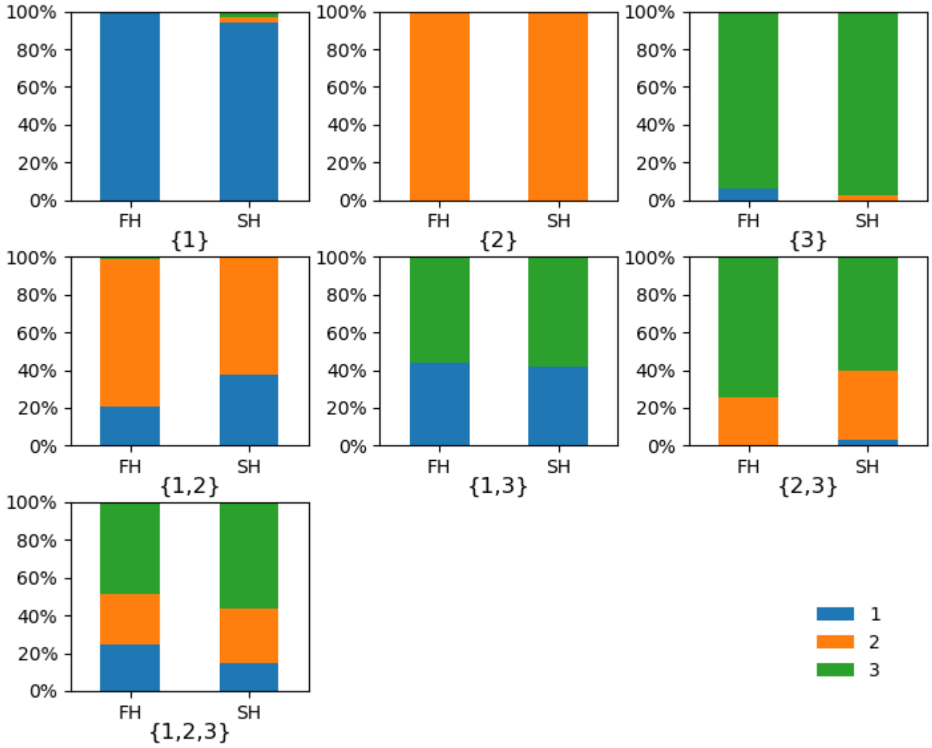


Figure A.3 shows the receiver's strategies by periods under Message Rule 2. The strategy frequency is essentially the same between the first and second half of the rounds. Only when the message received is {1,2} or {2,3}, the subjects turn to guess the smaller number contained in the message a little more frequently in the second half of the rounds, which is not a very significant change. In summary, both the sender and receiver's strategies in the first and second half of the rounds are consistent, indicating no apparent learning effects. The strategies are also consistent with the IAS solutions.

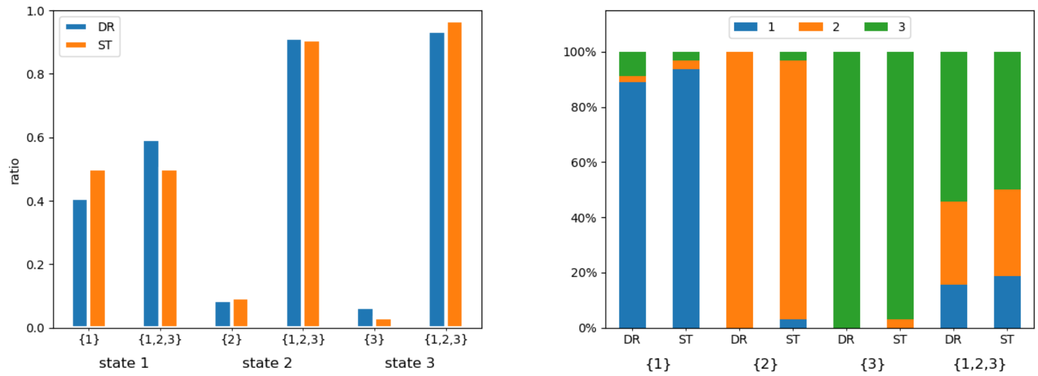
Figure A.3: Receiver strategy by periods: Message Rule 2



A.3.2 Strategies by Decision Elicitation Methods

Since different decision elicitation methods may influence subjects' behaviors, we compare the strategy frequency between the direct-response method rounds and the strategy method rounds.

Figure A.4: Strategies by decision elicitation methods: Message Rule 1



(a) Sender

(b) Receiver

Figure A.4 shows the strategy comparisons under Message Rule 1. A.4a is the sender strategy frequency. The results show there are no obvious differences between the two elicitation methods. Only when the state is 1, senders tend to send message {1,2,3} with a slightly higher ratio in direct-response method rounds than strategy method rounds. A.4b is the receiver strategy frequency. Similar to the sender strategy, no apparent behavior changes are observed. Therefore, the strategies from the direct-response method rounds and the strategy method rounds are consistent under Message Rule 1.

Figure A.5 compares the sender strategies under Message Rule 2. Similar to Message Rule 1, the strategies elicited from the two methods are essentially the same. Senders seem to keep silent a little more frequently in the strategy method rounds, but the differences are not significant.

Figure A.5: Sender strategy by decision elicitation methods: Message Rule 2

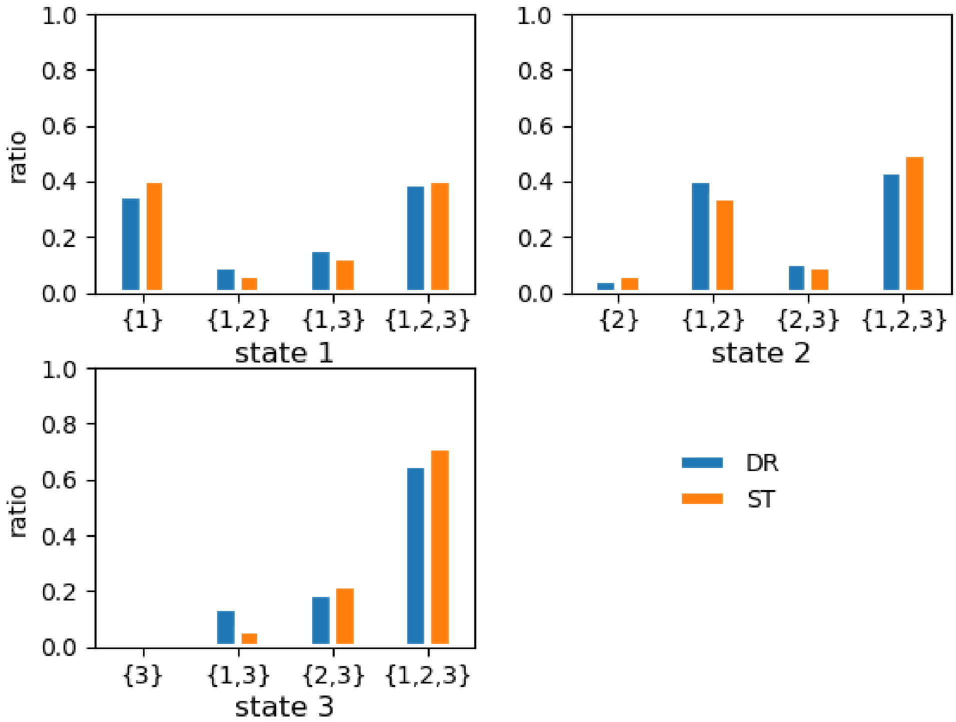
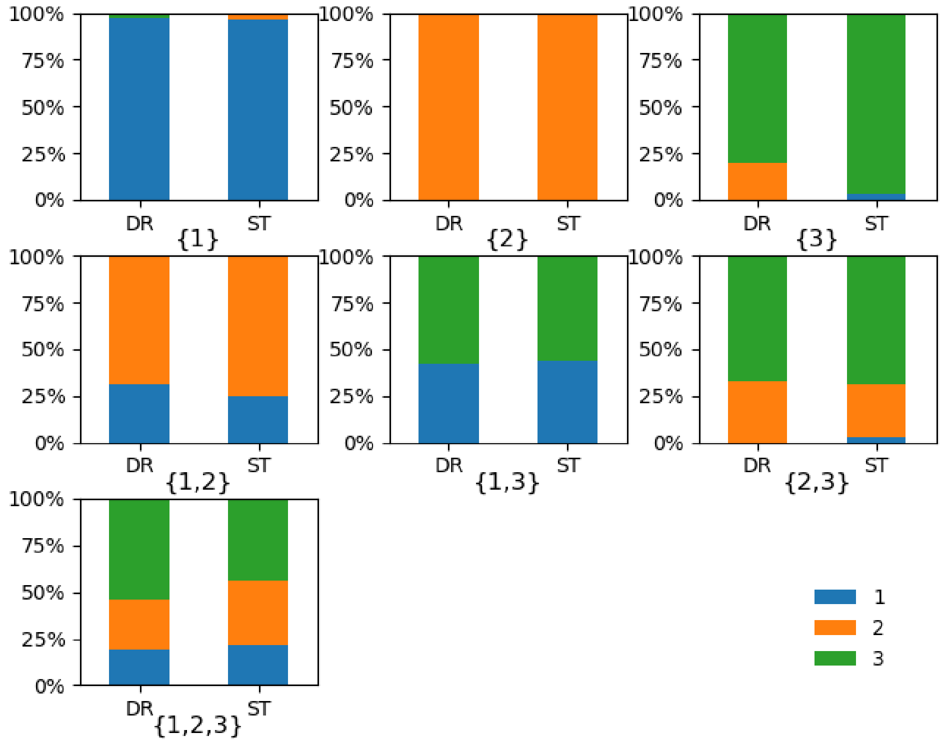


Figure A.6 shows the receiver strategies from the two decision elicitation methods under Message Rule 2. Like Message Rule 1, the strategy frequency shows similar patterns between the two methods. Only for message {3}, the ratio of guessing 2 is slightly higher from the direct-response method rounds. This is caused by a subject guessing 2 in one of the direct-response rounds, which might be a mistake and can be treated as an outlier. In general, both the sender and receiver's strategies are consistent across the decision elicitation methods.

Figure A.6: Receiver strategy by decision elicitation methods: Message Rule 2



A.4 Best Response to Beliefs

For a complicated game with multiple equilibria, the players may not have the correct beliefs of their opponents' strategies. However, players may still be able to respond optimally according to their beliefs if they are rational. Therefore, we further examine to what extent subjects best respond to their beliefs. The methods are similar to Hagenbach and Perez-Richet (2018).

Let the sender's belief on the receiver's actions under message M_i be $\beta_{M_i}(a)$, and the receiver's belief of the state under message m be $\beta_m(t)$, then the optimal response $(m^*(s), a^*(m))$ satisfies:

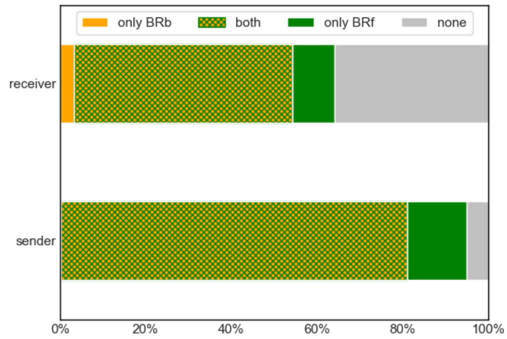
$$m^*(s) \in arg \max_{M_i \in M(s)} \sum_a u_s(a, s)\beta_{M_i}(a)$$

$$a^*(m) \in arg \max_{a \in S} \sum_{t \in m} u_r(a, t)\beta_m(t)$$

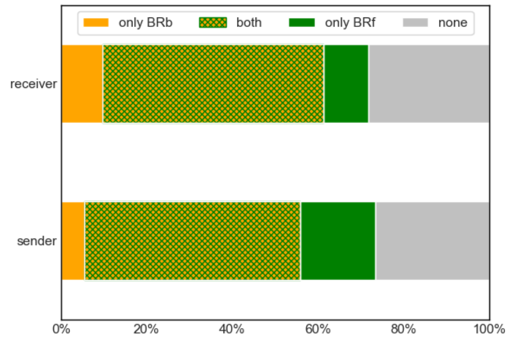
The results are shown in Figure A.7. We also examine to what extent the players' strategies are the best response to the empirical frequency (the real posterior probability) because the players might be able to take the correct actions by learning from experiences even though their beliefs are incorrect.

For both message rules, more actions are the best response to the empirical frequency than to subjects' beliefs, but the best response to the frequency and beliefs has a big range of overlap. Over 45% of the actions are the best response to both. This indicates that many subjects are able to update their belief in the right direction. This is consistent with the results of strategy frequency in Chapter 1 Section 5.1.

Figure A.7: Best Response



(a) Message Rule 1



(b) Message Rule 2

BRb is the best response to own beliefs. BRf is the best response to empirical frequency.

Under Message Rule 1, the senders' strategies match the best response well, with 94.7% are the best response to the frequency and 81% are the best response to both. Compared to the sender, receivers' performance is worse, with 54.2% actions are the best response to beliefs and 60.8% are the best response to the frequency. However, over half of the receivers' actions still match the best response. For the sender, the strategy options to consider are only the precise message and no information, which is easier for them to choose the message matching the best response to their beliefs. For the receiver, when the message {1,2,3} is received, actions can deviate from the best response because of uncertainty.

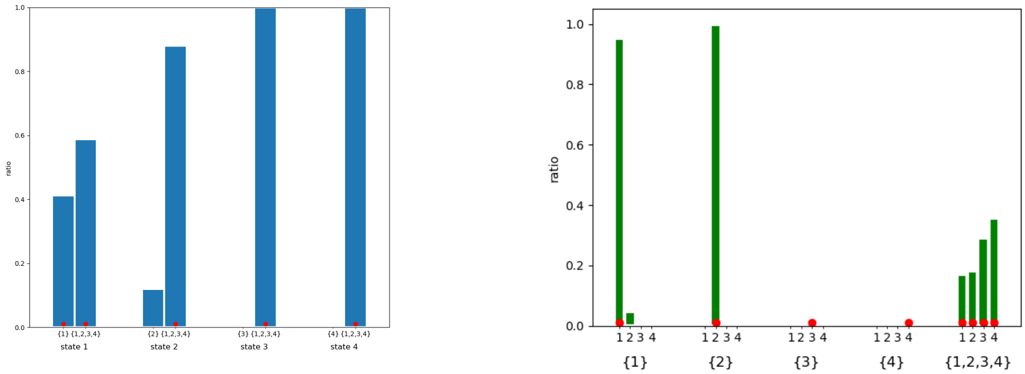
Under Message Rule 2, the ratio of the sender's strategies matching the best response drops to 73.4%, with 55.9% the best response to beliefs and 67.9% the best response to the frequency. With more strategy options after vague messages are allowed, it is harder for the sender to take the correct action. Additionally, the payoff range for vague messages and no information is the same, which adds uncertainty for the sender and causes the actions to deviate from the best response. For the receiver, the ratios of both best response to beliefs and best response to frequency increase. This is reasonable because when vague messages are allowed and sent more often, it narrows the receiver's choices and thus reduces the uncertainty for them. Therefore, the receiver's deviation from the best response also occurs less.

A.5 Robustness Test: Consistency on State Space

From the analysis on the 3-state game, our results show that there is more disclosure under Message Rule 2, and the sender tends to disclose more when the true state is smaller. To evaluate whether these patterns are consistent across the state space, we further conduct sessions on a similar 4-state game. We examine whether the strategies follow the two propositions in Chapter 1 Section 3.2, and compare the disclosure level between the two message rules.

Figure A.8 shows the frequency of strategies under Message Rule 1. For the sender, {1,2,3,4} is always sent under state 3 and 4, and the ratio of {1,2,3,4} sent under state 2 is 88%. Only when the state is 1, both messages are sent frequently, with message {1} sent 41% of the time and {1,2,3,4} 59% of the time. This is essentially consistent with Proposition 1 in Chapter 1 Section 3.2. For the receiver, when precise messages are received, most subjects can guess the number correctly. For the message {1,2,3,4}, all four integers are guessed, and the higher numbers are guessed with a little higher frequency, which is consistent with the patterns for the 3-state game. This also matches the receiver's behavior described in Proposition 1.

Figure A.8: Strategies: Message Rule 1



(a) Sender

(b) Receiver

Message {3} and {4} in (b) are blank because they are never received.

The messages (guesses) with a red dot below are the surviving strategies of the highest level senders (receivers) under the IAS solution.

Figure A.9: Sender Strategies: Message Rule 2

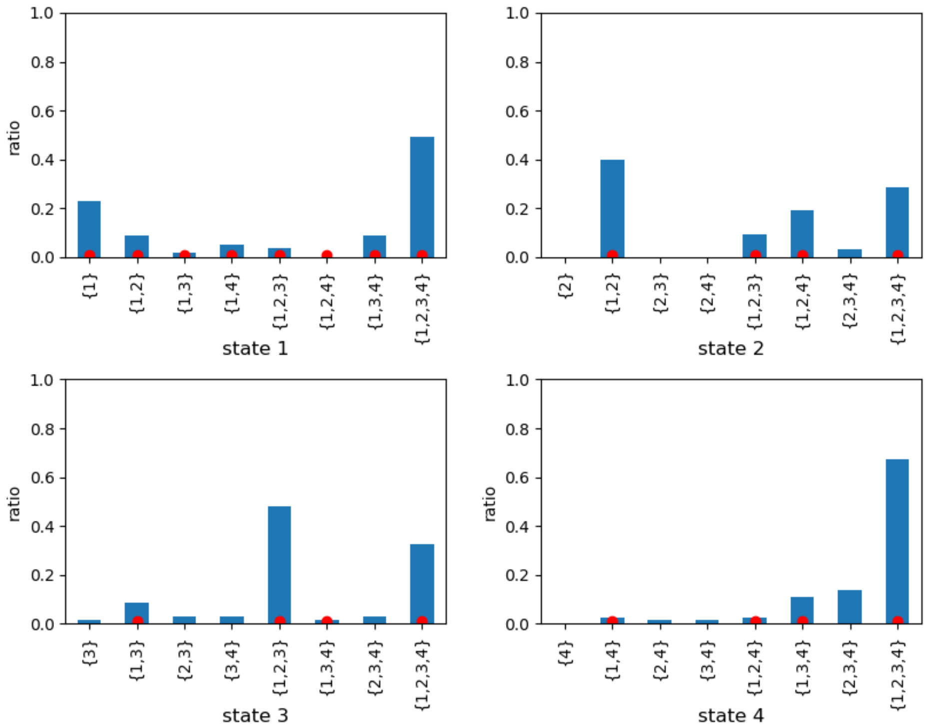
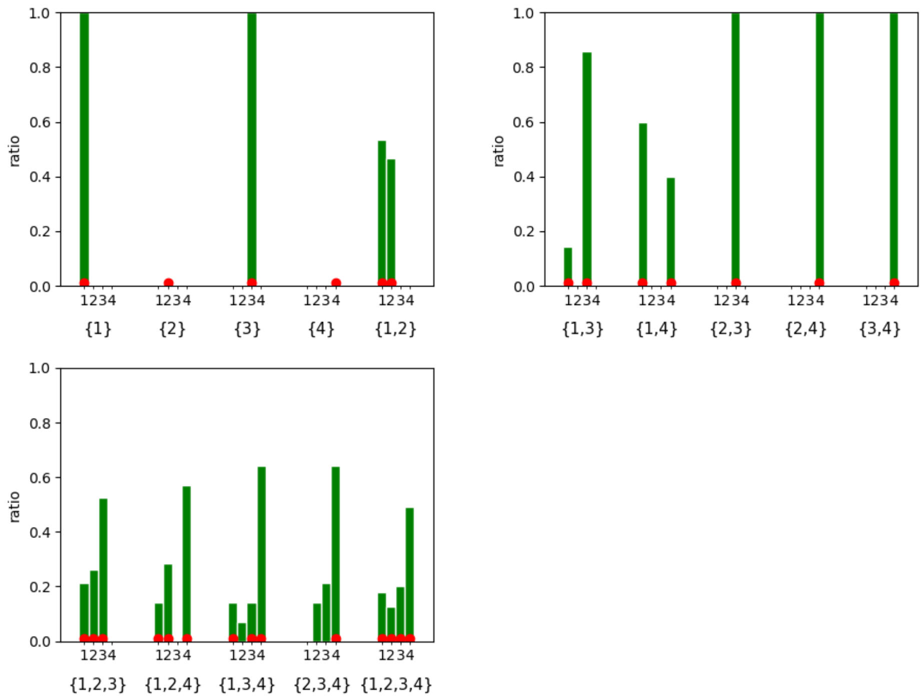


Figure A.9 shows the sender strategies under Message Rule 2 for each state. When the state is 1, the message {1,2,3,4} is sent most frequently with 49% of the time and message {1} 23% of the time. When the state is 2, message {1,2} has the highest frequency with 40%, then message {1,2,3,4} with 28%. Message {1,2,4} and {1,2,3} have also been sent, with the ratio of 19% and 10% respectively. The precise message {2} and vague messages {2,3}, {2,4} have never been sent. The message {2,3,4} have been sent but with a very low ratio (3%). When the state is 3, the mostly sent message is {1,2,3} with 48% of the time, and then message {1,2,3,4} with 32% of the time. The message {1,3} is sent with 8% while the frequency of the remaining messages is lower than 3%. When the state is 4, the sender chooses no information most of the time (the ratio of message {1,2,3,4} is 67%). Message {2,3,4} and {1,3,4} are also frequently sent with the ratio 14% and 11% respectively. The sender's strategies are consistent with Proposition 2, which indicates that only the messages containing the integer 1 would not be eliminated. For state 4, the message {2,3,4} has a relatively high chance to be sent. This is similar to the 3-state game, and the possible explanation is that, by IAS, only the highest level senders are able to eliminate this message.

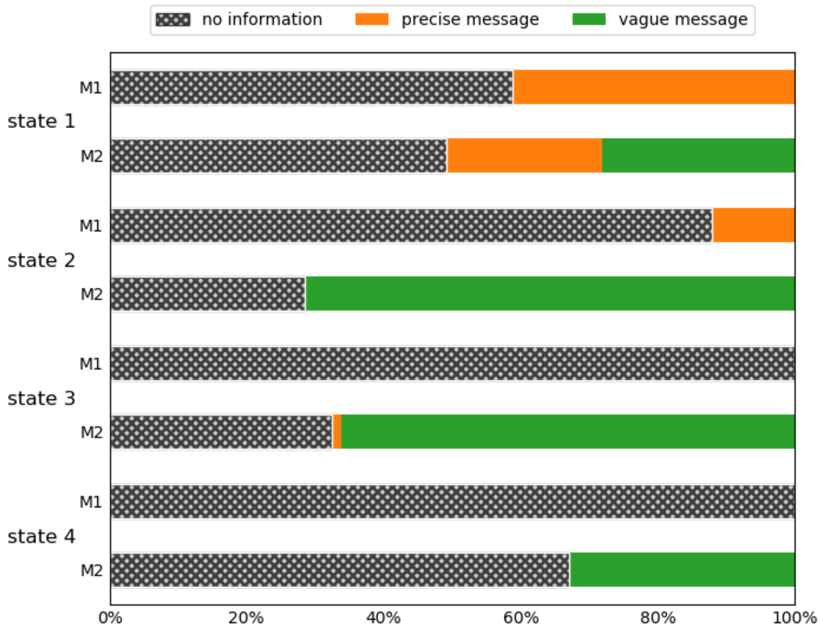
Figure A.10 reflects the receiver's strategies under Message Rule 2. Receivers are able to guess the state correctly when precise messages are received. For vague messages, when {2,3}, {2,4}, and {3,4} are received, receivers always guess the higher number in the message. This is consistent with Proposition 2, which indicates that receivers are rational enough to eliminate the smaller numbers in these three messages. When other vague messages containing number 1 are received, all numbers in the message have been guessed, which is also consistent with Proposition 2. For message {2,3,4}, receivers guess 4 most frequently with a ratio of 64.3%, but many are not be able to eliminate 2 and 3. This is reasonable because this elimination only happens for the highest-level receivers. When there is no information (message {1,2,3,4} received), receivers guess all 4 numbers. Like Message Rule 1 and the patterns in the 3-state game, the higher number is guessed with a higher chance.

Figure A.10: Receiver Strategies: Message Rule 2



Finally, we examined the disclosure level of the senders under both message rules. The results are shown in Figure A.11. There is clear evidence that more disclosure is achieved under Message Rule 2 than Message Rule 1, and it is mainly contributed by sending vague messages. Comparing states 2, 3, and 4 when there are conflicting interests between the sender and receiver, we can also observe that the disclosure level is higher when the state is a smaller number (33% for state 4, 67% for state 3, and 71% for state 2). This is consistent with the results found from the 3-state game, which suggests that the sender has more incentive to reveal information when the true state is small since the chance to gain benefits is lower without communication.

Figure A.11: Disclosure



Appendix B

Supplement to Chapter Two

B.1 Data sources

Our ridehail data is based on a unique dataset of 5.3 million ridehail trips in San Francisco from November 12, 2016 through December 21, 2016. The following summary is adapted from Cooper et al. (2018), to which the reader is referred for additional details.

Researchers at Northeastern University developed a method for obtaining information on the location of vehicles in space and time. They developed a computer program ("synthetic client") that emulates the requests that the Uber and Lyft client applications make to their servers and return information about the nearest available vehicles (with the driver's app active and indicating that there is no passenger in the vehicle). The data returned by the servers includes a unique identifier, vehicle type, a vector of timestamped latitude and longitude coordinates that reflects each vehicle's recent path, estimated wait time, and the presence of any peak pricing multipliers. When a vehicle driver has accepted a ride and is no longer available, or ended a shift, the vehicle no longer appears in the information returned by the servers. Similarly, when a vehicle driver drops off a passenger and is available again, or when a driver starts a shift, the vehicle appears in the information from the server.

An important distinguishing difference between the data revealed by Uber and Lyft is that, while Uber appears to assign a new unique identifier to every vehicle after it has completed a trip, Lyft allows the vehicle identifiers to persist across the entire sampling period. This persistence allowed Cooper et al. (2018) to impute origin-destination flows and to distinguish driver shift start and end times from trip start and end times. Approximately 200 synthetic client locations were used to collect data across all of San Francisco, which collected data continuously every five seconds from November 12, 2016 through December 21, 2016.

Trip records consisting of a pre-trip (search) segment and a trip (paid, with-passenger) segment were imputed from raw data through a series of data cleaning and processing techniques. The search segment is defined by the time and location a vehicle becomes available and the time and location its driver accepts a ride, often referred to as "P1". It is associated with a vector of timestamped latitude and longitude data representing its path. The paid segment is defined by the time and location the driver in the vehicle accepts a ride and the time and location that the driver and vehicle next become available.

Although they were not able to validate their estimates of the number of vehicles because the TNCs and regulators would not share even aggregate data summaries, Cooper et al. (2018) were able to validate that the information collected is deterministic, internally coherent, and consistent with external data sources about the overall San Francisco travel market. The data revealed to the synthetic clients appears to be deterministic because the researchers performed a series of tests in which all the synthetic clients were located at the same point, and all data returned by the TNC servers to these clients was identical. The coherence of the data is also confirmed in the data cleaning process where duplicative and consistent data is returned to separate synthetic clients. Finally, the cleaned data also shows tremendous consistency in the location and timing of TNC trips across both Uber and Lyft, as well as consistency with the location and timing of trips overall in San Francisco.

Ethical concerns were considered and analyzed before collecting the data. No personal information about any TNC drivers or passengers was collected. A series of tests were also performed that confirmed that the passive data collection by the synthetic clients did not affect fares or surge pricing and thus had no effect on traveler behavior. In addition, no rides were requested, so there was no effect on drivers, either. Ultimately, the only burden on the TNCs was having a couple hundred additional active accounts, out of tens of millions of total accounts worldwide.

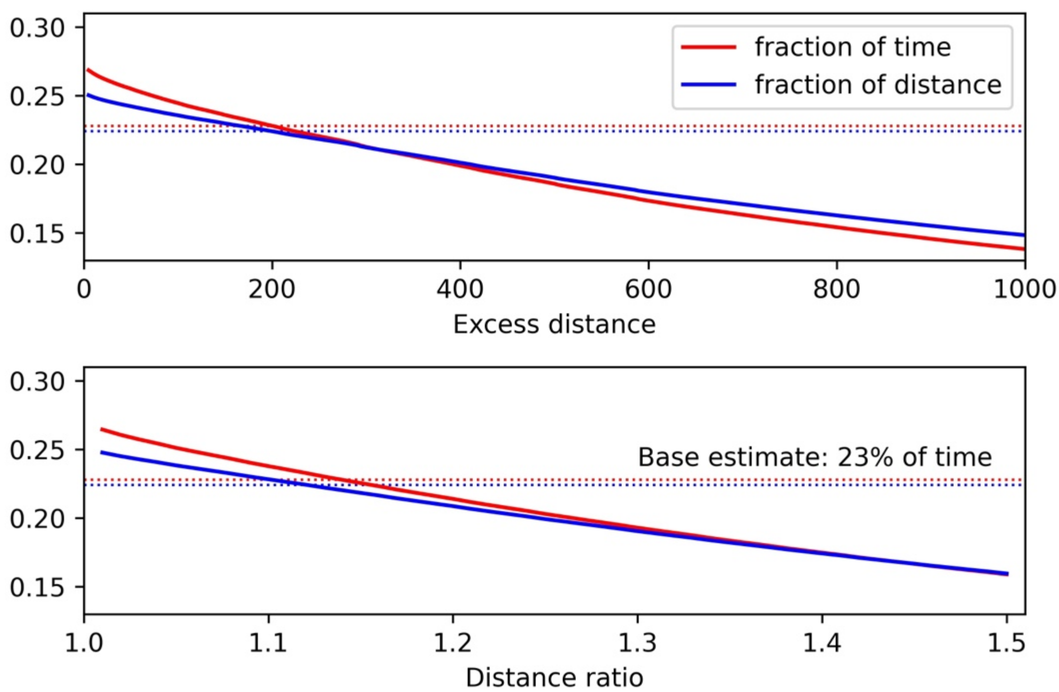
The Uber and Lyft data collected by Northeastern has several key limitations. First, data was only collected in San Francisco, so trips entering, leaving, or wholly outside of San Francisco are not captured. Second, true pickup locations are not known; they are based on the location a vehicle disappears from a datastream (although since this paper focuses on the search segments, this limitation is not material). Third, not all vehicles appear in the datastream. Both Uber and Lyft allow drivers to be matched with waiting riders while a ride is underway, so the driver will transition directly from one ride to the next without ever becoming "available." Fourth, UberPOOL and Lyft Line, like all services, do not appear in the datastream once a ride is accepted. For these shared services, it appears that only the first pickup and last dropoff would be observed, and intermediate pickups and drop-offs are omitted. Fifth, the data does not reveal any information about which product was selected, the number of passengers, fares paid and other demand related information. Finally, it has been reported that Uber creates fake data to give the appearance of greater supply of available vehicles than there are. While this last point cannot be entirely discounted, results of trip matching and the travel patterns that emerge are consistent with external data sources.

B.2 Sensitivity to cruising threshold

We classify points as cruising according to a two-part test: at the trip level (where the actual distance must be at least 200 meters longer than the shortest-path network distance) and at the point level (using the displacement criterion discussed in the Chapter 2 Research Approach section). The 200m threshold is intended to account for situations where a driver may take a longer route without cruising. A good example would be on streets that are not precisely parallel: alternative routes appear equivalent but one would be slightly longer.

The 200m threshold was developed and tested in previous work (Weinberger et al., 2020) and is based on the typical 100-150m block length in San Francisco. Going around the block involves a detour of more than 200m. However, 200m is an arbitrary choice. It is also not clear whether an absolute threshold (in meters) is preferable to a detour ratio, i.e., the ratio of actual to shortest-path distance. Therefore, Figure B.1 shows the sensitivity of our estimates of cruising to different choices of threshold, in absolute terms (upper panel) and as a ratio (lower panel).

Figure B.1: Sensitivity to cruising threshold



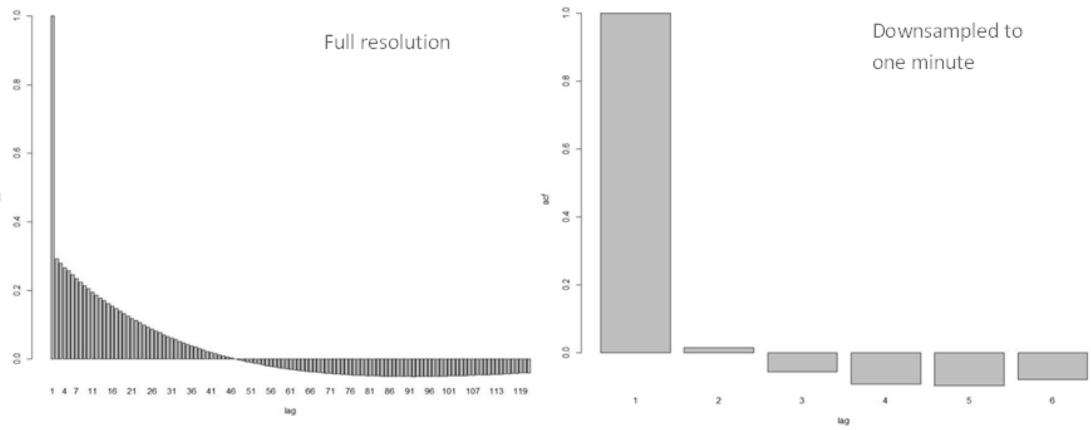
Eliminating the 200m threshold altogether creates an upper bound of about

25% of search travel being cruising. Doubling it to 400m reduces the estimated proportion of cruising to 20%. As the threshold becomes even more stringent, the proportion of cruising declines further, although these more stringent thresholds are likely to exclude much "true" cruising travel. The qualitative insights and conclusion from our analysis remain unchanged regardless of the threshold.

B.3 Regression models

Figure B.2 plots the regression residuals, while Tables B.1 through B.4 present alternative regression specifications to demonstrate the robustness of the results to alternative modeling assumptions.

Figure B.2: ACF Plots of Regression Residuals



These plots show the serial correlations of the residual terms of the regressions. The left plot is for the regression results reported in Table B.3, which indicate strong serial correlation that may affect the validity of the model. The right plot shows the residuals for our main regression with 1-minute resolution, as reported in Table 2.4. The plot shows there is no strong serial correlation and thus the effectiveness of downsampling the data to one-minute resolution.

Table B.1: Regression coefficients (Lyft Subsample)

	Reposition	Cruise		Reposition	Cruise
(Intercept)	3.670***	1.484***	Interaction: with HH density		
Demographic and neighborhood variables			Weekday	0.0003	–0.015
Fraction age 62+	–0.042***	–0.052***	Friday	0.025	0.019
HH density	0.012	–0.021	Time period: early AM	0.005	0.0005
Fraction of working age	–0.040***	–0.098***	Time period: AM	–0.114***	–0.112***
Employment density	–0.148***	–0.061***	Time period: midday	0.030***	0.005
Service and visitor employment density	0.097***	–0.031	Time period: PM	0.042***	0.040***
Fraction high income HHs	–0.101***	–0.040***	Time period: night	–0.067***	–0.042*
On-street parking capacity	0.004	–0.029***	Interaction: with employment density		
Off-street parking capacity (public)	–0.008	–0.044***	Weekday	0.108***	0.071***
Off-street parking capacity (residential)	–0.0001	0.039***	Friday	0.093***	0.045
Fraction Latinx residents	0.032***	–0.0001	Time period: early AM	0.388***	0.462***
Fraction African-American residents	–0.018***	–0.056***	Time period: AM	0.403***	0.470***
Fraction White residents	–0.038***	–0.001	Time period: midday	0.226***	0.219***
Driver experience (Lyft subsample only)			Time period: PM	0.056**	0.026
Driver experience	0.035***	0.008**	Time period: night	–0.120***	–0.042
Time and day of week variables			Interaction: with service/visitor employment density		
Time period: early AM	–0.313***	–0.044*	Weekday	–0.051**	–0.049**
Time period: AM	0.003	–0.035**	Friday	–0.041	–0.024
Time period: midday	–0.027***	–0.101***	Time period: early AM	–0.342***	–0.279***
Time period: PM	0.102***	0.010	Time period: AM	–0.119***	–0.118***
Time period: night	–0.015	0.175***	Time period: midday	–0.072***	–0.009
Friday	0.078***	–0.042***	Time period: PM	0.011	0.087***
Mon-Thurs	–0.034***	0.071***	Time period: night	0.062*	0.030
Lagged dependent variables					
Lag cruise	–1.187***	2.234***			
Lag park	–6.657***	–5.043***			

A positive coefficient for repositioning indicates that the driver is more likely to reposition away from a TAZ.

Estimates are from a point-level multinomial logistic regression at one-minute resolution, as in Table 2.4. However, the data is limited to the Lyft subsample, in order to capture the effects of driver experience. For computational reasons, we estimate using a random 2% sample of trips.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.2: Regression coefficients (Nested Logistic Regression)

	Reposition	Cruise		Reposition	Cruise
(Intercept)	2.596***	0.396***	Interaction: with HH density		
Demographic and neighborhood variables			Weekday	0.037***	0.002
Fraction age 62+	–0.025***	–0.009***	Friday	0.016*	–0.001
HH density	0.012	0.002	Time period: early AM	–0.075***	–0.001
Fraction of working age	0.019***	–0.013***	Time period: AM	–0.102***	–0.031***
Employment density	–0.152***	–0.018***	Time period: midday	–0.015**	0.001
Service and visitor employment density	0.043***	0.002	Time period: PM	0.023***	0.007*
Fraction high income HHs	–0.053***	–0.024***	Time period: night	–0.029***	–0.001
On-street parking capacity	0.019***	–0.001	Interaction: with employment density		
Off-street parking capacity (public)	0.021***	–0.001	Weekday	0.033***	0.016***
Off-street parking capacity (residential)	0.008	0.002	Friday	0.016	0.007
Fraction Latinx residents	0.022***	–0.007***	Time period: early AM	0.225***	0.090***
Fraction African-American residents	0.003	–0.007***	Time period: AM	0.311***	0.116***
Fraction White residents	–0.056***	–0.002	Time period: midday	0.175***	0.055***
Time and day of week variables			Time period: PM	0.038***	0.005
Time period: early AM	–0.245***	–0.019***	Time period: night	–0.067***	–0.022**
Time period: AM	–0.032***	–0.039***	Interaction: with service/visitor employment density		
Time period: midday	–0.029***	–0.035***	Weekday	–0.042***	–0.010*
Time period: PM	0.061***	–0.017***	Friday	–0.004	–0.001
Time period: night	–0.101***	0.036***	Time period: early AM	–0.197***	–0.061***
Friday	0.068***	–0.003	Time period: AM	–0.138***	–0.044***
Mon-Thurs	–0.050***	–0.010***	Time period: midday	–0.113***	–0.018***
Lagged dependent variables			Time period: PM	–0.033**	0.012
Lag cruise	–2.850***	0.399***	Time period: night	0.027	0.009
Lag park	–5.727***	–1.145***			

A positive coefficient for repositioning indicates that the driver is more likely to reposition away from a TAZ.

The estimates are from a nested logistic regression, which first models the decision to stay in the neighborhood ("park or cruise," nest one) vs reposition away to a different neighborhood (nest two). Then, for the first nest, it models the decision to park vs cruise.

Within-nest correlation: 0.227***

*** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B.3: Regression coefficients (fractional logistic regression at the TAZ level)

	Reposition	Cruise		Reposition	Cruise
(Intercept)	2.468***	1.558***	Interaction: with HH density		
Demographic and neighborhood variables			Weekday	0.088***	0.033***
Fraction age 62+	–0.106***	–0.092***	Friday	0.058***	0.012***
HH density	–0.105***	–0.019***	Time period: early AM	–0.070***	–0.041***
Fraction of working age	–0.014***	–0.093***	Time period: AM	–0.236***	–0.224***
Employment density	–0.519***	–0.241***	Time period: midday	0.033***	–0.042***
Service and visitor employment density	0.069***	–0.088***	Time period: PM	0.126***	0.036*
Fraction high income HHs	–0.201***	–0.120***	Time period: evening	0.103***	0.021***
On-street parking capacity	0.106***	0.015***	Interaction: with employment density		
Off-street parking capacity (public)	0.037***	–0.014***	Weekday	0.121***	0.112***
Off-street parking capacity (residential)	0.114***	0.114***	Friday	0.033***	0.026***
Fraction Latinx residents	0.084***	0.054***	Time period: early AM	0.931***	0.690***
Fraction African-American residents	–0.043***	–0.082***	Time period: AM	1.106***	0.867***
Fraction White residents	–0.083***	–0.028***	Time period: midday	0.600***	0.411***
Time and day of week variables			Time period: PM	0.239***	0.137***
Time period: early AM	–0.584***	–0.512***	Time period: evening	0.122***	0.089**
Time period: AM	–0.275***	–0.515***	Interaction: with service/visitor employment density		
Time period: midday	–0.272***	–0.526***	Weekday	–0.094***	–0.082***
Time period: PM	–0.020***	–0.340***	Friday	–0.005***	–0.001
Time period: evening	–0.049***	–0.228***	Time period: early AM	–0.598***	–0.329***
Friday	0.050***	–0.058***	Time period: AM	–0.467***	–0.299***
Mon-Thurs	–0.219***	–0.182***	Time period: midday	–0.280***	–0.071***
			Time period: PM	—0.067***	0.075***
			–0.045***	0.002*	

A positive coefficient for repositioning indicates that the driver is more likely to reposition away from a TAZ.

The estimates are from a fractional logistic regression model. Points are aggregated to the TAZ level, and the model estimates the proportion of points according to each behavior. Note that the lagged behaviors cannot be captured using this approach.

*** p<0.01, ** p<0.05, * p<0.1.

Table B.4: Regression coefficients (full resolution)

	Reposition	Cruise		Reposition	Cruise
(Intercept)	7.000***	2.408***	Interaction: with HH density		
Demographic and neighborhood variables			Weekday	0.032	–0.007
Fraction age 62+	–0.027*	–0.019	Friday	–0.020	–0.046
HH density	–0.003	–0.003	Time period: early AM	–0.044	0.007
Fraction of working age	0.0003	–0.045**	Time period: AM	–0.128***	–0.066
Employment density	–0.184***	–0.06	Time period: midday	0.039	0.041
Service and visitor employment density	0.025	0.04	Time period: PM	0.076**	0.051
Fraction high income HHs	–0.133***	–0.089***	Time period: night	–0.094*	–0.054
On-street parking capacity	0.047***	0.034*	Interaction: with employment density		
Off-street parking capacity (public)	–0.007	–0.028*	Weekday	0.038	0.032
Off-street parking capacity (residential)	0.008	0.014	Friday	–0.054	–0.098
Fraction Latinx residents	0.057***	0.043***	Time period: early AM	0.531***	0.387***
Fraction African-American residents	–0.017	–0.032**	Time period: AM	0.590***	0.576***
Fraction White residents	–0.031***	0.003	Time period: midday	0.322***	0.257***
Time and day of week variables			Time period: PM	0.017	0.016
Time period: early AM	–0.288***	–0.089*	Time period: night	–0.053	0.054
Time period: AM	–0.085**	–0.108***	Interaction: with service/visitor employment density		
Time period: midday	–0.095***	–0.113***	Weekday	–0.025	–0.012
Time period: PM	0.027	–0.036	Friday	0.098	0.129*
Time period: night	0.003	0.101**	Time period: early AM	–0.368***	–0.263**
Friday	0.048	0.008	Time period: AM	–0.299***	–0.337***
Mon-Thurs	–0.077***	–0.095***	Time period: midday	–0.206***	–0.116**
Lagged dependent variables			Time period: PM	–0.029	0.015
Lag cruise	–3.518***	4.658***	Time period: night	0.005	–0.051
Lag park	–12.598***	–8.211***			

A positive coefficient for repositioning indicates that the driver is more likely to reposition away from a TAZ.

Estimates are from a point-level multinomial logistic regression at one-minute resolution, as in Table 2.4. However, the full dataset is used, rather than downsampling to one-minute resolution. Downsampling mitigates the problems with serial correlation (see Figure B.1), but means that estimates are less precise (i.e., confidence intervals are wider).

*** p<0.01, ** p<0.05, * p<0.1.

Appendix C

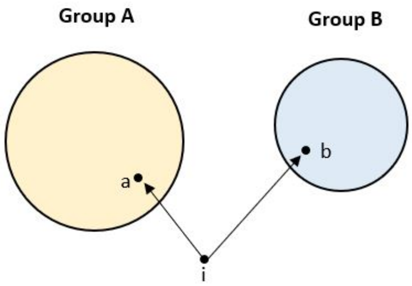
Supplement to Chapter Three

C.1 Proof

C.1.1 Proof of Proposition 1

Based on Proposition 1 in Golub and Jackson (2010), the opinions converge if every strongly connected absorbing set of nodes is aperiodic. In our model, $x_{i,t} = f\mu + (1-f)x_{i,t-1}$, so there is always a cycle from agent i to i with length 1. Therefore, every strongly connected absorbing set is aperiodic and will reach convergence. Then in equilibrium, because all agents within the same converged group have the same opinion, the group will reach full connections.

Next we need to prove that directed links from agents outside a fully connected converged group C to an agent in C does not exist. First, let us assume that in equilibrium, there are two converged groups A and B. An agent i outside group A and B connects to an agent a in group A and an agent b in group B, which can be shown below:



In equilibrium, $x_i = f\frac{x_a+x_b}{2} + (1-f)x_i$, so we get $x_i = \frac{x_a+x_b}{2} = \mu_i$. Because i connects to both a and b, it means that i's current payoff π_i should be higher than only connecting to a or b:

$$\begin{aligned}\pi_i &= 2(V - f(1-f)(\mu_i - x_i)^2 - f\frac{1}{2}[(x_a - \frac{x_a+x_b}{2})^2 + (x_b - \frac{x_a+x_b}{2})^2]) \\ &= 2V - \frac{1}{2}f(x_a - x_b)^2\end{aligned}$$

The payoff of only connecting to a is:

$$\begin{aligned}\pi_{ia} &= V - f(1-f)(x_a - x_i)^2 \\ &= V - \frac{1}{4}f(1-f)(x_a - x_b)^2\end{aligned}$$

By calculation, the payoff of only connecting to b is the same: $\pi_{ia} = \pi_{ib} = V - \frac{1}{4}f(1-f)(x_a - x_b)^2$. Then we should have $\pi_i - \pi_{ia} > 0$:

$$\begin{aligned}\pi_i - \pi_{ia} &= V - \frac{1}{2}f(x_a - x_b)^2 + \frac{1}{4}f(1-f)(x_a - x_b)^2 \\ &= V - \frac{1}{4}f(1+f)(x_a - x_b)^2 > 0\end{aligned}$$

So we have $(x_a - x_b)^2 < \frac{4V}{f(1+f)}$.

Now let's see whether a or b would prefer to connect to i. For a, assume they have $k \geq 1$

connections in Group A, then their current payoff without connection to i is $\pi_a = kV$. The payoff gains from connecting to i is:

$$\begin{aligned}
\pi_{ai} - \pi_a &= (k+1)(V - f(1-f)(\frac{kx_a + x_i}{k+1} - x_a)^2) - f\frac{k}{k+1}(x_a - x_i)^2 - kV \\
&= V - \frac{1}{4(k+1)}f(1+f)(x_a - x_b)^2 - \frac{k}{4(k+1)}f(x_a - x_i)^2 \\
&= V - \frac{f(1-f+k)}{4(k+1)}(x_a - x_b)^2 \\
&> V - \frac{f(1-f+k)}{4(k+1)}\frac{4V}{f(1+f)} \\
&> V - \frac{f(1+k)}{4(k+1)}\frac{4V}{f(1+f)} = \frac{f}{1+f}V > 0
\end{aligned}$$

Therefore, a would prefer to connect to i, and by symmetry, b also prefers to connect to i. Then Group A, Group B, and i will form a new strongly connected closed group with aperiodic nodes. Thus, the equilibrium cannot exists. For more general situations, the proof follows the same procedures.

C.1.2 Proof of Proposition 2

First, we consider the situation of $n = 2$. Then the payoffs for each of the two agents $\{i, j\} \in N$ when they connect to each other are as follows:

$$\pi_i = \pi_j = V - f(1-f)(x_i - x_j)^2$$

When $\pi_i = \pi_j \leq 0$, it is not profitable for the two agents to build links to each other. Then we can solve the condition for disconnection:

$$V \leq f(1-f)(x_i - x_j)^2$$

$$(\frac{V}{f(1-f)})^{\frac{1}{2}} \leq |x_i - x_j|$$

Next we need to prove that the link between i and j remains unprofitable regardless of any other existing links that i and j may have. Now we consider the situation of $n > 2$. Assume agent i already has $k \geq 1$ connections, then i's current payoff is:

$$\begin{aligned}
\pi_i =& k(V - f(1-f)(\frac{\sum_{l\in d_i} x_l}{k} - x_i)^2 - f\frac{1}{k}\sum_{m\in d_i}(x_m - \frac{\sum_{l\in d_i} x_l}{k})^2) \\
=& kV - \frac{1}{k}f(1-f)\sum_{l\in d_i}(x_l - x_i)^2 - \frac{2}{k}f(1-f)\sum_{l\in d_i}\sum_{m\in d_i, m>l}(x_l - x_i)(x_m - x_i) \\
&- \frac{1}{k}f\sum_{l\in d_i}\sum_{m\in d_i, m>l}(x_l - x_m)^2
\end{aligned}$$

and we have $\pi_i > 0$.

If i build a connection to j, the payoff changes to:

$$\begin{aligned}
\pi_i' =& (k+1)V - \frac{1}{k+1}f(1-f)[\sum_{l\in d_i}(x_l - x_i)^2 + (x_j - x_i)^2] \\
&- \frac{2}{k+1}f(1-f)[\sum_{l\in d_i}\sum_{m\in d_i, m>l}(x_l - x_i)(x_m - x_i) + (x_j - x_i)\sum_{l\in d_i}(x_l - x_i)] \\
&- \frac{1}{k+1}f[\sum_{l\in d_i}\sum_{m\in d_i, m>l}(x_l - x_m)^2 + \sum_{l\in d_i}(x_l - x_j)^2]
\end{aligned}$$

The profit gain by connecting to j is:

$$\begin{aligned}
\pi_i' - \pi_i =& V + \frac{1}{k(k+1)}f(1-f)\sum_{l\in d_i}(x_l - x_i)^2 - \frac{1}{k+1}f(1-f)(x_j - x_i)^2 \\
&+ \frac{2}{k(k+1)}f(1-f)\sum_{l\in d_i}\sum_{m\in d_i, m>l}(x_l - x_i)(x_m - x_i) \\
&- \frac{2}{k+1}f(1-f)(x_j - x_i)\sum_{l\in d_i}(x_l - x_i) \\
&+ \frac{1}{k(k+1)}f\sum_{l\in d_i}\sum_{m\in d_i, m>l}(x_l - x_m)^2 - \frac{1}{k+1}f\sum_{l\in d_i}(x_l - x_j)^2
\end{aligned}$$

Now set $V = f(1-f)(x_i - x_j)^2$, and build the inequality $\pi'_i - \pi_i > 0$, so i would prefer to connect to j. We need to prove this is not true:

$$\begin{aligned}\pi'_i - \pi_i =& \frac{k}{k+1} f(1-f)(x_j - x_i)^2 + \frac{1}{k(k+1)} f(1-f) \sum_{l \in d_i} (x_l - x_i)^2 \\ &+ \frac{2}{k(k+1)} f(1-f) \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_i)(x_m - x_i) \\ &- \frac{2}{k+1} f(1-f)(x_j - x_i) \sum_{l \in d_i} (x_l - x_i) \\ &+ \frac{1}{k(k+1)} f \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2 - \frac{1}{k+1} f \sum_{l \in d_i} (x_l - x_j)^2 > 0\end{aligned}$$

Then we can get:

$$\begin{aligned}&(1-f)[k^2(x_j - x_i)^2 + \sum_{l \in d_i} (x_l - x_i)^2 + 2 \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_i)(x_m - x_i) \\ &- 2k(x_j - x_i) \sum_{l \in d_i} (x_l - x_i)] \\ &> k \sum_{l \in d_i} (x_l - x_j)^2 - \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2\end{aligned}$$

Through some calculation, we can get

$$\begin{aligned}(1-f)[k \sum_{l \in d_i} (x_l - x_j)^2 - \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2] \\ > k \sum_{l \in d_i} (x_l - x_j)^2 - \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2 \qquad \text{(C.1)}\end{aligned}$$

Because

$$\begin{aligned}
\sum_{l \in d_i} (x_l - x_j)^2 &= \sum_{l \in d_i} (x_l - \mu_i + \mu_i - x_j)^2 \\
&= \sum_{l \in d_i} [(x_l - \mu_i)^2 + (\mu_i - x_j)^2 + 2(x_l - \mu_i)(\mu_i - x_j)] \\
&= k\sigma_i^2 + k(\mu_i - x_j)^2 \\
&= \frac{1}{k} \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2 + k(\mu_i - x_j)^2 \\
&\geq \frac{1}{k} \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2
\end{aligned}$$

We have:

$$\begin{aligned}
& k \sum_{l \in d_i} (x_l - x_j)^2 - \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2 \\
& \geq \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2 - \sum_{l \in d_i} \sum_{m \in d_i, m > l} (x_l - x_m)^2 = 0
\end{aligned}$$

Therefore, for inequality (C.1), we have LHS$\leq$RHS. There is a contradiction. By symmetry, we can also prove that it is not beneficial for j to connect to i.

C.2 More Simulation Results

C.2.1 Simulations with Larger N and k

Figure C.1: Simulation Results with $N = 15$

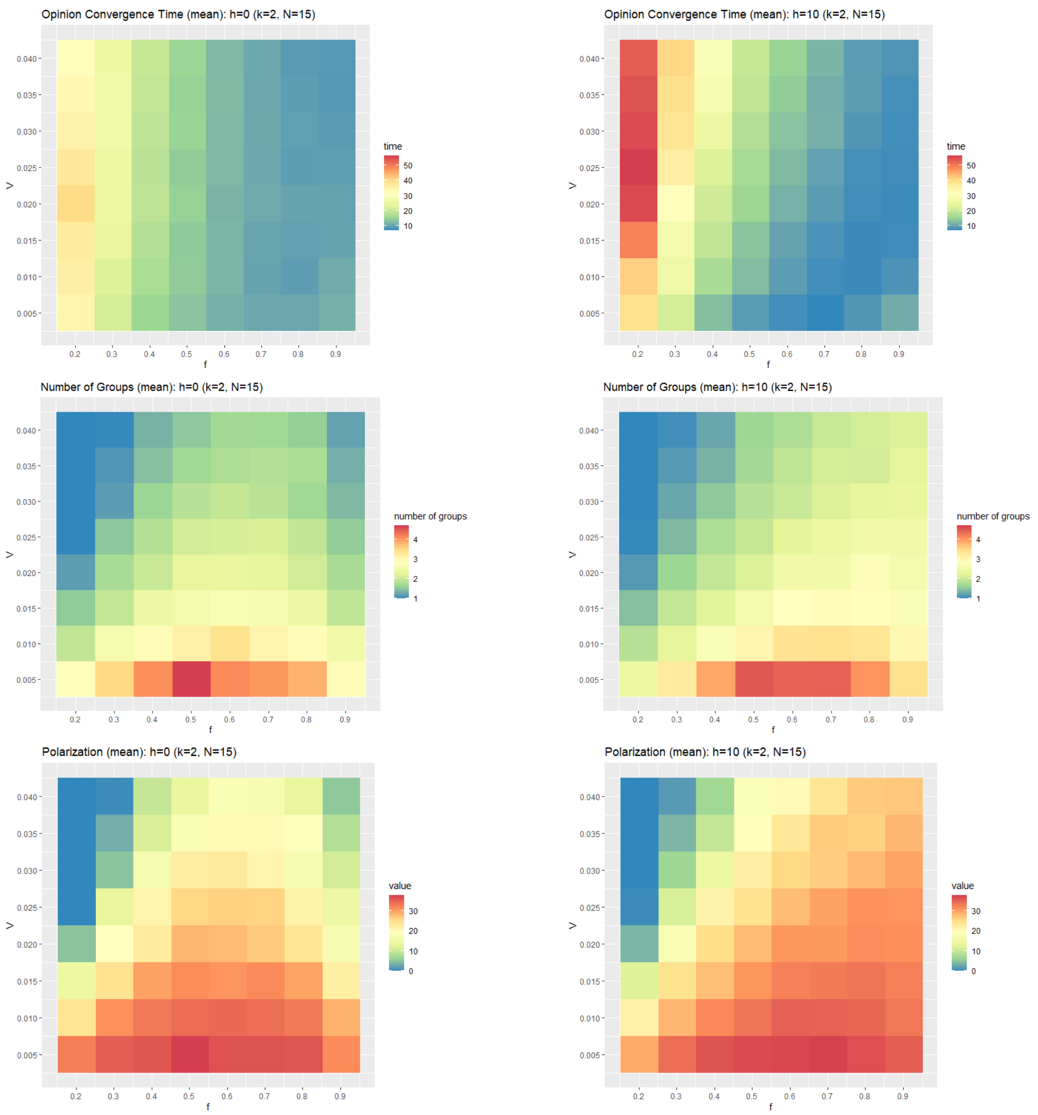
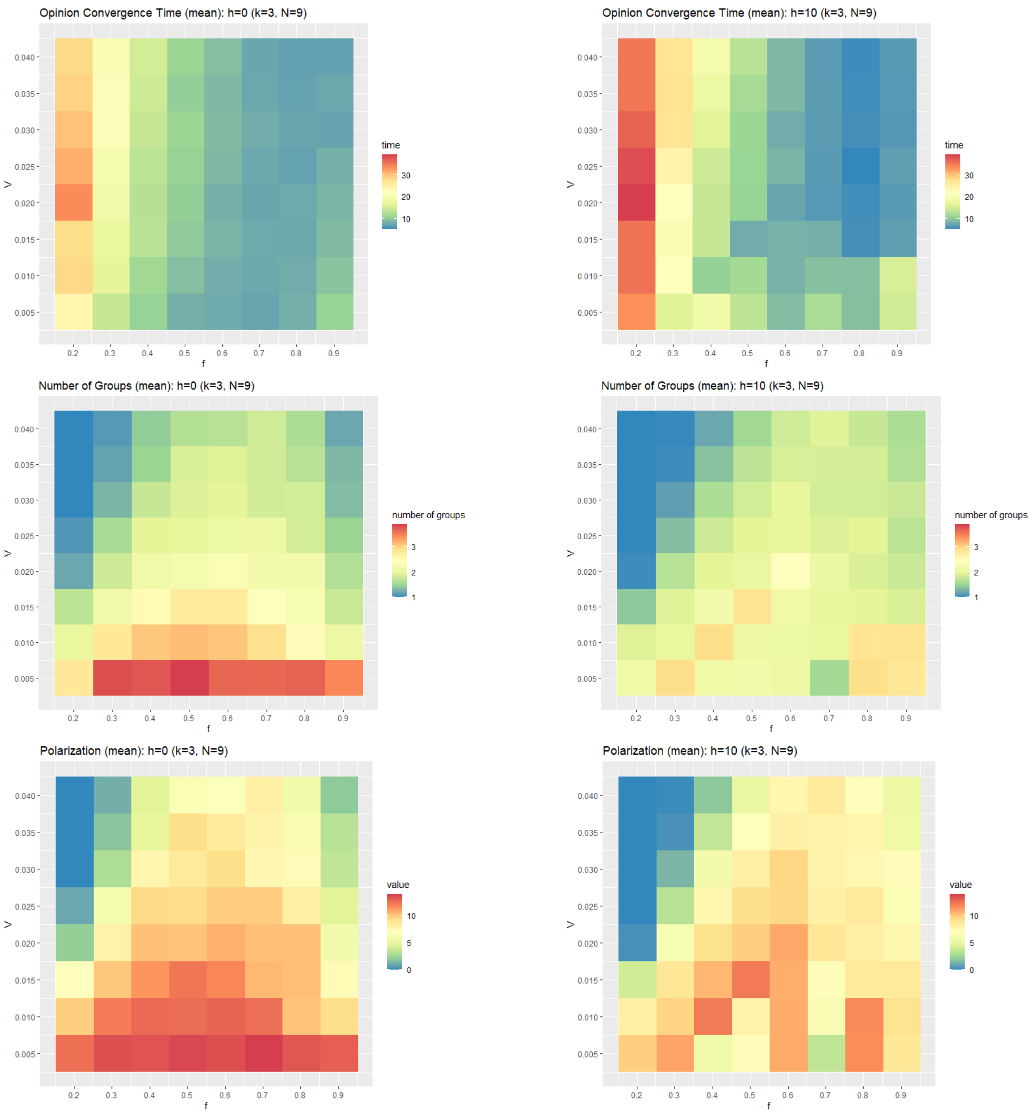
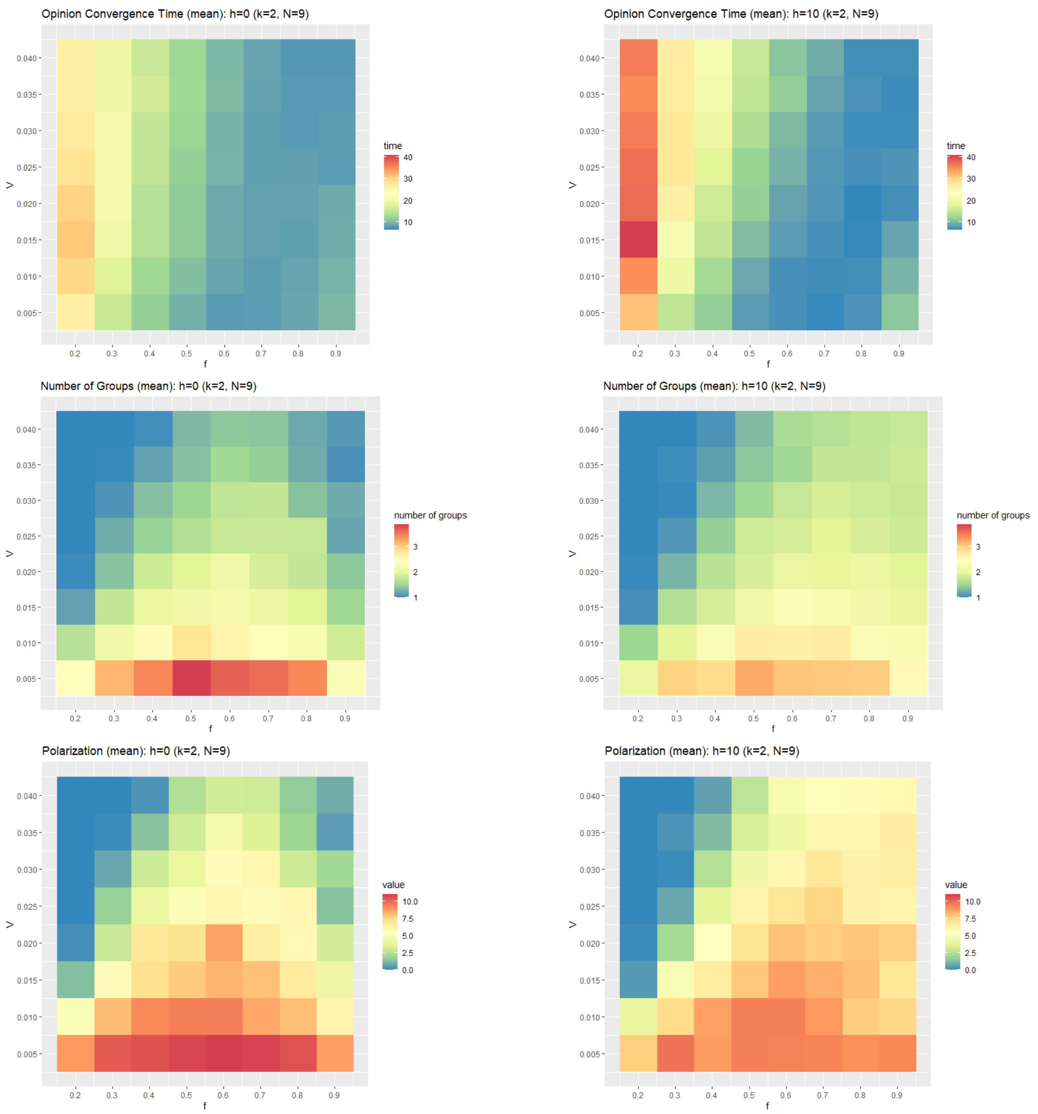


Figure C.2: Simulation Results with $k = 3$



C.2.2 Simulations for Experiment

Figure C.3: Simulation Results with Experiment Settings



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