# INCENTIVES: THEORY IN NETWORK GAMES AND AN APPLICATION FOR COVID-19 VACCINATION

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# Abstract

This dissertation consists of three essays on the intersection of incentives in theoretical network games and an application of incentives.

The first essay studies a buyer-seller network where sellers offer sign-up bonuses to buyers using points, a currency whose value depends on buyers' effort to learn how to use it. Buyers choose the optimal level of learning based on the total amount of points they can obtain. Based on the level of learning, they decide which offers from sellers to accept, with a heterogeneous transaction cost for each offer accepted. Real-world examples include sign-up bonus points for bank credit cards, chain hotel points, and chain restaurant points, where the value of the points is subjective to buyers' effort to learn how to use them. The paper explores the existence of a Subgame Perfect Nash Equilibrium (SPNE) on sellers' choices of sign-up bonus points offered to buyers. In addition, the paper provides comparative statics evaluating changes in the expected revenue return from buyers and network connections in the game.

The second essay starts with modeling a price transmission for intermediaries in a market network for identical goods. Intermediaries simultaneously post prices for their intermediation services, followed by producers choosing their connection strategies, and consumers choosing their buying decisions. We provide necessary and sufficient conditions for the existence of non-cooperative Nash Equilibria. Meanwhile, we prove the natural existence of cooperative outcomes under intermediaries' collusion. Furthermore, we provide comparative statics on the network expansions with new connections.

The third studies vaccine hesitancy in the Hawaii population. Understanding contributors to vaccine hesitancy and how they change over time may improve COVID-19 mitigation strategies and public health policies. To date, no mechanism explains how trust in and consumption of different sources of information affect vaccine uptake. A total of 1594 adults enrolled in our COVID-19 testing program completed standardized surveys on demographics, vaccination status, use, reliance, and trust in sources of COVID-19 information, from September to October 2021, during the COVID-19 Delta wave. Of those, 802 individuals (50.3%) completed a follow-up

survey, from January to February 2022, during the Omicron surge. Regression analyses were performed to understand vaccine and booster uptake contributors over time. Individuals vaccinated within two months of eligibility (*early vaccinees*) tended to have more years of schooling, with greater trust in and consumption of official sources of COVID-19 information, compared to those who waited for 3–6 months (*late vaccinees*), or those who remained unvaccinated at 6 months post-eligibility (*non-vaccinees*). Most (70.1%) early vaccinees took the booster shot, compared to only 30.5% of late vaccinees, with the latter group gaining trust and consumption of official information after four months. These data provide the foundation for a mechanism based on the level of trust in and consumption of official information sources, where those who increased their level of trust in and consumption of official information sources were more likely to receive a booster. This study shows that social factors, including education and individual-level degree of trust in (and consumption of) sources of COVID-19 information, interact and change over time to be associated with vaccine and booster uptakes. These results are critical for developing effective public health policies and offer insights into hesitancy over the course of the COVID-19 vaccine and booster rollout.

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# Chapter 1

# Introduction

*"An incentive is a bullet, a key: an often tiny object with astonishing power to change a situation." (Steven D. Levitt)*

Incentives, serving as one of the major motivators of human behaviors and choices, can be naturally generated, or strategically provided by sellers, employers, researchers, social planners, etc. For sellers, giving incentives to new buyers can easily attract new registrations from them, such as the free trials from streaming services, and sign-up bonuses from credit card issuers; For employers, giving incentives to employees can boost their energy to work towards employers' objectives; For researchers, giving incentives to their participants of surveys or experiments can easily generate the data to conduct their studies. Furthermore, for social planners, manipulating incentives is one of the most important ways to efficiently control the economy to achieve maximum social welfare. For instance, citizens have natural incentives to get vaccinated against Covid-19 to get rid of infections or serious symptoms, which benefits their well-being. Another key natural incentive of getting vaccinated is protecting the well-being of others around them. Except for religious reasons, however, citizens have concerns to vaccinations that make them hesitate, such as the price of vaccines, the side effects, the conspiracy theories, etc. Since vaccine hesitancy can undermine the public effort toward controlling the pandemic, social planners intervene in the market to strengthen the incentives. Examples include paying for all manufacturing and distributing of vaccines to make them completely free to citizens and working hard to promote the vaccines through official media sources. Some social planners even give extra monetary incentives to their citizens to get vaccinated, such as New York State[11].

Over the past several decades, the incentive theory has been widely discussed in the literature. Theoretical works focus on mechanisms and schemes of providing

incentives and the associated market outcomes[58, 23, 61, 4], while empirical works focus on the effectiveness of incentives and promotions provided by sellers to motivate consumer decisions[12, 63, 9, 31, 2]. Furthermore, over the recent decades, both theoretical and empirical works focus on the applications of incentive theory in different fields of economics, with selected works listed as follows.

**Labor economics.** As mentioned before, incentives are widely used by employers to motivate their employees toward some objectives. Designing how these incentives are distributed and predicting how they will make effects are the key questions from employers and social planners, as well as controlling their costs. Validating how these incentives perform under various schemes in motivating the employees and getting to the predicted outcome also matters to judge the quality of the incentive schemes. These topics are widely discussed in the previous literature. For instance, [4] focuses on the incentives applied to workers for their truthful comments on their peers to formulate reliable reputations and fix the inefficiency caused by equal-pay constraints. Another example is [49], which explores the effects of incentives out of workers' compensation insurance and their participation in these compensation programs.

**Health economics.** Incentives have wide applications in health economic problems. For instance, as one of the most important questions in health economics, the design of health insurance and its associated incentives is frequently discussed, including the health risk assessment and premium setting[74, 35], the establishment of incentive contracts of health insurances[34], the incentive programs to decrease the employee healthcare cost[62], etc. On the other hand, incentives also play key roles in public health pandemics, such as Covid-19. Despite the natural incentives of getting vaccine shots to avoid or reduce the anxieties of infections, several states in the United states, as well as some other cities in the world, even provided extra monetary incentives for vaccine uptake. Previous literature has addressed the effectiveness of these policies through empirical works. Examples include both papers suggesting that these policies are useful in motivating the vaccinations[11] and papers suggesting that these policies are useless[13]. In addition, similar topics are discussed in chapter 4 of this dissertation[41].

**Education economics.** Incentives also have wide applications in education economics. For instance, incentives serve as scholarships and fellowships in schools to motivate more efforts towards learning, the effect of which has been addressed in the previous literature[48, 8, 50]. In addition, incentives are also widely used in developing countries to motivate children to enroll in (attend) schools. Some social planners choose to offer this incentive to parents, and some social planners choose to offer this incentive directly to children (students). The effectiveness of both recipients

(parents and students) is discussed in the previous studies with various results. For instance, some papers claim that incentives offered to parents are effective to let their children go to school[16, 27], while some papers suggest that providing incentives directly to children yields more efficient outcomes[39]. Moreover, [69] discusses the school choices by parents and students under incentive programs with jurisdiction competitions.

This dissertation consists of three essays that attempt to shed some light on the incentives motivating and changing people's decisions.

The first essay establishes a frame based on a bipartite network with sellers and buyers, where sellers offer sign-up bonuses in points, a currency whose value depends on the effort that buyers invest to learn how to use it, as incentives to new buyers to attract their registrations. This work serves as an extension to the conventional incentive theory in sales markets, with the only change being the incentives themselves becoming learnable (not like monetary incentives that buyers can easily use with a fixed unit value, learnable incentives require learning to get a higher value while using them.). Many results are shown in the essay to be not consistent with intuitions and conventional incentive theory. Since there are plenty of sellers providing these variable valued incentives, such as credit card reward points, hotel points, and chain restaurant points, this essay helps better understand the outcomes from these markets.

The second essay starts by describing a tripartite sales network with producers and consumers bridged by price-setting intermediaries with assumptions of consistent pricing. This essay mainly focuses on the choice-deviating behaviors of intermediaries under different outcomes, driven by the incentives as higher revenue upon deviating their prices. The main result is shown by characterizing the specific parameters and network connections that intermediaries will deviate from forever (looping race), which in other words, the SPNE does not exist. In addition, the existence of some optimum with intermediaries cooperating (or colluding) to maximize their aggregate revenue is proven. Based on these fundamental outcomes, comparative statics exploring the changes in parameters and network connections are shown.

The third essay is a data-driven empirical work, focusing on the Covid-19 vaccination decisions of residents in Hawaii. Strong natural incentives exist in the vaccine uptake, as residents may get rid of, or at least avoid serious symptoms from Covid-19 infections. Despite the strong incentive, some residents still choose not to get the vaccines, based on various concerns. However, social planners need most residents to be fully vaccinated to reach herd immunity and end the pandemic. One of the most efficient ways to increase the proportion of vaccinated residents is promoting the vaccines through official media sources to strengthen the natural incentives as-

sociated with vaccines, by motivating more residents to be hassle-free and trust the vaccines. This essay focuses on the relationship between vaccine uptake in different stages after the official vaccine roll-out and residents' trust and consumption of various information sources. Our results show that official information sources play an important role in promoting both early and late adoptions of vaccines, and unofficial information sources are discouraging the adoption of vaccines, and this result is more significant after 2 months of the official vaccine roll-out. Furthermore, longitudinal analysis is shown, exploring the changes in trust and consumption of various information sources over the time period between the adoption of the first doses of vaccines and the booster shots. Significant increases are observed in trust in official information sources when getting a booster shot, on those who got their first doses of vaccines after at least 2 months of the official vaccine roll-out.

While the three essays are related in regard to incentives, they have been written so that each may be read independently of the others.

# Chapter 2

# Learnable Incentives in Sales Networks

## 2.1 Introduction

Sellers often give incentives to buyers to start a relationship with them. These incentives are referred to as sign-up bonuses, and can serve as a motivator for buyers to help cover the opportunity cost and potential risks of choosing a seller. Examples include free samples from grocery stores, free gift cards from phone carriers, free trials from streaming services, etc. Multiple studies have documented the effectiveness of sign-up incentives to motivate buyers' decisions [12, 63, 4, 9, 31, 2].

Although sign-up incentives and promotions have been widely studied, including the impacts sales in consumption [77], brand switching behaviors[64] and referral behaviors[80], this literature has been focused on monetary incentives. Instead, we study the case where sellers provide incentives in points, a currency whose subjective valuation depends on the buyers' effort toward learning how to use them. Although these points programs benefit sellers, they do not always benefit buyers. Since the incentives become learnable, buyers need to learn how to use these points to get a higher value from them, which greatly differs from simply using dollars or credits. However, learning is always associated with a learning cost, and buyers need to decide the optimal effort they invest in their learning.

Formally, we study a game in two steps for a set of sellers and buyers connected to each other in a bipartite network, where buyers may be connected to different sellers. In step 1, sellers offer identical sign-up bonus points simultaneously to buyers connected to them. In step 2, buyers learn how to use the sign-up bonus points and decide which sellers to choose with no restriction on the maximum number of sellers

from whom they can choose. We assume the buyers have a non-negative transaction cost for each seller they choose, preventing them from simply connecting to all sellers through their connections.

Notably, when deciding the optimal effort to invest in learning, all buyers in the network are assumed to focus on their possible total amount of sign-up bonus points. The potential number of sign-up bonus points considered by each buyer is the sum of sign-up bonus points provided by all sellers to which the buyer is connected, based on the assumption that they can choose unlimited sellers. Therefore, it is possible that a buyer considers a seller while deciding the optimal effort towards learning, but eventually does not choose the seller after learning. More extremely, some buyers might choose to learn a lot, yet end up not choosing a seller due to the low value from every seller in their network connections or their high transaction cost. In the previous literature, this phenomenon is named "meaningless learning" or "meaningless experience" [40, 82], and this phenomenon exists everywhere in people's daily life. For instance, one might find something interesting and choose to spend time researching it. After preliminary learning, they feel it to be not that interesting and give up further thought. Here the preliminary learning was a sunk cost, and this learning was defined as "meaningless." In this paper, the sign-up bonus points are assumed to be completely new to buyers before they learn, thus they do not have ex-ante estimations on the value of these points. Therefore, the choices on the optimal effort towards learning are derived and assumed to be based on the total amount of sign-up bonus points they can get, whatever the number of sellers these points are from[a]. Formal definitions and derivations of the learning process are shown in Equation A..1 in Section 2.1 and the Lemma A..2.1.

### 2.1.1 Potential Applications

In recent decades, many sellers have provided various learnable sign-up bonuses in points in the market, with both cooperation and competition with other sellers to formulate different networks. Our model can be applied to the following situation.

**Credit cards with reward point programs.** Many bankers post identical reward points to buyers, such as American Express Membership Reward Points (Amex MR), J.P. Morgan Chase Ultimate Rewards Points (Chase UR), Citi ThankYou Points (Citi TYP), Capital One Miles (C1 Miles), etc. These points are difficult to learn, since there are many ways to use them. For instance, one of the most popular point programs proposed by bankers in the U.S. is American Express Membership Rewards Points (AMEX MR), which has over 100 uses, including and not limited to redeeming check or statement credits, various merchant gift cards (Amazon, Red

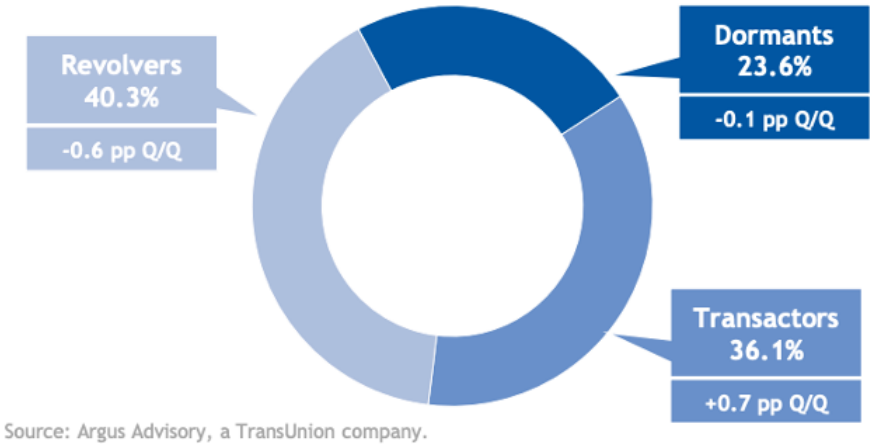



Figure 2.1: ABA national credit card usage data 2022 Q2 (newest). Revolvers: Credit cards with some carry-over balances (interest paying). Transactors: Credit cards with some balances but not carry-over (not interest paying). Dormants: Credit cards without balance during the 3 months of 2022 Q2.

Lobster, etc.), and transferring 1:1 to hotel points (Hilton, Marriott, etc.); transferring 1:1 to airline mileages (Delta Sky miles, ANA Mileage Club, etc.); purchasing airline tickets and hotel stays directly from AMEX Travel; making donations, etc[1]. Based on this, distinct redeeming values for buyers differ among these options, ranging from the lowest redeeming value of 0.6 cents per point when redeeming for cash or statement credits, to variable values while transferring points to airline mileages. In addition, these bankers are impacted by other bankers in the network, since buyers choose the optimal effort towards learning based on all point offers from all bankers that they can see through their connections. Therefore, consumers need to learn how to use those complicated point systems, and bankers need to determine how many points to offer. Furthermore, macro-level data (See Figure 2.1) is accessible for the usage of these credit services on American Bankers Association[2].

**Chain hotels with reward point programs.** A variety of chain hotels offer reward point programs, such as Marriott Bonvoy, Hilton Honors, World of Hyatt, etc. Consumers earn reward points for each dollar spent at these places and extra bonuses for each stay. Some hotels provide periodical sign-up bonus points for new registrations to attract new loyal consumers to their programs. For instance, the

[1]See details at `https://global.americanexpress.com/rewards`

[2]see details on `https://www.aba.com/-/media/documents/reports-and-surveys/2022-q2-credit-card-market-monitor.pdf?rev=b976da9db7e34af3a2771a0694aeeb01`

largest chain hotel group in the world, Marriott Bonvoy, offered a "stay twice get 1 free night" bonus for new registrations in recent years, where new travelers could get a free night certificate valued up to 25K points after their first two stays in any Marriott hotels. Under these designs, consumers need time to learn how to use these points and the free night certificates, and hotel groups need to determine what kind of bonuses to offer to new consumers.

**Chain restaurants with reward point programs.** A variety of chain restaurants promote their reward systems, such as McDonald's, Starbucks, Red Lobster, California Pizza Kitchen, etc. Consumers earn reward points for each dollar spent in these places. Many actively provide point sign-up bonuses for new registrations to attract new loyal consumers to sign up for their programs. For instance, Red Lobster has a loyalty program: Red Lobster Rewards, where extra reward points are given for signing up for an account. The number of sign-up bonus points usually fluctuates between 50 to 100 points, and every 125 points can be redeemed for a gift, valued from $5 to $20. Under these designs, consumers need time to learn how to use these points, and restaurants must determine how many points to offer new consumers.

### 2.1.2 Overview of the Model and the Results

In this paper, we study how learnable incentives drive the behavior where sellers post learnable sign-up bonuses and buyers decide whether or not to accept the bonuses. A sequential game with two steps is introduced in a bipartite network with sellers and buyers to answer this question, where sellers move first to choose sign-up (points) offers to attract buyers, followed by buyers learning how to use them and make their choices.

Based on the model, the existence of the Subgame Perfect Nash Equilibrium (SPNE) is proven. In addition, the existence of the seller-optimal (a sellers' cooperation-proof optimal, where sellers cooperate to maximize their aggregate revenue) and the discussions on social welfare are shown. A detailed discussion of the above elements is shown in Section 3.

We also study comparative statics evaluating several changes in the market. First, we see that even if the estimated revenue return from buyers decreases, some sellers' choices of sign-up bonus points may increase, and some sellers may be better off from the change, and vice versa. This result is inconsistent with the classical outcomes under adverse selections, since sellers are predicted to decrease their choices of incentives while buyers are less profitable in the classical incentive theory. What remains consistent with the classical theory is that at least one seller will decrease the choice of sign-up bonus points under this change.

Second, a seller may suffer from specific added connections to buyers. When a seller adds a connection to some buyers, only under a newly generated "bad SPNE", they can be worse off from the change, and there will be at least one SPNE ensuring all sellers are better off from this change. Detailed illustrations and proof of all the above results are shown as comparative statics in Proposition 3 and 4 in Section 5.

### 2.1.3 Related Literature

The traditional incentive theory has been widely studied in the past, where monetary rewards are used as incentives to attract buyers. However, the use of points, a currency whose value depends on buyers' efforts to learn how to use it, has not been studied in the literature. The model in this paper combines two parts: the incentive boosting buyers to learn, and the bipartite sales network consisting of sellers and buyers with those incentives.

The incentive boosting buyers' or participants' learning behaviors is widely discussed in the previous literature (such as attracting children to enroll to schools[6], attracting students to learn towards a better grade[48, 8, 50], attracting people to learn another language[52], attracting employees to learn towards a higher productivity[39], etc.). These works focus on the effectiveness of incentives to motivate people to learn. However, none of the above literature incorporates incentivized learning to sales networks with learnable incentives to explore the market outcomes based on these learning behaviors.

On the other hand, previous literature focuses on bipartite networks, which serve as the basic network structure in this paper. Examples include the fund transmission between mutual funds and portfolio holdings[25], resource transmission between planners and intermediaries[33], causal links between people and activities[67], etc. None of the network literature focuses on non-monetary incentives. This paper is the first work incorporating incentive boosting learning to the learnable incentives in a bipartite sales network to explore market outcomes.

The remainder of this paper is constructed as follows: Section 2 introduces two illustrative examples of the main model; Section 3 sets up the main model; Section 4 discusses the SPNE, the optimal and the social welfare derived by the main model under different connections and parameters; Section 5 reveals the comparative statics, including all counterfactual; Section 6 discusses an extension of the main model with sellers capping the maximum number of accounts opened by each buyer to dissuade the buyers with low long-term usage; Section 7 explores an extension of the main model where sellers cannot only decide the sign-up bonus points posted, but also decide whether and to what extent to actively provide learning support to buyers to

help them learn how to use these points; Section 8 concludes.

## 2.2 The Model

Consider a set of sellers $\mathcal{B} = \{1, 2, \ldots, b, \ldots, B\}$ interested in attracting a set of buyers $\mathcal{Q} = \{1, 2, \ldots, q, \ldots, Q\}$ by offering them sign-up bonuses. Buyers can accept offers from as many sellers as they want, and each seller $b$ offers an identical type of points $i_b$. Suppose each buyer $q$ is connected to a subset of sellers, denoted as $S_q \in \mathcal{B}$.

Given the network connections, suppose that each seller $b$ chooses a non-negative sign-up bonus $i_b \in \mathbb{R}_+$, and sellers have an expected revenue return per buyer $\bar{\mu} > 0$, based on each buyer's expected usage of each seller's products or services. On the other hand, each buyer $q$ is assumed a threshold whether to engage with a seller or not, denoted by $T_q \in \mathbb{R}$, which is based on buyer $q$'s actual usage of sellers' products or services (see Appendix A..1.1 for details on how the optimal usage $\bar{\mu}$ and $T_q$ are derived).

Given the learnable sign-up bonus $i_b$ from each seller $b$, each buyer $q$ has a chance to learn how to use these points offered by sellers he/she is connected to, and the learning curve is assumed directly to be a function of the aggregate sign-up bonus points $\sum_{b \in S_q} i_b$ that a buyer can see through his/her network connections, denoted by $\lambda_q : \mathbb{R}_+ \to \mathbb{R}_+$, which is continuous, second-order differentiable and monotonically increasing. When there is no confusion, we denote by $\lambda_q = \lambda_q(\sum_{b \in S_q} i_b)$ the total learning level of buyer $q$ (see Appendix A..1.2 for a detailed process of obtaining the optimal level of learning).

Given the learning level $\lambda_q$, the value received by buyer $q$ from the sign-up bonus points offered by seller $b$ is defined as a function of the learning level and the number of points offered by seller $b$, i.e., $V(\lambda_q, i_b) \geq 0$, which is assumed to be continuous, second-order differentiable and monotonically increasing in both $i_b$ and $\lambda_q$. Assuming that a buyer $q$ accepted the offer from seller $b$, the cost of offering the sign-up bonus for seller $b$ is defined as a function of the learning level $\lambda_q$ and the number of points posted $i_b$, i.e., $C(\lambda_q, i_b) \geq 0$, which is assumed to be continuous, second-order differentiable and monotonically increasing in both $i_b$ and $\lambda_q$. We assume that function $V(\lambda_q, i_b) > C(\lambda_q, i_b)$ and $\frac{\partial V(\lambda_q, i_b)}{\partial i_b} > \frac{\partial C(\lambda_q, i_b)}{\partial i_b}$ for all $\lambda_q > 0$ and $i_b > 0$.

The reason why the game formulates a network lies in the learning curve. Given the learning curve, buyers learn based on the incentives posted by all connected sellers, indicating that peer sellers' choices can impact each other, on reaching the thresholds of acceptance of buyers or raising the cost to offer the same incentive.

In the meantime, given that each buyer can choose unlimited sellers; the incentive offered by each seller impacts all sellers sharing buyers with it. Therefore, a network game exists.

The movement of this two-step game is defined as follows: In step 1, sellers simultaneously move first to choose their sign-up bonus points $i$ to offer consistently to all buyers connected, followed by step 2, where buyers learn how to use these points based on the learning curve $\lambda$ and the number of posted sign-up bonus points through their connections $\sum_{b \in S} i_b$, followed by choosing the subset of sellers with connections ($S$), based on the updated value of the sign-up bonus points offered $V(\lambda, i_b | b \in S)$ and their threshold of acceptance $T$. Furthermore, the strategy spaces and objective functions are formally defined in Definition 1.

**Definition 1 (Learnable Incentive Game)**
*The learnable incentive game is a two-step sequential game such that:*

- *The strategy space of each buyer $q$ is defined as multiple 0-1 decision variables as $d_{qb} \in \{0, 1\}, b \in S_q$ for the decision whether to choose a seller $b$ among all sellers in the subset $S_q$ connected to buyer $q$.*

- *The objective for all buyers is maximizing their utilities, and the utility function $u : \mathbb{R}_+^B \to \mathbb{R}_+^1$ of each buyer $q$ is the subtraction of the gross value of sign-up bonus points from all sellers decided to be chosen and the thresholds on choosing these sellers. That is, $u_q = \sum_{b \in S_q} (d_{qb} \times (V(\lambda_q(\sum_{\mathbf{b} \in S_q} i_{\mathbf{b}}), i_b) - T_q))$. In addition, if buyer $q$ is not connected to seller $b$, $d_{qb} = 0$.*

- *The strategy space of each seller $b$ is choosing a non-negative sign-up bonus (points) $i_b \in [0, \infty)$ offered publicly to buyers connected.*

- *The objective for all sellers is maximizing their profit, and the profit function $\pi : \mathbb{R}_+^1 \to \mathbb{R}_+^1$ of each seller $b$ is the expected profit made from all buyers connected. Suppose that $N_b$ represents the subset of buyers connected to seller $b$. The profit function of seller $b$ is then:*

$$\pi_b = \sum_{q \in N_b} (\bar{\mu} - C(\lambda_q(\sum_{\mathbf{b} \in S_q} i_{\mathbf{b}}), i_b)).$$

- *(The tie-breaking rule) Every buyer is assumed to accept an offer from a seller if the buyer is indifferent between accepting and rejecting the offer from the seller. In the meantime, if a seller is indifferent in its profit to posting multiple incentives given other sellers' choices, the seller would post the lowest one.*

Note that in a Learnable Incentive Game, sellers offer a single sign-up bonus to all buyers in their connections. On the other hand, buyers can choose to connect to as many sellers as they want in their network. In the meantime, given the unbounded value and cost, the game is still bounded by the finite $\bar{\mu}$, capping sellers' profit, so that sellers cannot post infinite incentives due to the loss of profit. Therefore, an SPNE may exist, and the existence is formally explored in Theorem 1.

Since this game is sequential, with sellers simultaneously moving in the first step, followed by buyers choosing sellers to get the incentives, the Subgame Perfect Nash Equilibrium (SPNE) is discussed in this game, instead of Nash Equilibrium, and the SPNE is determined mainly on sellers' decisions in the first step. Therefore, sellers need to consider the learning curve, the value function, and the transaction cost of buyers from the second step. Therefore, a Subgame Perfect Nash Equilibrium is defined in Definition 2.

**Definition 2 (Subgame Perfect Nash Equilibrium (SPNE))**
*The SPNE is achieved when buyers maximize their utility for each strategy of the sellers, and sellers maximize their utility. That is:*

- *For each $(i_b, i_{-b})$, each buyer $q$ chooses to connect to the set of sellers who maximize their utility. That is, the decision set $\{d^*_{qb}\}_{b\in S_q}$ satisfies $u_q(\{d^*_{qb}\}_{b\in S_q}) \geq u_q(\{d_{qb}\}_{b\in S_q})$, for any $\{d_{qb}\}_{b\in S_q} \neq \{d^*_{qb}\}_{b\in S_q}$.*
- *Let $N^*_b(i_b, i_{-b}) \subseteq N_b$ be the buyers who choose seller $b$ after maximizing their utility at the incentive profile $(i_b, i_{-b})$. Let $\pi^*_b(i_b, i_{-b})$ be the profit of seller $b$ at the vector of incentives $(i_b, i_{-b})$ when connected to the agents in $N^*_b$. Each seller $b$ maximizes its profit $\pi^*_b$. That is, the sign-up bonus (points) that the seller $b$ chooses reaches SPNE if $\pi^*_b(i^*_b, i_{-b}) \geq \pi^*_b(i_b, i_{-b})$, for any $i_b \neq i^*_b$, without changes to the choices of other sellers $i_{-b}$.*

The SPNE conditions clearly indicate that the buyer choices are robust, and there is an optimal choice per set of sign-up bonus points imposed by sellers. However, sellers may not get only one set of choices per network since one seller cannot determine its profit by itself unless there is an isolated subset of the network around the seller, i.e., all buyers the seller connects to do not have any other connections with other sellers. More conditions on the existence of multiple equilibria are discussed in section 4 based on networks with mixed connections.

Besides that, since sellers can sometimes cooperate, and there might be multiple sellers under the control of one seller, it is also important to consider the market optimal under seller cooperation. The seller-optimal (SO) is defined in Definition 3.

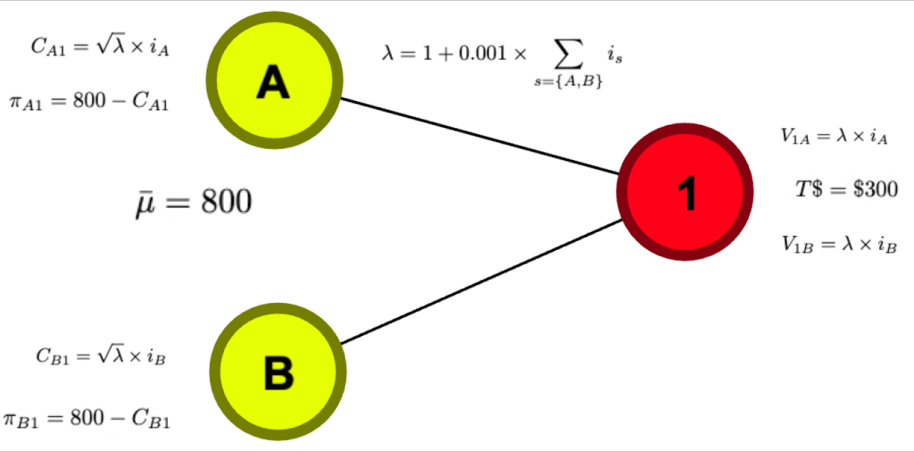



Figure 2.2: An example of a fully integrated network with the same Subgame Perfect Nash Equilibrium and the seller-optimal.

**Definition 3 (Seller-optimal (SO))**
*The seller-optimal (SO) is reached when the aggregate profit of all sellers* $\sum_{b\in\mathcal{B}} \pi_b$ *is maximized. That is, the set of sign-up bonus points all sellers choose* $\{i_b^o\}_{b\in\mathcal{B}}$ *reaches SO if:*

$$\sum_{b\in\mathcal{B}} (\pi_b^*(i_b^o, i_{-b}^o)) \geq \sum_{b\in\mathcal{B}} (\pi_b^*(i_b, i_{-b})), \forall \{i_b\}_{b\in\mathcal{B}} \neq \{i_b^o\}_{b\in\mathcal{B}}.$$

Given the definitions in the game, two categories of outcomes are explored: SPNE and SO, under different assumptions. The existence of SPNE and SO is discussed in sections 3 and 4. In addition, social welfare is also discussed.

## 2.3 Illustrative Examples

This section discusses two typical cases under specific network connections: one fully integrated network and one network with mixed connections.

### 2.3.1 A Fully Integrated Network with Buyers with Similar Needs

Consider a network with two independent sellers connected with one set of buyers with similar transaction costs, where the two sellers are denoted by $A$ and $B$, and

the buyer set is denoted 1, as shown in Figure 2.2. For ease of calculation and interpretation, the buyer set 1 is normalized to only 1 buyer in the calculation below. The value function of buyer 1 is denoted by the direct product of the learning level and the sign-up bonus points, while the cost function of sellers is denoted by the product of the square root of the learning level and the sign-up bonus points, i.e.,

$$\begin{cases} V_{1s} = \lambda \times i_s, s \in \{A, B\}; \\ C_{s1} = \sqrt{\lambda} \times i_s, s \in \{A, B\}, \end{cases}$$

where function $V_{1s}$ denotes the value of sign-up bonus points for buyer 1 from seller $s$, and $C_{s1}$ denotes the cost of sign-up bonus points transferred to buyer 1 from seller $s$. In addition, assume that both sellers have accurate predictions on the long-term usage of buyer 1 with a corresponding revenue return of \$800, hence an accurate $\bar{\mu} = \$800$. Therefore, the profit function of sellers is denoted as:

$$\pi_{s1} = 800 - C_{s1}, s \in \{A, B\},$$

where $\pi_{s1}$ denotes for the expected profit of seller $s$ made from buyer 1.

Based on the information above, a Subgame Perfect Nash Equilibrium can be generated in this network by $SPNE : \{i_A^* = i_B^* = 211\}$ (rounded up to integers) by substituting every element to the profit functions of both sellers and consider whether to set the sign-up bonus points that cover the transaction cost of buyer 1. For instance, seller $A$ solves:

$$\begin{cases} \underset{i_A}{max}\, \pi_{A1} = max\{800 - \sqrt{1 + 0.001 \times (i_A + i_B)} \times i_A, 0\}; \\ \qquad\qquad s.t. [1 + 0.001 \times (i_A + i_B)] \times i_A \geq 300, \end{cases}$$

while seller $B$ solves a similar problem:

$$\begin{cases} \underset{i_B}{max}\, \pi_{B1} = max\{800 - \sqrt{1 + 0.001 \times (i_A + i_B)} \times i_B, 0\}; \\ \qquad\qquad s.t. [1 + 0.001 \times (i_A + i_B)] \times i_B \geq 300. \end{cases}$$

Since this equilibrium $SPNE : \{i_A^* = i_B^* = 211\}$ is acquired directly from the calculations of the problem, and other connections do not exist, this Subgame Perfect Nash Equilibrium is the only Subgame Perfect Nash Equilibrium under this network. Furthermore, it is also worth exploring the Pareto Optimal to see social welfare. However, the Pareto Optimal of this game can never be achieved since the

social welfare is increased whenever any of the sellers increase their sign-up bonus points, i.e., the social welfare can be represented by substituting every element of this network as:

$$
\begin{aligned}
W &= \sum_{s=\{A,B\}} W_s + W_1 \\
&= \sum_{s=\{A,B\}} (800 - \sqrt{1 + 0.001 \times (\sum_{s=\{A,B\}} i_s)} \times i_s) + \sum_{s=\{A,B\}} \{[1 + 0.001 \times (\sum_{s=\{A,B\}} i_s)] \times i_s\} \\
&= 1600 + \sum_{s=\{A,B\}} \{i_s \times [1 + 0.001 \times (\sum_{s=\{A,B\}} i_s) - \sqrt{1 + 0.001 \times (\sum_{s=\{A,B\}} i_s)}]\},
\end{aligned}
$$

where $W$ denotes the aggregate welfare, while $W_s$ and $W_1$ denote the profit of seller $s$ and buyer 1, respectively. Since the following inequality always exists:

$$
[1 + 0.001 \times (\sum_{s=\{A,B\}} i_s)] > \sqrt{1 + 0.001 \times (\sum_{s=\{A,B\}} i_s)},
$$

while $i_A + i_B > 0$, the aggregate social welfare achieves its maximum when the sign-up bonus points from sellers $A$ and $B$ go to positive infinite. This inequality is caused by the higher learning levels under higher sign-up bonus points and the amount difference between the value function of buyers and the cost function of sellers under the same number of sign-up bonus points.

However, although social welfare is not exploitable, sellers do cooperate, collude or combine sometimes, and one seller can have multiple sources offering sign-up bonus points. Therefore, it is worth discussing what if the seller $A$ and seller $B$ belong to the same owner, and they cooperate on offering sign-up bonus points to maximize their aggregate profit. Under this situation, sellers $A$ and $B$ solve:

$$
\begin{cases}
\max\limits_{i_A, i_B} \pi_{A1} + \pi_{B1} = max\{800 - \sqrt{1 + 0.001 \times (i_A + i_B)} \times i_A, 0\} + \\
\qquad\qquad max\{800 - \sqrt{1 + 0.001 \times (i_A + i_B)} \times i_B, 0\}; \\
\qquad s.t. [1 + 0.001 \times (i_A + i_B)] \times i_A \geq 300. \\
\qquad\quad [1 + 0.001 \times (i_A + i_B)] \times i_B \geq 300.
\end{cases}
$$

Solving for the above equation can easily grant a seller-optimal at $\{i_A^* = i_B^* =$

211}, which is exactly the same as the Subgame Perfect Nash Equilibrium under this network. This result is reasonable, because that most fully integrated networks in the world have the same or similar Subgame Perfect Nash Equilibria and seller-optimal.

Thus, the questions arise. Since this market is under cooperative competition, it is unlikely that the Subgame Perfect Nash Equilibrium does not exist. However, there might be more than 1 Subgame Perfect Nash Equilibrium in the market, and the seller-optimal may differ from the Subgame Perfect Nash Equilibrium under other network connections. Another example is shown in the next subsection under different network connections to reveal the multi-equilibria situations.

### 2.3.2 A Network with Mixed Connections

Now consider a similar network with almost all elements in subsection 2.1, except for a new buyer 2 and a new link connection between buyer 2 and seller $B$, where buyer 2 is an exclusive buyer of seller $B$, while being not accessible by seller $A$. Suppose that the transaction cost of buyer 2 is \$500. In addition, the accurately estimated revenue return is decreased to $\bar{\mu} = 632$. As shown in Figure 2.3, all other settings are consistent with the network in subsection 2.1.

The methodology of solving the problem under the new network is consistent with the methodology in subsection 2.1, except for the possibilities of discontinuities, since the sign-up bonus points offered by seller $B$ may only cover the transaction cost of buyer 1, but not buyer 2, as buyer 2 has a higher transaction cost.

Under the same way of calculation, if seller $B$ decides to cover the transaction cost of buyer 2, the sign-up bonus points offered by seller $B$ can be calculated as $i_B^* = 366$, based on the inequality below:

$$(1 + 0.001 \times i_B) \times i_B \geq 500,$$

with the side profit for seller $B$ from buyer 2 at $\pi_{B2} = 204$. Under this situation, seller $A$ only needs $i_A^* = 193$ to attract buyer 1 to apply, based on the root from the following equation:

$$[1 + 0.001 \times (i_A + 366)] \times i_A \geq 300,$$

with side profit for seller $A$ from buyer 1 at $\pi_{A1} = 391$, while the side profit for seller $B$ from buyer 1 can then be calculated at $\pi_{B1} = 175$. Therefore, if seller $B$ decides to attract buyer 2, the maximal profit of seller $B$ is

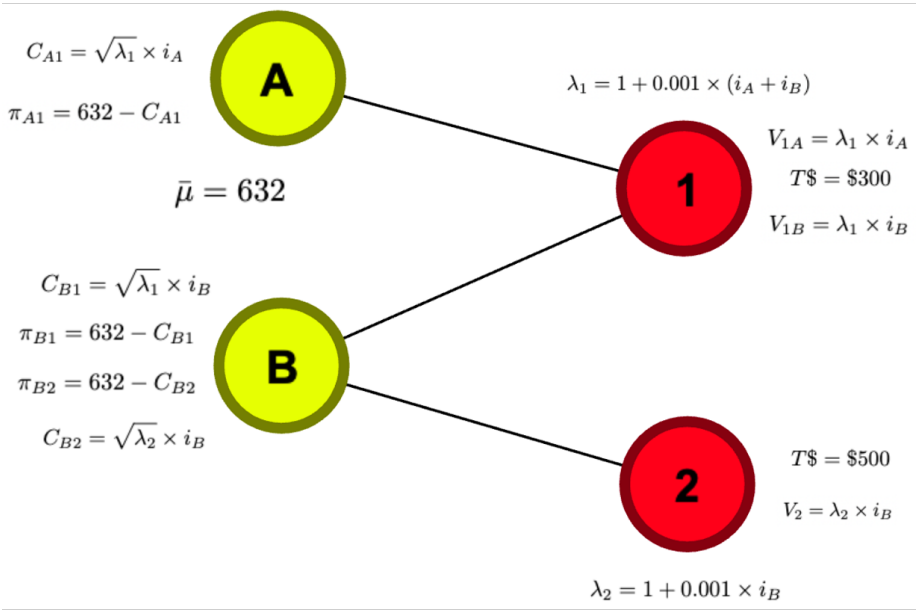



Figure 2.3: An example of a network with mixed connections. This game has more than 1 Subgame Perfect Nash Equilibria, and the seller-optimal is the same as one of the equilibria.

$$\begin{aligned}\pi_B &= \pi_{B1} + \pi_{B2} \\ &= 379.\end{aligned}$$

Given that $\pi_B = 379$ if attracting buyer 2, if seller $B$ decides not to attract buyer 2 and only cover the transaction cost of buyer 1, the game is back to subsection 2.1, and the outcome can be predicted at $\{i_A^* = i_b^* = 211\}$ with the maximal profit of seller $B$ at

$$\begin{aligned}\pi_B &= \pi_{B1} + \pi_{B2} \\ &= 380.\end{aligned}$$

Therefore, if the sellers' choice is sequential, and seller $B$ moves first, there will be only one Subgame Perfect Nash Equilibrium, which is that seller $B$ chooses not to attract buyer 2. However, since sellers make simultaneous decisions, it is also a Subgame Perfect Nash Equilibrium that seller $B$ decides to cover the transaction cost of buyer 2, unless the situation $\{i_A^* = 193, i_B^* = 366\}$ is not stable, where either seller $A$ or seller $B$ can yield a higher profit by deviating its choice while the other remains the same. Under this situation, since the sign-up bonus points of seller $A$ are derived from a single equation, seller $A$ is stable (does not deviate). The key point is whether seller $B$ wants to deviate from its decision to not attract buyer 2 and re-consider the sign-up bonus while $i_A^* = 193$ remains the same. Based on this test, if seller $B$ wants to deviate down, the result $i_B^* = 214$ can be solved from the following inequality:

$$[1 + 0.001 \times (193 + i_B)] \times i_B \geq 300,$$

where the profit of seller $B$ changes to 378, from only buyer 1. Since the deviated profit of 378 is lower than the pre-change profit of 379, seller $B$ does not choose to deviate, and the market achieves Subgame Perfect Nash Equilibrium. Therefore, there are two Subgame Perfect Nash Equilibria under this network. For better understanding, we also provide a quadratic form of this game under this network in this example (See Figure 2.4), which clearly shows the similarity between this game and the famous classical game of matching pennies or cooperation.

In addition, also from the quadratic form of the game, a seller-optimal is achieved at $\{i_A^* = 193, i_B^* = 366\}$ while seller $B$ attracts buyer 2, and the seller $A$ knows that

| | | Seller $B$ | |
|---|---|---|---|
| | $(\pi_A, \pi_B)$ | Consider consumer 2 $i_B^* = 366$ | Ignore consumer 2 $i_B^* = 211$ |
| Seller $A$ | Suppose that seller B will consider consumer 2: $i_A^* = 193$ | (***391***, 379) | (0, 0) |
| | Suppose that seller B will ignore consumer 2: $i_A^* = 211$ | (367, 377) | (***380***, 380) |

Figure 2.4: The quadratic form of this game. All numbers in the parentheses are the net profit of seller $A$ and $B$ under different decisions and expectations. Two Subgame Perfect Nash Equilibria are identified in the table, which is similar to the classical game of matching pennies.

seller $B$ will attract buyer 2, since under this condition, the sellers share the maximal aggregate profit. In addition to that, the Pareto Optimal still does not exist due to the difference between the value function for buyers and the cost function for sellers based on the learning curve.

Given the double equilibria of this network, it is notable to mention that if the accurate estimated revenue return to be $\bar{\mu} = 800$, consistent with example 1 (subsection 2.1), the benefits of attracting buyer 2 raises rapidly, and attracting buyer 2 becomes the dominant strategy for seller $B$, which yields only one Subgame Perfect Nash Equilibrium in this game, as shown in the Figure 2.5.

Therefore, many factors impact the existence of multiple Subgame Perfect Nash Equilibrium, including network connections, the estimated revenue return from buyers, the learning curve, the cost function for sellers to offer sign-up bonus points, the value function for buyers to use these points and the buyers' transaction cost. Detailed clarifications and discussions on this model are formally shown in sections 3 and 4, where the conditions for multiple Subgame Perfect Nash Equilibria are carefully stated.

Seller $B$

| Seller $A$ | $(\pi_A, \pi_B)$ | Consider consumer 2 $i_B^* = 366$ | Ignore consumer 2 $i_B^* = 211$ |
|---|---|---|---|
| | Suppose that seller B will consider consumer 2: $i_A^* = 193$ | (***559***, 715) | (0, 0) |
| | Suppose that seller B will ignore consumer 2: $i_A^* = 211$ | (535, 713) | (***548***, 548) |

Figure 2.5: The quadratic form of this game under a changed $\bar{\mu} = 800$. All numbers in the parentheses are the net profit of seller $A$ and $B$ under different decisions and expectations. Only one Subgame Perfect Nash Equilibria can be identified, and the seller-optimal is consistent with the Subgame Perfect Nash Equilibrium.

## 2.4 SPNE, Seller-Optimal and the Social Welfare

Given that the game is a two-step sequential game starting with sellers simultaneously choosing their sign-up bonus points, i.e., $\{i_b\}_{b\in\mathcal{B}}$, the existence of SPNE and Seller-optimal as discussed in this section, with the analysis on the social welfare.

### 2.4.1 The Existence and of SPNE

To solve for the SPNE of a learnable incentive game, a possible solution is to list all possible choices of all sellers, followed by multiple iterations to get SPNE. First, given the transaction cost $T_q$, the value function $V$, the learning function $\lambda_q$, and the network connections, if all sellers are given a subset of buyers that they would attract, a *minimum attracting choice* is the only outcome, defined below in Definition 4.

**Definition 4 (Minimum Attracting Choice (MAC))** *Let $N_b^M \subseteq N_b$ be a subset of buyers connected to seller $b$. For each seller $b$, let $i_b^M$ be the minimum incentive to attract all buyers in $N_b^M$, conditional on all other sellers' minimum attracting choices, such that*

$$i_b^M = \arg\min_{i_b}\{V(\lambda_q(\sum_{\mathbf{b}\in S_q} i_{\mathbf{b}}^M), i_b) \geq T_q, \forall q \in N_b^M\}. \tag{2.1}$$

Given $i_b^M$ of each seller $b$, let $i^M$ be a vector of Minimum Attracting Choice (MAC) of sellers, based on the subset of buyers $N^M = \{N_b^M\}_{b\in\mathcal{B}}$ that each seller $b$ attracts. In Lemma A..2.2 we show that a unique $i_M$ can be calculated for any subset of buyers $N^M$. The key points to prove the existence and uniqueness of MAC start with proving the equal-sharing outcome of fully integrated networks, followed by designing an algorithm sequencing the buyers in $N_b^M$, and proving that this algorithm is the only one making this work.

Let $n$ be the number of links (connections) in the network. From Definition 4, there are $2^n$ MACs in the network with $n$ links (For each link between a seller $b$ and a buyer $q$, the seller has two choices: adding the buyer to $N_b^M$ or not). The next Definition 5 shows the iterations of MAC, excluding those not possible ($i_b^M$ attracts a connected buyer out of $N_b^M$) and deviable ($i_b^M$ is not the best response of other sellers' choices $i_{-b}^M$ in the MAC).

**Definition 5 (Iterated MAC)** *MAC $i^M$ is defined as an Iterated MAC, denoted as $i^{M*}$ unless EITHER of the following conditions holds:*

- *There exists a seller $b$ with a buyer $q \in N_b$, but $q \notin N_b^M$, such that:*

$$V(\lambda_q(\sum_{\mathbf{b}\in S_q} i_{\mathbf{b}}^M), i_b^M) \geq T_q. \tag{2.2}$$

- *Let $i_b^{BR}|i_{-b}^M$ be the seller $b$'s best response to all other sellers' choices $i_{-b}^M$ in the MAC. There exists a seller $b$ such that:*

$$\pi_b^*(i_b^{BR}|i_{-b}^M) > \pi_b^*(i^M). \tag{2.3}$$

After iterating MACs, SPNE can be easily proved to be equivalent to *Iterated MAC*. It is worth exploring the existence of *Iterated MAC* (the existence of SPNE), as Theorem 1 below.

**Theorem 1 (The existence of SPNE)**

- *Any Iterated MACs are SPNE.*
- *In any learnable incentive game, there exists an SPNE.*

### 2.4.2 The Seller-Optimal

Given the learnable incentive game and the colluding settings of sellers, the existence of SO is easy to prove. Furthermore, the conditions on when the SO is supported by an SPNE are important, as shown in Proposition 1.

**Proposition 1 (Existence of SO and SPNE supported SO)**

- *In any learnable incentive game, an SO exists.*
- *The SO is supported by an SPNE unless for every iterated MAC attracting set $N^{M*}$, there exists a buyer $q$ out of a seller $b$'s attracting set $N_b^{M*}$, i.e. $q \notin N_b^{M*}$, such that:*

$$\sum \pi(N^M|q) > \sum \pi(N^{M*}),$$

*where $N^M|q$ is the MAC attracting set with buyer $q$ attracted.*

(See proof in Appendix.)

In addition, it is worthwhile to see what social planners can do to increase social welfare, which is discussed and shown in the next section.

### 2.4.3 The Social Welfare

We define the *social welfare* as the sum of the seller's profit and the sum of the buyers' utility. In a typical economy, a benevolent social planner would be interested in maximizing the social welfare.

It is impossible that a social planner may want to achieve maximum social welfare by adding some stipends to sellers and increasing their choices of sign-up bonus points. Detailed discussions are shown in Proposition 2.

**Proposition 2 (The Social Welfare and Incentives)**
*The social welfare of the market strictly increases in the sign-up bonus points offered by all sellers, and it does not have any maximum value upon the increase of sign-up bonus points.*

(See proof in Appendix.)

Social planners can still add stipends to sellers directly to incentivize them to increase their choices of sign-up bonuses to increase social welfare based on situational needs. Furthermore, not only can the choices of sign-up bonus points increase social welfare, but the parameters and network connections are also making sense indirectly in changing social welfare through their direct impacts on sign-up bonus (points) offers, as well as changing seller benefits and buyer benefits. Detailed discussion is shown in the propositions in section 5.

## 2.5 Comparative Statics

Given the SPNE, the SO, and social welfare in the learnable incentive game, it is shown that many factors are impacting the stable outcomes, yielding different outcomes under different conditions, mainly including changes in the values of parameters and the network connections. The following two subsections exploit the impacts caused by these changes, by formally providing the comparative statics of this game.

### 2.5.1 The Changes in Estimated Revenue Returns from Buyers

In the real world, the revenue return from buyers $\bar{\mu}$ depends on many elements of long-term usage: the card spends and the carry-over balances on credit cards; the frequency of travel on airlines and hotel groups, the willingness to visit the dining places as chain restaurants, etc. Therefore, this parameter increases if people are more willing to spend money, which often happens during the rapid growth or recovery of the economy. For instance, these situations are common in the real world, since people tend to spend more after severe shocks, such as the 2008 financial crisis and Covid-19. Vice versa, when people suffer from economic recessions or similar situations with less money to spend.

These changes may impact the stable outcome of sign-up bonus (points) offers after sellers observe that. Buyer benefits, seller benefits, and social welfare can also be impacted by them. The specific way to calculate and consider these changes still comes from the definition 1 of the game, and the formal comparative statics as shown in Proposition 3.

**Proposition 3 (Comparative Statics on changes of $\bar{\mu}$)**
*Consider a learnable incentive game that reached an SPNE under the estimated rev-*

*enue return $\bar{\mu}$. If the estimated revenue return $\bar{\mu}$ is increased to $\bar{\bar{\mu}}$, a new SPNE exists such that:*

- *The equilibrium sign-up bonuses (points) chosen by all sellers may increase or decrease.*
- *The utilities of all buyers may increase or decrease.*
- *The profits of all sellers may increase or decrease. Furthermore, a decrease in profit only occurs if more SPNE is generated after the change in $\bar{\mu}$. Furthermore, there exists an SPNE among all SPNE after the change, where the profits of all sellers with valuable buyers are strictly higher.*
- *The aggregate profit of all sellers strictly increases.*
- *The aggregate utility of all buyers does not decrease.*
- *The social welfare strictly increases.*

(See proof in Appendix.)

### 2.5.2 The Changes in Network Connections

Buyers are getting advertisements on these learnable incentives in their daily life from everywhere. While browsing social media like Instagram or Facebook, buyers may see advertisements from charge cards from American Express; while trying to book a United Airlines flight, buyers may see advertisements on UA credit card series from J.P. Morgan Chase Bank; While taking American Airlines flights, buyers may find in-flight offers on AAdvantage cards from Citi Bank or AAviator cards from Barclays Bank US; While dining in at Red Lobster locations, buyers may find the dine-in offers to join Red Lobster Rewards, etc. All these offers and advertisements show their sign-up bonuses (whether in points or dollars) on the first shot with the largest font, addressing the sign-up bonuses they offer.

Therefore, whenever a buyer gets attracted by one of those advertisements, a new connection between the buyer attracted and the seller offered the advertisement gets formulated, resulting in the fact that these added connections to the network are common in the real world.

On the other hand, the United States is a country of immigrants, and many residents and citizens decide to leave America for various reasons. Meanwhile, some buyers are having bad experiences with some sellers regarding other products, such

as UA basic economy class, so they decide to not attract the seller they are already connected to.

The impact of an added or deleted connection to the stable outcomes, seller benefits, buyer benefits, and social welfare is shown in Proposition 4.

**Proposition 4 (Comparative Statics on an Added Connection)**

*Consider a learnable incentive game that reached an SPNE. When a new connection is added to the network of the learnable incentive game, a new SPNE exists such that:*

- *The equilibrium sign-up bonuses (points) chosen by all sellers may increase or decrease. In addition, more or less SPNE may be generated in the market.*
- *The utilities of all buyers may increase or decrease under SPNE and SO.*
- *The profits of all sellers may increase or decrease under SPNE.*
- *The aggregate sellers' revenue under SO does not decrease (and vice versa).*
- *The social welfare may increase or decrease.*

(See proof in Appendix.)

Using one sentence to summarize Proposition 4, the stable market outcome can change in any way and any direction under an added or deleted connection between a seller and a buyer. Therefore, it is hard to predict what will happen when a buyer or a leaving buyer notices an advertisement, yielding uncertainty in the market.

## 2.6 Conclusion

Despite the wide application of learnable incentives, there have been few attempts to explore the market outcomes driven by these learnable incentives rather than more conventional monetary incentive schemes. This distinction is critical as the level of learning will affect the buyers' decision to sign up, and sellers' cost. Our work is the first paper modeling the use of learnable incentives in buyer-seller networks. The existence of SPNE is shown as a fundamental outcome of this game, with comparative statics exploring the changes in parameters and network connections. For wider application, two extensions are discussed with added assumptions and variables.

Notably, several results of this paper are not consistent with conventional incentive theory, including sellers raising their sign-up bonuses (points) and becoming better off under a lower estimated revenue return from buyers, and sellers being worse off with extra added connections.

To simplify our problem, we assumed that the learnable incentives, characterized as sign-up bonus points, are completely new to buyers. The extensions of the model should study how prior learning on how to use bonus points may affect the results in this paper. Another potential extension of this paper is making this game dynamic, where buyers continue paying effort towards learning, and sellers identify buyers with lower usage than their estimations in the longitudinal run. Similar problems are discussed in the previous literature, such as dynamic churning and consumer relationship managing[53], dynamic one-to-one consumer marketing[46], etc, however, results and mechanisms are predicted to be changed with (continual) learnable incentives, which the limitations of our model do not allow us to obtain. Another potential extension of this paper would explore the empirical relationship between buyer and seller choices, and the number of incentives offered, based on micro data on consumer choices when being attracted by learnable incentives. This approach would validate the results of this paper through a structural approach.

# Chapter 3

# Sales Network with Price-setting Intermediaries and Consistent Pricing

## 3.1 Introduction

Intermediation for goods and services has been widely used for centuries since the early markets, in a variety of markets such as retailers and international traders. More recently, intermediation has evolved for online markets, from travel agencies (Expedia, Airbnb, Bookings, Priceline, etc.) to selling discounted goods (Groupon, LivingSocial, etc.) to retail goods (Bestbuy, eBay, Amazon, etc.). Intermediation varies substantially, while even for the same good, the strategies used by intermediaries might be different.

For instance, there are many pricing strategies taken by different intermediaries in reality. For example, Bookings.com charges no entree fee with 10% of the aggregate revenue of the services selling successfully through Bookings.com; Groupons.com charges no entree fee with 50% of the aggregate revenue of the products selling successfully through Groupons.com. However, a Chinese Groupons company named Meituandianping charges a $1000 annual entree fee for each product/combo, with 30% of the products selling successfully through Meituandianping. Moreover, intermediaries like Sam's Club and Safeway customize prices to both producers and consumers for every participating item. Different pricing strategies exist, though a basic question remains: how should the intermediaries choose their pricing strategies

[0]Co-authored with Ruben Juarez.

based on their own situations on an identical good, and does market equilibrium exists?

To answer this question, we model a set of independent and private intermediaries who want to maximize their revenue by setting a pricing strategy. Based on that, we construct a tripartite network consisting of producers, consumers, and intermediaries between them. We assume that all producers are choosing those intermediaries bringing them positive profit with unlimited production, while all consumers need one product with a reservation price. Meanwhile, we restrict that each intermediary can only post ONE price to each side, which is consistent through all consumers and all producers, respectively.

In the first stage of the game, intermediaries post their prices to both producers and consumers. These prices may affect the producers' connecting decisions and consumers' buying decisions. In the second stage, producers choose which intermediaries to connect, followed by consumers choosing whether to buy and which intermediary to buy from to be the third stage. In this paper, we explore two types of outcomes. First, we consider Subgame Perfect Nash Equilibrium (SPNE), which follows the assumptions of Bertrand competition without any cooperation or collusion between intermediaries. Second, for more robustness of the outcome, we consider a cooperative optimal named Intermediary Collusion-proof Optimal (ICO), where intermediaries can negotiate and collude with each other to maximize their aggregate revenue, Here, both SPNE and ICO are based on the assumption that intermediaries cannot price-discriminate to either consumers or producers.

### 3.1.1 Overview of the Results

We describe our main results through a simple example. Consider a network with one producer, two intermediaries, and three consumers as shown in Figure 1. The producer has unlimited production, and the 3 consumers have \$10, \$8, \$10 as their reservation prices, respectively. To better illustrate the multiple equilibria, we normalize the initial price and costs from all producers as zero, and intermediaries set prices to consumers. Consumer 1 only knows intermediary 1, while consumer 3 only knows intermediary 2, and consumer 2 knows both intermediaries.

From this example, the prices of the two intermediaries can be shown as the three different equilibria discussed before with four different market situations:

**SPNE**: Without other assumptions, we cannot find an equilibrium (SPNE), since both intermediaries will deviate their prices forever. The process is as follows:

- They both preset a price of \$10;

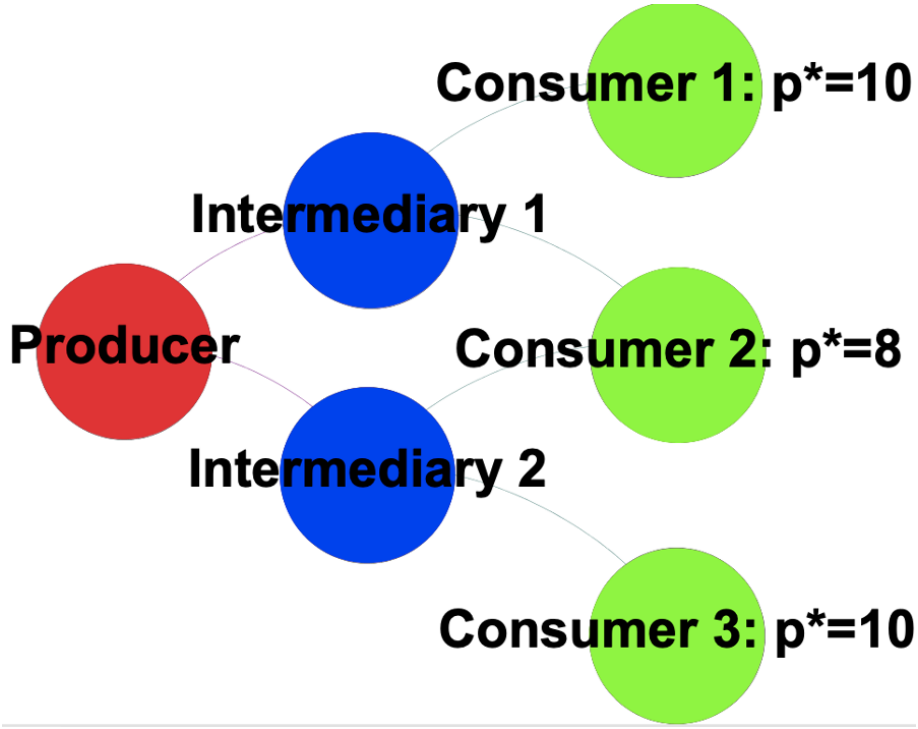



Figure 3.1: An example of no existence of market equilibrium.

- Intermediary 1 deviates its price to \$8;
- Intermediary 2 deviates its price to \$8-$\epsilon$;
- Intermediary 1 deviates its price to \$8-2$\epsilon$;
- ...
- Intermediary 1 deviates its price to \$5;
- Intermediary 2 deviates its price back to \$10;
- Intermediary 1 deviates its price up to \$8;
- Loop.

**ICO**: On the other hand, if we assume that the two intermediaries are now owned by one owner. Under such an assumption, we get the equilibrium as an Intermediary-collusion proof optimal (ICO), where the new equilibrium condition will be: one

intermediary, say intermediary 1 changes the price to \$8, while intermediary 2 still stays at the same price, \$10. Now they have their maximum joint revenue of \$26. The movements are shown as follows:

- Intermediary 1 changes its price to \$8;
- Collusive Optimal achieved, where the intermediaries are getting maximum joint revenue;
- Intermediary 1's profit: 8+8=\$16;
- Intermediary 2's profit: \$10;
- Now the two intermediaries get the maximum joint revenue of \$26.

**SPNE with new prices**: Now suppose the reservation price of consumer 2 has changed from \$8 to \$4. Even without any assumption, we can get the equilibrium (SPNE) with both intermediaries remaining at their original price: \$10. Therefore, both intermediaries will get a profit at \$10. The movements are shown as follows:

- Intermediary 1 remains its price at \$10;
- Intermediary 2 remains its price at \$10;
- Equilibrium achieved, since both intermediaries cannot deviate their price to get more profit;
- Intermediary 1's profit: \$10;
- Intermediary 2's profit: \$10;

This simple example shows the right-hand side of the network, which is only related to the unit prices, which are variable prices held by intermediaries. For this example, there also exists equilibriums on the left-hand side as fixed entree fees held by intermediaries.

From the structure of the network, the equilibrium fixed entree fees in both stable outcomes (ICO and SPNE with new prices) will be positive, since the producer wants to access all 3 consumers by connecting to both intermediaries. For instance, suppose that both producers can get a fixed profit of \$1 per good. Under SPNE with new prices, both intermediaries will post a fixed entree fee of \$1 to the producer, which is exactly the profit that the producer makes from the network. Under ICO, intermediary 1 will post a fixed entree fee of \$2, and intermediary 2 will post a fixed

entree fee of $1, which indicates the sales volume of 1 and 2, respectively. However, what if all consumers are connected to both intermediaries? Moreover, what if there are more producers in this network? Our full model contains all possibilities of the connections on both sides, and we provide proof for the multiple conditions on the existence of the market equilibrium. Our results work for a large variety of markets with intermediaries.

### 3.1.2 Related Literature

Intermediations are shown profitable to businesses, consumers, and intermediaries themselves (Dholakia, 2011)[19]. Meanwhile, some intermediation markets satisfy the conditions of "perfect competition" introduced by Makowsi and Ostroy (1987)[59], where if each agent's marginal product equals zero, then no one can exercise market power or change market outcomes. We will discuss a market that is fully integrated with multiple small-size markets.

Previous literature includes many discussions on the connections between intermediaries and producers or planners. Han and Juarez (2018)[33] provided and proved the existence of free intermediation in resource transmissions in a network; Manea (2018)[60] discussed the mechanism of the intermediations in resale networks. Besides, there are also some possible ways to allocate under changing network market structure (Jackson, 2005)[38]. Hagiu and Jullien (2011)[32] provided a set of strategies for intermediaries in the searching market where consumers search for merchants.

Previous literature also includes many discussions on the connections between intermediaries and producers or planners. The decision variables for intermediaries are prices charging both merchants and consumers, which is a typical kind of network discussed by Galeotti et al (2010)[28]. Therefore, for a market facing pricing problems, it is a Bertrand market proposed by Bertrand (1883)[7] and mathematically formulated by Edgeworth (1889)[22]. However, in Bertrand's market, every seller is supposed to post a price that is exactly the cost of the product, which is impossible for a real seller. To fix this problem, Salop and Stiglitz (1977)[72] provided a solution to this problem that the market was still profitable due to the limited productivity of the factories, while Dixon (1984)[20] provided a solution that the market was still profitable due to the convex production cost set. After then, economists turned to studying Cournot's (1838)[17] market on pricing decisions instead of Bertrand's market. However, the costs of most intermediations are near zero without any variable cost, and intermediaries do not need to produce. Therefore, the intermediaries' pricing decisions cannot be made by any existing literature. Meanwhile, there are both uninformed consumers that only know one intermediary and comparably informed

consumers that compare prices from some intermediaries (Varian, 1980)[79], which makes the market even more complicated.

The vertical market structures with intermediaries are also widely discussed in the previous literature. For instance, Baligh and Richards (1964) [5] discussed various vertical market structures and the corresponding predicted outcomes. Bushnell (2008) [10] validated these outcomes in electricity markets. In the meantime, Gans (2007) [29] explored the concentration rules in these markets.

The existing literature mainly focuses on the market with different prices on both sides of the network, which is not always possible in real markets. For instance, in a supermarket, every product has a consistent price for all consumers at one time, and it is impossible to post a different price for every consumer. Therefore, we focus on this issue by adding the assumption that all intermediaries are having one price set for both producers and consumers to keep consistency, which leads to the result of the non-existence of Nash equilibrium. We also discuss the equilibriums under collusions between intermediaries to prove the existence of optimal, as well as the network expansions under network change, including the change from a random market to a market with perfect competition.

The rest of this paper will be constructed as follows: Section 2 proposes a general model; Section 3 will discuss the existence of SPNE; Section 4 will discuss the existence of ICO; Section 5 is comparative statics of the market equilibrium under the market network shocks on consumer structure; and Section 6 concludes.

## 3.2 The Model

Consider a set of consumers $Q = \{1, 2, \ldots, q\}$ in need of some products. Consider a set of identical producers $Z = \{1, 2, \ldots, z\}$ who produce such products, and their products are of identical quality. However, they cannot reach each other, unless connected by intermediaries between them. The producers are assumed to have unlimited production. Consider a set of homogeneous intermediaries $N = \{1, 2, \ldots, n\}$ who can intermediate the products and formulate a sales network between producers and consumers.

**Definition 6 (Intermediation Problem)**

*An intermediation problem is a set of functions* $(u, V, F)$ *such that:*

- $u_{zi} : \mathbb{R}^1_+ \to \mathbb{R}^1$ *represents* ***producer*** $z$***'s utility*** *while choosing a* ***single intermediary*** $i$*. In our model,* ***producers earns revenues from its sales***

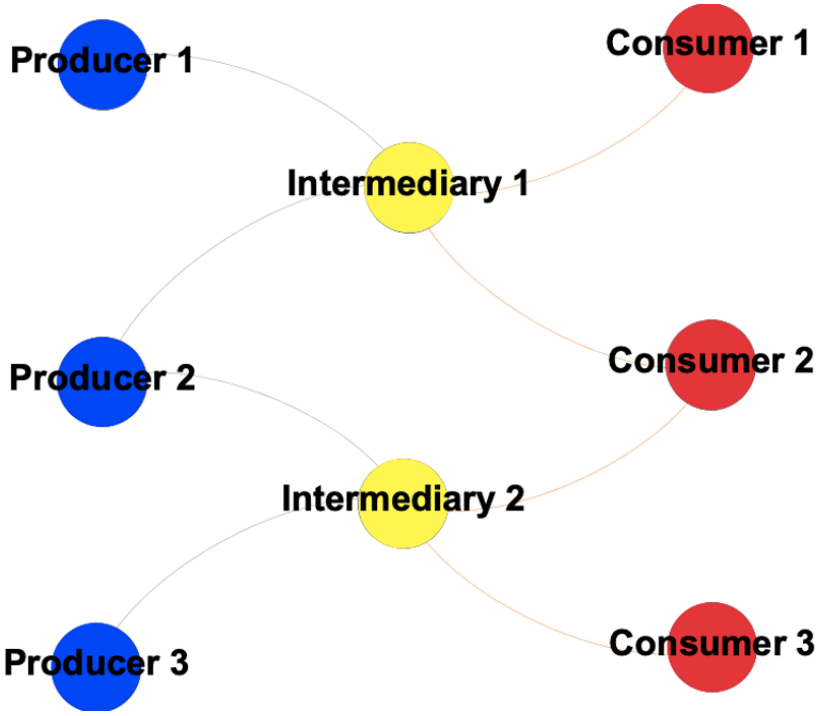



Figure 3.2: 2-intermediary full market with all kinds of consumers and producers

***volume, but not from the money transfer from consumers to intermediaries***, *where this preference is consistent with the profit made through the intermediary, i.e. producer $z$ has the following utility while connected to intermediary $i$.*

$$u_{zi}(S_{zi}) = \lambda \times S_{zi} - R_i, \tag{3.1}$$

*where a small number $\lambda > 0$ denotes the exogenous unit profit made for producers for each product. Here, we assume that this unit profit is consistent with all producers. $S_{zi}$ represents the sales volume for producer $z$ through intermediary $i$, while $R_i$ denotes the entree fee for that period charged by the intermediary $i$. We assume $u_{zi} = 0$ if producer $z$ decides not to connect to intermediary $i$.*

- $V_{qi} : \mathbb{R}^1_+ \to \mathbb{R}^1$ *represents* ***consumer*** *$q$**'s utility** while buying the desired product from* ***intermediary*** *$i$. We assume that consumer $q$'s utility $V_{qi}(p_i)$ is equal to the difference between their expected value of the good (reservation price) $v_q$ and price $p_i$ that they pay to the intermediary $i$.*

- *In this intermediation game, all producers hold the same prices of their goods, and they make a profit from their sales volume through intermediaries. Therefore, we assume that all prices and costs of producers are normalized to zero. Thus, all prices that are seen by consumers are determined by intermediaries. Similar assumptions and settings have been applied to various previous studies, such as the outcomes from vertical market structures [5] and the price markups in supply chains [55].*

- $F_i : \mathbb{R}^2 \to \mathbb{R}^1$ *represents* ***intermediary*** $i$***'s revenue function*** *while charging producers and consumers connected to it. Formally,* $F_i$ *has a fixed entree fee* $R_i$ *on the producers' side and a variable unit price* $p_i$ *on the consumers' side, respectively. This revenue is represented by* $F_i(p_i, R_i)$*. We assume* $F_i(0, 0) = 0$*, and the unit price* $p_i$ *is consistent through all consumers connected to it, while the entree fee* $R_i$ *is consistent through all producers connected to it.*

An intermediation problem consists of three functions: $u$, $V$, and $F$. First, the function $u$ represents the producers' utility, based on the choices of connection decisions made by producers. We assume this utility decreases in the entree fee charged by intermediaries while increasing in the number of products sold through intermediaries.

Second, the function $V$ represents the consumers' utility, based on the purchasing decisions of consumers. We assume this utility decreases in the price the buy the product upon the decision of buying, and this utility is zero upon the decision not to buy.

Third, the function $F$ represents the intermediaries' revenue, based on the network structure and the prices for producers and consumers. i.e. $(p_i, R_i)$. We assume that each intermediary can only post ONE set of $(p_i, R_i)$ for a kind of product to producers and consumers. Here, the function $F$ is not assured to be continuous, based on the market structure.

We study a three-stage game in the market. The game moves in the following sequence: in the first stage, intermediaries choose simultaneously and independently unit prices $p$ and entree fees $R$ to gain access to their outcome set. In the second stage, after observing the prices charged by the intermediaries, the producers choose a subset of intermediaries based on their connections, and in the third stage, the consumers choose to buy from an intermediary or give up buying.

**Definition 7 (Intermediation Game)**

*Given an intermediation problem* $(u, V, F)$*, the intermediation game is a sequential game of perfect information such that:*

- *Every producer $z$ is connected to a limited number of intermediaries, where the set of intermediaries that are connected to producer $z$ is denoted as $I_z$. Meanwhile, every consumer $q$ is connected to a limited number of intermediaries, where the set of intermediaries that are connected to consumer $q$ is denoted as $I_q$. All intermediaries can accept all connections from any consumers and producers, hence the network is an undirected network.*

- *The strategy space of intermediary $i$ is $([0, p_i^{max}], [0, R_i^{max}]), 0 \leq p_i^{max}, R_i^{max} \leq +\infty$.* ***The strategy of intermediary*** *$i$ is to set up a variable price $p_i \in [0, p_i^{max}]$ that consumers have to pay, in order to buy through intermediary $i$, as well as an entree fee $R_i \in [0, R_i^{max}]$ that producers have to pay, in order to sell products through intermediary $i$. In this game, we assume that each intermediary $i$ has only* ***ONE*** *price set $(p_i, R_i)$ across all producers and consumers connected to it.*

- *Given that one producer can choose as many intermediaries connected as they want. Therefore, the strategy of producer $z$ is a decision vector $\vec{D_z} = \{D_{zi}, i \in I_z\}$, such that $D_{zi} \in \{0, 1\}, \forall z, i$. Therefore, their payoff functions are $\vec{D_z} \times \vec{u_z} \equiv \sum_1^I D_{zi} \times u_{zi}$, where $\vec{u_z} = \{u_{zi}, i \in I_z\}$.*

- *The strategy of consumer $q$ is deciding whether to buy or not, and if they buy, which intermediary to choose, based on the connection with intermediaries. Therefore, the strategy of consumer $q$ is a vector, i.e. $\vec{d_q} = \{d_{qi}, i \in I_q\}$, such that $d_{qi} \in \{0, 1\}, \forall q, i$ and $\sum_1^I d_{qi} \leq 1$, since each consumer only needs one product. Therefore, their payoff functions are $\vec{d_q} \times \vec{V_q} \equiv \sum_1^I d_{qi} \times V_{qi}$, where $\vec{V_q} = \{V_{qi}, i \in I_q\}$.*

- *(Tie-breaking rules) We pre-assume that consumers randomly choose an intermediary to buy from, among the set of intermediaries with the same acceptable prices; also, producers randomly choose an intermediary to sell goods, among the set of intermediaries with the same consumer set and same fixed entree fees.*

- *The objective of each intermediary $i$ is to maximize the revenue they earn. We characterize the revenue function to the following form to be their payoff functions:*

$$F_i(p_i, R_i) = p_i S_i + R_i \times N_i, \tag{3.2}$$

*where $S_i$ denotes the total market sales volume that equals the sum of sales volume from each connected producer, i.e. $S_i = \sum_1^Z S_{zi}$. (note: if a producer*

*z does not connect to intermediary i, the corresponding $S_{zi} = 0$) Here, $N_i$ denotes the number of producers choosing intermediary i, which is endogenously increasing in $S_i$ while decreasing in $R_i$. Meanwhile, the revenue $F_i$ is strictly increasing in all four variables: $p_i$, $S_i$, $R_i$, and $N_i$.*

The rest of the paper imposes no restrictions on the strategy space of the intermediaries. Here, every intermediary $i$ aims at finding an equilibrium price $(p_i^*, R_i^*)$ for both sides of the game (consumers' and producers'). Intermediaries' move is the first stage of this game, so there may be a Subgame Perfect Nash Equilibrium in the game, since intermediaries will predict the producers' and consumers' move following on. Therefore, we define Subgame Perfect Nash Equilibrium (SPNE) for this game.

**Definition 8 (Subgame Perfect Nash Equilibrium)**

*The SPNE can be achieved while the market satisfies all the following conditions:*

- *Every consumer maximizes his/her utility $V$ by buying from the intermediary connected with the lowest price or not buying.*
- *Every producer maximizes its utility $u$ by choosing to the optimal subset of intermediaries connected.*
- *Every intermediary maximizes its revenue $F$ by choosing optimal $p$ and $R$ as its strategy $(p^*, R^*) \in \mathbb{R}_+^2$ to all producers and consumers connected to it.*

Without loss of reality, intermediaries are possible to collude with each other, though this condition is illegal in the US. However, it is entirely possible that intermediaries are cooperating under merger and acquisition. Therefore, to better model the optimization on the aggregate profit, we define a special outcome under the collusion between intermediaries to gain more robustness to the outcome.

**Definition 9 (Intermediaries Collusion-proof Optimal (ICO))**

*The ICO with Money Transfer can be achieved while the market satisfies all the following conditions:*

- *Every consumer maximizes his/her utility $V$ by buying from the intermediary connected with the lowest price or not buying.*
- *Every producer maximizes its utility $u$ by choosing to the optimal subset of intermediaries connected.*

- *Every intermediary maximizes the aggregate revenue of all intermediaries* $\sum F$ *by choosing optimal* $p$ *and* $R$ *as its strategy* $(p^*, R^*) \in \mathbb{R}^2_+$ *to all producers and consumers connected to it.*

- *Intermediaries are assumed to be able to collude while transferring money among them.*

The rest of the paper will be constructed around these three equilibriums talked above. Section 3 discusses the existence of SPNE, while Section 4 discusses the existence of ICO. Section 5 is some comparative statics under network expansion based on both SPNE and ICO, and section 6 concludes.

## 3.3 Subgame Perfect Nash Equilibria

Before we discuss the existence of SPNE, we need to propose the term "local optimal price". The local optimal price must be validated the existence in every consumer set.

**Lemma 1** *For any consumer set c consisting of a finite number of consumers with non-negative reservation prices and same connections, there is an optimal unit price along with the consumer set for a monopoly intermediary without competitors that optimize the profit earned from this consumer set, i.e.* $\exists p_c^* = \arg\max p_c \times S_c, \forall c$. *The* $p_c^*$ *is named "local optimal price of consumer set c".*

With the Lemma above, we introduce the conditions for the existence of SPNE below. To better illustrate the conditions of the existence of SPNE, we make an important definition below.

**Definition 10 (Valuable Consumer)**

*For an intermediary i in the network, if it ignores all other intermediaries in the market, it sees all consumers connected to it as exclusive consumers, denoted as* $c_{iALL}$. *Meanwhile, according to Lemma 1, there exists a local optimal price for this aggregate consumer set, which is denoted as* $p_i^{*ALL}$ *with the monopoly demand as* $S_i^{ALL}$ *under that local optimal price.*

*Suppose there exists a consumer c connected with intermediary i. If intermediary i does not consider consumer c, we define* $p_i^{*-c}$ *as the local optimal price for the aggregate consumer set without consumer c and its corresponding demand* $S_i^{-c}$.

*The consumer c is a valuable consumer of intermediary i if and only if intermediary i is strictly better off with consumer c, i.e.*

$$p_i^{*ALL} \times S_i^{ALL} > p_i^{*-c} \times S_i^{-c} \tag{3.3}$$

From the definition above, there exist two kinds of consumers for an intermediary: valuable and non-valuable. For instance, suppose an intermediary is connected to two consumers 1 and 2 with reservation prices at \$4 and \$10, respectively. Here, consumer 1 is not a valuable consumer for the intermediary, since the intermediary gets maximal profit at \$10 from consumer 2, whether it has consumer 1 or not. However, if the reservation price of consumer 1 changes to 6, consumer 1 is a valuable consumer for the intermediary now, since the intermediary gets maximal profit at \$12 with consumer 1, which is higher than \$10 without consumer 1.

Based on the definition above, we show the conditions for the existence of the SPNE in Theorem 1 below.

**Theorem 2** *Consider a market with intermediaries selling identical goods between producers with unlimited productions. There exists a set of non-negative fixed price (entree fee) and variable price $(R_i^*, p_i^*)$ for each intermediary to be a market equilibrium (SPNE)* ***UNLESS*** *it satisfies* ***all*** *of the following three conditions:*

- *There exists at least one intermediary $i$ with at least one exclusive consumer with a positive reservation price and at least one non-exclusive consumer with a positive reservation price.*
- *There exists at least one consumer $c$ as a non-exclusive consumer connected to intermediary $i$ being a valuable consumer of intermediary $i$ and some other intermediary $j$ that it is also connected to.*
- *There exists at least one intermediary $j$ connected with consumer $c$ that if the reservation price of consumer $c$ is substituted by the local optimal price of intermediary $j$ for all consumers connected, i.e. $p_j^{*ALL}$, consumer $c$ is still a valuable consumer of intermediaries $i$.*

The proof of Theorem 1 is supported by the following lemma.

**Lemma 2** *For each vector of variable prices, $p$, there always exists a set of entry fees such that no intermediary wants to deviate under both outcomes (SPNE/ICO), i.e. $\exists R_i^*, \forall i$.*

The existence of SPNE is a formal illustration of the example in the example of Section 1.1. As shown in Theorem 1, the conditions for the existence of SPNE are only related to the network structure on the right-hand side and the consumers'

willingness to pay (reservation price). This result can be utilized in many situations in the real world, such as the policymakers making policies on the markets with intermediaries to control the prices.

Meanwhile, the non-existence of SPNE indicates that the behavior of intermediaries is not predictable under some market conditions, just like the matching pennies game, where the prices are always fluctuating even if there are no other price-affecting factors. Meanwhile, the same goods in two supermarkets with some distance between them are always having different fluctuating prices, because they always have exclusive consumers and valuable non-exclusive consumers.

Referring back to the example in Section 1.1, in the first case under SPNE, the non-exclusive consumer 2 is a valuable consumer for both intermediaries, resulting in the non-existence of SPNE. However, in the third case under SPNE with new prices, the non-exclusive consumer 2 is not a valuable consumer for either intermediary (because an intermediary achieves maximal profit on the right-hand side of the network while setting a unit price at \$10 with two exclusive consumers with their reservation prices at \$4 and \$10, respectively), resulting in the existence of SPNE.

Meanwhile, for SPNE, there exists an extreme case in this problem, which is with the assumption that all consumers are having the same willingness to pay (reservation price). Under this condition, we have a corollary to discuss the existence of SPNE.

**Corollary 1** *If all consumers in the market are having the same willingness to pay (reservation price), there exists SPNE* **if and only if** *there does not exist such an intermediary that is connected to both exclusive consumers and non-exclusive consumers.*

The Corollary above indicates that the market is difficult to achieve SPNE facing the situation that all consumers are having same reservation prices. In other words, if a market achieves SPNE, the market tends to have consumers with different reservation prices. Also, intermediaries are more likely to compete with each other in this market environment, since all consumers connected are valuable consumers for all intermediaries.

On the other hand, the specific conditions based on *Lemma 2* on the left-hand side are provided below, which include the conditions on zero entree fees.

**Theorem 3**

***a)*** *Under SPNE, the $R_i^*$ for intermediary $i$ is ZERO if it satisfies* ***ALL*** *of following three conditions:*

- *Intermediary $i$ does not have any exclusive valuable consumer or exclusive producer.*
- *All producers connected to intermediary $i$ can access all consumers connected to intermediary $i$ through other intermediaries.*
- *All intermediaries sharing all or part of consumers connected to intermediary $i$ have no exclusive consumer, either.*

*Under ICO, it is impossible to make any $R_i^*$ for any intermediary $i$ to be zero.*

***b)*** *On the other hand, a producer will make zero profit under ICO, and it will also make zero profit under SPNE if it satisfies* ***ANY*** *of the following three conditions:*

- *It is only connected to one intermediary.*
- *All intermediaries that it is connected to are only having exclusive consumers connected to them.*
- *All intermediaries that it is connected to have their own exclusive producers connected to them.*

The above equilibrium explains why some intermediaries are having positive entree fees, while others are having zero entree fees. Also, because of the differences in the network connections on the left-hand side, there are significant differences in the entree fees charged between online and offline intermediaries. For instance, a hotel can choose and register on all online trip-booking websites at the same time, but a farmer cannot access all supermarkets in the market.

A typical numerical example of Theorem 2 is given here in Figure 3. There are two intermediaries sharing one producer and 2 consumers with complete connections. Suppose the producer can earn \$1 per good sold through intermediaries. Under SPNE, according to Theorem 1, there exists a market equilibrium with both intermediaries' unit prices to converge to \$0, while the fixed entree fee from both intermediaries goes to \$0 as well, since the producer can access the two intermediaries through any of the two intermediaries, which matches the definition of the perfect competition. Therefore, the producer is making a profit of \$2 under SPNE and such network connections. However, under ICO, both intermediaries post a unit price at \$5 to get the maximum joint profit, and both intermediaries will post \$2 as a fixed entree fee as an optimal outcome. Here, the specific outcome should be as follows: the producer randomly chooses ONE intermediary with prices $(p^*, R^*) = (5, 8)$, while another intermediary is not selected to intermediate the good. The total revenue of intermediaries under ICO is \$12, and the producer is not making a profit.

The following Section 4 focuses on the ICO defined in Definition 4 in Section 2.

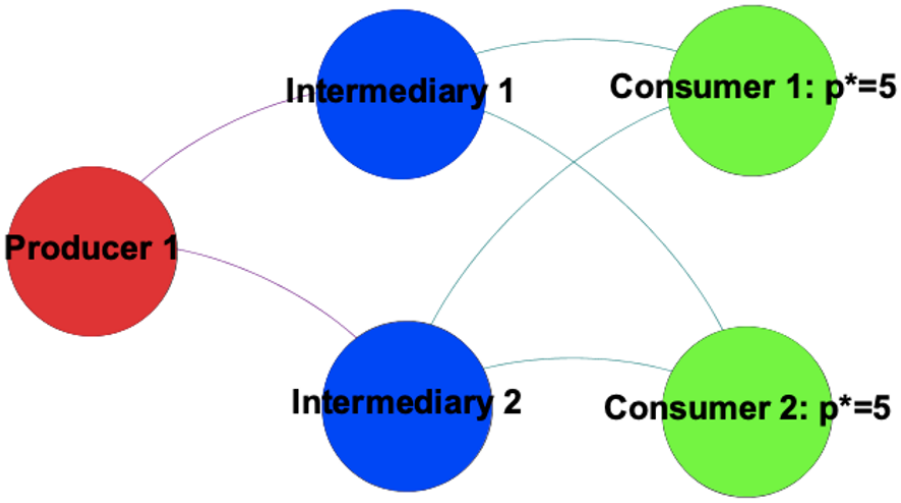



Figure 3.3: An example of the conditions on the fixed entree fees.

## 3.4 Intermediaries Collusion-proof Optimal

In the previous section, the SPNE is a non-cooperative equilibrium, which indicates that cooperation and collusion between intermediaries do not exist. However, the possibility of intermediary collusion always exists. For example, if two intermediaries are combined to be one intermediary, it is equivalent to the situation that they are colluding, and their problem becomes joint optimization of two intermediaries.

Therefore, we exploit the existence of ICO.

**Theorem 4 (The existence of ICO and when it is supported by SPNE.)**

- *In any intermediation game, an ICO always exists.*
- *The ICO is supported by an SPNE if all shared consumers are only valuable to one or fewer intermediaries.*

Therefore, the market with intermediary collusion is more robust and predictable than the completely non-cooperative market. There might be lots of real markets taking these assumptions and achieving ICO through this kind of mechanism. For instance, the Chinese Groupon company "Meituandianping" was formally two separate companies as "Meituan" and "Dianping", while they combined in 2015. Therefore, the goods on both intermediaries are now far more expensive than before, which

is indicated in *Theorem 4*. Section 5 will focus on both SPNE and ICO (with or without money transfer) to provide comparative statics.

## 3.5 Comparative Statics on a Network Expansion

It is often the case that the consumer's connection changes. For instance, in online travel agencies, consumers might become aware of new websites; for discounted resales market, consumers might become aware of different sellers; or for supermarkets, consumers might become aware of a new supermarket nearby. The scenarios have implications both for the consumer who expands their connections but also have externalities for other agents and intermediaries. In this section, we will discuss the changes in market equilibrium when the connection of one consumer expands.

### 3.5.1 The General Case

For the general case, we only discuss the statics under ICO, since the network expansion may destroy the SPNE. Meanwhile, we will discuss the network changes under SPNE in Section 5.2.

In order to formalize this, we denote by $B^i(N)$ the consumers who purchase from intermediary $i$ at the equilibrium of network $N$ at price $p_i(N)$. The following result qualifies the changes on the addition of one link to the network as represented in Figure 3.4.

**Proposition 5** *Under ICO, suppose a consumer $c \in B^x(N)$ notices a new intermediary $y$ and increases his/her connection by connecting to intermediary $y$, i.e. $c \in B^y(N^*)$.*

*i. If $p_y < p_x$*

- *Consumer $c$ is not worse off;*
- *Any consumer $d \in B^x(N)$ is not worse off;*
- *Any consumer $d \in B^y(N)$ is not better off;*
- *The price $p_x$ offered by intermediary $x$ does not increase;*
- *The price $p_y$ offered by intermediary $y$ does not decrease;*
- *Intermediaries are not better off.*

*ii. If $p_y > p_x$*

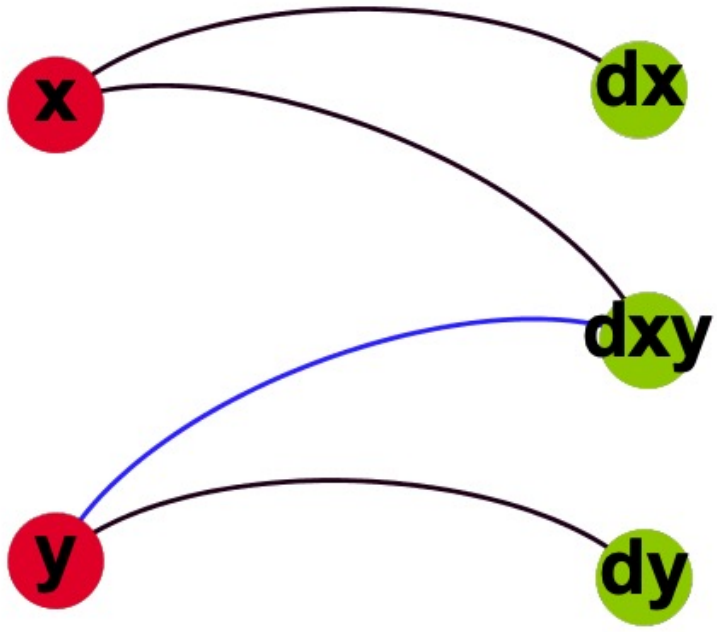



Figure 3.4: At the original network $N$, consumers $d_x$ and $d_{xy}$ are connected to intermediary $x$, and consumer $d_y$ is connected to intermediary $y$. The expanded network $N^*$ consists of $N$ plus the additions of the connection between $d_{xy}$ and $y$.

- *Consumer $c$ is not worse off or better off;*
- *Any consumer $d \in B^x(N)$ is not worse off or better off;*
- *Any consumer $d \in B^y(N)$ is not worse off or better off;*
- *The price $p_x$ offered by intermediary $x$ does not change;*
- *The price $p_y$ offered by intermediary $y$ does not change;*
- *Intermediaries are not worse off or better off.*

The implications at the equilibrium of the addition of a new link depend on whether the changing consumer is now connected to a cheaper or more expensive intermediary. The prices and revenues in the market could not be changed if the changing consumer connects to a more expensive intermediary. However, these implications are clear if the consumer connects to a cheaper intermediary: he will enjoy a lower or same price, while the price of the intermediary previously with a higher

price does not increase. It also positively affects the remaining consumers connected to the intermediary to whom he was previously connected, but it surprisingly harms the remaining consumers connected to the intermediary to whom he was newly connected.

For example, referring to Figure 4, if consumer $d_x$ and $d_{xy}$ have the same reservation prices at \$10, and consumer $d_y$ has a reservation price at \$1, according to ICE, intermediary $x$ and $y$ post their prices at \$10 and \$1 before the change, respectively. While consumer $d_{xy}$ notices the intermediary $y$, according to ICE, intermediary $y$ will raise its price to \$10, aiming at maximizing the total revenue of the two intermediaries. Therefore, consumer $d_y$ is worse off, since he/she cannot buy anything now to avoid negative utility.

What is surprising again is that the extra connections will not help intermediaries, where they will either be worse off or the same as before, even if they are colluding.

### 3.5.2 The market change to the Perfect Competition

Our next result considers both SPNE and ICO for the extreme case while repeating the changes from the above part for maximum times until the market is fully integrated, which evaluates the changing process to a fully integrated market by adding links to the original network under both ICO and SPNE. (shown in Figure 5)

We have a proposition to show the effects of changes.

**Proposition 6** *While new links are added to the network of the market, there will be more and more same prices in the market. While the market is fully integrated, the prices from all intermediaries will converge to be the same. However, the final prices from intermediaries and their processes of changing vary under SPNE or ICO as follows:*

*i. If the market is under SPNE,*

- *All consumers are not worse off;*
- *All intermediaries are not better off;*
- *All producers are not worse off;*
- *In the new equilibrium, all unit prices from all intermediaries converge to 0.*

*ii. If the market is under ICO,*

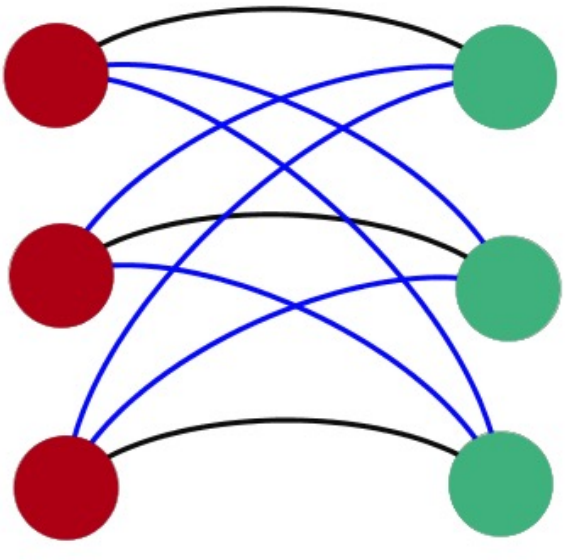


Figure 3.5: At the original network, all consumers are non-overlapping consumers, which only buy goods and services from one intermediary. By repeating the changes in Proposition 2, all consumers are aware of all intermediaries gradually in the process and formulated an expanded network.

- *Consumers previously paying the highest price will not be worse off;*
- *Consumers previously paying the lowest price will not be better off;*
- *Producers are not better off or worse off;*
- *Intermediaries are not better off.*

What is surprising is the fact that while consumers are fully integrated to be non-exclusive consumers, the effect differs significantly between SPNE and ICO. These implications are as follows: while others and he is learning new intermediaries at the same time, he probably will pay a higher price as a result under ICO, but he will pay a zero unit price under SPNE. Meanwhile, same as the results in Section 5.1, extra connections will not help intermediaries under ICO, even if the intermediaries are colluding.

The intermediaries are not better off in the fully integrated markets, since they can no longer perform price discrimination anymore. For instance, referring to Figure 5, suppose that the three consumers have their reservation prices at \$10, \$8, \$2. Before the change, they are non-exclusive consumers, resulting in the unit prices of the three intermediaries being \$10, \$8, \$2, respectively, which are exactly the same as

the reservation prices of the consumers, and the aggregate revenue for intermediaries are \$20. However, while the market is fully integrated after the change, since all consumers are connected to all intermediaries, all intermediaries can only choose the local optimal price of the three consumers, which is \$8, and intermediaries can only have a joint revenue of \$16 under this price. Therefore, intermediaries lose their joint revenue of \$4 under the market change.

### 3.5.3 A change from SPNE to ICO

A special case can be: two independent intermediaries are now owned by one owner. An example of this is shown in the Introduction part, the Chinese Groupon company: Meituandianping. The Meituandianping was previously two independent Groupon companies charging no fixed entree fee. However, they combined to be a kind of monopoly and posted a fixed entree fee of \$1000 per year for every good participating, immediately after the combination. Here, we have a corollary for this kind of change.

**Corollary 2** *While a market changes from competitive conditions (SPNE) to cooperative conditions (ICO) by intermediary collusions or combinations, intermediaries are not worse off, while producers and consumers are not better off.*

The above corollary validates the Axiom in the game theory that cooperation can always achieve better aggregate benefits than competition for a certain role in the market. However, the monopolist is bad for all other roles in the market, which includes consumers and producers. From the point of view of welfare analysis, this kind of condition should be avoided.

## 3.6 Conclusion

This paper investigates how intermediaries choose pricing strategies based on market network structures and consumers' willingness to pay. Based on our works above, we successfully propose the conditions for the existence of non-cooperative equilibria and cooperative equilibria that are more robust. Meanwhile, we discuss the comparative statics under the market change.

However, this paper assumes unlimited production. The production limitations may impact our results. Future work should include the limited production for the existence of non-cooperative equilibria. Making this game a repeated game with dynamic solutions is also a possible way to extend this paper.

# Chapter 4

# Dynamics of Trust and Consumption of COVID-19 Information Implicate a Mechanism for COVID-19 Vaccine and Booster Uptake

## 4.1 Introduction

COVID-19 vaccination provides strong protection against severe consequences of SARS-CoV-2 infection, including hospitalizations and deaths [26, 18]. The United States is one of several vaccine-producing countries where the domestic supply has far exceeded the demand since June 2021 [24]. Vaccine hesitancy (including delay or refusal) continues to undermine COVID-19 mitigation strategies [26, 30] by preventing herd immunity and perpetuating viral spread. To overcome this barrier, significant efforts have been made to promote vaccine uptake. For example, multiple states have provided vaccine incentives, with mixed results of effectiveness [13, 11], while vaccine mandates, focusing initially on essential workers and high-risk businesses, have increased vaccine uptake [42, 45]. However, few studies have captured the nuanced changes in the attitudes and perceptions toward the COVID-19 vaccine during its rollout, and the mechanisms underlying its uptake remain incompletely

[0]Co-authored with Ruben Juarez, Blane K. Garcia, May Okihiro, Krit Phankitnirundorn, Alika K. Maunakea.

understood.

To accelerate population-level coverage of COVID-19 mitigation strategies involving vaccines, understanding the dynamics of vaccine and booster hesitancy is crucial. Although prior population studies demonstrated that vaccine hesitancy is associated with distrust and misinformation [51, 56], none have yet reported whether these factors are directly associated with under-vaccination rates in disproportionately affected populations. Meanwhile, recent studies examining the social and behavioral characteristics of unvaccinated individuals have shown that socioeconomic factors (including education and income) impact willingness to be vaccinated, as do race, religious beliefs, and political preferences [26, 47, 3, 66, 36]. Other studies indicate that people refuse vaccination due to misinformation and inaccurate advertisements, especially on social media [15, 21, 75]. Together, these studies highlight the importance of trust in, and consumption of, accurate information relevant to the COVID-19 vaccine. However, how these factors interact to influence an individual's decision about vaccination is not fully understood. This is particularly important in Hawaii, especially for the severely under-vaccinated Native Hawaiian population, where trust in the government has been historically problematic [43, 44].

To gain insight into such interactions, we collected data from a survey of adults in the state of Hawaii from September to October 2021 over the course of the COVID-19 vaccine rollout. The intake survey was conducted during a significant Delta-driven surge in COVID-19 cases, and a follow-up survey from January to February 2022, during a significant Omicron-driven surge in cases. Notably, the survey-based data collected comprised common data elements as part of the National Institutes of Health (NIH) Rapid Acceleration of Diagnostics in Underserved Populations (RADx-UP) initiative [78]. The participants in our study included a large proportion of Native Hawaiian and other Pacific Islanders, who, as a whole, have been slow to initiate and complete the COVID-19 vaccine series [1]. Herein, we show for the first time the dynamics of vaccine hesitancy, as individuals become eligible for vaccination, identifying key factors that include trust in and consumption of COVID-19-relevant information, with changes in these factors by the participants over approximately four months between study enrollment and follow-up. Despite our focus on Hawaii's population, these results confirm social factors previously implicated in vaccine hesitancy more broadly, which also translates to booster hesitancy, and offer insights into how these factors interact to influence vaccine uptake.

## 4.2 Materials and Methods

Taking advantage of the infrastructure developed in partnership with the NIH RADx-UP initiative at the University of Hawaii, and five federally qualified health centers within the state, we collected data from an online survey (administered via Qualtrics) of 1594 adult Hawaii residents during the COVID-19 testing rollout by the Pacific Alliance Against COVID-19[1] from September to November 2021. These participants were recruited from COVID-19 testing events at community and health centers throughout the state of Hawaii, or other PAAC studies. Fifty percent of these participants (802) completed a follow-up survey from January to February 2022.

The surveys included over 100 questions related to demographics, vaccination status, and attitudes towards vaccination. For this analysis, we considered the time that individuals received the vaccine as a dependent variable, and participants were stratified into three groups based on the time (in months) they initiated the first dose of any of the three FDA-approved COVID-19 vaccines (Pfizer-BioNTech, Moderna, and Johnson & Johnson's Janssen) after eligibility: (1) *early vaccinees*, those vaccinated within two months of eligibility; (2) *late vaccinees*, those vaccinated 3–6 months after eligibility; and (3) *non-vaccinees*, those who refused vaccination 6 or more months after eligibility, or who were only vaccinated due to a mandate by their employer or the government.

Survey questions also included how much participants trusted—and how often they used or consumed—various sources of information. The data were categorized into *official* sources of information, which included government, healthcare providers, and traditional channels of communication, such as TV, radio, and print news; and *unofficial* sources of information, which included social media channels, friends, family, acquaintances, and faith leaders (see the precise definition of these variables in Appendix C..1, Definition 11). Table 4.1 lists the demographic statistics of the data used in our analyses. We examined 17 independent variables, including education level and trust in and consumption of various information sources, as well as 4 aggregated variables, including *the official* trust index, *unofficial* trust index, *official* information consumption index, and *unofficial* information consumption index (see below and also Appendix C..1, Definition 11, on how these indexes were generated). All independent variables were semi-quantified, based on the descriptive rating scale, and normalized between 0 and 1. The *official/unofficial* trust and consumption indexes were computed as the average of trust and consumption within a subset of *official/unofficial* sources.

To identify factors underlying vaccine hesitancy, our regression models were sep-

[1](PAAC, `www.paac.info`, accessed on 21 July 2022)

Table 4.1: Demographic statistics on the survey data, including descriptive statistics showing the count and percentage of participants in each vaccination stage. In addition, the numbers of returning participants in all vaccination stages are shown.

| **Characteristic** | **Early Vaccinee** | **Late Vaccinee** | **Non-Vaccinee** |
|---|---|---|---|
| $\boldsymbol{N = 1594}$ | $\boldsymbol{N = 1150}$ [1] | $\boldsymbol{N = 145}$ [1] | $\boldsymbol{N = 299}$ [1] |
| [2] **Sex *** | | | |
| Female ($N = 1115$) | 810 (73%) | 103 (9%) | 202 (18%) |
| Male ($N = 459$) | 330 (72%) | 42 (9%) | 87 (19%) |
| [2] **Race **** | | | |
| Caucasian ($N = 253$) | 181 (72%) | 17 (7%) | 55 (22%) |
| Native Hawaiian ($N = 598$) | 381 (64%) | 73 (12%) | 144 (24%) |
| Pacific Islander ($N = 56$) | 33 (59%) | 5 (9%) | 18 (32%) |
| Asian ($N = 602$) | 504 (84%) | 40 (7%) | 58 (10%) |
| Other ($N = 84$) | 50 (60%) | 10 (12%) | 24 (29%) |
| Unknown ($N = 1$) | 1 (100%) | 0 (0%) | 0 (0%) |
| [2] **Education **** | | | |
| 6th–12th grade ($N = 25$) | 7 (28%) | 7 (28%) | 11 (44%) |
| High school ($N = 248$) | 125 (51%) | 43 (17%) | 78 (32%) |
| Technical degree ($N = 523$) | 355 (68%) | 61 (12%) | 107 (20%) |
| Bachelor's degree ($N = 435$) | 346 (80%) | 24 (6%) | 65 (15%) |
| Graduate degree ($N = 337$) | 305 (91%) | 7 (2%) | 25 (7%) |
| [2] **Age **** | | | |
| 18 to 39 ($N = 689$) | 418 (61%) | 76 (11%) | 195 (28%) |
| 40 to 59 ($N = 731$) | 574 (79%) | 61 (8%) | 96 (13%) |
| 60 or older ($N = 174$) | 158 (91%) | 8 (5%) | 8 (5%) |
| [2] **Returning Participants **** | | | |
| Number of returning participants (percentage out of each category) | 530 (46%) | 100 (69%) | 161 (54%) |
| Number of participants with booster shots (percentage out of returning participants in each category) | 438 (83%) | 32 (32%) | 0 (0%) |

[1]: $n$ (%). Percentage out of each subgroup, unless other specified. [2]: Pearson's chi-squared test. Statistical significance at * $p < 0.05$, ** $p < 0.01$ are shown.

arated into two parts: (1) breakdown probit regression analysis for the comparison of individuals, based on the categories of *early, late, or non-vaccinees*; and (2) longitudinal analysis of individuals.

Probit regressions were used to estimate the probability that individuals were *early, late, or non-vaccinees*. These probit regression models included two groups compared in each regression. We performed two sets of comparisons: (1) *early vaccinees* versus everyone else, and (2) *late vaccinees* versus *non-vaccinees*. The respective identification models were related as the following Equations (4.1) and (4.2):

$$early_{ic} = \alpha + \beta \times trust_{ic} + X_{ic} + u_{ic}; \tag{4.1}$$

and

$$late_{ic} = \alpha + \beta \times trust_{ic} + X_{ic} + u_{ic}, \tag{4.2}$$

where the variable $early_{ic}$ equals 1 if the participant $i$ is an *early vaccinee* and 0 otherwise; the variable $late_{ic}$ equals 1 if the participant $i$ is a *late vaccinee* and 0 if a *non-vaccinee*. Meanwhile, $X_{ic}$ is a control variable that includes individual-level race, sex, age, education, and the CDC social vulnerabilities of the community where the individual lives (see details at `https://www.atsdr.cdc.gov/placeandhealth/svi/index.html`, accessed on 21 July 2022). The trust variable index, $Trust_{ic}$, is substituted by the consumption variable, $Consume_{ic}$, when estimating the information consumption indexes. The residual term is represented by $u_{ic}$.

The longitudinal analysis focused on the changes between the entry time point and the returning time point. The regression model is as follows; Equation (4.3):

$$Trust_i = \gamma \times second_i + \delta_i + u_i, \tag{4.3}$$

where $Trust_i$ serves as the information trust indexes as dependent variables, which is substituted by the consumption variable, $Consume_i$, when estimating the information consumption indexes; $second_i$ is a dummy variable indicating whether the entry is from the second survey (follow-up survey) or not, and $\delta_i$ is the individual fixed effect. $\gamma$ is the major estimator of the changes between the entries, in the two surveys, for the same participants. Moreover, the difference-in-difference analysis (as shown in Equation (4.4)) compares the changes of these indicators across groups (*early vaccinees* vs. *late vaccinees*) between the two surveys, thus yielding the regression model as follows; Equation (4.4):

$$\begin{aligned} Trust_i = &\gamma_1 \times second_i \times stage_i + \\ &\gamma_2 \times second_i + \gamma_3 \times stage_i + \delta_i + u_i, \end{aligned} \tag{4.4}$$

where $stage_i = 1$ indicates the comparable group, and $stage_i = 0$ indicates the control group. For instance, in the comparison of changes between early and late vaccinees, $stage_i = 1$ if the individual is identified as a late vaccinee. Additionally, $u_i$ serves as the residual term in all equations above.

For our difference-in-difference analysis, the main research question focused on the comparison between early and late vaccinees between the two entries from the two surveys among participants with booster shots. However, in order to strengthen the correlation between the late vaccinees who received the booster shots and changes in the trust and/or consumption of information sources compared to early vaccinees, we performed a parallel trend analysis. A parallel trends analysis, also known as pre-trends, is the replicated work of the whole set of the analysis to the control group (i.e., *early* and *late vaccinees* without booster shots, in this case). This is always used in the identification strategies of difference-in-difference analyses to strengthen the correlation identified in the analysis to the treatment group (i.e., *early* and *late vaccinees* with booster shots, in this case), replicating the exact same analysis to those without booster shots. The stronger correlation was proven by showing the significance in the main analysis but not in the parallel trend analysis.

## 4.3 Results

We tested the hypothesis that education and information in official sources increase vaccine uptake and information in unofficial sources contributes to the refusal and hesitancy toward vaccines. Furthermore, the effects of these variables change across time, being associated with the decisions on booster uptakes. In particular, we sought to identify whether there was a level of trust in official or unofficial sources that associated with individuals who were vaccinated to receive the booster shot.

### 4.3.1 Social Factors That Contribute to the Early Adoption of COVID-19 Vaccines

Social factors that contribute to the early adoption of the COVID-19 vaccines (as soon as individuals become eligible) have yet to be determined. Based on prior reports examining the impacts of education, trust, and consumption of information on individual decision-making [43], we performed a probit regression analysis (Equation (4.1)) using data measuring these social factors collected from individual participants, comparing that of early vaccinees to all others. The results in Figure 4.1 (left side) suggest a significant positive impact of the level of education on early

vaccinees, independent of other factors. Individuals with advanced degrees were 52% [$p < 0.001$, 95% CI = (41%, 62%)] more likely to be early vaccinees, compared to those who lacked education beyond grades 6–12. This value is equivalent to a 5.8% increase in the probability of being an early vaccinee for each year of education past the 12th grade.

In addition to education, we found that trust in (and consumption of) information sources play a role in early vaccine uptake. Results in Figure 4.1 (left side) show the marginal effect (probability increase) of being an early vaccinee for each information source for an individual who increases his/her rating from the lowest rating on the 5-point descriptive rating scale (does not trust at all) to the highest rating (a great deal of trust). We note that for this analysis, the marginal effect shown in Figure 4.1 was performed independently of the other variables. As shown in Figure 4.1 (left side), individuals with a great deal of trust in doctors have a 57% [$p < 0.001$, 95% CI = (44%, 70%)] higher likelihood of being early vaccinees relative to those who do not at all trust in doctors. Similar values are shown in Table 4.1 for the government [37%, $p < 0.001$, 95% CI = (30%, 44%)], the COVID-19 task force [34%, $p < 0.001$, 95% CI = (27%, 40%)] and print and online news [25%, $p < 0.001$, 95% CI = (17%, 32%)].

Meanwhile, trust in unofficial information sources played less of a role than in official information sources for the early adoption of the vaccine. Trust in faith leaders had an 11% decrease [$p < 0.001$; 95% CI = ($-16$%, $-4.7$%)] and trust in other people around had a 7.4% increase [$p = 0.040$; 95% CI = (0.4%, 15%)] in the probability of being an early vaccinee. Trust in family and friends and social media were not associated with the probability of being an early vaccine.

Similar to trust in official information sources, consumption (in all six elements of official sources) was positively associated with the probability of being an early vaccinee. Results in Figure 4.1 (left side) show the marginal effect (probability increase) of being an early vaccinee for each information source for an individual who increased his/her rating from the lowest rating on the 5-point descriptive rating scale (never consumed) to the highest rating (always consumed). Individuals who always consumed information from local governments were 39% more likely [$p < 0.001$; 95% CI = (30%, 47%)] to be early vaccinees than those who never consumed. Similar values are shown in Table 4.1 for other official information sources, including the federal government [32%; $p < 0.001$; 95% CI = (24%, 40%)], the CDC website [23%; $p < 0.001$; 95% CI = (15%, 30%)], TV news [20%; $p < 0.001$; 95% CI = (12%, 28%)], doctors [18%; $p < 0.001$; 95% CI = (10%, 25%)], and print or online news [14%; $p = 0.001$; 95% CI = (5.4%, 22%)]. Consumption of unofficial information sources was not associated with early vaccination uptake.

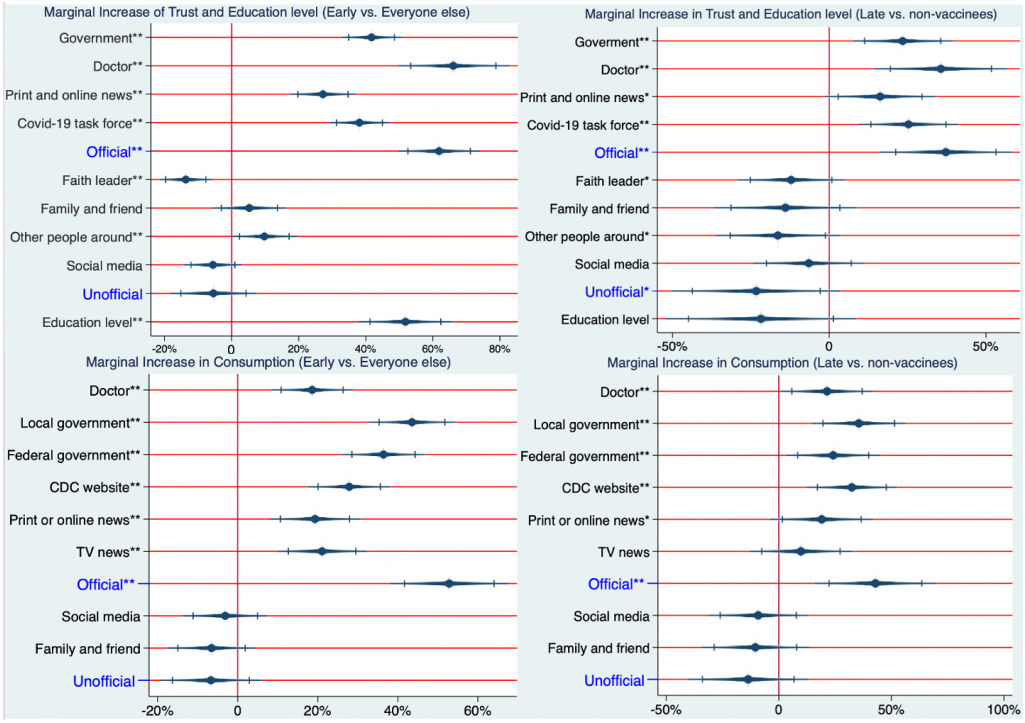



Figure 4.1: Regression results outlying the impacts of education, trust, and consumption variables on vaccination uptake. For this analysis, the impact of each variable is shown independently of the others. The values and the intervals in the graphs indicate the probability increase/decrease of being an early vaccinee or a late vaccinee, based on education, trust, and consumption variables, surrounded by 95% confidence intervals of those probabilities. Statistical significance (at * $p < 0.05$ and ** $p < 0.01$) is shown for each variable on trust in and consumption of various information sources.

Aggregate indexes for trust in and consumption of official and unofficial information sources were created by averaging the scores of the respective official and unofficial sources (see Appendix C..1 Definition 11). Early vaccination was associated with the aggregate indexes of trust and consumption in official information sources. Individuals with a great deal of trust in all official sources of information were 55% [$p < 0.001$; 95% CI = (46%, 65%)] more likely of being early vaccinees, compared to those whose levels of trust were not at all in all official sources. Similarly, individuals who always consumed all official information sources were 46% [$p < 0.001$; 95% CI = (35%, 57%)] more likely to be early vaccinees, compared to those who never consumed any of the official information sources. Meanwhile, the aggregate indexes of trust in and consumption of unofficial information were not associated with the probability of being an early vaccinee.

### 4.3.2 Social Factors That Contribute to the Late Adoption of COVID-19 Vaccines

Understanding contributing factors to vaccine uptake after early vaccinees have been vaccinated allows for the development of more targeted strategies for unvaccinated individuals in the middle of a vaccine rollout. Thus, we applied a probit regression analysis (Equation (4.2)), to compare social factors between late vaccinees and non-vaccinees.

Similar to *early vaccinees*, we found that trust in and consumption of information sources played a role in the vaccinations of *late vaccinees*. Results in Figure 4.1 (right side) show the marginal effect (probability increase) of being a *late vaccinee* for each information source measured for an individual who increased his/hers rating from the lowest rating on the 5-point descriptive rating scale (do not trust at all) to the highest rating (a great deal of trust). We note that for this analysis, the marginal effect shown in Figure 4.1 was performed independently of the other variables. As shown in Figure 4.1 (right side), individuals with a great deal of trust in doctors had a 36% [$p < 0.001$; 95% CI = (19%, 53%)] higher likelihood of being late vaccinees relative to those who did not trust at all in doctors. Similar values are shown in Figure 4.1 (right side) for the government [24%; $p < 0.001$; 95% CI = (11%, 36%)], the COVID-19 task force [26%; $p < 0.001$; 95% CI = (14%, 38%)], and print and online news [17%; $p = 0.013$; 95% CI = (3.9%, 31%)]. We note that the results in the comparison between *late vaccinees* and *non-vaccinees* have consistent trends and similar levels of significance to the results in the comparison between *early vaccinees* and others, but with lower coefficients.

Meanwhile, trust in unofficial information sources played less of a role than trust

in official information sources. Trust in faith leaders had a 13% decrease [$p = 0.050$; 95% CI = (−26%, −0.29%)] and trust in other people around had a 18% decrease [$p = 0.017$; 95% CI = (−34%, −3.1%)] in the probability of one being a late vaccinee instead of a non-vaccinee. Trust in family and friends and social media were not associated with the probability of being a late vaccine.

Similar to trust in official information sources, consumption in five of the elements of official sources was positively associated with the probability of being a late vaccinee. Results in Figure 4.1 show the marginal effect (probability increase) of being a late vaccinee for each information source for an individual who increased his/her rating from the lowest rating on the 5-point descriptive rating scale (never consume) to the highest rating (always consume). Individuals who always consumed information from local governments were 34% more likely [$p < 0.001$; 95% CI = (18%, 50%)] to be late vaccinees than those who never consumed. Similar values are shown in Figure 4.1 for other official information sources, including the federal government [24%; $p = 0.003$; 95% CI = (8.1%, 40%)], the CDC website [31%; $p < 0.001$; 95% CI = (15%, 46%)], Doctors [21%; $p = 0.012$; 95% CI = (5%, 37%)], and print or online news [18%; $p = 0.047$; 95% CI = (0.2%, 36%)]. None of the elements related to the consumption of unofficial sources showed significant impacts on late vaccination.

Late vaccination is associated with the aggregate indexes of trust in and consumption of official information sources. Individuals with a great deal of trust in all official sources of information were 39% [$p < 0.001$; 95% CI = (22%, 55%)] more likely to be late vaccinees, compared to those whose levels of trust were not at all in all official sources. Similarly, individuals who always consumed all official information sources were 41% [$p < 0.001$; 95% CI = (20%, 62%)] more likely to be late vaccinees, compared to those who never consumed any of the official information sources. Meanwhile, the aggregate indexes of trust in and consumption of unofficial information were not associated with the probability of being an early vaccinee. Interestingly, the aggregate index of trust in unofficial information was associated with late vaccination, where individuals with a great deal of trust in all unofficial sources of information were 25% [$p < 0.001$; 95% CI = (−46%, −5%)] less likely of being late vaccinee, compared to those whose levels of trust were 'not at all' in all unofficial sources. We note that the aggregate indexes of consumption of unofficial information were not associated with the probability of being a late vaccinee.

Notably, one's level of education did not play a statistically significant role in the late adoption of vaccination, and its coefficient was negative, as shown in Figure 4.1 (right side).

### 4.3.3 Longitudinal Changes in Trust and Consumption of COVID-19 Information That Associate with the Adoption of COVID-19 Vaccine Boosters

How factors that contribute to the COVID-19 vaccine booster uptake relate to the trust and consumption of COVID-19 information has yet to be studied. Based on Equation (4.3), our longitudinal sampling provided insight into how information, trust, and consumption changed for vaccinated individuals who received boosters. Specifically, we observed changes in these metrics over a 6-month period at the individual level and associated these changes with booster uptake. Results from this regression analysis (Equation (4.3)) are shown in Figures 4.2 and 4.3. We observed a significant increase in the level of trust in, and consumption of, official sources of information associated with the COVID-19 vaccine booster shots among late vaccinees [13%; $p = 0.001$; 95% CI = (0.062, 0.205)] and [11%; $p = 0.024$; 95% CI = (0.015, 0.198)], respectively. However, early vaccinees did not significantly change their levels of trust in and consumption of official sources of information [$-0.007$, $p = 0.485$; 95% CI = ($-0.025$, 0.012)] and [$-0.004$, $p = 0.654$; 95% CI = ($-0.021$, 0.013)]. This is likely due to the overall higher levels of trust in and consumption of official sources of information among early vaccinees at entry and prior to their booster eligibility, relative to the levels expressed by late vaccinees.

Stratifying official and unofficial information sources, more nuanced associations between trust in and consumption of various sources of information and booster uptake were observed (Figures 4.2 and 4.3). First, we observed significant increases in trust in three sources of official information (government, doctors, and the COVID-19 task force) associated with COVID-19 vaccine booster shots among late vaccinees [15%; $p = 0.005$; 95% CI = (0.052, 0.025)], [24%; $p < 0.001$; 95% CI = (0.19, 0.29)] and [11%; $p = 0.077$; 95% CI = ($-0.013$, 0.23)], respectively, while trust in print and online news did not reach significance among early vaccinees. Additionally, we observed significant changes, albeit to a smaller degree, of trust in one source of unofficial information (family and friends) associated with COVID-19 vaccine booster shots among early vaccinees [$-3.3$%; $p = 0.035$; 95% CI = ($-0.064$, $-0.002$)], respectively. Furthermore, we observed significant increases in the consumption of only two of the official sources of information (local government and federal government) associated with COVID-19 vaccine booster shots among late vaccinees [24%; $p = 0.003$; 95% CI = (0.091, 0.39)] and [26%; $p = 0.002$; 95% CI = (0.11, 0.41)], respectively. Interestingly, the consumption of information from doctors did not show any significant change, in contrast to the comparison of trust. This may indicate that late vaccinees chose to receive booster shots because of the increased trust in

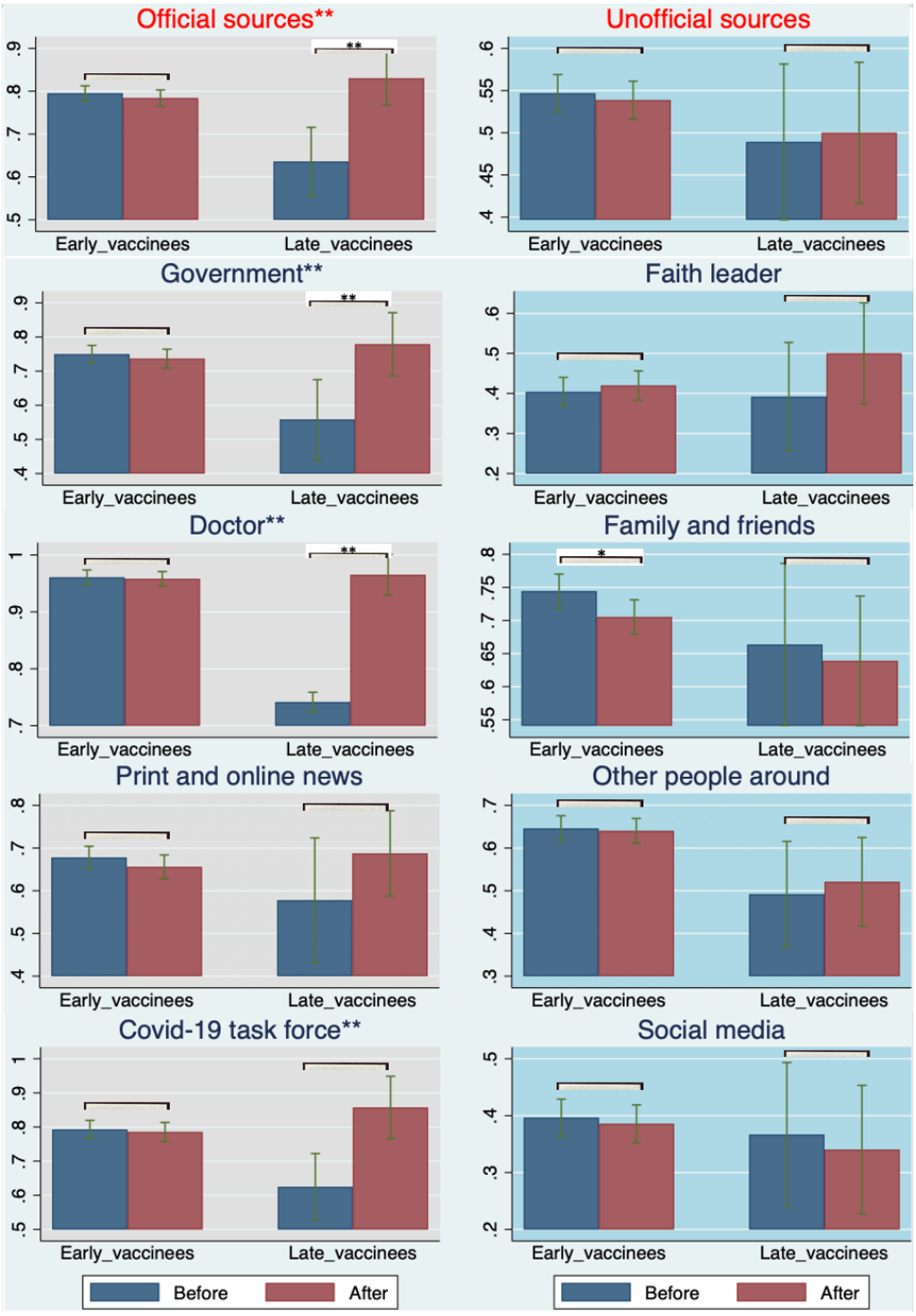



Figure 4.2: For all early and late vaccinees who received their booster shots, the graphs depict the mean values of trust indexes before and after the booster shots. For each group, separate $t$-tests were performed, and $p$-values are reported at the top of each group being compared (gray shadow: official sources; blue shadow: unofficial sources). The star levels on the titles are the comparison between early and late vaccinees on the difference before and after the booster shots. (Statistical significance at * $p$ ¡ 0.05 and ** $p$ ¡ 0.01 are shown.)

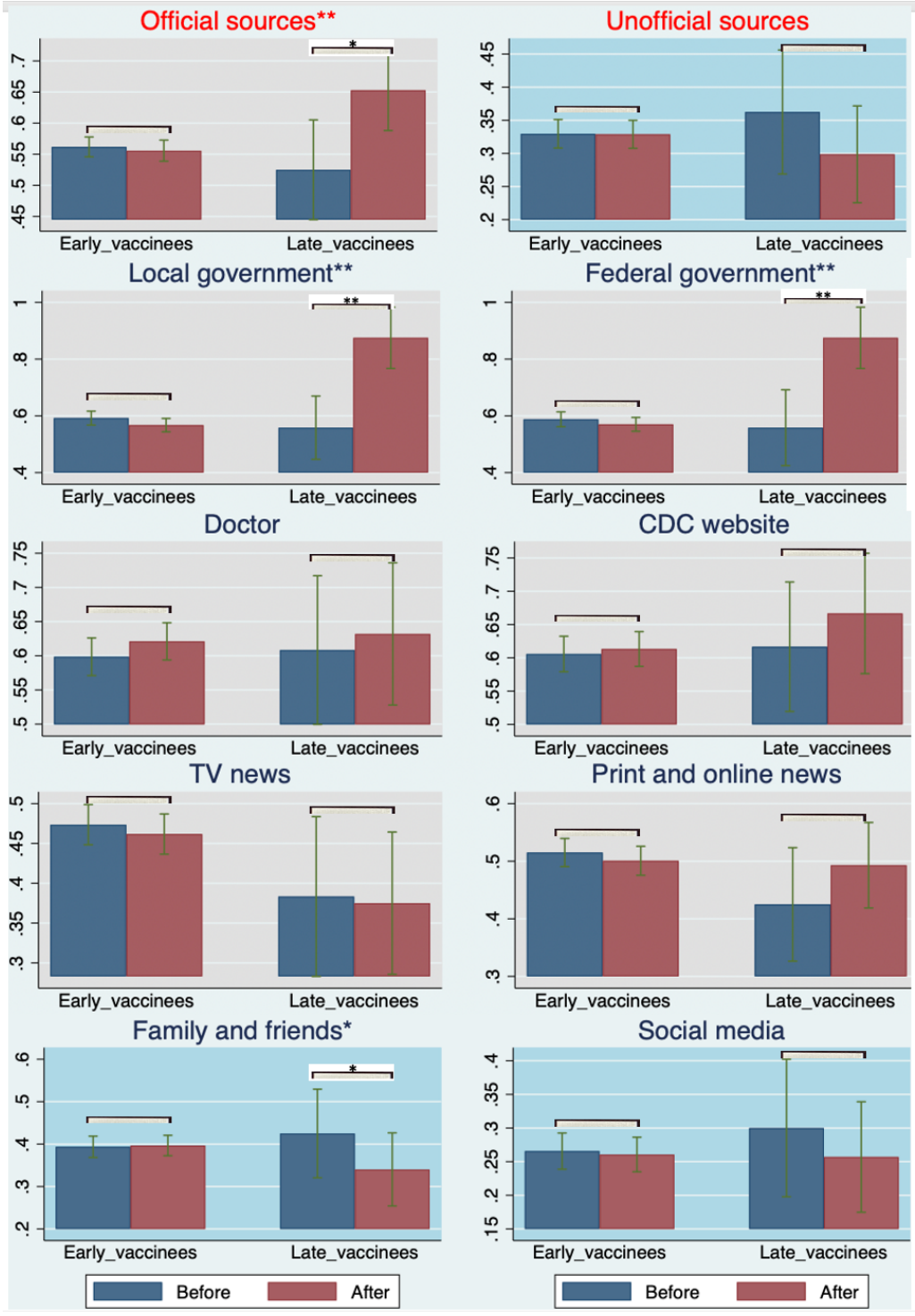



Figure 4.3: For all early and late vaccinees who received their booster shots, the graphs depict the mean values of consumption indexes before and after the booster shots. For each group, separate $t$-tests were performed, and $p$-values are reported at the top of each group being compared (gray shadow: official sources; blue shadow: unofficial sources). The star levels on the titles are the comparison between early and late vaccinees on the difference before and after the booster shots. (Statistical significance at * $p < 0.05$ and ** $p < 0.01$ are shown.)

their doctors, rather than increased consumption of information. Additionally, we observed a significant decrease in the consumption of only one of the sources of unofficial information (family and friends) associated with COVID-19 vaccine booster shots among late vaccinees [$-14\%$; $p = 0.019$; 95% CI = $(-0.26, -0.025)$]. This was in contrast to the comparison of trust in this source of information, which may indicate that late vaccinees received their booster shots because they consumed less information from their families and friends, rather than an increased trust in this source of information.

Finally, based on Equation (4.4) (difference-in-difference analysis), we observed a significantly higher degree of change in trust in and consumption of official information compared from late vaccinees to early vaccinees by [16%; $p < 0.001$; 95% CI = (0.096, 0.217)] and [11%; $p = 0.004$; 95% CI = (0.035, 0.178)], respectively (see Appendix C..4, Table C..3). This result may indicate that late vaccinees were more impacted than early vaccinees by trust in and consumption of official information with respect to booster shots.

To strengthen the correlation and minimize any possible bias, we used a parallel trend analysis based on the same equation of difference-in-difference analysis (Equation (4.4)) for all returning participants without a booster shot under the same regression equations. All early and late vaccinees without booster shots were compared. As shown in Appendix C..5 Table C..5, there were no significant changes in the degree of trust in and consumption of official sources of information among early and late vaccinees without booster shots. Meanwhile, we considered another set of comparisons of the longitudinal changes in their trust in and consumption of official and unofficial information sources between those with booster shots and without. This set of comparisons was done both among early and late vaccinees; no significant differences were observed among early vaccinees, and significant increases were observed among late vaccinees, which was consistent with our analysis above. Collectively, these analyses support the stronger correlation between increased trust in and consumption of official information sources and booster uptake among late vaccinees.

## 4.4 Discussion

Vaccination has been considered one of the most effective long-term public health strategies to mitigate the severe consequences due to COVID-19 [14]. However, vaccine hesitancy remains a considerable barrier to this strategy. Therefore, identifying social factors that associate with vaccine hesitancy and how they may change over the time it takes to reach herd immunity has significant public health implications.

Although our findings provide an avenue to design dynamic public health policies that include education, consumption, and trust in COVID-19 information, the content of these policies is time-dependent. Herein, we identified how social factors associated with vaccine hesitancy likely influence decisions regarding vaccine uptake over the course of a recent COVID-19 vaccine rollout.

In the first two months of COVID-19 vaccine eligibility in Hawaii, one's level of education was a significant factor associated with vaccine uptake. However, it was not a significant factor for individuals who waited to vaccinate three or more months after being eligible. Instead, for these individuals, their decisions to vaccinate during this time were significantly associated with trust in and consumption of COVID-19 information. Indeed, trust in and consumption of official sources of COVID-19 information increased the probability of vaccination for individuals who did not vaccinate within three months of eligibility. On the other hand, trust in and consumption of unofficial sources of COVID-19 information decreased the probability of vaccinations among these individuals. Prior research has demonstrated that trust in official information sources impacted vaccination hesitancy and refusal, even before vaccine development [65], noting psychological differences between those accepting, hesitating, and refusing future vaccinations. Trust in official sources has also been shown to be an important factor for vaccine uptake [43, 73].

The negative relationship between trust in unofficial sources and vaccine uptake might indicate that such sources actively discourage vaccination and potentially include factors such as the spread of misinformation (previously implicated in contributing to reduced vaccine uptake) [56, 15, 68]. Our results suggest that to increase the vaccinations of non-vaccinees, governments and official sources of information should complement their campaigns by appealing to unofficial information providers, including community members, faith leaders, and social media influencers.

Our findings are also relevant to COVID-19 booster hesitancy. *Early vaccinees*, already having high levels of trust in official sources, maintained their levels of trust and were boosted at high rates (70.3%). *Late vaccinees* who were boosted increased their information trust to levels similar to *early vaccinees*. In comparison, trust levels of *late vaccinees* who eschewed boosting remained similar to levels at study entry, suggesting a "threshold" of trust that must be reached for accepting follow-up boosters. Consequently, COVID-19 mitigation policies should incorporate interventions that foster trust in official sources of COVID-19 information, and promote health literacy at the early and late stages of the booster rollout.

This study has several limitations. Our survey was a convenience sample within the state of Hawaii that included all major ethnic groups and similar age distributions as the state of Hawaii. The sample collected was biased towards females and

individuals with higher education levels, and adjustments were not made to match the state population. In addition, the survey may not necessarily represent the populations of other states (or the nation as a whole). Indeed, our survey collected statewide information from Hawaii, a multicultural state rich with predominantly Asian, White, Native Hawaiian, and Pacific Islander races, yet lacking significant representation from other races, including Blacks, Hispanics, and Native Americans. To minimize this limitation, we note that our robustness check (see Appendix C..2 Table C..1) showed that race was not a significant contributor in our analyses, even while this relationship is considered well established [81, 54]. Another study limitation is that our model does not account for other factors, such as income, household size, the pace of vaccine development, job type/sector, risk of COVID-19 exposures, pre-existing medical conditions, and political preferences, which all may influence vaccine uptake [71, 57, 70]. To minimize this limitation, we controlled for other demographic variables, including race, sex, age, and education, as well as the Social Vulnerability Index (SVI) of where individuals live, which uses census data to identify and map places where a community may have more difficulty preventing human suffering and financial loss in a disaster [76]. Notably, the SVI is negatively associated with vaccine uptake in a large nationwide study [37], and we similarly found such a correlation in our data from Hawaii. However, when accounting for education level, and consumption of and trust in COVID-19 information, we found that the SVI is no longer associated with vaccine uptake.

Another limitation is our broad interpretation of official vs. unofficial sources of information. For example, while news outlets were considered official, we note that political leanings of specific news networks likely influenced COVID-19 information, while even government recommendations, at times, lacked consistency. By contrast, sources deemed unofficial could disseminate quite accurate information, depending on their own knowledge gatherings. While corrections for these confounders would likely be infeasible, the results provide insight into how and where people obtain their health information and their health promotion behaviors. As such, the data informs us about the following steps, the need to understand how people develop trust, or mistrust, in public information dissemination, and strategies to effectively promote accurate health information and COVID-19 mitigation measures.

Vaccines have the potential to decrease the adverse effects of COVID-19, with significant benefits for all. However, these benefits are only possible in a population where the vaccine is widely used. Results of this study offer insight into the nuances of vaccine hesitancy, which suggest how relevant interventions may be tailored to increase vaccine and booster uptakes.

# Chapter 5

# Summary and Directions for Future Research

## 5.1 Summary

Incentives commonly appear in various situations in daily life, directly or indirectly. They are studied in game theory, in the scopes of economics, management science and marketing science, and have a wide range of applications motivating people or parties in various directions, such as motivating workers to reach higher job performances in labor markets, motivating students to reach higher grades in educational institutions, motivating buyers and consumers to buy from or start a relationship with sellers in sales markets, motivating citizens to get vaccinated against pandemics, etc. All of these researches rest on the assumption that providing incentives and manipulating the number of incentives can help influence decisions and future outcomes. To explore the power of incentives, one of the ways is to study the Nash Equilibria and stable outcomes under the impacts of these incentives, which describes how incentive proposers, incentive recipients and social planners predict the market outcomes and take moves. Therefore, the existing unique Nash Equilibrium in the market can offer the best prediction power to the market, which benefits everyone in the game. However, there might be various conditions leading to the non-existence of Nash Equilibrium or multiple Nash Equilibria, confusing the players of the game and social planners.

The organizing theme of this dissertation regards the existence and uniqueness of Nash Equilibria: When and what can break the existence or uniqueness of Nash Equilibria? The answer depends on how the incentive network is formed, and what are the values of key parameters. These questions are explored in network game

settings, associated with comparative statics upon changes after the stable outcomes are met. In the meantime, do the incentives play a role and help motivate people in their actions or decisions? This question is discussed in an application of health officials promoting vaccinations.

Chapter 2 investigates how sellers set incentives in a learnable form of sign-up points to attract buyers in a seller-buyer bipartite network. The research focuses on the existence and uniqueness of SPNE as the major stable outcome of the market. In this chapter, the information about the network structure, including links and weight of connection, is complete information for all sellers. The main factors determining the equilibrium outcomes are network connections, the exogenous expected revenue return of offering incentives, and the heterogeneous transaction cost of buyers accepting an offer. The main theorem shows that the necessary and sufficient condition for the uniqueness of SPNE is that there exists no *critical buyer* in the network, which makes sellers hesitate on the choices of incentives.

This chapter also discusses the comparative statics of SPNE, focusing on the changes in outcomes upon connection or parameter changes. Two extensions are discussed with more assumptions and restrictions than the main model. The findings in this chapter can be applied to many incentive problems in the real world, including the social planners' policy-making problem on regulating incentive markets.

Chapter 3 investigates how intermediaries set consistent prices to buyers in a seller-intermediary-buyer tripartite network. The research focuses on the existence of SPNE as the major stable outcome of the market. In this chapter, the information about the network structure, including links and weight of connection, is complete information for all sellers and intermediaries. The main factors determining the existence of an SPNE are network connections and the heterogeneous maximum acceptable price of buyers. The main theorem shows the necessary and sufficient condition for the existence of SPNE.

This chapter also discusses the comparative statics of SPNE, focusing on the changes in outcomes upon connection or parameter changes. The findings in this chapter can be applied to many sales problems with consistent-pricing intermediaries in the real world, including the social planners' policy-making problem on regulating sales markets.

Chapter 4 investigates the role of various information sources in vaccine-uptake decisions. The research quantifies participants' trust in and consumption of various information sources, to evaluate the impact of them whether participants got the Covid-19 vaccines and if so, the time of getting them. The main results of the chapter reveal the strong positive impact of official information sources in promoting people to get vaccinated, and some negative impact of unofficial information sources

making people hesitate in getting vaccinated. Education plays a role in the early stage of vaccination decisions, but not in the late stage after 2 months of vaccine roll-out.

This chapter also discusses the strong correlations between longitudinal changes in various information sources and the booster uptake among those participants eligible to get a booster shot. The results show a significant increase in the trust in and consumption of official information sources strongly correlated with the booster uptake among those participants getting their first vaccine shot in a late stage (after 2 months of vaccine roll-out). The findings in this chapter can be applied to many health-economic and public health problems, as well as problems in natural incentives, to promote people's decisions.

## 5.2 Further Directions

There are several open questions for future research that thread through the chapters in this dissertation. Chapters 2 and 3 utilize the game theory approach to study the sales network with incentives described in Chapter 1. In particular, Chapter 2 studies the network structures and key parameters that break the uniqueness of SPNE, and it covers extensions on networks with more restrictions and flexibility. Chapter 3 studies the price competition of intermediaries on networks with complete information about network structure, thus it studies the tripartite network structure. One interesting extension for these chapters is to extend the analysis by allowing the network to be more general than the bipartite or tripartite network, such as the stable outcomes when buyers can refer to each other and share their opinions. Another interesting extension for both of these chapters is to consider the endogenous network formation, under which conditions, the sellers and intermediaries could choose which agent to link with and invest in the quality of the connection. Under this scenario, all players in the game, including sellers, intermediaries, and buyers, can choose to remove any connections and promote new connections, which can be seen as the long-run outcome of strategic behaviors. Furthermore, incomplete information, including endogenous probabilistic gain and loss of sellers and intermediaries, is another interesting extension of the two chapters. For instance, if sellers and intermediaries do not know the complete connection patterns of other sellers and intermediaries, they need to make decisions based on probabilities, and multi-objective optimizations or robust optimizations may be needed for these scenarios.

Another interesting development of this model is to extend the network games in these chapters to the case that multiple sellers or intermediaries make strategic decisions in different periods based on the network they build. This could be achieved,

for example, by developing a dynamic game theory model including the decisions about connection and incentives or price to study the network structure in a stable state and dynamic choices in the long run. This is valuable, especially to the model in chapter 1, where continued learning can be assumed by buyers, and sellers can remove the unfavorable buyers (with low revenue returns) in the long run to increase profits. The dynamic game will be not only interesting to characterize the equilibrium of incentive and connection decisions in chapter 2, but also provide another source of incentives for intermediaries in chapter 3 to stabilize and negotiate their prices with other intermediaries for the element of repeated cooperation, which will include the problem of strategy-proof mechanism settings.

Chapter 4 studies the application of natural incentives with vaccines, and how social planners have promoted them, especially through official media and information sources. The result in this chapter shows the important role of various information sources in promoting vaccines and booster shots to control the spread and fatal consequences of Covid-19 in Hawaii. This chapter can be extended to a larger and wider database to study various research questions worldwide in regard to the effect of various information sources on promoting various outcomes. The result of research on these questions will be helpful for the government's management policy interested in information sources and social media. Entrepreneurs can also benefit from these studies in regard to establishing media platforms and finding the right scope.

Finally, with regard to real-world phenomena, incentive problems are not only in games and effect validations but also in mechanism designs on when and whether to offer incentives, which can be widely applied to various scenarios faced by social planners and business owners, such as international trading, social learning, information or knowledge transmission, etc. How will the role of incentives change based on the network structure for the different environments? From the planner's perspective, how to design a mechanism to maximize social welfare, giving players in the game the possibility of strategically posting incentives? What kind of intervention can planners use to reduce systemic risk through regulations or subsidies on incentives? This is a fruitful direction that will enrich the models of incentives described in this dissertation.

As the research on incentive networks is diverse, so are the perspectives and approaches to understanding it. Management scientists prefer to explore how businesses can earn through strategically posting various incentives, while computer scientists study 'what' the incentive network looks like, associated with the corresponding consequences, based on measurements, like degree, centrality, clustering, disclosure, and community, including the observation that the degree distribution of many networks satisfies power law. Economists, on the other hand, look at the problem as a rational

agent's strategic behavior on posting or receiving incentives based on the transaction cost and benefit obtained from the network structure and key parameters and try to understand 'why' rational agents form a network are like this, associated with 'what' social planners should react and control this market to ensure social welfare.

While methodological approaches in economics, especially from game theory and econometric designs, have been used in different chapters in this dissertation, they can be complemented by the approaches of other fields as well. Such approaches, like the ones on multi-objective and probabilistic optimizations brought by management scientists, the computing designs brought by computer scientists, and other-regarding preferences brought by other social scientists, should help make the models and results in this dissertation even more aligned to real-life problems. This should make incentive theory and its applications an even more relevant and active research area for years to come, which will bridge fields and use concepts from different fields beyond economics, management sciences, computer sciences, and social sciences.

# Appendix A.

# Supplemental Information of Chapter 2

## A..1 Formal Definitions of Usage and Learning

### A..1.1 Exogenous: Buyer Usage, Transaction Cost and Seller Revenue

Each buyer $q$ is assumed a usage $\alpha^*_{qb} \geq 0$ in the foreseeable future after choosing a seller $b$ and getting the sign-up bonus from seller $b$. This usage represents buyer $q$'s actual long-term needs of seller $b$'s product or service. Therefore, the usage $\alpha^*_{qb}$ is heterogeneous without any restrictions, differing across each pair of buyers and sellers. The optimal usage $\alpha^*_{qb}$ is chosen by buyer $q$ through the following equation:

$$\alpha^*_{qb} = \arg\max_{\alpha_{qb}}(u(\alpha_{qb}) - c(\alpha_{qb})),$$

where $u(\alpha_{qb}) \geq 0$ denotes for the utility of using the product or service of seller $b$, and $c(\alpha_{qb}) \geq 0$ denotes for the corresponding cost. From there, the long-term value of seller $b$'s product or service $L_{qb} \in R$ for buyer $b$ is defined based on the optimal usage $\alpha^*_{qb}$ as follows:

$$L_{qb} = u(\alpha^*_{qb}) - c(\alpha^*_{qb}).$$

In this model, this long-term value is assumed to be consistent among all sellers

the buyer $q$ chooses, while heterogeneous differing among buyers, i.e. $L_q \in R$. Another key variable of buyers is the transaction cost, where each buyer $q$ is assumed a transaction cost $t_q \geq 0$ of choosing each seller in $S_q$, since it takes time and risk to choose a seller. No restrictions are imposed to $t_q$ as well, which can be heterogeneous (different among buyers). From there, a threshold of acceptance $T_q \in R$ of buyer $q$ can be defined as the subtraction of the transaction cost and the long-term value, i.e.

$$T_q = t_q - L_q,$$

At the same time, seller $b$ gains revenue from consumer $q$'s usage of its product or service, denoted for $\mu_{bq}(\alpha^*_{qb})$. However, this value cannot be easily obtained by sellers. Without loss of reality, due to information inconsistency, sellers usually cannot gain complete information of buyers, under the law of privacy protections. Therefore, all they have are estimations of buyers' usage based on the incomplete information they obtained, as well as the (corresponding) estimated revenue returns, which are assumed to be consistent on all buyers among all sellers in this paper, denoted as $\bar{\mu}$.

In this model, the threshold of acceptance of buyer $q$: $T_q$, and the estimated revenue return of each buyer for sellers: $\bar{\mu}$, are assumed directly as exogenous variables.

### A..1.2 Exogeneous: Learning Decisions of Buyers

Suppose that $\sum i \in [0, \infty)$ denotes for all sign-up bonus points a buyer can see through his/her network connections, and $\lambda \in [1, \infty)$ denotes for the learning level chosen by buyers to learn how to use those points. Assuming buyers pay a variable learning cost $X(\lambda)$, and the value of the sign-up bonus points are given by $V(\sum i, \lambda)$, buyers solve:

$$\lambda^* = \arg\max_{\lambda}(V(\sum i, \lambda) - X(\lambda)), \tag{A..1}$$

with the assumption that both $V$ and $X$ are continuous and second-order differentiable in the domains of $\sum i$ and $\lambda$. Without loss of reality, this value function $V$ is assumed to be strictly increasing in both $\sum i$ and $\lambda$, and the cost function $X$ is assumed to be strictly convex in the domain of $\lambda$, where both the value function and the learning cost are exogenous. Furthermore, if the value function is concave in the learning level, i.e., $\frac{\partial^2 V(\sum i, \lambda)}{\partial \lambda^2} \leq 0$, the optimal learning curve $\lambda^*$ is bounded (cannot go to infinite) and strictly increasing in the sum of all sign-up bonus points

$\sum i$ that a buyer can see through network connections (see details in Lemma A..2.1 in Appendix). Given both the exogenous learning cost of buyers and the exogenous value functions, for ease of calculation in the rest of the paper, the optimal learning curve can be assumed directly associated with (increasing in) $\sum i$, i.e., $\lambda^*(\sum i)$.

For instance, the learning curve of the examples shown in section 3 is derived by the following value function and the learning cost function specially:

$$\begin{cases} V(\sum i, \lambda) = (\sum i) \times \lambda; \\ X(\lambda) = 500 \times (\lambda - 1)^2. \end{cases}$$

By substituting them into Equation A..1 and solving for $\lambda^*$, the optimal learning curve $\lambda^*(i)$ is solved to be linearly increasing in the aggregate sign-up bonus points $\sum i$ that the buyer can potentially get through network connections:

$$\lambda^* = 1 + 0.001 \times (\sum i). \tag{A..2}$$

# A..2 Lemmas and Proofs

## A..2.1 Lemma B1

This Lemma studies the buyer choices on their learning efforts regarding learnable incentives. Suppose that a buyer can see a total of sign-up bonus points of $i \in [0, \infty)$ units, and the learning level he/she chooses is supposed to be $\lambda \in [1, \infty)$, associated with learning cost $X(\lambda)$ to be strictly convex and monotonically increasing in $\lambda$. The value function $V(i, \lambda)$ denotes for the value that a buyer can potentially get from these sign-up bonus points, which is strictly increasing in both $i$ and $\lambda$. If the value function $V(i, \lambda)$ is concave in the learning level $\lambda$, the optimal learning curve $\lambda^*(i)$ is strictly increasing in $i$. (This Lemma studies the sufficient condition only, where the necessary condition conflicts with the reality.) Furthermore, the value of sign-up bonus points under the minimum effort towards learning, i.e., $\lambda = 1$, is assumed to be $i$ itself, and the value under the condition of $i = 0$ is assumed to be 0, regardless of $\lambda$, while the learning cost $X(\lambda)$ is assumed to be 0 under the condition that $\lambda = 1$ i.e.,

$$\begin{cases} V(i, \lambda) = i | \lambda = 1; \\ V(i, \lambda) = 0 | i = 0, \forall \lambda. \\ X(\lambda) = 0 | \lambda = 1. \end{cases}$$

In addition, if the value function and the learning cost are specially assumed to be as follows:

$$\begin{cases} V(i,\lambda) = (i) \times \lambda; \\ X(\lambda) = 500 \times (\lambda - 1)^2, \end{cases}$$

the optimal learning curve can be derived to:

$$\lambda = 1 + 0.001 \times i,$$

**Proof.** Given all these information, as stated in Equation A..1 in the manuscript, the buyer solves:

$$\max_{\lambda}(V(i,\lambda) - X(\lambda)).$$

First, since $V(i,\lambda)$ is concave in the learning level $\lambda$, and $X(\lambda)$ is strictly convex, the subtraction of them can yield to 0 at some positive threshold $\lambda^T$ if $i > 0$, while $X > V$ if $\lambda > \lambda^T$, and $V > X$ if $\lambda < \lambda^T$. Therefore, under $i > 0$ the optimal learning level $\lambda^*$ is between 0 and $\lambda^T$, i.e., $\lambda \in (0, \lambda^T)$. Therefore, the optimal learning curve is bounded upon $i > 0$. Meanwhile, if $i = 0$, since $V = 0$ and $X$ is strictly increasing in $\lambda$, the optimal learning level is 0, i.e., $\lambda^* = 0$, which is still bounded.

Second, since it is bounded, $V$ is concave, and $X$ is strictly convex, the subtraction $V - X$ is concave, where the problem can be solved by the first order derivatives. Deriving down the problem, the problem changes to:

$$\frac{\partial V(i,\lambda)}{\partial \lambda} = \frac{dX}{d\lambda}.$$

Since $X$ is strictly convex, $\frac{dX}{d\lambda}$ is increasing in $\lambda$. Meanwhile, since $V$ is concave in $\lambda$, $\frac{\partial V(i,\lambda)}{\partial \lambda}$ is not increasing. Therefore, there exists an intersection of the two curves that maximizes the subtraction. Meanwhile, since the value function $V$ is strictly increasing in $i$, the intersection moves up upon the increase of $i$. Given that $\frac{dX}{d\lambda}$ is increasing in $\lambda$, the intersection is also moving right. In other words, the optimal $\lambda^*$ is strictly increasing in $i$.

Third, the example is easy to calculate. Given that:

$$\begin{cases} V(i,\lambda) = (i) \times \lambda; \\ X(\lambda) = 500 \times (\lambda - 1)^2, \end{cases}$$

the FOC can be derived to:

$$i = \frac{\partial V(i,\lambda)}{\partial \lambda} = \frac{dX}{d\lambda} = 1000 \times (\lambda - 1).$$

Solving for the above equation, the optimal learning curve is easily yielded to be:

$$\lambda = 1 + 0.001 \times i.$$

■

## A..2.2 Lemma B2 (Convergence of MAC)

For any set of $N^M$, there exists a unique MAC $i^M$.

**Proof.** Step 1: *The equal sharing rule holds if all sellers' attracting sets are fully integrated.*

Suppose a network with 2 sellers $A$ and $B$ connected with 1 buyer $q$. Assume both $N_A^M$ and $N_B^M$ include buyer $q$. The algorithm for calculating MAC starts with seller $A$ choosing the best response based on $i_B = 0$. i.e. $i_A$ is the solution to the equation as follows:

$$V(\lambda_q(i_A + 0), i_A) = T_q.$$

After seller $A$ making the move, seller $B$ makes the move, where $i_B$ is the solution to the equation as follows:

$$V(\lambda_q(i_B + i_A), i_B) = T_q.$$

Since the learning curve $\lambda_q$ is strictly increasing in both $i_A$ and $i_B$, and the value function strictly increases in the learning level $\lambda_q$ and the sign-up bonus (points) $i_A$ and $i_B$, the MAC results in $i_A = i_B$.

For robustness check, let $\delta$ to be a small number, after the MAC reaches $i_A^M = i_B^M$, if seller $A$ changes to $i'_A = i_A^M - \delta_A$, seller seller $B$ can change to $i'_B = i_B^M + \delta_B$ to attract buyer $q$ again, i.e.

$$V(\lambda_q(i_B^M + \delta_B + i_A^M - \delta_A), i_B^M + \delta_B) = T_q.$$

Given that the learning curve $\lambda_q$ is strictly increasing in both $i_A$ and $i_B$, and the value function strictly increases in the learning level $\lambda_q$ and the sign-up bonus (points) $i_A$ and $i_B$, two results come up: $\delta_B < \delta_A$, and

$$V(\lambda_q(i'_A + i'_B), i'_A) < T_q. \tag{A..3}$$

To attract buyer $q$ again, seller $A$ needs to change to $i''_A$, where

$$|i_A^M - i''_A| < |i_B^M - i'_B|.$$

After seller $A$ choosing $i''_A$, $i'_B$ is higher than the minimum value for seller $B$ to attract buyer $q$, i.e.

$$V(\lambda_q(i''_A + i'_B), i'_B) > T_q.$$

Therefore, the seller $B$ changes down its choice, and so on... Eventually, the outcomes will return to $i^M = (i_A^M, i_B^M)$, where $i_A^M = i_B^M$.

This result can be extended to multiple sellers and buyers, where all buyers can be represented by the buyer with the highest threshold to attract. This equal-sharing rule can also be induced to multiple sellers.

Step 2: *In any two-seller network, for any set of $N^M$, there exists a unique MAC $i^M$.*

Suppose seller $A$ and seller $B$ are attracting some buyers through mixed connections (they both have exclusive buyers and shared buyers in their attracting set $N_A^M$ and $N_B^M$).

Let $E_A$ be the minimum incentive to attract all exclusive buyers in $N_A^M$. $E_A$ can be easily calculated by attracting the exclusive buyer with the highest transaction cost. The same thing is defined as $E_B$ for exclusive buyers in $N_B^M$.

Let $K$ be the minimum incentive to attract all shared buyers in $N_A^M$ ($N_B^M$), based on the equal-sharing rule defined in step 1, where $K$ is calculated by:

$$V(\lambda_q(K + K), K) = T_q,$$

where buyer $q$ is the shared buyer with the highest threshold to attract.

The key point to solve for MAC is depending on which of the minimum incentives is the highest among the 3. There are 2 conditions as follows, yielding different MAC:

1. $\max\{E_A, E_B, K\} = K$: In this case, $i^M = (K, K)$, because they only need to focus on their shared buyers, while under $K$ and $K$, all exclusive buyers are automatically attracted.

2. $\max\{E_A, E_B, K\} = E_A$: In this case, $i_A^M = E_A$, and $i_B^M = \max\{E_B, EK\}$,

where $EK$ is determined by the following equation:

$$V(\lambda_q(EK + E_A), EK) = T_q,$$

where buyer $q$ is the shared buyer with the highest threshold to attract.

(Other possibilities can be induced by symmetry.)

A unique MAC always exists because the above 2 conditions cover all possibilities.

Step 3: *In any 3-seller network, for any set of $N^M$, there exists a unique MAC $i^M$.*

Suppose sellers $A$, $B$, and $C$ are attracting some buyers through mixed connections (all of them have exclusive buyers and shared buyers in their attracting set $N_A^M$, $N_B^M$, and $N_C^M$).

Consistent with Step 2, let $E_A$, $E_B$, and $E_C$ be the minimum incentive to attract their exclusive buyers. Let $K_{AB}$, $K_{AC}$, $K_{BC}$ and $K_{ABC}$ be the minimum incentive to attract shared buyers between $AB$, $AC$, $BC$ and among $ABC$, based on the equal-sharing rule. For instance, $K_{AB}$ is defined by:

$$V(\lambda_q(K_{AB} + K_{AB}), K_{AB}) = T_q,$$

where buyer $q$ is the partially shared buyer between sellers $A$ and $B$ with the highest threshold to attract, and $K_{ABC}$ is defined by:

$$V(\lambda_q(K_{ABC} + K_{ABC} + K_{ABC}), K_{ABC}) = T_q,$$

where buyer $q$ is the fully shared buyer with the highest threshold to attract.

The way of solving MAC in the 3-seller network is similar to the algorithm in Step 2. The key point to solve for MAC is depending on which of the minimum incentives is the highest among the 7. There are 3 conditions as follows, yielding different MAC:

1. $\max\{E_A, E_B, E_C, K_{AB}, K_{AC}, K_{BC}, K_{ABC}\} = K_{ABC}$: In this case,

$$i^M = (K_{ABC}, K_{ABC}, K_{ABC}),$$

because they only need to focus on their fully shared buyers, while under $(K_{ABC}, K_{ABC}, K_{ABC})$, all exclusive buyers and partially shared buyers are automatically attracted.

2. $\max\{E_A, E_B, E_C, K_{AB}, K_{AC}, K_{BC}, K_{ABC}\} = K_{AB}$: In this case, $i_A^M = i_B^M = K_{AB}$, $i_C^M = \max\{E_C, EK_{AC}, EK_{BC}, EK_{ABC}\}$, where $EK_{AC}$ is determined by the following equation:

$$V(\lambda_q(EK_{AC} + K_{AB}), EK_{AC}) = T_q,$$

where buyer $q$ is the partially shared buyer between seller $A$ and $C$ with the highest threshold to attract.

$EK_{ABC}$ is determined by the following equation:

$$V(\lambda_q(EK_{ABC} + K_{AB} + K_{AB}), EK_{ABC}) = T_q,$$

where buyer $q$ is the fully shared buyer among all sellers with the highest threshold to attract.

3. $\max\{E_A, E_B, E_C, K_{AB}, K_{AC}, K_{BC}, K_{ABC}\} = E_A$: In this case, $i_A^M = E_A$, while $i_B^M$ and $i_C^M$ need a new round of comparison to determine.

Given $i_A^M = E_A$, let $K_{AB}|E_A$, $K_{AC}|E_A$ and $K_{ABC}|E_A$ be the updated minimum incentive to attract buyers in set $AB$, $AC$ and $ABC$, where $K_{AB}|E_A$ is calculated by:

$$V(\lambda_q(E_A + K_{AB}|E_A), K_{AB}|E_A) = T_q,$$

where buyer $q$ is the partially shared buyer between seller $A$ and $B$ with the highest threshold to attract, and $K_{ABC}|E_A$ is calculated based on equal-sharing rule:

$$V(\lambda_q(E_A + K_{ABC}|E_A + K_{ABC}|E_A), K_{ABC}|E_A) = T_q,$$

where buyer $q$ is the fully shared buyer among all sellers with the highest threshold to attract.

Given the above definitions, there are 3 conditions as follows. yielding different MAC:

3.1. $\max\{E_B, E_C, K_{BC}, K_{AB}|E_A, K_{AC}|E_A, K_{ABC}|E_A\} = K_{ABC}|E_A$: In this case,

$$i^M = (E_A, K_{ABC}|E_A, K_{ABC}|E_A),$$

because sellers $B$ and $C$ only need to focus on the fully shared buyers, where all exclusive buyers and partially shared buyers are automatically attracted.

3.2. $\max\{E_B, E_C, K_{BC}, K_{AB}|E_A, K_{AC}|E_A, K_{ABC}|E_A\} = K_{BC}$: In this case,

$$i^M = (E_A, K_{BC}, K_{BC}),$$

because sellers $B$ and $C$ only need to focus on the partially shared buyers between sellers $B$ and $C$, where all other buyers are automatically attracted.

3.3. $\max\{E_B, E_C, K_{BC}, K_{AB}|E_A, K_{AC}|E_A, K_{ABC}|E_A\} = E_B$ or $K_{AB}|E_A$: In this case, $i_B^M = E_B$ or $K_{AB}|E_A$. After determining $i_B^M$, $i_C^M$ can be determined by replicating the process described in condition 2.

(Other possibilities can be induced by symmetry.)

Given the above 3 conditions covering all possibilities, a unique MAC always exists.

Step 4: *Inductions and Algorithms on calculating MAC ensuring a unique MAC for each $N^M$ in any network.*

Algorithm: A unique MAC can be calculated in steps as follows:

**1**. Group all buyers based on their connections;

**2**. Find the buyer with the highest threshold to attract in each group.

**3**. Calculate the minimum incentive to attract all buyers for each group. (Directly toward exclusive buyers. Equal-sharing toward shared buyers.)

**4**. Find the maximum value and the corresponding buyer group among the above minimum incentives.

**5**. Assign the value found in **4** to all connected sellers of that group of buyers.

**6**. If there are still $i_b^M$ yet to determine for some seller $b$, repeat from **2** conditional on those determined values. If not, then every seller $b$ is assigned a $i_b^M$, done.

proof: First, sellers assigned values in **5** of the first loop reached their minimum attracting incentives, because they could not find a lower choice to attract the group of buyers found in **4** of the first loop. Second, sellers assigned values in **5** of the second loop reached their minimum attracting incentives, where given the choices set in the first loop, they could not find a lower choice to attract the group of buyers found in **4** of the second loop. Starting from here, all sellers reached their minimum attracting incentives in the last loop. Therefore, in the coalition with a MAC, the MAC can also be calculated when a new seller is added to the network, starting from re-grouping those buyers based on the new seller, where this algorithm ensures a MAC $i^M$ for each $N^M$ chosen.

In the meantime, the MAC calculated in this way is the unique MAC for the $N^M$. Starting from the first loop of the algorithm, the seller(s) assigned values in **5** have only one choice, regardless of other sellers' choices. This can be proved by contradiction. Suppose that a seller $b$ has another choice $i'_b$ other than $i_b^M$ calculated in **5**, conditional on any choices of other sellers:

- $i'_b < i_b^M$: These sellers need to attract the group of buyers identified in **4**, and all other sellers are not connected to the group of buyers identified in **4**. Therefore, other sellers' choices do not affect the decision on attracting the group of buyers. Given that $i'_b < i_b^M$, other sellers sharing the group of buyers have to post a higher incentive to attract them. According to Step 1, seller $b$ cannot attract the group of buyers under this, which contradicts the $N_b^M$. Therefore, $i'_b$ does not exist.

- $i'_b > i_b^M$: Similar to the proof above, only the buyers identified in **5** need to

attract the group of buyers identified in **4**. Given that $i'_b < i_b^M$, other sellers sharing the group of buyers can post a lower incentive to attract them. According to Step 1, $i'_b$ is not the minimum incentive for the seller $b$ to attract the group of buyers, which contradicts the definition of MAC. Therefore, $i'_b$ does not exist.

Given that the sellers assigned values in **5** in the first loop have only one choice, similar inductions can be made to sellers in all loops. Therefore, all sellers have only one choice, indicating a unique MAC.

■

### A..2.3 Proof of Theorem 1

**Proof.**

Iterated MAC and SPNE.

According to Definition 2, the seller $b$'s choice reaches SPNE if $\pi_b^*(i_b^*, i_{-b}) \geq \pi_b^*(i_b, i_{-b})$, for any $i_b \neq i_b^*$, based on an optimal selection of the subset of connected buyers $N_b^*$. By deleting all deviable choices that there exists a seller deviating its choice under $i_b^M$, i.e.

$$\pi_b^*(i_b^{BR}|i_{-b}^M) > \pi_b^*(i_b^M|i_{-b}^M).$$

Each seller in all remaining MACs does not deviate from its choice, indicating that $N_b^{M*} = N_b^*$, and an iterated MAC is an SPNE.

The existence of SPNE.

Given the existence and uniqueness of MAC under each set of sellers' buyer-attracting choices $N^M$, the always existence of SPNE is straightforward to prove by the following two steps:

Step 1: *Buyers bring lower costs to sellers to attract, when shared.*

This claim can be proved by an easy example. Suppose a seller $b$ is connected with a buyer $q$. Buyer $q$ is a shared buyer of seller $b$ and some other sellers, but all other sellers have a preset incentive choice of 0. To attract buyer $q$, seller $b$ needs to post $E$ as a minimum attracting choice, such that:

$$V(\lambda_q(E), E) = T_q.$$

Suppose another seller $-b$ sharing the buyer changes its choice to $\delta > 0$. The new minimum choice of the seller $b$ to attract buyer $q$ can be calculated to $EK|\delta$, such that:

$$V(\lambda_q(EK|\delta+\delta), EK|\delta) = T_q.$$

Here, the interesting point is whether buyer $q$ brings a lower cost to seller $b$. The cost before the change is:

$$C_{bq} = C(\lambda_q(E), E),$$

and the cost after the change is:

$$C'_{bq} = C(\lambda_q(EK|\delta+\delta), EK|\delta),$$

conditional on the equation:

$$V(\lambda_q(E), E) = V(\lambda_q(EK|\delta+\delta), EK|\delta) = T_q. \tag{A..4}$$

Given that $V(\lambda_q, i_b) > C(\lambda_q, i_b)$ and $\frac{\partial V(\lambda_q, i_b)}{\partial i_b} > \frac{\partial C(\lambda_q, i_b)}{\partial i_b}$ for all $\lambda_q > 0$ and $i_b > 0$ (assumed in the third paragraph of Section 2), we have:

$$V(\lambda_q(EK|\delta+\delta), EK|\delta) - C(\lambda_q(EK|\delta+\delta) > V(\lambda_q(E), E) - C(\lambda_q(E), E). \tag{A..5}$$

Substituting Equation A..4 to A..5, we have:

$$C(\lambda_q(EK|\delta+\delta), EK|\delta) < C(\lambda_q(E), E), \tag{A..6}$$

which is $C'_{bq} < C_{bq}$. Therefore, buyer $q$ has a lower cost on seller $b$ to attract, if some other connected sellers post a positive incentive to increase the learning level of buyer $q$. In other words, if seller $b$ decided not to attract buyer $q$ before, and some sellers sharing buyer $q$ DECREASE their choices, seller $b$ will never deviate to attract buyer $q$, due to a higher marginal cost. Therefore, an algorithm is introduced in the next step to prove the convergence of SPNE.

Step 2: An iterated MAC can always be converged (with the algorithm to claim).

Algorithm:

**1**. Filter out all impossible MACs as defined in Equation 2.2.

**2**. Set the MAC coalition to be all buyers in the network, i.e. $N_b^M = N_b$. Check if any seller satisfies Equation 2.3. If not, the MAC of $N_b$ is the SPNE. If yes, move to **3**.

**3**. Similar to the algorithm in the proof of Lemma A..1.2, group all buyers based on their connections, and calculate the minimum incentive to attract each buyer. (exclusive or equal-sharing)

**4**. Find out all sellers satisfying Equation 2.3, and identify the buyer with the highest minimum incentive to attract.

**5**. Delete the buyer from their $N_b^M$. Note: If the buyer is included in multiple sellers' $N_b^M$ that satisfies Equation 2.3, delete from all these sellers' $N_b^M$. However, if the buyer is also included in the sellers that do not satisfy Equation 2.3, do not delete the buyer from their $N_b^M$.

**6**. Get the new MAC with the change in **5**. Check if any seller satisfies Equation 2.3. If not, the MAC of $N_b$ is the SPNE. If yes, loop to **3**.

Proof:

To ensure the algorithm works, the key point is: *no seller can be better off from the MAC in **2** by adding a buyer into the coalition* in any loop of the algorithm, so that the coalition constantly deletes buyers without adding, and the SPNE will eventually converge.

To clarify that, let a seller $b$ be a seller identified in **4** and deleted a buyer from its coalition in **5** in a loop. Let $i_b^M$ be the incentive of the MAC in **2**, and $i_b'^M$ be the incentive of the MAC in **6**. According to **5**, the deleted buyer has the largest threshold to attract in the seller $b$'s previous coalition. Therefore, after the buyer is deleted, we have:

$$i_b'^M < i_b^M. \tag{A..7}$$

First, according to the result from Step 1, in the next loop, those sellers, connected with the deleted buyer, but previously did not include them in their coalitions will never add them, since they will pay a higher cost than before to add them, with the lower incentives of other buyers.

Second, in the new MAC, given that $i_b'^M < i_b^M$, those sellers $-b$ sharing other buyers connected with seller $b$ does not decrease their incentives so that they can still attract them. i.e.

$$i_{-b}'^M \geq i_{-b}^M. \tag{A..8}$$

Under this, if seller $b$ deviates back in the next loop to attract the deleted buyer, seller $b$ pays the same cost to attract the deleted buyer, but a higher cost to attract other buyers, because of the higher learning levels. Therefore, seller $b$ will never add the deleted buyer back to its coalition.

To summarize, since all sellers never add the deleted buyer to their coalitions, the SPNE can be converged by the single-direction deletions.

Note that this algorithm can also start from zero coalition and add up buyers, and a different SPNE may be converged.

■

## A..2.4 Proof of Proposition 1

**Proof.**

1. The existence of SO. First, the existence of SO is straightforward, since there does not exist a network structure making SO disappears. Second, only one SO exists in the market, since the SO solves:

$$\{i_b^*\}_{b\in\mathcal{B}} = \arg\max_{\{i_b\}_{b\in\mathcal{B}}} \sum_{b\in\mathcal{B}}\sum_{q\in N_b} (\bar{\mu} - C_b(\lambda_q(\sum_{\mathbf{b}\in S_p} i_{\mathbf{b}}), i_b)) \tag{A..9}$$

$$s.t. T_q \leq V_q(\lambda_q(\mathbf{b}), i_{\mathbf{b}}), \forall q | d_{qb} = 1, \tag{A..10}$$

and only 1 set of solutions can be found in the above maximization.

2. The conditions making an SPNE support SO.

Sufficient condition: Given that for every SPNE, there exist some other solutions leading to a higher aggregate profit, the SO is not equivalent to any SPNE. Therefore, the SO is not supported by an SPNE.

Necessary condition: Suppose that there are 2 SPNE, denoted as $M1$ and $M2$ in the network, wherein SPNE 1, seller $b$ has one more buyer $q$ than in SPNE 2. From the definition of SPNE, we have $i_b^{M1} > i_b^{M2}$ and:

$$\pi_b(i_b^{M1}, i_{-b}^{M1}) > \pi_b(i_b^{M2}, i_{-b}^{M1})$$

and

$$\pi_b(i_b^{M2}, i_{-b}^{M2}) > \pi_b(i_b^{M1}, i_{-b}^{M2}).$$

Easily, the inequality can be proved to hold for all other sellers $-b$, where $i_{-b}^{M1} \leq i_{-b}^{M2}$. From there, an inequality exists in the profit function of other sellers:

$$\pi_{-b}(i_b^{M1}, i_{-b}^{M1}) > \pi_{-b}(i_b^{M1}, i_{-b}^{M2}).$$

Since both attracting buyer $q$ and not attracting buyer $q$ yield SPNE, the following inequality also holds:

$$\pi_{-b}(i_b^{M1}, i_{-b}^{M1}) - \pi_{-b}(i_b^{M2}, i_{-b}^{M2}) > \pi_b(i_b^{M2}, i_{-b}^{M2}) - \pi_b(i_b^{M1}, i_{-b}^{M1}).$$

Re-arranging the above equation, the following inequality appears:

$$\pi_{-b}(i_b^{M1}, i_{-b}^{M1}) + \pi_b(i_b^{M1}, i_{-b}^{M1}) > \pi_{-b}(i_b^{M2}, i_{-b}^{M2}) + \pi_b(i_b^{M2}, i_{-b}^{M2}),$$

indicating that attracting buyer $q$ is more profitable for sellers at the aggregate level. Therefore, if there exists no seller that can contribute to a higher aggregate profit by attracting more buyers in any SPNE, the SO is supported by an SPNE.

■

## A..2.5 Proof of Proposition 2

**Proof.** To consider the aggregate social welfare, it is equivalent to consider the individual pairs, where each pair consists of a seller and a buyer, where the seller offers the buyer a sign-up bonus (points), and the buyer accepts the offer. Given these information, the buyer $q$'s utility can be written as

$$u_{qb} = V(\lambda_q(i_b, i_{-b}|b, -b \in S_q), i_b) - T_q.$$

Meanwhile, the profit of seller $b$ can be written as :

$$\pi_{bq} = \bar{\mu} - C(\lambda_q(i_b, i_{-b}|b, -b \in S_q), i_b). \tag{A..11}$$

Therefore, adding them together yields the following equation:

$$u_{qb} + \pi_{bq} = \bar{\mu} - T_q + V(\lambda_q(i_b, i_{-b}|b, -b \in S_q), i_b) - C(\lambda_q(i_b, i_{-b}|b, -b \in S_q), i_b),$$

where $\bar{\mu}$ and $T_q$ are just constant numbers, which can be ignored while calculating the impact from $i_b$. Meanwhile, since the contents in the parentheses of value function $V_{qb}$ and cost function $C_{bq}$ are consistent, they can be simplified as $V(i_b, i_{-b})$ and $C(i_b, i_{-b})$, and the social welfare changes to $V(i_b, i_{-b}) - C(i_b, i_{-b})$. Per assumptions in the model in section 3, where $V(\lambda_i(i), i)$ is strictly higher than and first-order dominates $C(\lambda_i(i), i)$, this welfare is strictly increasing in $i_b$, given $i_{-b}$ remains changed.

This result iS for every $b \in \mathcal{B}$, and therefore, any increase in any $i_b$ strictly yields higher social welfare, and it does not have a maximum value. ■

### A..2.6 Proof of Proposition 3

**Proof.** The comparative statics on aggregate variables are straightforward to calculate, where the aggregate profit of sellers can be written as:

$$\Pi_B = \sum_{b \in \mathcal{B}} (\sum_{q \in N_b} (\bar{\mu} - C(\lambda_q (\sum_{\mathbf{b} \in S_q} i_{\mathbf{b}}), i_b))),$$

which can yield the (strict) always increasing in the estimated revenue return from buyers $\bar{\mu}$, since the function already covers all connections in the network.

Similarly, the aggregate utility of buyers can be written as:

$$U_Q = \sum_{q \in \mathcal{Q}} \sum_{b \in S_q} (d_{qb} \times (V(\lambda_q (\sum_{\mathbf{b} \in S_q} i_{\mathbf{b}}), i_b) - T_q)),$$

which is strictly increasing in the choices of sign-up bonuses (points) $i_b$ from sellers and the decision variable $d_{qb}$ from buyers. Therefore, if sellers do not modify their connections, the aggregate buyer utility remains the same, while if at least one seller decides to add at least one connection, the aggregate buyer utility increases. Consequently, the aggregate buyer utility in not decrease upon the increase in $\bar{\mu}$.

Based on the calculations of the aggregate profit of sellers and the aggregate utility of buyers, since the social welfare is calculated by adding up those two variables, i.e.,

$$W = \Pi_B + U_Q,$$

the social welfare strictly increases upon the increase on in the estimated revenue return from buyers $\bar{\mu}$, as an aggregation of an increasing component and a non-decreasing component.

The comparative statics on individual variables are more complicated, since they are actively impacted by network structures, where they cannot be compared by just taking derivatives. However, these points can be proved via examples, especially those seemingly counter facts.

Assume a network structure as Figure A..1, where the learning curve, the cost

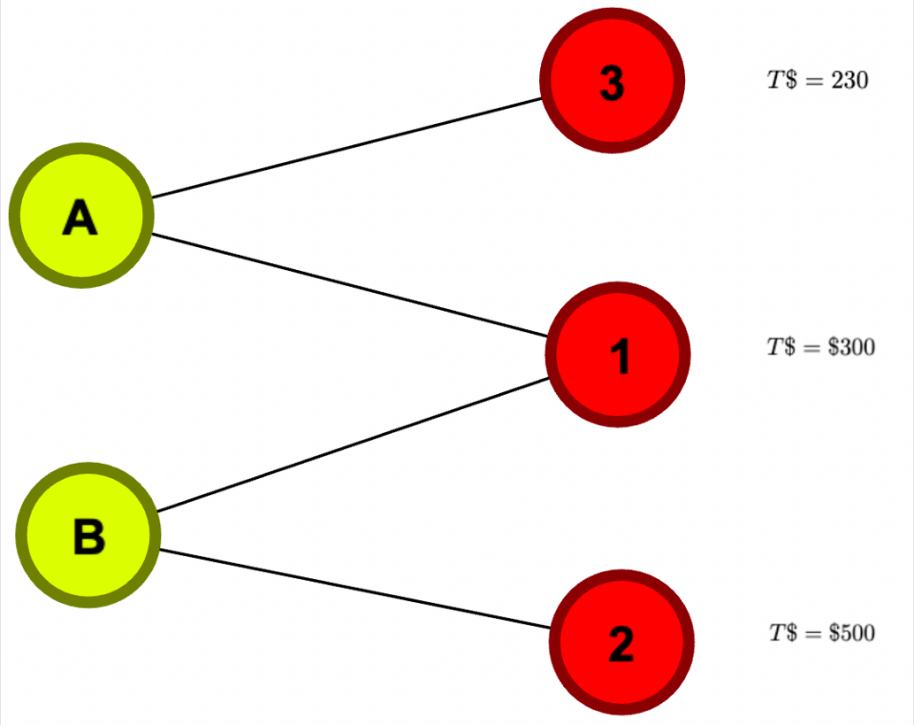



Figure A..1: A special network with both exclusive and non-exclusive buyers. Given the network structure and the transaction cost of buyers, everything could happen to this network upon changes in $\bar{\mu}$. (The learning curve, the cost function, and the value function are assumed to be consistent with the example in section 2.2.)

function, and the value function are assumed to be consistent with the example in section 2.2. Keeping the expected revenue gain from each buyer still to be $\mu = \$1000$, to simplify the proof, the example is shown by modifying the estimated return from buyers $\bar{\mu}$. Certainly, the proposition can also be proved by moving $\bar{\mu}$, or moving the two variables together.

**Condition 1**

Assume that the $\bar{\mu}$ changes from 800 to 810. Simply replicating the calculations in section 2.2, it is straightforward to get the only SPNE at $(i_A^*, i_B^*) = (193, 366)$, where all buyers are attracted through network connections by seller $A$ and $B$, whenever $\bar{\mu}$ locates at 800 or 810. Therefore, since the equilibrium choices of sign-up bonuses (points) remain the same, the utility of each buyer in the network remains the same, while all sellers are better off from a higher $\bar{\mu}$.

**Condition 2**

Assume that the $\bar{\mu}$ changes from 630.9 to 1000. This is a little tougher than the previous one. To attract buyer 2, the MAC are located at $(i_A^*, i_B^*) = (193, 366)$, while the profit of seller $B$ is:

$$\begin{aligned}\pi_B &= ((630.9 - 366 * \sqrt{(1 + 0.001 * 366)}) \\ &\quad + (630.9 - 366 * \sqrt{(1 + 0.001 * (366 + 193))}) \\ &= 377.05.\end{aligned}$$

Meanwhile, given that $i_A^* = 193$, if seller $B$ decides to ignore the buyer 2, the new optimal sign-up bonus (points) set by seller $B$ deviates to $i_b' = 214$, which can be calculated by solving:

$$V_1 = i_b' * (1 + (i_b' + 193)) = 300 = T_1.$$

At $i_b' = 214$, the profit of seller $B$ can be calculated as:

$$\begin{aligned}\pi_B' &= ((630.9 - 214 * \sqrt{(1 + 0.001 * (214 + 193))}) \\ &= 377.06 > 377.05.\end{aligned}$$

Therefore, at MAC $(i_A^*, i_B^*) = (193, 366)$, $i_B$ deviates down, hence not an SPNE (buyers 2 is definitely not attracted under $\bar{\mu} = 630.9$, and the only SPNE is $(i_A^*, i_B^*) = (211, 211)$, where the profit of seller $B$ is:

$$\begin{aligned}\pi_B' &= ((630.9 - 211 * \sqrt{(1 + 0.001 * (211 + 211))}) \\ &= 379.29.\end{aligned}$$

(buyer 1 is valuable to seller $A$, based on the replications of the above calculations)

Nevertheless, under $\bar{\mu} = 1000$, by replicating the above calculations, an SPNE is achieved while buyer 2 is attracted, based on a higher profit with attracting buyer 2. However, under the MAC upon seller $B$ not attracting buyer 2, i.e., $(i_A^*, i_B^*) = (211, 211)$, the profit of seller $B$ is:

$$\begin{aligned}\pi'_B &= ((1000 - 211 * \sqrt{(1 + 0.001 * (211 + 211))}) \\ &= 748.39.\end{aligned}$$

However, seller $B$ can deviate its choice up to $i'_B = 366$ to get a higher profit by considering buyer 2 back, where the profit of seller $B$ is:

$$\begin{aligned}\pi_B &= ((1000 - 366 * \sqrt{(1 + 0.001 * 366)}) \\ &\quad + (1000 - 366 * \sqrt{(1 + 0.001 * (366 + 211))}) \\ &= 1112.62 > 748.39.\end{aligned}$$

Therefore, the buyer 2 does not deviate.

By calculations above, in the movement of $\bar{\mu}$ from 630.9 to 1000, an SPNE change occurs from $(i^*_A, i^*_B) = (211, 211)$ to $(i^*_A, i^*_B) = (193, 366)$. Therefore, under this SPNE change, both sellers are better off; both buyer 1 and 2 are better off, while buyer 3 is worse off with a lower value of the sign-up bonus (points) due to limited connections.

**Condition 3**

Can sellers be worse off? Suppose that the $\bar{\mu}$ changes from 630.9 to 631. The calculations already show that the only SPNE under $\bar{\mu} = 630.9$ is $(i^*_A, i^*_B) = (211, 211)$. Under MAC $(i^*_A, i^*_B) = (211, 211)$ while seller $B$ does not attract buyer 2, the profit of seller $B$ is:

$$\begin{aligned}\pi'_B &= (630.9 - 211 * \sqrt{(1 + 0.001 * (211 + 211))}) \\ &= 379.39;\end{aligned}$$

where if the seller $B$ wants to deviate back to reconsider buyer 2, the profit of seller $B$ changes to:

$$\begin{aligned}\pi_B &= (631 - 366 * \sqrt{(1 + 0.001 * 366)}) \\ &\quad + 631 - 366 * \sqrt{(1 + 0.001 * (366 + 211))}) \\ &= 374.62 < 379.39.\end{aligned}$$

Therefore, seller $B$ does not deviate at MAC $(i^*_A, i^*_B) = (211, 211)$.

Meanwhile, under the MAC $(i^*_A, i^*_B) = (193, 366)$ while seller $B$ considers buyer

2, the profit of seller $B$ is:

$$\begin{aligned}\pi_B &= (631 - 366 * \sqrt{(1 + 0.001 * 366)}) \\ &\quad + (631 - 366 * \sqrt{(1 + 0.001 * (366 + 193))}) \\ &= 377.25\end{aligned}$$

where if the seller $B$ wants to deviate back to ignore buyer 2, the profit of seller $B$ changes to:

$$\begin{aligned}\pi_B &= (631 - 214 * \sqrt{(1 + 0.001 * (214 + 193))}) \\ &= 377.16 < 377.25.\end{aligned}$$

Therefore, seller $B$ does not deviate at MAC $(i_A^*, i_B^*) = (193, 366)$. In this case, two SPNE exist in this network. Then the interesting fact happens: if the equilibrium changes from $(i_A^*, i_B^*) = (211, 211)$ to $(i_A^*, i_B^*) = (193, 366)$ as one of the two possibilities from this change of $\bar{\mu}$, the profit of seller $B$ decreased from 379.02 to 377.25, although there is a higher estimated return from buyers $\bar{\mu}$ in the market. This kind of situation for the seller $B$ is called "bad SPNE" in the abstract and introduction of this paper.

Walking out of this example, the Proposition also mentioned a necessary condition that sellers can only be worse off under newly generated multiple SPNE, and there always exists an SPNE ensuring all sellers are better off among the multiple SPNE. These two features can be proved together by exploiting the generation of multiple SPNE in the process of the elevation of $\bar{\mu}$. We will show the proof under the increase of $\bar{\mu}$ below.

**Step 1**

Suppose fixed the network structure (connections) with a mixture of exclusive and non-exclusive buyers and an initial $\bar{\mu}$ to be low enough, while the network initially has only 1 SPNE. Along with the gradually increasing $\bar{\mu}$, let "critical threshold" be the point that a seller starts to consider posting a positive incentive. At the first critical threshold, suppose that buyer $q$ exclusively connected to seller $b$ becomes critical, the market has two SPNE as $(i_b^q, i_{-b}|i_b^q)$ and $(i_b^{-q}, i_{-b}|i_b^{-q})$, indicating the two SPNE either considering buyer $q$ or not. Within them, $(i_b^{-q}, i_{-b}|i_b^{-q})$ is exactly the previous SPNE before $\bar{\mu}$ reaches the threshold, since buyer $q$ is ignored. Meanwhile, $(i_b^q, i_{-b}|i_b^q)$ is a new SPNE, which is proved to possibly make seller $b$ worse off, as shown in the example.

However, a fact always holds and will be proved, where under the same SPNE $(i_b^{-q}, i_{-b}|i_b^{-q})$ with before, all sellers (including seller $b$) are better off. This proof is straightforward, since the buyer choices do not change under the same equilibrium sign-up bonuses (points), while in the profit function of each seller $b$,

$$\pi_b = \sum_{q \in N_b} (\bar{\mu} - C(\lambda_q(\sum_{\mathbf{b} \in S_q} i_{\mathbf{b}}), i_b)),$$

where $\pi_b$ is strictly increasing in $\bar{\mu}$, given fixed buyer choices. Therefore, at the first critical threshold, all sellers are better off under $(i_b^{-q}, i_{-b}|i_b^{-q})$, which is one of the two SPNE.

**Step 2**

The same SPNE as before, i.e., $(i_b^{-q}, i_{-b}|i_b^{-q})$, always ensures all sellers are better off than before. However, after the rate of the estimated return from buyers $\bar{\mu}$ increases past the first critical threshold, the SPNE $(i_b^{-q}, i_{-b}|i_b^{-q})$ may not hold any more at the second critical threshold, when

$$\pi_b(i_b^q, i_{-b}|i_b^{-q}) > \pi_b(i_b^{-q}, i_{-b}|i_b^{-q}),$$

where the situation is similar to *condition 2* several paragraphs above, where seller $B$ would choose $i_B = 366$ to consider buyer 2, even if $i_A = 211$, where seller $A$ expects seller $B$ to ignore buyer 2. In the general settings, all that needs to be proved is that seller $b$ is still possible to be better off after the same SPNE no longer holds. Apparently, since $\pi_b(i_b^{-q}, i_{-b}|i_b^{-q})$ is the profit of seller $b$ staying at the original SPNE, the new SPNE $\pi_b(i_b^q, i_{-b}|i_b^{-q})$ dominating it yields to higher profit of seller $b$. Therefore, at the second critical threshold, the network still exists an SPNE that all sellers with at least one valuable buyer are better off.

Besides these two steps, if the network does not yield to multiple SPNE, where the network either does not own valuable exclusive buyers, or there are too many exclusive buyers, along with the estimated return from buyers $\bar{\mu}$ going up, the change of SPNE would either follow step 1 (still same SPNE) or follow step 2 (dominating new SPNE), which indicates that the situation that sellers are worse off is only generated by multiple SPNE (necessary condition proved). Certainly, the sufficient condition does not hold in this case.

■

## A..2.7 Proof of Proposition 4

**Proof.** This Proposition can be proved by an example, since all bullet points in this proposition are possibilities. See Figure A..2, the original network was a fully integrated network with sellers $A$ and $B$ connected with a buyer 1. A connection between seller $B$ and buyer 2 is added to this network. If we model $\bar{\mu} = 631$, $T_1 = 300$ and $T_2 = 500$, the problem is exactly consistent with the example in Section 2.2, where with added connection, one more SPNE was generated, and $\pi_B$ can fall from \$380 to \$379 in that game. In that case, if the equilibrium of $\{i_A^* = 192; i_B^* = 366\}$, buyer 1 got better off, seller $B$ got worse off, seller $A$ got better off, and the social welfare got better off. However, under the SPNE of $\{i_A^* = 211; i_B^* = 211\}$, everything remains the same.

Now consider a new setting, where $\bar{\mu} = 631$, $T_1 = 500$ and $T_2 = 0$. In this case, it yields only 1 equilibrium, but different then before. The older equilibrium can be written as $\{i_A^* = 310; i_B^* = 310\}$, while the new SPNE changes to $\{i_A^* = 366; i_B^* = 0\}$. Therefore, in this case, buyer 1 is worse off; seller $A$ is worse off; seller $B$ is better off, and the social welfare decreases. Vise versa for deleted connections.

■

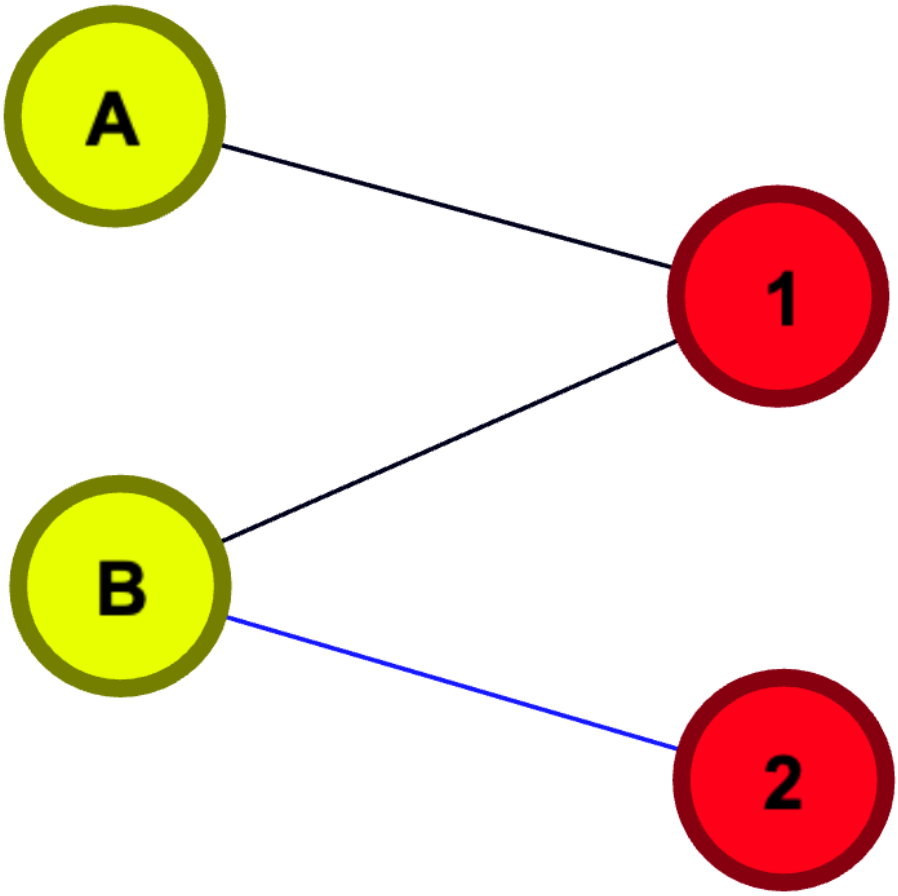



Figure A..2: The previous network only contains seller $A$ and seller $B$ connected to buyer 1. The market is changed by adding a connection between seller $B$ and buyer 2. Everything could happen to this network with the new connection, depending on the transaction cost of buyers 1 and 2.

# Appendix B.

# Lemmas and Proofs of Chapter 3

**Lemma 1** For any consumer set $c$ consisting of a finite number of consumers with non-negative reservation prices and same connections, there is an optimal unit price along with the consumer set for intermediaries that optimize the profit earned from this consumer set, i.e. $\exists p_c^* = \arg\max p_c \times S_c, \forall c$. The $p_c^*$ is named "local optimal price of consumer set $c$".

**Proof.** Since $p_c \times S_c$ is increasing in both $p_c$ and $S_c$, while demand is always not increasing in price, i.e. $S_c$ is not increasing in $p_c$. Meanwhile, $p_c$ and $S_c$ are both non-negative. Hence, the function $p_c \times S_c$ is quasi-concave with a non-negative maximal point. Therefore, $\exists p_c^* = \arg\max p_c \times S_c, \forall c$. Besides, the revenue $p_c \times S_c$ is NOT a continuous function, since the correlation between $S_c$ and $p_c$ is not continuous due to the discrete consumer set.

■

**Lemma 2** For each vector of variable prices, p, there always exists a set of entry fees such that no intermediary wants to deviate under both outcomes (SPNE/ICO), i.e. $\exists R_i^*, \forall i$.

**Proof.** Since there is already a robust outcome on the right hand side of the network, we define some outcome variables as follows. Suppose intermediary $i$ has a robust unit price $p_i^*$ and its corresponding sales volume $S_i^*$. In addition, suppose each producer can get a exogeneous unit profit of $\lambda$ through each product sold by intermediaries. Here, for intermediary $i$,

- If it has at least one exclusive producer, it can just post a fixed entree fee being equal to the total profit earned by an exclusive producer, i.e. $R_i^* = S_i^* \times \lambda$, regardless of other producers, since it can get all products needed from the exclusive producer under unlimited production.

- If it does not have exclusive producer, it will post a zero entree fee, i.e. $R_i^* = 0$ without any exclusive consumer, while posting a positive entree fee being equal to the profit made from exclusive consumers for producers, i.e. $R_i^* = S_i^{ex*} \times \lambda$ with at least one exclusive consumer, where $S_i^{ex*}$ denotes for the sales volume of exclusive consumers connected with intermediary $i$, since producers can access non-exclusive consumers through other intermediaries.

**Therefore, the equilibrium fixed entree fee exists under SPNE.**

On the other hand, if intermediaries are colluding with each other, the optimal can be identified as $\sum_i R_i^* = \lambda \times \sum_i S_i^*$, since intermediaries are colluding to get all profits from producers.

**Therefore, the equilibrium fixed entree fee exists under ICO.**

■

**Theorem 1** Consider a market with intermediaries selling identical goods between producers with unlimited productions. There exists a set of non-negative fixed price (entree fee) and variable price $(R_i^*, p_i^*)$ for each intermediary to be a market equilibrium (SPNE) **UNLESS** it satisfies **all** of following three conditions:

- There exists at least one intermediary $i$ with at least one exclusive consumer with a positive reservation price and at least one non-exclusive consumer with positive reservation price.
- There exists at least one consumer $c$ as a non-exclusive consumer connected to intermediary $i$ being a valuable consumer of intermediary $i$ and some other intermediary $j$ that it is also connected to.
- There exists at least one intermediary $j$ connected with consumer $c$ that if the reservation price of consumer $c$ is substituted by the local optimal price of intermediary $j$ for all consumers connected, i.e. $p_j^{*ALL}$, consumer $c$ is still a valuable consumer of intermediaries $i$.

**Proof.** To prove this theorem, I provide proof for both sufficient condition and necessary condition.

- **Sufficient condition**: Given that consumer $c$ is a valuable consumer for both intermediary $i$ and $j$, according to the definition of valuable consumers, we have:

$$\begin{cases} p_i^{*ALL} \times S_i^{ALL} > p_i^{*-c} \times S_i^{-c}; \\ p_j^{*ALL} \times S_j^{ALL} > p_j^{*-c} \times S_j^{-c}. \end{cases}$$

Therefore, both intermediaries deviate their prices to compete for consumer $c$. If both intermediaries do not have other consumers, they will post prices to zero. However, intermediary $i$ has at least one exclusive consumer with a positive reservation price, which means that the minimum profit of intermediary $i$ is above zero, i.e. $\pi_i^{min} > 0$. From then, there is a threshold for the price of intermediary $i$ between the reservation price of consumer $c$ and 0, i.e. $p_i^T > 0$. Therefore, if intermediary $j$ deviates its price to $p_i^T$, the price of intermediary $i$ goes back to its local optimal price. Meanwhile, the consumer $c$ is still valuable to intermedairy $i$, even if some other intermediary $j$ deviates its price firstly to $p_j^{ALL}$, which indicates that intermediary $i$ will not stop its deviation at the first shot of intermediary $i$'s deviation. Consequently, they will keep deviating until $p_i^T$ to formulate a loop. Therefore, the SPNE does not exist.

- **Necessary condition**: According to Axiom, "A if B" is equivalent to "not B if not A". Therefore, to prove "If SPNE does not exist, these conditions hold", we prove "if these conditions do not hold, SPNE exists".
  - **There does not exist an intermediary with both exclusive consumers and non-exclusive consumers**: then all intermediaries are either having only non-exclusive consumers or only exclusive consumers. If an intermediary $i$ only has exclusive consumers, its price will be a monopoly price that is equal to the local optimal price of its consumer set, i.e. $p_i^* = p_{ic}^*$; if an intermediary $i$ only has non-exclusive consumers, its price will be a zero price due competition with other intermediaries, i.e. $p_i^* = 0$. Thus, SPNE exists because of the robust prices.
  - **There exists an intermediary $i$ with at least one exclusive consumer and at least one non-exclusive consumer, but for each intermediary with exclusive consumers and non-exclusive consumers, all non-exclusive consumers are not valuable**: All non-exclusive consumers are not valuable, i.e. for any non-exclusive consumer $c$ connected with intermediary $i$, $p_i^{*ALL} \times S_i^{ALL} \leq p_i^{*-c} \times S_i^{-c}, \forall c$. Therefore, all intermediaries will not compete for the non-exclusive consumers, and they will ignore those consumers, which is equivalent to the market with only exclusive consumers. Thus, SPNE exists because of the robust monopoly prices.

– **There exists an intermediary $i$ with at least one exclusive consumer and at least one non-exclusive consumer, and some of non-exclusive consumers are valuable consumers. However, each valuable non-exclusive consumer $c$ connected to every intermediary $i$ is not a valuable consumer for any other intermediary $j$**: Any non-exclusive consumer $c$ being a valuable consumer for intermediary $i$ is not a valuable consumer for any other intermediary $j$, i.e.

$$\begin{cases} p_i^{*ALL} \times S_i^{ALL} > p_i^{*-c} \times S_i^{-c}; \\ p_j^{*ALL} \times S_j^{ALL} \leq p_j^{*-c} \times S_j^{-c}; \\ \forall i, j, c. \end{cases}$$

Here, intermediary $i$ will deviate its price to compete for $c$ but intermediary $j$ will ignore consumer $c$, hence the price of intermediary $i$ will be deviated equal to or below $p_c^R$, while the price of intermediary $j$ remaining same as before. Thus, SPNE exists because of the robust prices.

– **There exists an intermediary $i$ with at least one exclusive consumer and at least one non-exclusive consumer, and there exists a consumer $c$ as a non-exclusive consumer connected to intermediary $i$ being a valuable consumer of intermediary $i$ and some other intermediary $j$ that it is also connected to. However, for all intermediaries sharing consumer $c$ with intermediary $i$, if substituting the reservation price of consumer $c$ to be any $p_j * ALL$, consumer $c$ is no longer a valuable consumer of intermediary $i$.**: Although intermediary $i$ deviates its price at the first shot, but it will stop deviating at the second shot, because intermediary $j$ at deviating the price to a low level that cannot be accepted by intermediary $i$. Therefore, intermediary $i$ gives up consumer $c$ and only focus on other consumers. Replicating the discussion in last bullet point, the price will go to a robust level, which indicates that SPNE exists.

Therefore, after discussing all possibilities that violates the conditions of non-existence of SPNE, we have proved that under violations of any conditions of non-existence of SPNE, SPNE exists, hence the non-existence of SPNE can only be caused of the conditions of non-existence of SPNE in Theorem 1.

■

**Theorem 2**

**a)** Under SPNE, the $R_i^*$ for intermediary $i$ is ZERO if it satisfies **ALL** of following three conditions:

- Intermediary $i$ does not have any exclusive consumer or exclusive producer.
- All producers connected to intermediary $i$ can access all consumers connected to intermediary $i$ through other intermediaries.
- All intermediaries sharing all or part of consumers connected to intermediary $i$ have no exclusive consumer, either.

Under ICO, it is impossible to make any $R_i^*$ for any intermediary $i$ to be zero.

**b)** On the other hand, a producer will make zero profit under ICO, and it will also make zero profit under SPNE if it satisfies **ANY** of following three conditions:

- It is only connected to one intermediary.
- All intermediaries that it is connected to are only having exclusive consumers connected to them.
- All intermediaries that it is connected to has their own exclusive producers connected to them.

**Proof.**

- Under SPNE: Intermediary $i$ does not have its exclusive consumer, and all producers connected to intermediary $i$ can access all consumers connected to intermediary $i$ through other intermediaries, which indicates that the situation that a producer have to choose it to access some consumers does not exist. Meanwhile, all intermediaries sharing all or part of consumers connected to intermediary $i$ have no exclusive consumers, which indicates that the situation that other intermediaries only focus on their exclusive consumers due to high reservation prices. Hence, intermediary $i$ has to post a zero entree fee to be chosen by producers.
- Under ICO: Since intermediaries are now able to transfer money while colluding, they can post a same entree fee to producers, as long as the producer can still make profit. Even producers only choose some of intermediaries, they can transfer their money to those who are not chosen. Hence, intermediary $i$ is can post a positive entree fee to be chosen by producers.

- For producers, there are three conditions making them gaining zero profit:
  - It is only connected to one intermediary: Due to the unlimited production, the intermediary it is connected to will only focus on this producer and post an entree fee that is exactly same with the profit of the producer. Therefore, the producer will get zero profit.
  - All intermediaries that it is connected to are only having exclusive consumers connected to them: Under this condition, we can split the network to linear subnetworks with the producer, one intermediary and its exclusive consumers. From this view, intermediaries will set a monopoly unit price to consumers and an entree fee that is exactly same with the profit of the producer. Therefore, the producer will get zero profit.
  - All intermediaries that it is connected to has their own exclusive producers connected to them: According to the first point of Theorem 2, while an intermediary has an exclusive producer, it will only focus on this producer and post an entree fee that is exactly same with the profit of the producer. Therefore, if all intermediaries it connects to have their exclusive producers, the dominant strategy for it is not to connect to any intermediary to keep a zero profit instead of getting a negative profit.

■

**Theorem 3**

- In any intermediation game, an ICO always exists.
- The ICO is supported by an SPNE if all shared consumers are only valuable to one or fewer intermediaries.

**Proof.**

Point 1: In any intermediation game, an ICO always exists.

According to the definition of ICO, intermediaries are colluding with each other to maximize their aggregate revenue. Therefore, they solve the following problem under ICO on the right-hand side:

$$p_i^* \equiv \arg\max_{p_i} \sum_i (F_i), \forall i. \tag{B..1}$$

Since every intermediary aims at maximizing the total revenue of all intermediaries, no intermediary deviates its price, which indicates that the outcome on both sides is robust, hence ICO always exists.

Point 2: The ICO is supported by an SPNE if and only if all shared consumers are only valuable to one or fewer intermediaries.

This point is proved by 3 steps as follows:

Step 1: *If all shared consumers are only valuable to one or fewer intermediaries, there exists an SPNE.*

Given that all shared consumers are only valuable to one or fewer intermediaries, they are equivalent to exclusive consumers to those intermediaries that they are valuable to. Therefore, according to the proof of the necessary conditions of Theorem 1, there exists an SPNE.

Step 2: *If all shared consumers are only valuable to one or fewer intermediaries, the prices posted to consumers are the same between SPNE and ICO.*

If the network has only exclusive consumers, it is equivalent to the fully-discrete network where each intermediary only considers a bunch of exclusive consumers. Therefore, the prices posted to consumers are the same between SPNE and ICO.

Step 3: *If all shared consumers are only valuable to one or fewer intermediaries, the intermediation fees posted to producers are the same between SPNE and ICO.*

If the right-hand side of the network is fully discrete, producers can never access a consumer through two intermediaries. Therefore, producers make zero profit under both SPNE and ICO, and the intermediation fees posted to producers are the same between SPNE and ICO.

■

**Proposition 1** Under ICO, suppose a consumer $c \in B^x(N)$ notices a new intermediary $y$ and increases his/her connection by connecting to intermediary $y$, i.e. $c \in B^y(N^*)$.

i. If $p_y < p_x$

   - Consumer $c$ is not worse off;
   - Any consumer $d \in B^x(N)$ is not worse off;
   - Any consumer $d \in B^y(N)$ is not better off;
   - The price $p_x$ offered by intermediary $x$ does not increase;
   - The price $p_y$ offered by intermediary $y$ does not decrease;
   - Intermediaries are not better off.

ii. If $p_y > p_x$

- Consumer $c$ is not worse off or better off;
- Any consumer $d \in B^x(N)$ is not worse off or better off;
- Any consumer $d \in B^y(N)$ is not worse off or better off;
- The price $p_x$ offered by intermediary $x$ does not change;
- The price $p_y$ offered by intermediary $y$ does not change;
- Intermediaries are not worse off or better off.

**Proof.** First, we consider the case under $p_y < p_x$. Before this change, since this condition is under ICO, intermediary $y$ is stabilized at a lower unit price than intermediary $x$. $y$ has a new consumer with a higher reservation price, hence it either keep its price and enjoy the new customer, or increase its price, depending on the reservation prices of consumers originally connected to $y$. Meanwhile, intermediary $x$ would either keep its price for the remaining consumers, or lower its price, based on the reservation prices of consumers originally connected to $x$. Therefore, Consumer $c$ is not worse off with lower or same price; The aggregate revenue will not increase, since the change will either make intermediary $y$ lose some original consumers, or the consumer $c$ pays less amount with new connections. Meanwhile, any consumer $d \in B^x(N)$ is not worse off, and any consumer $d \in B^y(N)$ is not better off, based on the new prices of the two intermediaries.

Second, we consider the case under $p_y > p_x$. Before this change, since this condition is under ICO, intermediary $y$ is stabilized at a higher unit price than intermediary $x$. $y$ has a new consumer with a lower reservation price, hence it keeps its price and ignores the new customer to maintain same aggregate profit, instead of lowering its price to compete with intermediary $x$. In the meantime, intermediary $x$ notices this change, and it will keep its price, since it cannot do anything to increase the aggregate profit. Therefore, both intermediaries keep their price, and consumer $c$, as well as any consumer $d \in B^x(N)$ and any consumer $d \in B^y(N)$ is not worse off or better off with same price.

■

**Proposition 2** While new links are added to the network of the market, there will be more and more same prices in the market. While the market is fully integrated, the prices from all intermediaries will converge to be same. However, the final prices from intermediaries and their processes of changing vary under SPNE or ICO as follows:

i. If the market is under SPNE,

   - All consumers are not worse off;
   - All intermediaries are not better off;
   - All producers are not worse off;
   - In the new equilibrium, all unit prices from all intermediaries converge to 0.

ii. If the market is under ICO,

   - Consumers previously paying the highest price will not be worse off;
   - Consumers previously paying the lowest price will not be better off;
   - Producers are not better off or worse off;
   - Intermediaries are not better off.

**Proof.** Under SPNE, the unit prices and the fixed entree fees can vary between intermediaries, depending on their connections with consumers and producers. However, after the change, according to Bertrand (1883), the equilibrium prices and entree fees for all intermediaries will change to 0 under SPNE based on the perfect competition. Therefore, all intermediaries are not better off due to the zero price, all producers and all consumers are not worse off due to the zero unit prices and zero fixed entree fees.

However, under ICO, although the unit prices and the fixed entree fees will converge to a same value, but their prices after the change are different from those under SPNE, where the price set for any intermediary $i$ after the change goes to:

$$\begin{cases} p_i^* = p_{cALL}^*, \forall i \\ R_i^* = \dfrac{1}{I} \times S_{cALL}^* \times \lambda, \forall i. \end{cases}$$

where $p_{cALL}^*$ represents for the local optimal price for all consumers, $S_{cALL}^*$ denotes for the corresponding aggregate demand under $p_{cALL}^*$, and $I$ denotes for the number of intermediaries in the network. Here, all intermediaries are having same expected revenue after the change. Therefore, consumers previously from the intermediary with highest price will not be worse off due to the lower or same unit price, while consumers previously from the intermediary with lowest unit price will not be better off due to higher or same unit price. Meanwhile, since all producers are still making zero profit, they are not better off or worse off. Furthermore, all intermediaries are

not able to carry out price discriminations based on the incomplete connections, which leads to the consequence that intermediaries are not better off due to lower or same aggregate revenue.

■

**Corollary 1** If all consumers in the market are having same willingness to pay (reservation price), there exists SPNE **if and only if** there does not exist such an intermediary that is connected to both exclusive consumers and non-exclusive consumers.

**Proof.**

- **Sufficient condition**: Given that there does not exist such an intermediary that is connected to both exclusive consumers and non-exclusive consumers, all intermediaries are either having only non-exclusive consumers or only exclusive consumers. If an intermediary $i$ only has exclusive consumers, its price will be a monopoly price that is equal to the local optimal price of its consumer set, i.e. $p_i^* = p_{ic}^*$; if an intermediary $i$ only has non-exclusive consumers, its price will be a zero price due competition with other intermediaries, i.e. $p_i^* = 0$. Thus, SPNE exists because of the robust prices.

- **Necessary condition**: If there exists at least one intermediary with at least one exclusive consumer and at least one non-exclusive consumer, given that all consumers are holding same reservation prices, i.e. $v_i = v_j, \forall i, j$, for any intermediary $i$ and with consumer $c$, we have

$$\begin{cases} p_i^{*ALL} = p_i^{*-c} \equiv v_c, \forall i, c \\ S_i^{*ALL} > S_i^{*-c}, \forall i, c. \end{cases}$$

  Therefore, for any intermediary $i$ sharing any consumer $c$ with any other intermediary $j$, there are:

$$\begin{cases} p_i^{*ALL} \times S_i^{ALL} > p_i^{*-c} \times S_i^{-c}; \\ p_j^{*ALL} \times S_j^{ALL} > p_j^{*-c} \times S_j^{-c}. \end{cases}$$

  According to Theorem 1, there does not exist SPNE under above conditions, hence if there exists at least one intermediary with at least one exclusive consumer and at least one non-exclusive consumer, and all consumers are holding same reservation prices, there does not exist SPNE. As a consequence, if

there exists a SPNE, there does not exist a intermediary with both exclusive consumers and non-exclusive consumers while all consumers are holding same reservation prices.

■

# Appendix C.

# Supplemental Materials of Chapter 4

## C..1 The Formal Definition of the Essential Variables in This Paper

Our six essential variables are vaccination stage, education level, official trust index, unofficial trust index, official information consumption index, and unofficial consumption index. These variables are generated from the survey as follows:

**Definition 11 (Variables generated and quantified)**

- *The vaccination stage reveals the decisions of the participants on getting vaccines, which is divided into three categories:*
  - ***Early Vaccinee**: A participant is defined as an early vaccinee if and only if he/she initiated his/her first dose within 2 months of being eligible for the vaccinations;*
  - ***Late Vaccinee**: A participant is defined as a late vaccinee if and only if he/she did not initiate his/her first dose within 2 months of being eligible for the vaccinations, but a dose was finally initiated within 6 months after being eligible;*
  - ***Non-vaccinee**: A participant is defined as a non-vaccinee if and only if he/she never initiated a dose within 6 months after being eligible, or he/she finally initiated it but was required to do so because of the vaccine*

*mandate declared by the State of Hawaii on 5 August 2021 and implemented on 13 September 2021.*

- ***The education level*** *is normalized between [0, 1] from the choices given to participants, from the lowest "6th to 8th grade" as 0, "9th to 12th grade, no diploma" as* $\frac{1}{5}$*, "High school graduate or GED completed" as* $\frac{2}{5}$*, "Some college level / Technical / Vocational degree" as* $\frac{3}{5}$*, "Bachelor's degree" as* $\frac{4}{5}$ *to the highest "other advanced degree (Master's, Doctoral degree)" as 1. The value is null upon the answer "I don't want to answer this question".*

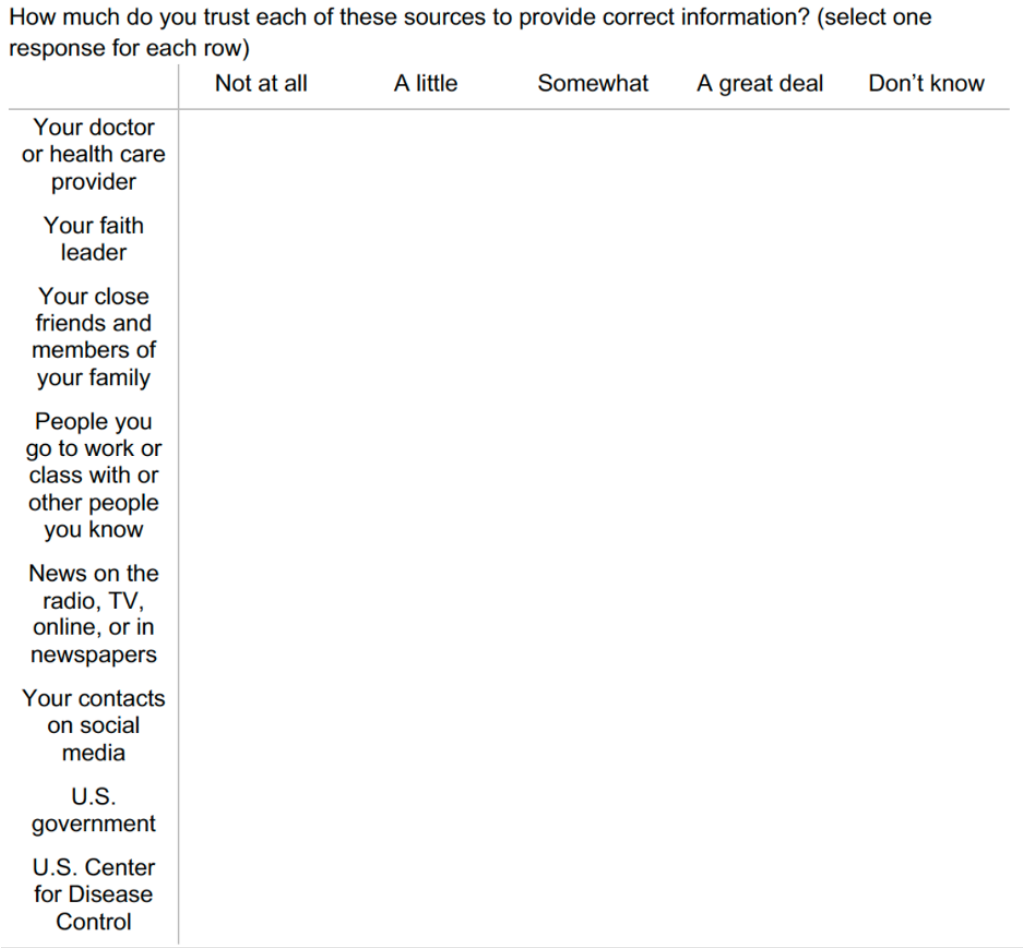
- ***The trust index*** *for each source of COVID-19 information is represented by [0, 1] from a 5-point descriptive rating scale ranging from "Not at all" (0), "Not sure" (*$\frac{1}{4}$*), "A little" (*$\frac{1}{2}$*), "Somewhat" (*$\frac{3}{4}$*) to "A great deal" (1). Data collected from individuals allowed us to compute eight indexes: government trust, doctor trust, TV news, and other official media trust, COVID-19 task force trust, faith leader trust, family and friend trust, other people around trust and the social media (e.g., Facebook, Twitter) trust. See Figure C..1 for the screenshot of the original question on trust indexes.*

- ***The official trust index*** *takes the average of four trust indexes for each source: government trust, doctor trust, TV news, and other official media trust, and the COVID-19 task force trust.*

- ***The unofficial trust index*** *takes the average of four trust indexes: faith leader trust, family and friend trust, other people around trust, and social media (e.g., Facebook, Twitter) trust.*

- ***The consumption index*** *for each source of COVID-19 information is represented by [0, 1] from a 5-point descriptive rating scale ranging from "Never" (0), "Rarely" (*$\frac{1}{4}$*), "Sometimes" (*$\frac{1}{2}$*), "Often" (*$\frac{3}{4}$*) to "Always" (1). Data collected from individuals allowed us to compute eight indexes: federal government information consumption, state government information consumption, medical providers (doctor) information consumption, TV news information consumption, healthcare website information consumption, family and friends information consumption, and social media (e.g., Facebook, Twitter) information consumption. See Figure C..2 for the screenshot of the original question on consumption indexes.*

- ***The official information consumption frequency index*** *takes an average of six consumption frequency indexes: federal government information*


How much do you trust each of these sources to provide correct information? (select one response for each row)

| | Not at all | A little | Somewhat | A great deal | Don't know |
|---|---|---|---|---|---|
| Your doctor or health care provider | | | | | |
| Your faith leader | | | | | |
| Your close friends and members of your family | | | | | |
| People you go to work or class with or other people you know | | | | | |
| News on the radio, TV, online, or in newspapers | | | | | |
| Your contacts on social media | | | | | |
| U.S. government | | | | | |
| U.S. Center for Disease Control | | | | | |

Figure C..1: The original question in both of our surveys on trust indexes.

*consumption, state government information consumption, medical providers (doctor) information consumption, TV news information consumption, health-care website information consumption, and print or online news information consumption.*

- ***The unofficial information consumption frequency index*** *takes an average of two consumption frequency indexes: family and friends information consumption and social media (e.g., Facebook, Twitter) information consumption.*

How often do you use or rely on the following sources to get information? (select one response for each row)

| | Never | Rarely | Sometimes | Often | Always |
|---|---|---|---|---|---|
| Friends, family or neighbors (not including Facebook or social media) | | | | | |
| Providers (e.g., your Doctor, Pharmacist, etc.) | | | | | |
| Local government officials (e.g., Governor, Mayor) | | | | | |
| Federal Government (e.g., President, Center for Disease Control) | | | | | |
| Medical/Health websites (e.g., CDC, WebMD) | | | | | |
| Print or online news | | | | | |
| TV or radio | | | | | |
| Social Media (Instagram, Facebook, YouTube, TikTok) | | | | | |
| Place of work or school | | | | | |

Figure C..2: The original question in both of our surveys on consumption indexes.

**C..2 Statistical Result Table on the Probit Regressions on the Likelihood of Being an *Early Vaccinee* and a *Late Vaccinee***

**C..3 Statistical Results Table on the Probit Regressions on the Likelihood of Being an *Early Vaccinee* and a *Late Vaccinee*, While All Trust and Consumption Variables Are in the Same Regressions**

**C..4 Statistical Results Table from the Longitudinal Regressions on Trust in and Consumption of Each Information Source**

**C..5 Results from the Difference-in-Difference Approach and the Corresponding Parallel Trends for Participants without Booster Shots**

Table C..1: Percentage changes as marginal effects of the probit correlation between the probability of being an early/late vaccinee and the education, trust, and consumption variables, which are parallel with Figure 4.1. For this analysis, the impact of each variable is shown independently of the others.

| **Independent Variables** | **Early Vaccinees vs. Everyone Else— Probability [1]** | **Late Vaccinees vs. Non-Vaccinees— Probability [2]** |
|---|---|---|
| **Official Trust** | **55% **** | **39% **** |
| Government trust | 37% ** | 24% ** |
| Doctor trust | 57% ** | 36% ** |
| Print and online news trust | 25% ** | 17% * |
| COVID-19 task force trust | 34% ** | 26% ** |
| **Unofficial Trust** | | **−25% *** |
| Faith leader trust | −11% ** | −13% * |
| Family and friends trust | | |
| Other people around trust | 7% * | −18% * |
| Social media trust | | |
| **Official Consumption** | **46% **** | **42% **** |
| Doctor consumption | 18% ** | 21% * |
| Local government consumption | 39% ** | 34% ** |
| Federal government consumption | 32% ** | 24% ** |
| CDC website consumption | 23% ** | 31% ** |
| Print and online news consumption | 14% ** | 18% * |
| TV news consumption | 20% ** | |
| **Unofficial Consumption** | | |
| Family and friends consumption | | |
| Social media consumption | | |
| Education | 52% ** | |
| **Control Variables** | | |
| Gender FE | Y | Y |
| Age | Y ** | Y |
| Social vulnerability | Y * | Y * |
| Race FE | Y | Y |

[1]: The marginal probability changes on each 1-point estimate elevation in the independent variables, based on the probit analysis on the comparison between early vaccinees and all others.

[2]: The marginal probability changes on each 1-point estimate elevation in the independent variables, based on the probit analysis on the comparison between late vaccinees and non-vaccinees. (Standard errors are in parentheses.) (Significance level: * $p < 0.05$, ** $p < 0.01$) (Probability shown only for significant independent variables).

Table C..2: Percentage changes as marginal effects of the probit correlation between the probability of being an early/late vaccinee and the education, trust, and consumption variables, while all independent variables of individual trust and consumption variables are incorporated into the same regression. We provide this table as a robustness check to identify the variables with a strong correlation with vaccine uptake whenever other variables are controlled.

| **Independent Variables** | **Early Vaccinees vs. Everyone Else— Probability [1]** | **Late Vaccinees vs. Non-Vaccinees— Probability [2]** |
|---|---|---|
| **Official Trust** | | |
| Government trust | 24% ** | |
| Doctor trust | 42% ** | 23% * |
| Print and online news trust | | |
| COVID-19 task force trust | | |
| **Unofficial Trust** | | |
| Faith leader trust | −13% ** | |
| Family and friends trust | | |
| Other people around trust | | −24% ** |
| Social media trust | −15% ** | |
| **Official Consumption** | | |
| Doctor consumption | | |
| Local government consumption | 23% ** | 40% * |
| Federal government consumption | | −33% * |
| CDC website consumption | | 23% * |
| Print and online news consumption | | |
| TV news consumption | | |
| **Unofficial Consumption** | | |
| Family and friends consumption | | |
| Social media consumption | | |
| **Control Variables** | | |
| Education | Y ** | Y |
| Gender FE | Y | Y |
| Age | Y ** | Y |
| Social vulnerability | Y * | Y * |
| Race FE | Y | Y |

[1]: The marginal probability changes on each 1-point estimate elevation in the independent variables, based on the probit analysis on the comparison between early vaccinees and all others.
[2]: The marginal probability changes on each 1-point estimate elevation in the independent variables, based on the probit analysis on the comparison between late vaccinees and non-vaccinees. (Standard errors are in parentheses.) (Significance level: * $p < 0.05$, ** $p < 0.01$) (Probability shown only for significant independent variables).

Table C..3: Demographic statistics on the survey data, including descriptive statistics showing the count and percentage of participants at each vaccination stage. In addition, the numbers of returning participants at all vaccination stages are shown.

| **Trust in Official Information Sources** | **Official Overall** | **Government** | **Doctor** | **Print or Online News** | **COVID-19 Task Force** |
|---|---|---|---|---|---|
| Booster—ALL [1] | 0.008 (0.009) | 0.011 (0.013) | 0.017 * (0.0085) | −0.012 (0.015) | 0.010 (0.014) |
| Booster—Early vaccinees [2] | −0.007 (0.010) | −0.003 (0.014) | −0.003 (0.008) | −0.017 (0.016) | −0.005 (0.015) |
| Booster—Late vaccinees [3] | 0.13 ** (0.034) | 0.15 ** (0.049) | 0.24 ** (0.023) | 0.033 (0.088) | 0.11 (0.059) |
| Booster difference-in-difference—Late vs. Early [4] | 0.16 ** (0.031) | 0.16 ** (0.043) | 0.24 ** (0.024) | 0.060 (0.072) | 0.14 ** (0.052) |
| Trust in unofficial information sources | Unofficial Overall | Faith leader | Family and friends | Other people around | Social media |
| Booster—ALL [1] | −0.005 (0.011) | 0.028 (0.016) | −0.032 * (0.015) | −0.002 (0.016) | −0.012 (0.018) |
| Booster—Early vaccinees [2] | −0.003 (0.011) | 0.029 (0.016) | 0.033 * (0.016) | −0.001 (0.017) | −0.008 (0.019) |
| Booster—Late vaccinees [3] | −0.011 (0.059) | 0.098 (0.077) | −0.054 (0.093) | −0.011 (0.085) | −0.076 (0.085) |
| Booster difference-in-difference—Late vs. Early [4] | −0.011 (0.049) | 0.029 (0.067) | −0.002 (0.076) | −0.004 (0.070) | −0.062 (0.070) |
| Consumption of four information sources | Official Overall | Doctor | Local government | Federal government | CDC website |
| Booster—ALL [1] | 0.005 (0.009) | 0.022 (0.016) | 0.007 (0.014) | 0.013 (0.014) | 0.011 (0.014) |
| Booster—Early vaccinees [2] | −0.004 (0.009) | 0.026 (0.017) | −0.019 (0.0140 | −0.013 (0.013) | 0.007 (0.015) |
| Booster—Late vaccinees [4] | 0.11 * (0.044) | 0.033 (0.078) | 0.24 ** (0.072) | 0.26 ** (0.074) | 0.033 (0.071) |
| Booster difference-in-difference—Late vs. Early [4] | 0.11 ** (0.036) | −0.016 (0.063) | 0.28 ** (0.058) | 0.28 ** (0.061) | 0.038 (0.058) |
| Consumption of the other four information sources | Print or online news | TV news | Unofficial Overall | Family and friends | Social media |
| Booster—ALL [1] | −0.005 (0.014) | −0.017 (0.014) | −0.003 (0.010) | −0.001 (0.014) | −0.005 (0.013) |
| Booster—Early vaccinees [2] | −0.012 (0.015) | −0.012 (0.015) | 0.003 (0.011) | 0.007 (0.014) | −0.001 (0.014) |
| Booster—Late vaccinees [3] | 0.065 (0.066) | 0.011 (0.074) | −0.092 (0.055) | −0.14 * (0.056) | −0.043 (0.067) |
| Booster difference-in-difference—Late vs. Early [4] | 0.078 (0.054) | −0.018 (0.060) | −0.083 * (0.044) | −0.12 * (0.048) | −0.050 (0.053) |

[1] OLS regression on the comparison before and after the booster shot, individually for all participants with booster shots.

[2] OLS regression on the comparison before and after the booster shot, individually for early vaccinees with booster shots.

[3] OLS regression on the comparison before and after the booster shot, individually for late vaccinees with booster shots.

[4] OLS regression on the comparison between early and late vaccinees regarding the comparison before and after the booster shot, individually for all participants with booster shots. (Standard errors are in parentheses) (significance level: * $p < 0.05$, ** $p < 0.01$).

Table C..4: Regression results outlying the longitudinal changes of returning participants with boosters on trust in and consumption of official and unofficial information sources before and after the booster shot. The four rows below focus on everyone with booster shots, every early vaccinee, every late vaccinee, and the differences between early and late vaccinees in these changes, respectively. These results are based on OLS regressions, and the coefficients are directly interpretable as unit percentage changes.

| **Independent Variables** | **Official Trust** | **Unofficial Trust** | **Official Consumption** | **Unofficial Consumption** |
|---|---|---|---|---|
| Changes in trust and consumption for boosted participants between before and after the booster. | | | | |
| Booster—ALL [1] | 0.008 | −0.005 | 0.005 | −0.003 |
| | (0.009) | (0.011) | (0.009) | (0.010) |
| Booster—Early vaccinees [2] | −0.007 | −0.003 | −0.004 | 0.003 |
| | (0.010) | (0.011) | (0.009) | (0.011) |
| Booster—Late vaccinees [3] | 0.13 ** | −0.011 | 0.11 * | −0.092 |
| | (0.034) | (0.059) | (0.044) | (0.055) |
| Booster difference-in-difference—Late vs. Early [4] | 0.16 ** | −0.011 | 0.11 ** | −0.083 |
| | (0.031) | (0.049) | (0.036) | (0.044) |

[1] OLS regression on the comparison before and after the booster shot, individually for all participants with booster shots.

[2] OLS regression on the comparison before and after the booster shot, individually for early vaccinees with booster shots.

[3] OLS regression on the comparison before and after the booster shot, individually for late vaccinees with booster shots.

[4] OLS regression on the comparison between early and late vaccinees regarding the comparison before and after the booster shot, individually for all participants with booster shots. (Standard errors are in parentheses) (Significance level: * $p < 0.05$, ** $p < 0.01$).

Table C..5: Robustness check (parallel trends): Regression results outlying the longitudinal changes of all returning participants on trust in and consumption of official and unofficial information sources between their first and second entries. The rows focus on all returning participants, returning early vaccinees, returning late vaccinees, and the differences between early and late vaccinees, respectively. These results are based on OLS regressions controlled for individual fixed effects, and the coefficients are directly interpretable as unit percentage changes.

| **Independent Variables** | **Official Trust** | **Unofficial Trust** | **Official Consumption** | **Unofficial Consumption** |
|---|---|---|---|---|
| Changes in trust and consumption for all returning participants between their first and second entries. | | | | |
| Without booster—ALL | 0.002 | 0.008 | −0.019 | 0.020 |
| | (0.014) | (0.014) | (0.011) | (0.014) |
| Without booster—Early vaccinees | 0.010 | 0.014 | −0.033 | −0.007 |
| | (0.021) | (0.023) | (0.017) | (0.021) |
| Without booster—Late vaccinees | 0.027 | 0.044 | 0.013 | 0.059 |
| | (0.034) | (0.035) | (0.027) | (0.039) |
| Without booster difference-in-difference—Late vs. Early | 0.011 | 0.024 | 0.048 | 0.073 * |
| | (0.034) | (0.035) | (0.027) | (0.037) |
| Returning difference-in-difference—getting booster vs. not (early vaccinees) | 0.003 | −0.040 | 0.041 | 0.014 |
| | (0.031) | (0.036) | (0.025) | (0.030) |
| Returning difference-in-difference—getting booster vs. not (late vaccinees) | 0.057 | −0.001 | 0.084 * | −0.080 |
| | (0.033) | (0.045) | (0.038) | (0.041) |

(Standard errors are in parentheses) (significance level: * $p < 0.05$, ** $p < 0.01$).

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