The Dissertation Committee for Liangfei Qiu Certifies that this is the approved version of the following dissertation:

Essays on the Economics of Information Systems

Committee:

Andrew B. Whinston, Supervisor

Dale Stahl

Thomas Wiseman

Maxwell Stinchcombe

Haiqing Xu

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by

Liangfei Qiu, B.Eco.; M.Eco.; M.S.Econ.

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Dedication

Dedicated to my parents and my wife Bei Cao.

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Essays on the Economics of Information Systems

Liangfei Qiu, Ph.D.

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Supervisor: Andrew B. Whinston

Information technology and social media have been a driving force in the economy and have transformed all aspects of business in recent decades. Understanding social networks is necessary to evaluate their impacts and examine key business issues involving information and technological innovations.

The dissertation contains three chapters exploring those issues. In the first chapter, I propose an optimal procurement mechanism for mobile data offloading, covering both technological and business aspects. The unprecedented growth of cellular traffic driven by web surfing, video streaming, and cloud-based services is creating challenges for cellular service providers to fulfill the unmet demand. My present work contributes to the existing literature by developing an analytical model, which considers the unique challenge of integrating the longer range cellular resource and shorter range WiFi hotspots.

In the second chapter, I examine the effect of a social network on prediction markets using a controlled laboratory experiment. In prediction markets, people place bets on events that they think are most likely to happen, thus revealing in a sense the nature of their private information. Through a randomized experiment, I show that when the cost of information acquisition is low, a social-network-embedded prediction market outperforms a non-networked prediction market.

The third chapter studies different forms of social learning in the context of location-based networks: observational learning and the saliency effect. In recent years, the location-sensing mobile devices offer geographic location capabilities to share users' information about their locations with their friends. In our context, observational learning corresponds to the fact that "check-ins" made by friends help users learn the quality information of a venue; the saliency effect refers to that check-ins lead some of the uninformed consumers to discover a new venue.

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1.1 Introduction

We are witnessing an explosion of mobile data traffic driven by web surfing, video streaming, and online gaming. Global mobile data traffic grew 70 percent in 2012 and will increase thirteen-fold between 2012 and 2017.[1] The increasing popularity of smartphones has caused the surge in data usage. In 2012, the typical smartphone generated 50 times more mobile data traffic than the typical non-smartphone (Cisco 2013). Cloud applications and services such as Netflix, YouTube, Pandora, and Spotify contribute to the unprecedented growth of cellular traffic.

The huge amount of data traffic poses a challenge to the network infrastructure: Cellular networks are overloaded and congested during peak hours because of insufficient capacity. Network congestion can lead to a bad user experience and churn. In this study, we propose an optimal procurement mechanism to solve the challenge of effectively fulfilling the unmet demand from consumers for network providers, such as AT&T and Verizon.

In previous literature, researchers proposed several solutions from both technical and economic aspects: (1) increasing the number of cellular towers or deploying the cell-splitting technology[2]; (2) upgrading the network to fourth-generation (4G) networks such as Long Term Evaluation (LTE), High Speed Packet Access (HSPA) and WiMax; (3) expanding capacity by acquiring of the spectrum of other networks, such as the attempted

[1] Global mobile data traffic reached 885 petabytes per month at the end of 2012, up from 520 petabytes per month at the end of 2011 (Cisco 2013).
[2] See Balachandran et al. (2008). ("While cell-splitting provides capacity benefits, it could be quite expensive and economically infeasible since in addition to the base station hardware/deployment cost, each of the new bases needs to be provided with backhaul connectivity either via wireline access or microwave links.")

purchase of T-Mobile USA by AT&T; (4) adopting smart data pricing mechanisms (e.g. usage-based and app-based pricing plans) to constrain the heaviest mobile data users, instead of using flat-rate pricing plans with unlimited data (Sen et al. 2012)[3]; and (5) offloading data traffic to WiFi networks (Bulut and Szymanski 2012).

Although all these solutions help solve the problem, each of them has its advantages and disadvantages. The first and second solutions require heavy investments, and getting government approval for building new cell towers can take two years.[4] It is extremely expensive to increase the number of cellular base stations just for peak traffic demands. As a result, all cellular networks augment the first and second solutions with other approaches to expanding capacity. The third solution suffers from regulatory constraints. Cramton, Skrzypacz, and Wilson (2007) showed that an important market failure arises in spectrum auctions with dominant incumbents. They suggest that the Federal Communications Commission (FCC) should place limits on how much spectrum AT&T and Verizon are allowed to buy. This concern is also reflected in the action taken by the FCC to block the recent merger between AT&T and T-Mobile.[5]

Because of these technical, economic and regulatory constraints, the fifth solution, using WiFi hotspots for mobile data traffic offloading, seems to be one of the most promising approaches in augmenting solutions (1) and (2). WiFi hotspots refer to third-party hotspot owners, such as local restaurants, bookstores, and hotels, which offer WiFi service to their customers. WiFi offloading could potentially be a win-win solution: The cellular service provider achieves significant savings by not building more cellular

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[3] Gupta et al. (2011) shows that the average net benefits realized under congestion-based pricing tend to be higher than the average net benefits realized under flat-rate pricing. However, pure usage based plans might backfire by singling out the smartphone users who have the highest potential for future revenue.

[4] See http://www.businessweek.com/technology/content/aug2009/tc20090823_412749.htm.

[5] Another example of regulation is the Net Neutrality Rules that have become a subject under fierce debate (Cheng, Bandyopadhyay, and Guo 2011).

base stations just for the peak traffic demands. The WiFi Hotspots gain additional revenue from their otherwise wasted spare capacity. Mobile data offloading will become a key industry segment in the near future, and cellular service providers show great interests in this approach: KDDI Corporation, a principal telecommunication provider in Japan, has cooperated with about 100,000 commercial WiFi hotspots by March 2012 (Aijaz et al. 2013). However, offloading data traffic to third-party WiFi hotspots is not purely a technology augmenting the existing cellular network. It is also a practical mechanism design problem, considering the economic incentives of third-party WiFi hotspots. Instead of focusing only on technical aspects, smart data offloading requires us to combine both the technology of computing and auction theory to solve the challenge of effectively using WiFi hotspots (Bichler, Gupta, and Ketter 2010).

There were several challenges in the design of this procurement auction system. First, the longer range cellular resource introduces coupling between the shorter range WiFi hotspots. In reality, WiFi networks usually have a more limited range than cellular resources. In the model, we partition the range of a cellular tower into several WiFi regions. The cellular capacity can serve data traffic in any region, whereas the WiFi resource can only serve local traffic. Second, the data traffic is uncertain and changes frequently over time. It is critical to provide real-time support for computing the optimal contract. Third, Dong et al. (2012) proposed a Vickrey-Clarke-Groves (VCG) type auction for mobile data offloading. A VCG auction is socially efficient, but it is not optimal for the cellular network (the buyer). A typical VCG mechanism leads to an overpayment to suppliers (Chen et al. 2005). The simulation results in our study show that, as compared with the standard VCG auction, a procurement auction with contingent contracts can significantly improve the cellular network’s expected payoff. In general, our study is a combination of analytical modeling and simulations with real data. The main contribution is to introduce and analyze a new procurement mechanism with contingent contracts to meet these challenges in a realistic environment.

Our insights also apply more generally to optimal mechanism design in a class of supply chain problems. Conceptually, the key problem in the purchase of WiFi capacity is to determine the optimal procurement strategy in the presence of product flexibility and information asymmetry between suppliers (WiFi hotspots) and the downstream firm (cellular service provider). This procurement problem in the wireless industry can be extended to a more general setting where (1) the downstream firm owns in-house capacity (cellular capacity) that can be used for multiple products (the wireless service in different WiFi regions); (2) The product-flexible capacity is limited, and the firm needs to procure products from multiple upstream suppliers; and (3) Each supplier is specialized and can only produce one product (each WiFi hotspot can only serve local traffic). Given the presence of limited product-flexible capacity (in-house capacity) and upstream suppliers, the downstream firm needs to design an optimal procurement auction when the customer demand is volatile and unpredictable. This procurement auction design becomes complicated when the downstream firm faces product flexibility and information asymmetry. In the procurement of WiFi capacity, the cellular resource can serve traffic in any WiFi region, whereas the WiFi capacity can only serve local traffic. Buying more resources from a local WiFi hotspot frees up more in-house cellular capacity to serve unsatisfied demand in other WiFi regions. This procurement scenario is common when companies are investing in product-flexible capacity that entails the ability to produce multiple products on the same capacity, and the ability to reallocate capacity between products (Goyal and Netessine 2011). Many manufacturing and service companies use flexible capacity to hedge against uncertainty in future demand (Fine and Freund 1990; Van Mieghem 1998, 2004).[6]

1.2 Literature Review

The majority of the extant literature on supply chain management has focused on scenarios where adding product-flexible capacity is beneficial (Goyal and Netessine 2011). Janakiraman, Nagarajan, and Veeraraghavan (2009) considered a firm that produces multiple products each period, using a shared resource with limited capacity, in a periodically reviewed stochastic inventory model. Simchi-Levi and Wei (2012) studied the performance of flexibility designs when a chain of partial flexibility is implemented.

The literature provides a theoretical foundation for researchers and further galvanizes us into seeking a deeper understating of the following general research question: Given the presence of limited product-flexible capacity, what is the optimal procurement auction mechanism for the downstream firm? Federgruen and Yang (2011) analyzed the downstream firm's optimal procurement strategy with unreliable suppliers. Their analytical model is formulated as a single-agent optimization problem. The underlying assumption is the symmetric information between suppliers and the downstream firm. In our study, we relax this assumption by introducing a game-theoretical model with asymmetric information in the presence of product-flexible capacity. The downstream firm procures products from the suppliers before the actual demand is known, and optimally allocates its in-house capacity to produce different products when the demand is realized. In this process, the downstream firm makes the following decisions: How to allocate its product-flexible capacity to produce different

[6] In the automotive industry, the plants for most of the automobile companies are much more flexible than before: Ford's Rouge Plant can manufacture nine different products (Goyal and Netessine 2011).

products? How much quantity should be procured from each supplier? What is the corresponding payment scheme for each supplier? Our theoretical model provides an auction framework to answer these questions in the context of the wireless industry. In this study, the theoretical results complement the existing literature on product line designs when the product-flexible capacity is limited (Simchi-Levi and Wei 2012; Netessine and Taylor 2007). Netessine, Dobson, and Shumsky (2002) analytically characterized the critical effects of increasing demand correlation between products on the flexible capacity decisions. We also find that the demand correlation as well as the level of in-house capacity plays a crucial role in the optimal design of procurement mechanisms. When the demand correlation is highly positive or the in-house capacity is relatively large, the optimal procurement mechanism is a global auction including all upstream suppliers; otherwise, it is optimal to hold separate auctions for each product.[7]

The present study is closely related to the literature on auction design. Dasgupta and Spulber (1989) extended the standard fixed quantity auction and studied a quantity auction that allows the quantity of the goods purchased to be endogenously based on the submitted bids. In many procurement situations, the buyer cares about other attributes in addition to price when evaluating the submitted bids. In a multi-attribute scoring auction, suppliers submit multidimensional bids, and the contract is awarded to the supplier who submitted the bid with the highest score according to a scoring rule. Che (1993) developed a scoring procurement auction in which suppliers bid on two dimensions of the good. This scoring auction allows only sole sourcing. However, offloading data traffic to multiple WiFi hotspots is naturally done in our procurement setting. Bapna et al. (2009) analyzed multiple overlapping auctions that are conducted to sell identical items by an identical seller. In a keyword advertising market, Liu et al. (2010) studied a weighted

[7] In our wireless context, a separate auction refers to a local auction within a WiFi region.

unit-price rule that is different from previous scoring auctions. Adomavicius et al. (2012) examined the impact of feedback on the outcomes and dynamics of the multi-attribute auctions using a laboratory experiment. Auctions with contingent contracts have been widely studied in economics literature.[8] Hansen (1985) studied an auction with contingent payments. DeMarzo et al. (2005) proposed security-bid auctions in which bidders compete for an asset by bidding with securities whose payments are contingent on the asset's realized value. Chen et al. (2009) showed that the procurement auctions with contingent contracts can manage the project failure risk of suppliers and significantly improve both social welfare and the buyer's payoff. The model in our study differs from such auctions in the application setting and auction formats.

Our research is also related to the computer science literature on mobile data offloading (Balasubramanian et al. 2010; Dong et al. 2012; Iosifidis et al. 2013). The tight integration of economics and computational technology in our system is seen as crucial to address issues surrounding the data traffic support for cloud-based services on mobile networks, such as business collaboration tools, which require sufficient download and upload speeds. Practical mechanism design requires an explicit consideration of computational constraints (Bichler, Gupta, and Ketter 2010). In our real-time auctions, computing and finding the corresponding contingent contract fast is critical. The number of contingent contracts we can implement is subject to computing speeds. Recent advances in parallel computing, such as the open source cluster computing system, Spark,[9] makes it faster to find contingent contracts in large databases. With extremely fast computing speeds, our auction system can compute and implement a huge number of

[8] A contingent contract is a type of forward contract that depends on the realizations of some uncertain events. For example, a contract can be contingent on the uncertain demand or the future spot market price.

[9] Spark is an open source cluster computing system that aims to make data analytics fast. It provides primitives for in-memory cluster computing: Data can be loaded into memory and be queried repeatedly much more quickly than with disk-based systems, like Hadoop MapReduce.

contingent contracts — a task that was once considered computationally prohibitive and significantly improve the cellular network's expected gain.

1.3 A Benchmark Model: Single WiFi Region

A cellular network provides service to its customers who demand bandwidth. Congestion results when network capacity cannot satisfy instantaneous user demand. When the user demand for mobile data is below a certain threshold X_B, the cellular service provider faces no additional cost except the sunk cost of buying the spectrum and keeping the system running. However, when the demand $\tilde{X}$ exceeds the threshold, the cellular service provider incurs a cost of $C_0(\tilde{X} - X_B)$. The threshold $\mathrm{X_B}$ is the cellular capacity [10] owned by the service provider. The standard metrics used in the telecommunications industry to measure quality of service (QoS), such as Erlang B formula and Kleinrock delay formula, depend on the difference between user demand and capacity or their ratio (Pinto and Sibley 2013). In our problem setting, $\tilde{X} - X_B$ is the difference between user demand and capacity. Note that capacity should not be interpreted as a strict output limit, but rather as a factor in maintaining QoS. The cost function $C_0(\cdot)$ is strictly increasing and strictly convex, which captures the rapidly rising cost of congestion (e.g., dissatisfied customers, or churn). A similar convex cost function has been widely used in modeling the congestion cost of the Internet (Dong et al. 2012). Apparently, we have $C_0(x) = 0$ for any $x \leq 0$. Denote $c_0(x) = C_0'(x)$ as the marginal cost of congestion.

[10] $\mathrm{X_B}$ is interpreted as the channel capacity stated by the Shannon–Hartley theorem (Kennington et al. 2011). The theorem shows that when the information transmitted rate is less than $\mathrm{X_B}$, the probability of error at the receiver can be made arbitrary small. When the information transmitted rate is greater than $\mathrm{X_B}$, the probability of error increases as the information transmitted rate is increased.

We model the demand for bandwidth as a random variable $\tilde{X}$ with a cumulative distribution function $G(\tilde{X})$ in the support $[0,1]$[11]. Given the unprecedented growth rate of mobile data demand and the high cost associated with congestion, the cellular network is interested in procuring spare resources from third-party WiFi hotspots.

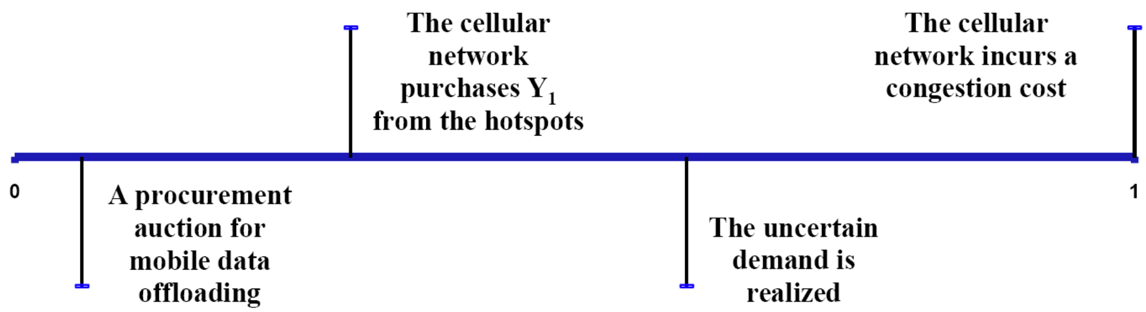

Figure 1.1: Timeline for a Single Region Auction

In this benchmark model, we assume: (1) A single winning hotspot obtains the procurement contract. (2) The range of a cellular base station (a cell sector) is the same as the range of a hotspot (a WiFi region), for simplicity. Thus, we only have a single WiFi region in a cell sector. We relax these two assumptions in the next section.

The timeline for this benchmark model is shown in Figure 1.1. If the cellular network purchases Y_1 units of bandwidth from the hotspot, then the expected reduction of congestion cost for the cellular network is

$$V(Y_1) = \int_0^1 C_0(\tilde{X} - X_B)dG(\tilde{X}) - \int_{X_B+Y_1}^1 C_0(\tilde{X} - X_B - Y_1)dG(\tilde{X}), \quad (1.1)$$

which is the valuation that the cellular network attaches to the additional bandwidth Y_1. The first part $\int_0^1 C_0(\tilde{X} - X_B)dG(\tilde{X})$ is the expected congestion cost without procuring

[11] Note that the assumption of the support is essentially saying that demand is bounded, which is without loss of generality for any realistic situation. Of course, the interpretation of 1 will be different for different scenarios. For example, 1 could be interpreted as 1 terabyte per second or 10 terabytes per second.

from WiFi hotspots, and the second part, $\int_{X_B+Y_1}^{1} C_0(\tilde{X}-X_B-Y_1)dG(\tilde{X})$ is the expected congestion cost when the purchase quantity is Y_1.

Because

$$V'(Y_1)=\int_{X_B+Y_1}^{1} C_0'(\tilde{X}-X_B-Y_1)dG(\tilde{X})>0 \tag{1.2}$$

and

$$V''(Y_1)=-\int_{X_B+Y_1}^{1} C_0''(\tilde{X}-X_B-Y_1)dG(\tilde{X})-C_0'(0)g(X_B+Y_1)<0,$$

where $g(\cdot)$ is the density function of $\tilde{X}$. $V(Y_1)$ is strictly increasing and strictly concave, which is not surprising given that the cost of congestion is convex.

We assume that the cost function for hotspot i to provide capacity Q to the cellular network is

$$C(Q,\theta_i)\equiv\int_0^Q c(q,\theta_i)dq, i=1,2,\ldots,n.$$

where $c(q,\theta_i)\geq 0$ is the marginal cost function for hotspot i, and where θ_i represents each hotspot's private information about the cost of capacity provision. The cost of providing bandwidth for a hotspot is based on its instantaneous user demand and many other considerations that may not be revealed to the cellular network. For example, congestion encourages customers of hotspots to balk and cause a negative impact on hotspots' profits. This impact might differ among different hotspots, and only hotspots know the actual impact. We assume $c_q(q,\theta_i)\geq 0$ to capture the fact that the marginal cost of providing capacity for each hotspot increases as more capacity is provided to the cellular network. Marginal costs are increasing and convex in the cost parameter, $c_\theta \geq 0$, $c_{\theta\theta}\geq 0$. Also, we assume $c_{q\theta}\geq 0$. Hotspots' cost parameters are independently and identically distributed with a continuously differentiable cumulative distribution function $F(\cdot)$ defined on $[\underline{\theta},\bar{\theta}]$ which is common knowledge. Define $H(\theta)\equiv F(\theta)/F'(\theta)$, and let $H(\theta)$ be an increasing function of θ. This assumption of monotone hazard rate is satisfied by commonly used distribution functions such as the uniform distribution.

It follows from Dasgupta and Spulber (1989) that the optimal allocation can be implemented via a quantity auction (sealed bid) where

• The cellular service provider announces a payment-bandwidth schedule $B = B(Q)$;

• Each hotspot chooses the bandwidth they want to sell given $B(Q)$; and

• The hotspot choosing to provide the highest capacity, Q, wins the auction and sells the chosen capacity to the cellular service provider.

This quantity auction is optimal for the cellular service provider if we assume that a single winner emerges. Given the payment-bandwidth schedule $B(Q)$, the hotspots' biding strategy is denoted by $Q(\theta)$: A hotspot with private cost parameter, $\theta \in [\underline{\theta}, \bar{\theta}]$, bids $Q(\theta)$. Let θ^* be a threshold cost parameter: Hotspots for which the cost parameter exceeds θ^* do not bid, while those with $\theta < \theta^*$ bid according to $Q(\theta)$. This represents the individual rationality constraint.

Proposition 1.1 (Single Region) In the optimal quantity auction, the payment-bandwidth schedule $B^*(Q)$ and the optimal bidding strategy $Q^*(\theta)$ are given by the following equations:

$$B^*(Q) = C(Q, Q^{-1}(Q)) + \frac{\int_{Q^{-1}(Q)}^{\theta^*} \left(1-F(x)\right)^{n-1} C_\theta(Q^*(x), x)dx}{\left(1-F(Q^{-1}(Q))\right)^{n-1}}, \tag{1.3}$$

$$V'(Q^*(\theta)) = C_Q(Q^*(\theta), \theta) + C_{Q\theta}(Q^*(\theta), \theta)H(\theta), \tag{1.4}$$

where $Q^{-1}(\cdot)$ denotes the inverse function of $Q^*(\cdot)$. The cellular service provider's expected gain is

$$n\int_{\underline{\theta}}^{\theta^*} \left(1 - F(\theta)\right)^{n-1} F'(\theta)[V(Q) - C(Q, \theta) - C_\theta(Q, \theta)H(\theta)]d\theta. \tag{5}$$

Under asymmetric information, this is the highest expected profit for the cellular service provider when it must procure from a single winning hotspot.

Proof. See Appendix A.

Note that the hotspot with the lowest θ always wins the auction, because it has the lowest marginal cost of providing bandwidth and provides the highest Q under the payment-bandwidth schedule $B(Q)$. In equation 1.5, $n\big(1-F(\theta)\big)^{n-1}F'(\theta)$ is the density of the lowest θ. The cellular service provider's benefit is the expected reduction of the congestion cost, which is given by equation 1.1. $C(Q,\theta)+C_\theta(Q,\theta)H(\theta)$ is the "virtual cost" the cellular service provider pays to the winning hotspot. Under complete information, the payment to the winning hotspot is the cost $C(Q,\theta)$. The information asymmetry is reflected in the term $C_\theta(Q,\theta)H(\theta)$, which is the information rent of the winning hotspot.

1.4 Multiple WiFi Regions

1.4.1 A Non-Contingent Procurement Auction

In the benchmark model, we assume that only a single hotspot wins the auction. However, the WiFi capacity for one hotspot is limited, and relying on multiple hotspots is optimal because of the convexity of the congestion cost functions. The benchmark model also assumes that the range of a cellular base station is the same as the range of a hotspot. However, cellular resources and WiFi resources actually have different spatial coverages. In suburban areas, a typical cellular base station covers 1-2 miles (2-3 km) and in dense urban areas, it may cover one-fourth to one-half mile (400-800 m). A typical WiFi network has a range of 120 feet (32 m) indoors and 300 feet (95 m) outdoors.[12]

[12] See http://en.wikipedia.org/wiki/Wifi, and http://en.wikipedia.org/wiki/Cell_site.

Therefore, we need to partition a cell sector into several regions. In Figure 1.2, a red circle is a WiFi region. Usually, a WiFi region has several WiFi hotspots that are close together.

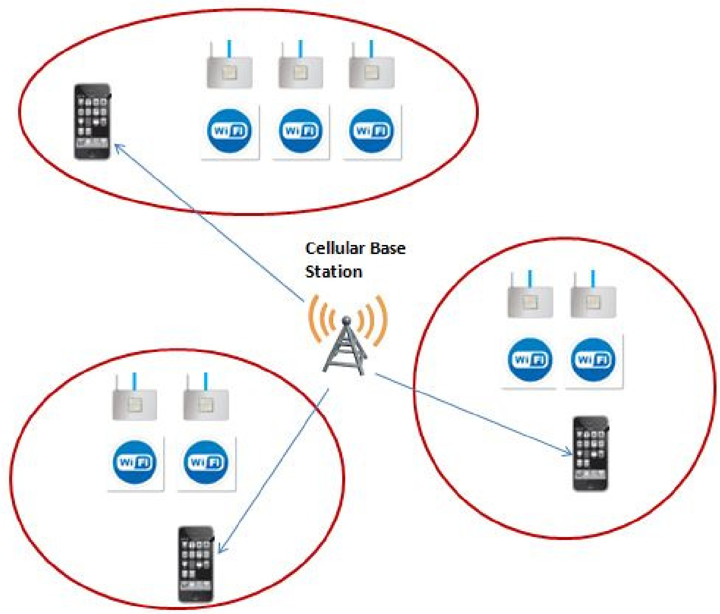

Figure 1.2: Multiple WiFi Regions

Now suppose there are M WiFi regions in a cell sector, $1,2,\cdots,M$, and the demand for region m is $\tilde{X}_m$. The demand vector $(\tilde{X}_1,\tilde{X}_2,\cdots,\tilde{X}_M)$ has a joint distribution function $G(\tilde{X}_1,\tilde{X}_2,\cdots,\tilde{X}_M)$. We assume the same congestion cost function of the cellular service provider for all regions. Cellular resources can serve traffic in any region m, whereas WiFi hotspots in region m can only serve local traffic.[13] In Figure 1.2, a hotspot located in a WiFi region cannot serve the demand in another region. A

[13] A WiFi hotspot might be on the boundary of two regions. In Section 6, we generate regions by clustering the WiFi hotspots using k-means method. Note that for simplicity, we assume that cellular capacity can be reallocated seamlessly from one WiFi region to another. In practice, some cellular capacity can be redirected (e.g., core processing for the base station), and some capacity cannot be redirected (e.g., radio capacity for directional antennas – these cover only a certain direction and angular range).

unique challenge in the procurement auction is that the longer range cellular resource introduces coupling between the shorter range WiFi hotspots. The procurement problem in one WiFi region is not independent of the procurement problem in another region, because purchasing more WiFi capacity from a local WiFi hotspot in one region frees up more cellular capacity that can be used to serve the demand in another region. In this section, we derive the optimal auction rule under different spatial coverages.

The timeline for a multiple region auction is shown in Figure 1.3. The cellular service provider follows a two-step decision procedure: In the first stage, it purchases WiFi capacity from hotspots in different regions. In the second stage, the cellular service provider adjusts the allocation of cellular resources across regions.

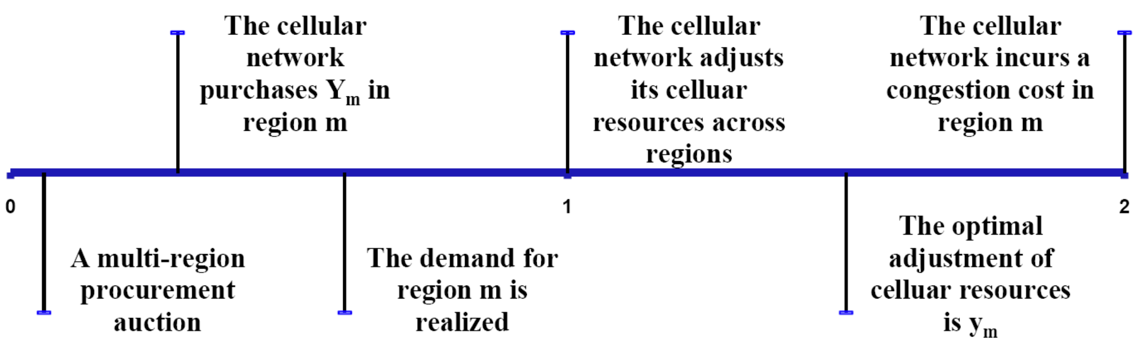

Figure 1.3: Timeline for a Multiple Region Auction

We first focus on the optimization problem in the second stage. If the cellular service provider purchases Y_m units of bandwidth from hotspots in region m, then the expected congestion cost is

$$\mathrm{Min}_{y_1,y_2,\cdots,y_M} \int_0^1 \int_0^1 \cdots \int_0^1 \sum_{m=1}^{M} C_0(\tilde{X}_m - Y_m - y_m) dG(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$$
$$s.t.\ \sum_{m=1}^{M} y_m = X_B, y_m \geq 0,\ \text{for } m = 1,2,\ldots M, \tag{1.6}$$

where y_m is the amount of cellular capacity allocated to region m. The cellular service provider can adjust the allocation of cellular resources across regions through varying y_m. Purchasing more capacity from a local WiFi hotspot frees up more cellular resources, which can be allocated to other regions. Note that the value of this minimization problem is the expected congestion cost when the service provider can integrate both cellular resources and WiFi resources.

Similarly, without hotspots, the expected congestion cost is

$$\mathrm{Min}_{y_1,y_2,\cdots,y_M} \int_0^1 \int_0^1 \cdots \int_0^1 \sum_{m=1}^{M} C_0(\tilde{X}_m - y_m) dG(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$$

$$s.t.\ \sum_{m=1}^{M} y_m = X_B, y_m \geq 0,\ \text{for}\ m = 1,2,\ldots M.$$

The value of this minimization problem is the expected congestion cost when the service provider relies solely on cellular resources.

Because $C_0(\cdot)$ is convex, using Jensen's inequality, we have

$$\sum_{m=1}^{M} C_0(\tilde{X}_m - y_m) \geq M \cdot C_0\left(\frac{1}{M}\sum_{m=1}^{M} (\tilde{X}_m - y_m)\right) = M \cdot C_0(\bar{X})$$

$$\sum_{m=1}^{M} C_0(\tilde{X}_m - Y_m - y_m) \geq M \cdot C_0\left(\frac{1}{M}\sum_{m=1}^{M} (\tilde{X}_m - Y_m - y_m)\right) = M \cdot C_0(\bar{X} - \bar{Y}) \quad (1.7)$$

where

$$\bar{X} = \frac{\tilde{X}_1 + \tilde{X}_2 + \cdots + \tilde{X}_M - X_B}{M}, and\ \bar{Y} = \frac{Y_1 + Y_2 + \cdots + Y_M}{M}.$$

If we define $X = \tilde{X}_1 + \tilde{X}_2 + \cdots + \tilde{X}_M - X_B$ as the total excess demand of the sector, $\bar{X} = X/M$ can be interpreted as the average excess demand across regions. The optimal allocation of cellular resources should be $y_m^* = (\tilde{X}_m - \bar{X}) - (Y_m - \bar{Y})$ with using WiFi hotspots and $y_m^* = \tilde{X}_m - \bar{X}$ without using hotspots.

For such allocations of cellular resources across regions to be feasible, we need $y_m^* \geq 0$, or equivalently,

$$\frac{X_B}{M} \geq \left(Y_m - \frac{1}{M}\sum_{m=1}^{M} Y_m\right) - \left(\tilde{X}_m - \frac{1}{M}\sum_{m=1}^{M} \tilde{X}_m\right), \quad (1.8)$$

for $m = 1,2,\ldots,M$, and for all possible realizations of private cost parameters (θ_i, θ_{-i}). The condition is more likely to be satisfied if bandwidth demand and hotspots supply are relatively homogeneous across regions or if X_B is relatively large. Alternatively, the condition is more likely to be satisfied if more hotspot bandwidth supply is available in regions with more bandwidth demand (i.e., $\tilde{X}_m$ and Y_m are positively correlated). Apparently, the second condition is a reasonable assumption because the economic incentive to supply bandwidth is larger in regions with high demand. In this section, we assume inequality 1.8 is always satisfied.

The expected reduction of congestion cost for the cellular service provider after the procurement of hotspot bandwidth is

$$V(Y_1, Y_2, \cdots, Y_M) = M\int_0^1 \int_0^1 \cdots \int_0^1 C_0(\bar{X})dG(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M) - M\int_0^1 \int_0^1 \cdots \int_0^1 C_0(\bar{X} - \bar{Y})dG(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M).$$

Because the valuation function is only a function of $\tilde{X}_1, \cdots, \tilde{X}_M$ through $\bar{X}$, we denote the distribution of $\bar{X}$ as $\bar{G}$ and rewrite the valuation as

$$V(Y_1, Y_2, \cdots, Y_M) = V(\bar{Y}) = M\int_0^1 C_0(\bar{X})d\bar{G}(\bar{X}) - M\int_{\bar{Y}}^1 C_0(\bar{X} - \bar{Y})d\bar{G}(\bar{X}) \quad (1.9)$$

Note the similarity between the valuation function for the case of a single region (equation 1.1) and the valuation function for the case of multiple regions (equation 1.9), which immediately implies that $V(\bar{Y})$ is also increasing and concave in $\bar{Y}$. Indeed, the single region case can be viewed as the same as a multiple-region case in which $M = 1$.

Because the valuation function is only a function of $Y_1, \cdots, Y_M$ through $\bar{Y}$, the task of undertaking multiple procurements in multiple regions is essentially the same task as undertaking a single procurement in one sector in which the bandwidth capacity is procured from several hotspots in different regions. When condition 1.8 is satisfied, the WiFi capacity in different regions is a perfect substitute for each other in the cellular service provider's view. In other words, we are dealing with a variable quantity procurement auction with multiple winners. In the first stage, the cellular service provider's optimization problem is characterized as a direct revelation game in which hotspots announce their types and truthful revelation is a Bayes-Nash equilibrium. We adopt the notational convention of writing $\theta_{-i} = (\theta_1, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots, \theta_n)$. The optimal allocation for the cellular service provider can be implemented via a direct revelation mechanism where

- The cellular service provider announces a payment-bandwidth schedule $P_i(\theta_i, \theta_{-i})$, and a bandwidth allocation schedule $q_i = Q(\theta_i, \theta_{-i})$;

- Hotspot i reports the private cost parameter θ_i given $P_i(\theta_i, \theta_{-i})$ and $Q(\theta_i, \theta_{-i})$;
- Hotspot i provides bandwidth $q_i = Q(\theta_i, \theta_{-i})$ to the cellular service provider and its payment is $P_i = P_i(\theta_i, \theta_{-i})$.

The optimal mechanism $\left(P_i^*(\theta_i, \theta_{-i}), Q^*(\theta_i, \theta_{-i})\right)$ for the cellular service provider is given by the following proposition:

Proposition 1.2 (Multiple Regions) In the optimal direct revelation mechanism, all hotspots truthfully announce their cost parameters θ. The optimal bandwidth allocation schedule $q_i = Q^*(\theta_i, \theta_{-i})$, for $i = 1,2,\ldots n$ is given by:

$$\hat{V}'\left(\sum_{i=1}^{n} q_i\right) = c(q_i, \theta_i) + c_\theta(q_i, \theta_i)H(\theta_i).$$

where $V(\bar{Y}) = \hat{V}\left(\sum_{i=1}^{n} q_i\right) = M\int_0^1 C_0(\bar{X})d\bar{G}(\bar{X}) - M\int_{\frac{1}{M}\sum_{i=1}^{n} q_i}^{1} C_0\left(\bar{X} - \frac{1}{M}\sum_{i=1}^{n} q_i\right)d\bar{G}(\bar{X})$. The optimal payment schedule $P_i = P_i^*(\theta_i, \theta_{-i})$, for $i = 1,2,\ldots n$ is given by:

$$P_i^*(\theta_i, \theta_{-i}) = C(Q^*(\theta_i, \theta_{-i}), \theta_i) + \int_{\theta_i}^{\theta^*} C_\theta(Q^*(\theta, \theta_{-i}), \theta)d\theta.$$

The cellular service provider's expected gain is

$$E\left[\hat{V}\left(\sum_{i=1}^{n} Q^*(\theta_i, \theta_{-i})\right) - \sum_{i=1}^{n} C(Q^*(\theta_i, \theta_{-i}), \theta_i) - \sum_{i=1}^{n} C_\theta(Q^*(\theta_i, \theta_{-i}), \theta_i) H(\theta_i)\right].$$

Under asymmetric information, this is the highest expected profit for the cellular service provider when it can procure capacity from multiple hotspots in different regions (second best).

Proof. See Appendix A.

In the direct revelation game, hotspot i announces its cost parameter θ_i. The capacity it needs to provide is $q_i = Q^*(\theta_i, \theta_{-i})$, and its payment is $P_i = P_i^*(\theta_i, \theta_{-i})$. This optimal mechanism is a global auction including all hotspots from different regions. Note that launching separate auctions within each region is not optimal because the cellular resource can serve traffic in any region. The intuition is that procuring more WiFi resources in one region frees up more cellular resources, and the cellular service provider can allocate the cellular resources to other regions. In equilibrium, the virtual marginal costs $c(q_i, \theta_i) + c_\theta(q_i, \theta_i)H(\theta_i)$ are equalized across hotspots in different regions, and the marginal benefits of procuring WiFi capacity should be equalized across regions as well. In addition, the number of hotspots might be small in some specific regions. The global auction effectively creates the inter-region competition among the hotspots when the intra-region competition is limited. Under our procurement mechanism, the network becomes more resilient because the peak data traffic can be seamlessly offloaded to some nearby hotspots with minimal service disruption. The procedure of computing the optimal procurement auction is included in Appendix B.

1.4.2 A Contingent Procurement Auction

In the previous section, the procurement mechanism is implemented before the demand is realized. In this sense, there is an ex-post inefficiency: The cellular service provider might purchase either too much or too little bandwidth. Contingent contracts can be useful in mitigating this problem. In this section, the auction rule is contingent on demand uncertainty.

A prerequisite for a contingent contract is that the uncertain demand should be contractable, which means the realized demand must be one that both cellular service provider and hostpots can observe and measure and that neither side can covertly manipulate. An increasingly important response to cost pressure in supply chains is the information sharing between retailers and suppliers (Aviv 2001). Emerging technologies, such as Electronic Data Interchange (EDI) and Radio Frequency Identification (RFID), facilitate sales data-sharing and make the design of contingent contracts more practical and reliable. In our problem settings, the cellular service provider can directly observe the demand information, but the hotspots cannot observe it. In this section, we show that the cellular service provider does not have incentive to misreport the private demand information. Therefore, the design of a procurement auction with contingent contracts is practical.[14]

Now we present a theory on how to design the optimal multi-region procurement auction with contingent contracts. Following from equation 9, the expected reduction of congestion cost for the cellular service provider after the procurement of hotspot bandwidth given the realization of the demand $(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$ is

$$U(Y_1, Y_2, \cdots, Y_M) = U(\overline{Y}) = M \cdot C_0(\bar{X}) - M \cdot C_0(\bar{X} - \overline{Y}),$$

[14] Sharing demand information with hotspots is a type of open book policy for a cellular service provider. The continuing interaction between a cellular service provider and hotspots makes contingent contracts more reasonable and attractive.

where $\bar{X} = \frac{\tilde{X}_1+\tilde{X}_2+\cdots+\tilde{X}_M-X_B}{M}$. $U(\bar{Y})$ is also increasing and concave in $\bar{Y}$. When the demand is realized, the cellular service provider can observe a vector of demand, $(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$, and then announces a vector, X_a, to the hotspots.

The optimal allocation for the cellular service provider can be implemented via a direct revelation mechanism where

• The cellular service provider announces a payment-bandwidth schedule $P_i(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$, and a bandwidth allocation schedule $q_i = Q(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$;

• Hotspot i reports the private cost parameter θ_i given $P_i(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$ and $Q(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$;

• After the demand is realized, the cellular service provider announces the demand information, X_a.

• Hotspot i provides bandwidth $q_i = Q(\theta_i, \theta_{-i}, X_a)$ to the cellular service provider and its payment is $P_i = P_i(\theta_i, \theta_{-i}, X_a)$.

Note that X_a can be some value other than $(\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$. However, we show that $X_a = (\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$ in equilibrium in the following proposition.

Proposition 1.3 In the equilibrium of a multi-region procurement auction with contingent contracts, the cellular service provider truthfully announces the demand information: $X_a = (\tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$.

Proof. See Appendix.

This proposition shows that in equilibrium the cellular service provider will truthfully report the demand information. The intuition is that if the cellular service provider misreports the demand information, it distorts the bandwidth provision of WiFi hotspots and reduces the expected payoff of the cellular service provider.

We still assume that inequality 1.8 is always satisfied, and the optimal mechanism $\left(P_i^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M), Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right)\right)$ for the cellular service provider is given by the following proposition:

Proposition 1.4 In a multi-region procurement auction with contingent contracts, the optimal bandwidth allocation schedule $q_i = Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right)$, for $i = 1,2,\ldots n$ is given by:

$$\widehat{U}'\left(\sum_{i=1}^{n} q_i\right) = c(q_i, \theta_i) + c_\theta(q_i, \theta_i)H(\theta_i). \tag{1.10}$$

where $U(\bar{Y}) = \widehat{U}\left(\sum_{i=1}^{n} q_i\right) = M \cdot C_0(\bar{X}) - M \cdot C_0\left(\bar{X} - \frac{1}{M}\sum_{i=1}^{n} q_i\right)$. The optimal payment schedule $P_i = P_i^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$, for $i = 1,2,\ldots n$ is given by:

$$\begin{aligned} P_i^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M) &= C\left(Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right), \theta_i\right) \\ &+ \int_{\theta_i}^{\theta^*} C_\theta\left(Q^*\left(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right), \theta\right) d\theta. \end{aligned}$$

The cellular service provider's expected payment is

$$E\begin{bmatrix} \sum_{i=1}^{n} C\left(Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right), \theta_i\right) \\ + \sum_{i=1}^{n} C_\theta\left(Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M\right), \theta_i\right)H(\theta_i) \end{bmatrix}. \tag{1.11}$$

Proof. See Appendix.

This proposition is similar to Proposition 2.2, but the optimal mechanism depends on the contingent demand. Therefore, this contingent procurement mechanism can improve the ex-post efficiency.

1.5 Extension

In Section 1.4, we assume that $y_m^* \geq 0$ for all m, or equivalently, the cellular capacity X_B is sufficiently large such that for all m and all possible realizations of cost parameters (θ_i, θ_{-i}) drawn from the distribution $F(\cdot)$, condition 1.8 is always satisfied:

$$\frac{X_B}{M} \geq \left(Y_m - \frac{1}{M}\sum_{m=1}^{M} Y_m\right) - \left(\tilde{X}_m - \frac{1}{M}\sum_{m=1}^{M} \tilde{X}_m\right).$$

We call it the feasibility condition. Under a contingent procurement mechanism, the equilibrium quantity purchased in region m, $Y_m = \sum_{i \in \Psi_m} Q^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$, where Ψ_m is the set of hotspots in region m. Note that condition 8 may hold for some realizations of cost parameters (θ_i, θ_{-i}) but not for some others. Our feasibility condition requires that condition 8 holds for every realization of cost parameters (θ_i, θ_{-i}).

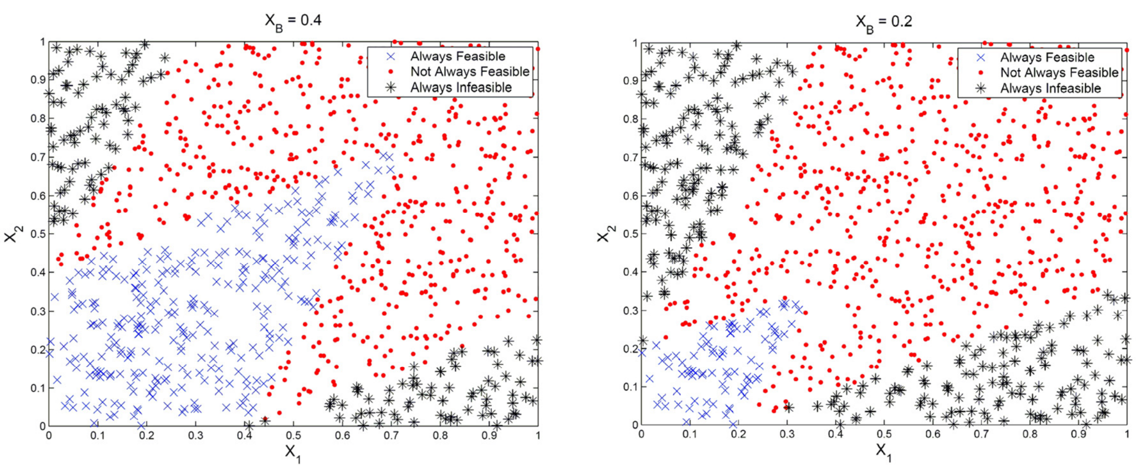

Figure 1.4: Illustrating Examples of the Feasibility Condition

In this section, we introduce a modified contingent procurement mechanism to discuss the optimal procurement mechanism when the feasibility assumption is relaxed. We start with a simple toy model with two WiFi regions, that is, $M = 2$.

To gain some intuitions about the feasibility condition, we depict two illustrating examples in Figure 1.4. We assume that there are two WiFi regions ($M = 2$), and that each region has four hotspots ($n = 8$). The congestion cost functions for the service provider and WiFi hotspots are simple: $C_0(x) = 2x^2$, and $C(x, \theta_i) = \left(\frac{1}{2} + \theta_i\right) x^2$, where the private cost parameters for hotspots, θ_i, is drawn from a uniform distribution $U[0,1]$ for 1,000 times. The data traffic for each region, $\widetilde{X}_m$, $m = 1,2$, is drawn from independent standard uniform distributions $U[0,1]$ for 1,000 times. In the figure, The blue "X"s indicate that the feasibility condition is always satisfied when the demand is $\left(\widetilde{X}_1, \widetilde{X}_2\right)$, the red dots indicate that condition 1.8 is violated for some realizations of cost parameters (θ_i, θ_{-i}) drawn from the distribution $F(\cdot)$, and the black stars indicate that condition 8 is violated for all possible realizations of cost parameters (θ_i, θ_{-i}) drawn from the distribution $F(\cdot)$. When the feasibility condition is always satisfied (the blue "X"s), the optimal procurement mechanism is the global auction we discussed in Section 1.4.2. When the feasibility condition is always violated (the black stars), the marginal benefits of procuring WiFi capacity for the cellular service provider cannot be equalized across different regions. In this case, a separate local auction for each region is optimal. Our modified mechanism mainly focuses on the third scenario: the condition 1.8 is violated for some realizations of cost parameters (θ_i, θ_{-i}) (the red dots). The cellular capacity, X_B, is set to be 0.4 in the left panel and 0.2 in the right panel. Figure 1.4 shows that the feasibility condition is more likely to be violated when the demands are unbalanced or X_B is small.

Under the modified mechanism, the allocation scheme of cellular resource is denoted by a vector $\left\{\lambda_m\left(\theta_i, \theta_{-i}, \widetilde{X}_1, \widetilde{X}_2\right)\right\}$, $m = 1,2$, where $\lambda_m\left(\theta_i, \theta_{-i}, \widetilde{X}_1, \widetilde{X}_2\right)$ is the fraction of cellular resource allocated in region m, and it is a function of the reported types of hotspots and the demand contingency.

The modified procurement mechanism for two regions is described as follows:

- The cellular service provider announces a payment-bandwidth schedule $P_i(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)$, an allocation scheme of cellular resource $\{\lambda_m(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\}$, and a WiFi bandwidth allocation schedule $q_i = Q\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right)$, $m = 1,2$;
- Hotspot i reports the private cost parameter θ_i;
- Hotspot i provides bandwidth $q_i = Q\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right)$ to the cellular service provider, and its payment is $P_i = P_i(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)$.

Let's define y_m^{**} as the optimal amount of cellular capacity allocated to region m when we don't consider the constraint $y_m \geq 0$, so y_m^{**} is the solution to the following congestion cost minimization problem when Y_m is the optimal procurement quantity in region m:

$$\min_{y_1, y_2} \sum_{m=1}^{2} C_0(\tilde{X}_m - Y_m - y_m)$$
$$s.t. \sum_{m=1}^{2} y_m = X_B.$$

and

$$\begin{aligned} y_m^{**} &= (\tilde{X}_m - \bar{X}) - (Y_m - \bar{Y}) \\ &= (\tilde{X}_m - \bar{X}) - \left[\sum_{i\in\Psi_m} Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2\right) - \frac{1^n}{2_{i=1}} Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2\right)\right], \end{aligned}$$

where $Q^*\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2\right)$ is given by equation 1.10 when $M = 2$. The optimal modified mechanism $(P_i^{**}, q_i^{**}, \lambda_m^{**})$ for the cellular service provider is given by the following proposition:

Proposition 1.5 If $M = 2$ and the feasibility condition is not satisfied, the optimal allocation allocation scheme of cellular resource is given by

$$\lambda_m^{**}(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2) = \begin{cases} 0, & \text{if } y_m^{**} < 0, \\ \frac{y_m^{**}}{X_B}, & \text{if } 0 \le y_m^{**} \le X_B, \\ 1, & \text{if } y_m^{**} > X_B, \end{cases}$$

We denote $Q^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)$ as the solution given by equation 1.10. If $\lambda_m^{**} = y_m^{**}/X_B$, the optimal bandwidth allocation schedule q_i^{**} is given by

$$q_i^{**} = Q^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2), i \in \Psi_m.$$

If $\lambda_m^{**} = 0$ or 1, q_i^{**} is given by

$$C_0'\left(\tilde{X}_m - \lambda_m^{**} X_B - \sum_{i \in \Psi_m} q_i^{**}\right) \tag{1.12}$$

$$= c(q_i^{**}, \theta_i) + c_\theta(q_i^{**}, \theta_i) H(\theta_i), i \in \Psi_m,$$

The optimal payment schedule $P_i^{**}(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)$, for $i = 1,2,\ldots n$, is given by:

$$P_i^{**}(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2) = C(q_i^{**}, \theta_i) + \int_{\theta_i}^{\theta^*} C_\theta(q_i^{**}, \theta) d\theta. \tag{1.13}$$

Proof. See Appendix A.

We briefly outline the steps of the proof here. First, we need to show that the proposed mechanism is incentive compatible: Given the modified mechanism $(P_i^{**}, q_i^{**}, \lambda_m^{**})$, each hotspot does not have an incentive to misreport its private cost parameter. Then, we need to show that the proposed mechanism is optimal for the cellular service provider. The intuition is that when the feasibility condition is satisfied, the modified mechanism is equivalent to the optimal mechanism described in Proposition 1.4. Note that when the feasibility condition is satisfied, it is optimal for the cellular service provider to organize a global auction that includes all hotspots from different regions. When the feasibility condition is not satisfied, an optimal mechanism is to allocate all cellular capacity to one region, and then organize a separate local auction for each region. We show that the expected payoff of the cellular service provider in our modified mechanism is the same as the payoff under two separate local auctions when the feasibility condition is not satisfied.

We can extend our modified mechanism to the case that $M > 2$. The approach is that the multiple region case can be converted to the case that $M = 2$.

Let's denote y_{mk}, for $k = 1,2,\ldots M$ and $m = 1,2,\ldots,k$, as the solution to the following congestion cost minimization problem:

$$\min_{y_{mk}} \sum_{m=1}^{k} C_0(\tilde{X}_m - Y_{mk} - y_{mk}) \qquad (1.14)$$

$$s.t. \sum_{m=1}^{k} y_{mk} = X_B,$$

where Y_{mk} is the optimal procurement quantity in region m when the participating hotspot $i \in \cup_{j=1}^{k} \Psi_j$: $Y_{mk} = \sum_{i\in\Psi_m} Q_k^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_k)$. $Q_k^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_k)$ is given by equation 1.10 when the participating hotspot $i \in \cup_{j=1}^{k} \Psi_j$. We sort y_{mk} into descending order in an iterated way. Step (1) $y_{1M} \geq y_{2M} \geq \ldots \geq y_{MM}$; Step (2) for region $m = 1,2,\ldots,M-1$ in Step 1, we solve the minimization problem 1.14 when $k = M-1$, and sort y_{mM-1}: $y_{1M-1} \geq y_{2M-1} \geq \ldots \geq y_{M-1,M-1}$, ...; Step $(k+1)$ for region $m = 1,2,\ldots,M-k$ in step k, we solve the minimization problem 1.14 when $k = M-k$, and sort $y_{m,M-k}$: $y_{1M-k} \geq y_{2M-k} \geq \ldots \geq y_{M-k,M-k}$, $k = 2,3,\ldots,M-1$. The optimal modified mechanism when $M > 2$ is given by the following proposition:

Proposition 1.6 If $M > 2$ and the feasibility condition 1.8 is not satisfied, the optimal allocation scheme of cellular resource is given by the following iterated process: If $y_{MM} \geq 0$, then $\lambda_m^{**} = y_{mM}/X_B$, for $m = 1,2,\ldots,M$. If $y_{MM} < 0$, then $\lambda_M^{**} = 0$, and if $y_{M-1,M-1} \geq 0$, then $\lambda_m^{**} = y_{mM-1}/X_B$, for $m = 1,2,\ldots,M-1$. If $y_{M-1,M-1} < 0$, then

$\lambda^{**}_{M-1} = 0$, …, and if $y_{M-k,M-k} \geq 0$, then $\lambda^{**}_{m} = y_{mM-k}/X_B$, for $m = 1,2,\ldots, M-k$. If $y_{M-k,M-k} < 0$, then $\lambda^{**}_{M-k} = 0$.

If $\lambda^{**}_{m} = y_{mM-k}/X_B$, the optimal bandwidth allocation schedule q^{**}_{i} is given by:

$$q_i^{**} = Q^*_{M-k}\big(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_{M-k}\big), \text{ for } i \in \Psi_m.$$

If $\lambda^{**}_{m} = 0$, q^{**}_{i} is given by:

$$C_0'\big(\tilde{X}_m - \textstyle\sum_{i \in \Psi_m} q_i^{**}\big) \tag{1.15}$$

$$= c(q_i^{**}, \theta_i) + c_\theta(q_i^{**}, \theta_i)H(\theta_i), \qquad \text{for } i \in \Psi_m,$$

The optimal payment schedule P_i^{**}, for $i = 1,2,\ldots n$ is given by:

$$P_i^{**} = C(q_i^{**}, \theta_i) + \int_{\theta_i}^{\theta^*} C_\theta(q_i^{**}, \theta)d\theta. \tag{1.16}$$

1.6 Simulation Studies

Applying our model to the network data from one of the largest U.S. service providers, we address the following question in this section: As compared with the standard VCG auction, how much can our optimal procurement auction improve the cellular network's expected payoff? The Monte Carlo simulation results demonstrate that, as compared with the standard VCG auction, our contingent procurement auction significantly improves the cellular network's expected payoff. We also evaluate the impact of the cellular capacity and the relative cost of deploying cellular resources on the performance difference between these two mechanisms.

Before we do the comparison, we will first review the multi-unit VCG auction for procurement in our context. The following list describes the VCG procurement auction:

- Invite each hotspot to report its cost parameter θ. Denote the submitted cost parameters as $\{\theta_1, \theta_2, \cdots, \theta_n\}$.
- Under the VCG mechanism, the socially efficient allocation minimizes the sum of the expected congestion cost of the cellular service provider and the cost of

hotspots. According to equation 1.7, we have the sum of the expected congestion cost, and the minimization problem is formalized as follows:

$$\min_{q_1,q_2,\ldots,q_k} M\int_0^1\int_0^1\cdots\int_0^1 C_0(\bar{X}-\bar{Y})dG(\tilde{X}_1,\tilde{X}_2,\cdots,\tilde{X}_M)+\sum_{i=1}^{n} C(q_i,\theta_i)$$

$$s.t.\, q_i \geq 0, \quad \text{for } i = 1,2,\ldots,n,$$

$$\bar{Y}=\frac{1}{M}\sum_{i=1}^{M} Y_i=\frac{1}{M}\sum_{i=1}^{M} q_i.$$

• Let $\pi(\theta_1,\theta_2,\cdots,\theta_k)$ be the optimal value of the objective function, and let $(q_1^*,q_2^*,\cdots,q_n^*)$ be an optimal solution to the cost minimization problem. Let $\pi_{-i}(\theta_{-i})$ be the optimal value of the objective function with the additional constraint $q_i=0$ (i.e., hotspot i does not participate in the auction).

• The cellular service provider will pay hotspot i according to the following:

$$P_i=\pi_{-i}(\theta_{-i})-\pi(\theta_1,\theta_2,\cdots,\theta_n)+C(q_i^*,\theta_i) \tag{1.17}$$

where $\pi_{-i}(\theta_{-i})-\pi(\theta_1,\theta_2,\cdots,\theta_n)$ is the bonus payment to hotspot i, representing the positive externality that hotspot i is imposing on the cost minimization problem. The cellular service provider pays hotspot i its cost $C(q_i^*,\theta_i)$, plus its contribution to the cost minimization problem. This payment internalizes the externality.

• Hotspot i provides capacity q_i^* and receives payment P_i.

Note that the VCG auction is both truth-telling and socially efficient by standard arguments. All hotspots bid their cost parameters truthfully, irrespective of other hotspots' bids. The VCG mechanism guarantees the minimum total cost. However, it leads to an overpayment to hotspots that is shown in the simulation.[15]

[15] Note that this VCG mechanism is not contingent on the realized demand. We also simulate the performance of a contingent VCG mechanism. The basic results of performance comparison remain unchanged.

In our simulations, we consider a typical urban neighborhood in New York City, NY, USA, as shown in Figure 1.5. We define a cell sector as the range of the cell tower. Our dataset consists of the location information of 14,576 cell towers from a large cellular provider in the U.S. In our simulation study, we pick a cell tower in New York City from the full list of cell towers and simulate the mobile data demand in this sector. In Figure 1.5, T represents the cell tower, and others are 69 WiFi hotspots in the given cell sector.[16] Following Dong et al. (2012), we set the communication range for a cell tower as 250m, and set the communication range for Wi-Fi as 100m. The following steps describe the procedure of simulations:

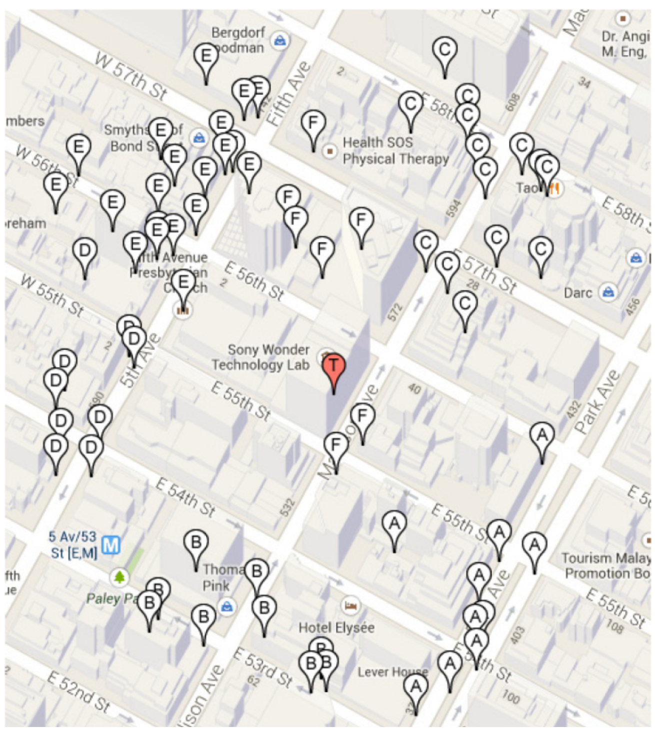

Figure 1.5: Area Map of A Typical Cell Sector

[16] Locations of commercial WiFi hotspots are from http://wigle.net.

• Generating traffic demands in the given cell sector: To gain a sense of the population density in the coverage area of the cell tower, we use 2010 census data, which contains the land area coverage and population density of each zip code. Combining the market share of this service provider for the first quarter 2013[17], we estimate the number of users in the given cell sector. On average, smartphone users consume about 1GB data per month, but the usage patterns of mobile data is highly uneven.[18] Paul et al. (2011) and Jin et al. (2012) found that a small number of heavy users contribute to a majority of data usage in the network. To consider the heterogeneity of data usage and the effects of peak hours, we simulate individual data usage from the byte distribution in Jin et al. (2012).[19]

• Generating WiFi regions in the cell sector: Dong et al. (2012) showed that the appropriate number of WiFi regions in a cell sector is six. Following their approach, we generate six WiFi regions by clustering the WiFi hotspots using k-means. In Figure 1.5, Region A, Region B, ... , and Region F indicate which region the WiFi hotspots belong to.

• Generating traffic demands in each WiFi region: We use two different methods to place users in the cell sector and assign them to the corresponding WiFi regions according to their locations. (1) All users are randomly placed in the cell sector. (2) All users are placed according to the densities of the hotspots.[20] After placing all the

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[17] See http://www.talkandroid.com/159929-t-mobile-loses-market-share-while-verizon-and-att-continue-to-dominate.

[18] See http://www.fiercewireless.com/special-reports/average-android-ios-smartphone-data-use-across-tier-1-wireless-carriers-thr-1#ixzz2ZSpDoS5Z.

[19] We obtain the quantiles of the byte distribution from Jin et al. (2012) and generate inidvidual usage using the Johnson System. We also adjust the usage by considering the effect of peak hours, see http://chitika.com/browsing-activity-by-hour.

[20] To calculate the densities of the hotspots for different locations, we divide the square circumscribing the cell sector into a 20 by 20 array of grids. By default, each grid has a weight of 1, except the grids whose centers are not in the range of the tower. The grid's weight is increased by the number of hotspots whose locations are inside the grid. Then, a list of grid indices is created according to the weight of each grid.

users, a nearest hotspot is calculated for each user location. If the distance between the nearest hotspot found and the user location is less than the hotspot range (100m), the user is counted as one of the regional population according to the WiFi region; otherwise, the user is considered as in the region with no hotspots (region 0). We run 1,000 simulations to generate traffic demands in each WiFi region.

• Generating cell tower capacity: The cell tower capacity is set to three carriers, that is, three times 3.84 MHz (Dong et al. 2012). Data spectral efficiency varies across towers from 0.5 to 2 bps/Hz.[21] We set spectral efficiency to be 1 by default and then vary the spectral efficiency to evaluate its impact. Note that when the user demand for mobile data is below 80% of the cell tower capacity, the cellular service provider faces no congestion cost.

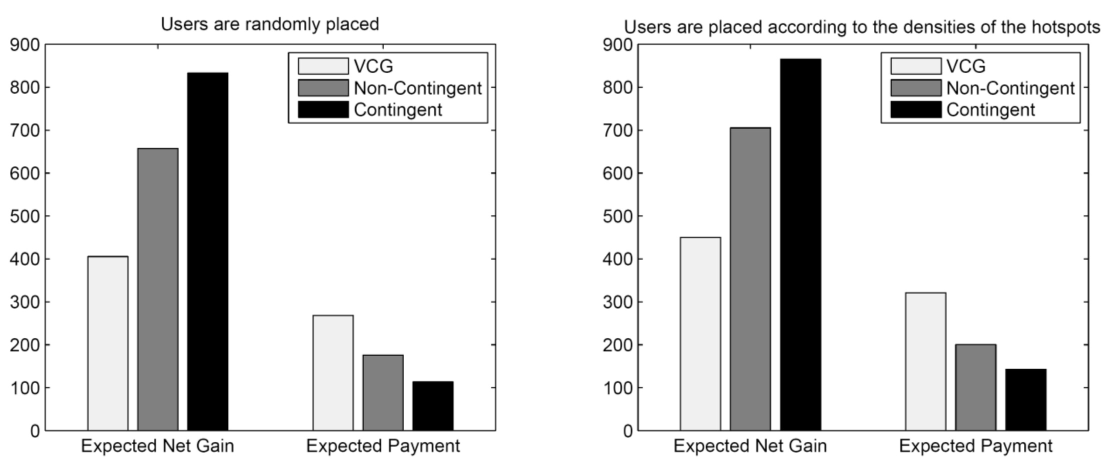

Figure 1.6: The Performance Comparison of the Procurement Mechanisms for the Service Provider

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Finally, for each user, a grid index is first uniformly chosen from the list, and then the location of the user is uniformly chosen from the range of the grid with the grid index just picked.

[21] See http://www.rysavy.com/Articles/2011_05_Rysavy_Efficient_Use_Spectrum.pdf

Using the algorithms in Section 1.4 and Section 1.5, we conduct a variety of simulations to compute the corresponding allocation under the VCG mechanism, the non-contingent procurement auction described in Section 1.4.1, and our contingent procurement auction (CPA). The relative cost of deploying cellular resources as compared with WiFi resources affects the bandwidth allocation result. Dong et al. (2012) assumed that spectrum cost is always higher than WiFi and that WiFi is always preferred when the cellular service provider is overloaded. Joseph et al. (2004) assumed that the relative cost of deploying cellular resources as compared with WiFi resources is 4:1. We follow their assumptions and set the parameter values: $C_0(x) = 0.5 \cdot ax^2$, and $C(x, \theta_i) = (0.5 + \theta_i)x^2$, where $a = 4$, by default. In the simulation, we vary a to evaluate its impact. A hotspot's private cost parameters θ_i is drawn from a standard uniform distribution $U[0,1]$ for 1,000 times.

The simulation result of the performance comparison is shown in Figure 1.6. In the left panel, the users are randomly placed in the cell sector. In the right panel, the users are placed according to the densities of the hotspots. The two panels show similar results: our non-contingent procurement auction significantly outperforms the VCG mechanism in terms of the expected net gain of the cellular service provider (the expected net gain = the reduction of congestion cost - the payment to hotspots). The contingent arrangements can further improve the expected gain of the cellular service provider. Note that both of the panels suggest that the VCG mechanism leads to an overpayment to hotspots. Our contingent mechanism reduces procurement cost by 57.7% in the left panel and by 55.4% in the right panel compared to the VCG mechanism.

Data spectral efficiency varies across cell towers using different wireless technologies. An increase in spectral efficiency significantly contributes to tower capacity (Dong et al. 2012). Figure 1.7 evaluates the impact of spectral efficiency (cell tower capacity) on the performance difference, which is defined as the difference between the service provider's expected net gain under the proposed CPA system and the gain under the VCG mechanism.[22] Note that the unit of the performance difference is normalized, and we are only interested in the trend. We find that as the cellular capacity increases, the advantage of our CPA system, in comparison with the VCG mechanism, decreases. This is because the bandwidth purchased from the WiFi hotspots also decreases with the cellular capacity (see the dashed line in Figure 1.7). The service provider is less willing to purchase WiFi resources when it owns a relatively large cellular capacity, and the overpayment problem in the VCG mechanism is thus less detrimental to the service provider's expected gain. This simulation result suggests that the proposed CPA system is particularly useful when the cell tower capacity is relatively small.

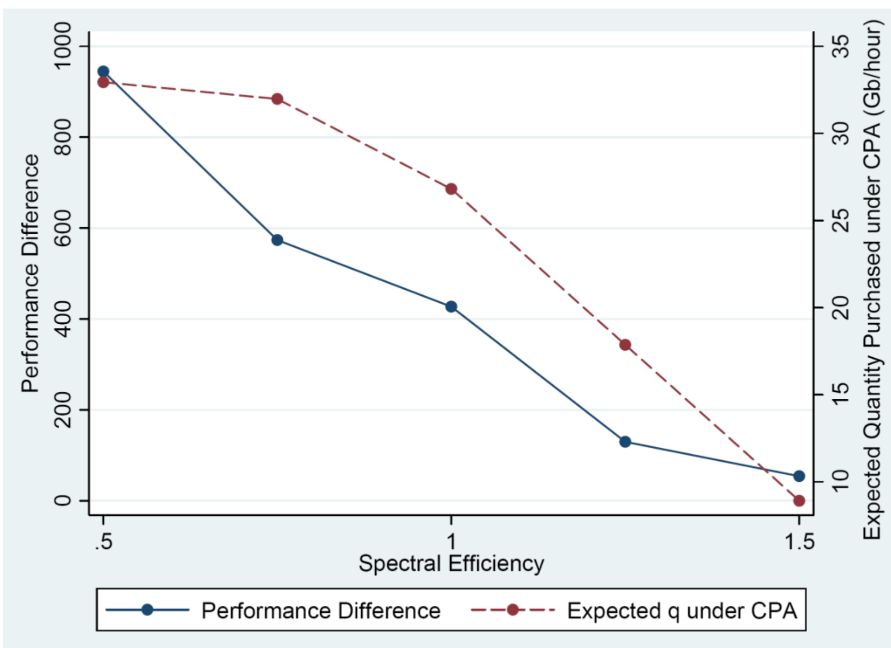

Figure 1.7: Performance Difference and Cell Tower Capacity

[22] The simulation results are similar when the users are randomly placed or are placed according to the densities of the hotspots, so here we only present the result when the users are randomly placed.

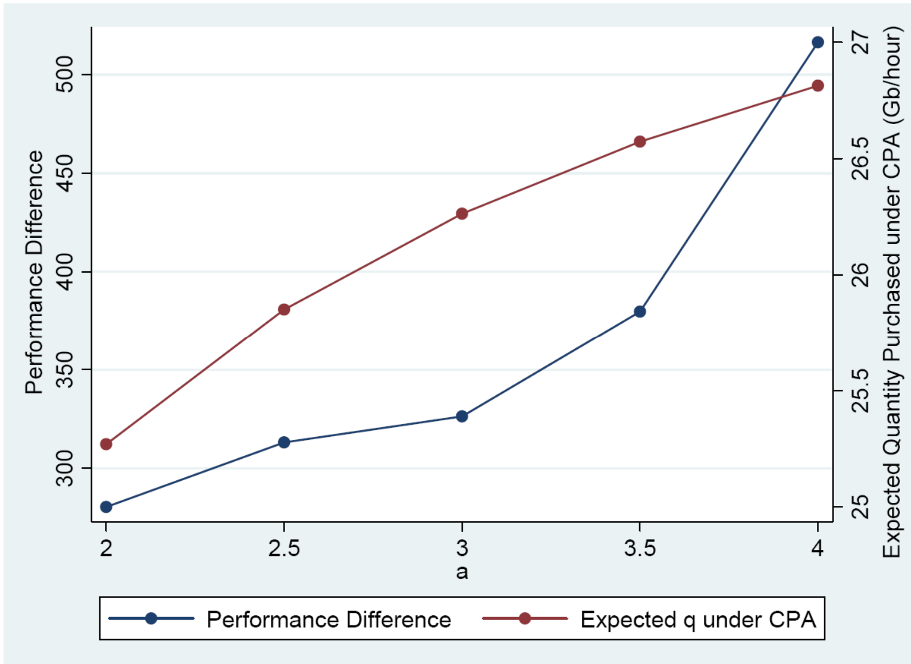

Figure 1.8: Performance Difference and Relative Cost of Deploying Cellular Resources

We also vary the relative cost of deploying cellular resources as compared with WiFi resources to evaluate its impact. Figure 1.8 shows that as the relative cost parameter a increases, the advantage of our CPA system as compared with the VCG mechanism increases. When the relative cost of deploying cellular resources is high, the service provider is more willing to procure from the WiFi hotspots, which exacerbates the overpayment problem in the VCG mechanism. Therefore, the advantage of our CPA system increases with the relative cost parameter a.

1.7 Managerial Implications and Discussions

In the previous sections, our procurement mechanism was a static model. The present study could also apply to dynamic real-world settings by using a real-time auction. In a dynamic model, we assume that the cost parameter of hotspot i at time t,

θ_{it}, is drawn from a distribution with a cumulative distribution function $F_t(\cdot)$. If t' denotes peak hours and t'' denotes off-peak hours, we have $F_{t'}(\cdot)$ fist-order stochastically dominates $F_{t''}(\cdot)$.

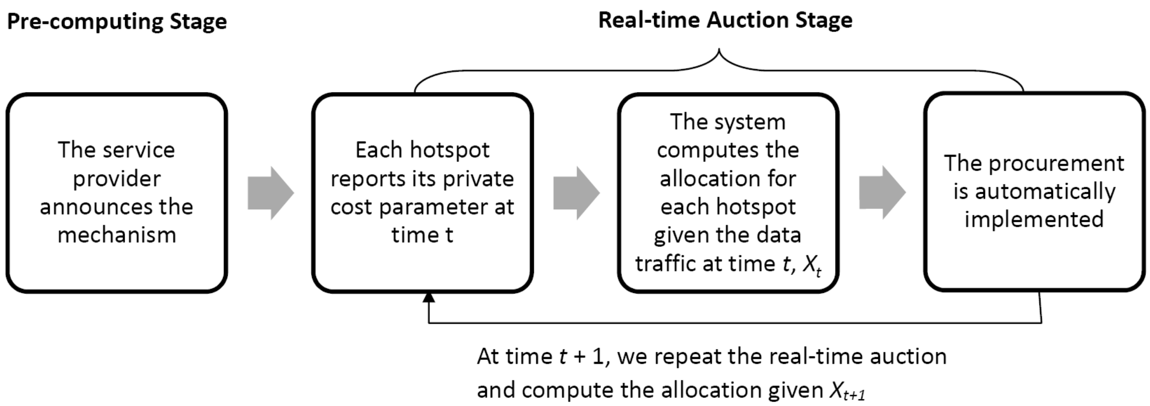

Figure 1.9: The Process Flow for the Automated Auction System

The process flow for a dynamic model is shown in Figure 1.9. Step 1 computes the optimal mechanism including the optimal payment schedule, $P_i^*(\theta_i, \theta_{-i}, \widetilde{X}_1, \widetilde{X}_2, \cdots, \widetilde{X}_M)$, and the optimal bandwidth allocation schedule, $Q(\theta_i, \theta_{-i}, \widetilde{X}_1, \widetilde{X}_2, \cdots, \widetilde{X}_M)$, according to Proposition 1.4. We call Step 1 the pre-computing stage. After data traffic is generated at time t, an auction system automatically bids for hotspots given θ_{it}, the negative impact parameter based on the instantaneous user demand. Note that θ_{it} is a function of the instantaneous user demand. The functional forms are specified by hotspots in advance, but the value of θ_{it} varies over time. Our system finds the corresponding contingent contract: $P_i^*(\theta_{it}, \theta_{-ii}, \widetilde{X}_1, \widetilde{X}_2, \cdots, \widetilde{X}_M)$ and $Q(\theta_{it}, \theta_{-it}, \widetilde{X}_1, \widetilde{X}_2, \cdots, \widetilde{X}_M)$ given the data traffic at time t, $X_t = (\widetilde{X}_{1t}, \widetilde{X}_{2t}, \cdots, \widetilde{X}_{Mt})$, and the auction results are shown, all in a fraction of a second. We call Step 2 - Step 4 the real-time auction stage. Like the display advertising auctions (McAfee, 2011), speed is of the essence in our real-time procurement auction, because the slow process of showing the auction results would sacrifice the cellular service provider's profit. Bichler, Gupta, and Ketter (2010) also addressed the need for real-time intelligence in dynamic markets. At time $t+1$, we repeat the real time stage and show the corresponding auction results when the data traffic is $X_{t+1} = (\widetilde{X}_{1t+1}, \widetilde{X}_{2t+1}, \cdots, \widetilde{X}_{Mt+1})$.

The actual auctions and offloading to WiFi would need to be integrated with the policy management infrastructure, which is able to supply some of the key variables in the auction valuation: (1) the currently offered data traffic, (2) the capacity of each cell tower, and (3) the congestion cost when offered traffic exceeds capacity (e.g., in terms of rejected sessions or excessive delay). This procurement auction relies on automation technology and becomes a type of information systems: completely integrate all relevant information into the supply chain through wireless networks. Our procurement mechanism extends beyond the limits of service providers' cellular resource to interconnect multiple hotspots in different regions by allowing for real-time and accurate data sensing. This leads to a more precise monitoring and control of mobile data offloading. The function of our procurement systems is similar to the algorithmic trading in financial markets (Hendershott et al. 2011). Both of them are examples of the technological change of computation and use computer algorithms to automatically make decisions.

Our automated auction system is a vivid illustration of the power of Cyber-Physical Systems (CPS). CPS are integrations of computation with physical processes (Lee 2008), and in our context, embedded computers and networks monitor and control the data offloading processes. The literature on CPS mainly focused on the feedback loop where physical processes affect computation and vice versa (Lee 2008). The economic incentives of different entities have been overlooked in the design of CPS. Our automated auction system consists of multiple self-interested WiFi hotspots each operating according to its own objectives, and the strategic behaviors of these hotspots may make predictable and reliable real-time performance difficult. We address this issue by using economic theory to design an incentive compatible procurement mechanism. The conventional data offloading is on the basis of the access network discovery and selection function (ANDSF)[23] that processes static WiFi offload policies. Recently, the intelligent mobile solution company, Tekelec, Inc., has developed its Mobile Policy Gateway (MPG)[24] to implement complex WiFi offload policies. The Tekelec MPG enables support for our smart data offloading based on the real-time auction approach.

In terms of the system design, one might wonder why cellular service providers wouldn't build their own hotspots instead of procuring capacity from hotspots. In fact, we have seen some pilot projects for self-managed hotspots (Aijaz et al. 2013). However, to fully reap the benefits of offloading, cellular service providers need to ensure that their customers are able to offload data as frequently as possible. Iosifidis et al. (2013) pointed out that directly managing a hotspot is very expensive and even impractical in some cases. The option of more hotspots directly managed by the service provider is always available, but not cost-effective. Paul et al. (2011) found that 28% of subscribers generate traffic only in a single hour during peak hours in a day. Offloading traffic to third party hotspots overcomes the obstacle of managing a hotspot and ensures the high availability of WiFi resources. This strategy allows operators to handle mobile data traffic with reduced capital and operational expenditures. Another question related to the design of our system is whether service providers should use competitive bidding instead of

[23] The purpose of the ANDSF is to assist user equipment to discover and select non-3GPP networks such as WiFi and WiMax.

[24] See http://www.tekelec.com/2012-press-releases/tekelec-and-roke-partner-to-deliver-policyonthemobile-solutions.aspx.

negotiation to select a contractor (a WiFi hotspot). Bajari et al. (2009) considered several determinants that may influence the choice of auctions versus negotiations. For complex projects, auctions may stifle communication between the buyer and the contractor. But for products with standardized characteristics, competitive bidding is perceived to be a better way to select the lowest cost bidder. In our context, the WiFi capacity satisfies the standard assumption of well defined products in auction literature.

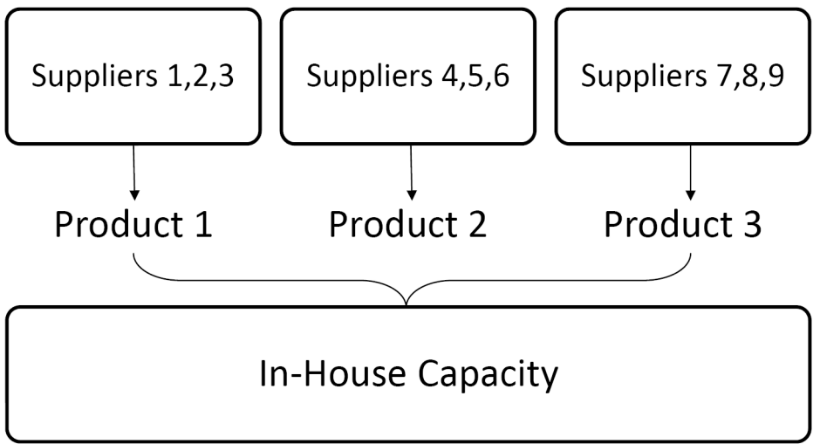

Figure 1.10: A Supply Chain of Procuring Multiple Products

The model in the present study can be generalized to discussing a supply chain problem of procuring multiple products. The independent management of procuring multiple products could be inefficient in the presence of limited product-flexible capacity (Demirel 2012). Van Mieghem and Rudi (2002) studied newsvendor networks allowing for multiple products. In our theoretical model, the wireless service in different WiFi regions can be thought of as different products in the supply chain problem. When we consider the procurement of third party WiFi capacity, the service provider owns the cellular capacity that can serve traffic in all WiFi regions, whereas each WiFi hotspot can only serve local traffic. A similar supply chain problem is shown in Figure 1.10: Consider a firm that produces multiple products using a shared resource (in-house capacity) that is common to products 1, 2, and 3. Because of capacity limitations, the firm also may need to procure the products from different suppliers. In this example, suppliers 1, 2, and 3 only produce product 1; suppliers 4, 5, and 6 only produce product 2, and so on. Because the in-house capacity is a shared resource that can be used for all products, we cannot decompose this supply chain problem into several independent procurement problems. Our theoretical model provides an auction framework for the downstream firm to optimally integrate the upstream capacity with its own product-flexible capacity.

1.8 Conclusions

In the present study, we designed an optimal procurement auction with contingent contracts for mobile data offloading. The integration of both cellular and WiFi resources significantly improves mobile bandwidth availability. A unique challenge in this procurement auction is that the longer range cellular resource introduces coupling between the shorter range WiFi hotspots. We characterized the Bayesian-Nash equilibrium of the auction and computed the corresponding contingent contract. The simulation results showed that our procurement auction significantly outperforms the standard VCG auction. Our analysis is also useful for mechanism designers in developing procurement auctions in the presence of product-flexible capacity.

In the telecommunications industry, consumers, especially business users, are concerned about mobile QoS because the effects of congestion are costly to them. For simplicity, we abstracted away the consumer side in our model. It is possible that congestion costs may lead consumers to respond by switching to a different provider, or by changing their usage behavior. It would therefore be interesting to consider how rational consumers would behave in the presence of large congestion costs. A future direction is to study the procurement auction when consumers form rational expectations of the network congestion (Su and Zhang 2009). It allows the cellular service provider to consider various types of QoS warranties; that is, when a severe congestion occurs, the cellular service provider compensates business users through monetary payments, or other forms of goodwill. The provision of warranties may serve as signals of QoS for cellular service providers.

The present study has several limitations. We assume that WiFi hotspots can always provide the promised capacity. However, WiFi hotspots need to purchase WiFi capacity from internet service providers (ISP). What if hotspots cannot deliver the capacity because of a problem on the ISP side? The procurement auction might be plagued with a chosen hotspot's failure or correlated failures (Chen, Kataria, and Krishnan 2011). To better manage the suppliers' failure risks, the design of our procurement mechanism should include a contingent payment when a hotspot fails in the future research (Chen et al. 2009). When multiple hotspots fail, the problem becomes even more widespread and network managers must then address the most severe outages first. Successful automated auction systems must be robust to unexpected failures.

In our present study, we also assume that the cost function is purely related to the relationship between capacity and traffic and abstract away the setup costs which could not be traffic related (e.g., the cost to establish business agreements and security mechanisms with WiFi hotspots, and the handshaking and hand-off costs for each traffic flow). Incorporating these costs in the future research can provide a more practical view of our procurement mechanism.

Another limitation of the present study is the use of only one cellular service provider in the procurement auctions. An important direction for future research is to extend our model to a setting with multiple cellular service providers. The wireless services market is highly concentrated.[25] On the regional level the concentration is more severe: Often only two cellular service providers are true head-to-head competitors in a given area. In many geographical markets, one cellular service provider may dominate and operate as a monopoly (Cramton et al. 2007). In this case, a procurement auction framework with one cellular service provider is appropriate. However, for example, an intense duopoly competition has arisen between Verizon and AT&T in some other areas. Thus, in the problem setting of two competing cellular service providers, the design of the optimal procurement auction remains an open question.

[25] The most widely used measure of market concentration is the Herfindahl-Hirschman Index (HHI). HHI in the wireless services industry at the end of 2005 was over 2,700.6 (Cramton et al. 2007).

Chapter 2: Information Exchange in Prediction Markets: Do Social Networks Promote Forecast Efficiency?

2.1 Introduction

Prediction markets have long been regarded as an effective way to tap into the wisdom of crowds by aggregating dispersed information within a social system (Berg and Rietz 2003). Several empirical studies have demonstrated the power of prediction markets in areas such as political science (Berg et al. 2008), supply chain management (Guo, Fang and Whinston 2006), marketing (Chen and Plott 2002), and finance (Berg, Neumann, and Rietz 2009). In most of the previous literature, researchers have assumed that the participants in the prediction markets are isolated: They receive small bits and pieces of independent information and cannot affect the decisions of other participants. However, in reality, people often mobilize their social networks to collect information and opinions on a variety of issues. CNBC recently reported an effective information exchange network through which tweeting with fellow farmers has become a way for participants in a far-flung and isolating business to compare notes on everything from weather conditions to new fertilizers.[26] These tweets are dramatically accelerating the flow of information that may give investors an edge in the commodities market. With the advance of information technologies and the rise of social media, information exchange is ubiquitous these days. Indeed, people can use their smartphones or computers to share information with their social network neighbors at almost any place, at any time. The ubiquity of information exchange on social networks and the lack of understanding about their effects on prediction markets motivate us to explore the following research question: How does information exchange among the participants of a prediction market

[26] The information is from CNBC News, March 8, 2011. The CNBC reporter called the phenomenon "Trading on Twitter." Grisafi, known as @IndianaGrainCo on Twitter, said he tweets with at least 15 farmers on a regular basis to check on crop conditions.

affect the behavior and performance of the participants as well as the performance of the prediction market?

Only a few attempts have been made in the previous literature to address this research question or other similar questions. For example, in a different context, Coval and Moskowitz (2001) asked a similar question and found that social networks help fund managers earn above-normal returns in nearby investments: The average fund manager generates an additional 2.67% return per year from local investments, relative to nonlocal holdings. The closest research to the present paper is a recent work that used game theory to study the Bayes-Nash equilibrium of an incomplete information game among participants in a social-network-embedded prediction market (Qiu, Rui, and Whinston 2013a, b). They found a symmetric equilibrium by which participants with few social connections typically exert effort to acquire information, whereas participants with many social connections typically free-ride others' information. However, in their stylized model, they made several simplifying assumptions: 1) people can always observe information from their direct neighbors; and 2) people are fully rational and have infinite computation capacity to integrate information in an optimal way.

Apparently, these assumptions might not hold in some real-world contexts. However, relaxing these assumptions in an analytical model could easily yield intractability of the results. To further our understanding of the research question without confining ourselves to these assumptions, we take a different approach in this paper by carrying out an experimental study. In particular, to address the research question, we test a series of hypotheses through our experiments. First, we test how participants' degree (the number of social connections) in the social network influences their decisions regarding whether to invest in information acquisition and affects their performance in the form of earnings. Following Qiu, Rui, and Whinston (2014a, b), information acquisition in our paper specifically refers to information gathering from outside sources and does not include asking network neighbors for information. Unlike an experimental approach, the traditional econometric methods are often subject to identification difficulty because the network structure is usually endogenously determined (Manski 1993), as a result, empirically disentangling the unobserved individual characteristics (e.g., the predictive ability) from the actual effects of network degree on an individual's information acquisition and prediction performance is difficult. In our controlled experiment, participants are randomly assigned to different network positions, which allows us to identify the causal relationship between network structure and the individual's information acquisition and prediction performance. The experimental results are consistent with the theoretical prediction: participants with higher degrees in the social network are less likely to invest in information acquisition, compared with participants that have lower degrees, and they actually earn more by free-riding neighbors' information.

Second, the wisdom of crowd effect has been extensively studied in the literature (Lorenz et al. 2011): The average of many individuals' estimates can cancel out errors and be surprisingly close to the truth. However, this approach requires independent estimates, which are rare in a social networking world. Lorentz et al. (2011) demonstrate that sharing information corrupts the wisdom of the crowds. Contrary to previous work, our study shows that information sharing in a social network need not undermine the wisdom of crowd effect. The experimental results suggest that when the cost of information acquisition is low, a social-network-embedded prediction market outperforms a prediction market without a social network in terms of prediction accuracy. On the other hand, when the cost of information acquisition is high, we do not find any significant difference between the performances of these two types of prediction markets.

In addition to these two major hypotheses, we also test whether the structure of the underlying social network has any effect on the performance of prediction and the experimental results suggest that network structure does matter.

2.2 Literature Review

A large body of literature explores the role of social networks in student alcohol use (Gaviria and Raphael 2001), product adoption (Aral and Walker 2011), financial markets (Cohen, Frazzini, and Malloy 2008), the use of technology (Wattal, Racherla, and Mandviwalla 2010; Stieglitz and Dang-Xuan 2013), and health plan choice (Sorensen 2006). The standard empirical approach is a regression of an individual's behavior on his or her social connectedness or his or her peers' behaviors. The growing literature on the identification of the effect of network structure and social influence has recognized an econometric challenge: The network structure is endogenously determined (Garg, Smith, and Telang 2011). In our context, the network structure can be the result of past prediction performance. The confounding factors, such as participants' unobserved characteristics, make it difficult to identify the causal effect of network structure on an individual's behavior. For example, the positive correlation between social connectedness and individuals' prediction performance can be driven either by the actual social effect or the unobserved individual characteristics. In the first case, individuals gain from their social ties. In the second case, individuals self-select their friends and tend to associate with the participants having high predictive ability. Both of the two cases are theoretically plausible and need to be empirically distinguished. Failure to account for the second case might lead to an overestimation of the effect of social connectedness.

Researchers in the existing empirical literature have addressed this econometric challenge using different approaches. One approach was the use of natural experiment

(Zhang and Wang 2012). Sacerdote (2001) studied peer effects among college roommates in a natural experiment: Freshmen entering Dartmouth College were randomly assigned to dorms and to roommates. A second approach relied on the panel nature of the data to control the unobserved characteristics. Sorensen (2006) examined the effect of social learning on University of California employees' choices of health plans using a rich panel data set. After controlling for the department-specific unobservables, the estimated social effects were smaller but remained significant. A third approach was the use of exogenous instrument variables. Gaviria and Raphael (2001) corrected the spurious estimates of school-based peer effects by instrumenting for peer behavior using the average behavior of the peers' parents. Our method belongs to a fourth approach: a randomized laboratory-controlled experiment. In our present experiment, participants are randomly assigned to different network positions in prediction markets.

The present study is also closely related to the literature on prediction markets. Researchers in previous studies have focused on how to elicit dispersed private information, for example, by using some variation of scoring rules. Scoring rules do not suffer from the irrational participation or thin market problems that plague standard prediction markets. They instead suffer from a thick market problem, namely how to produce a single consensus estimate when different people give differing estimates. Hanson (2003) suggested a new mechanism for prediction markets, the market scoring rule, which combines the advantages of markets and scoring rules. The market scoring rule avoids the problems by being automated market makers in the thick market case and simple scoring rules in the thin market case. Fang, Stinchcombe, and Whinston (2010) proposed a proper scoring rule that elicits agents' private information, as well as the precision of the information. In their work, the agents' private signals are independent. In our present social-network-embedded prediction market, the information that participants have is correlated with that of their friends.

The present work is also related to the work on network games by Galeotti et al. (2010), who provided a framework to analyze strategic interactions in an incomplete information network game. Golub and Jackson (2010) discussed how network structure influences the spread of information and the wisdom of the crowds.

A handful of research has examined the mechanisms of prediction markets using laboratory experiments. Healy et al. (2010) found that the performance of the prediction market mechanisms is significantly affected by the complexity of the environment. Jian and Sami (2012) compared two commonly used mechanisms of prediction markets: the probability-report mechanism and the security-trading mechanism. A great deal of attention has also been paid to the experimental work that considers the effect of exogenously specified network structures on outcomes (Çelen and Hyndman 2012). Hinz and Spann (2008) examined the effects of different network structures on bidding behaviors in name-your-own-price auctions. Bapna et al. (2011) studied the effect of the strength of social ties on Facebook using a field experiment. To the best of our knowledge, our paper is the first to study the effect of network structure on individual behavior and on forecasting performance in prediction markets using a laboratory controlled experiment, thus enriching the literature by identifying the causal effect of the social network on prediction markets.

2.3 A Simple Model of a Social-Network-Embedded Prediction Market

2.3.1 Model Setup

In this section, we set up a simple model of a social-network-embedded prediction market, which both captures the key features of the experiment and serves as the benchmark for the hypotheses we test in the experiment. Table 1 summarizes the notations used for our model.

Table 2.1: Summary of Notations

V	The random variable that the principal wants to forecast
n	The number of participants in the prediction market
V_0	The prior mean of V
ρ_V	The prior precision of V
k_i	The number of Participant i's friends
S_i	Participant i's private signal
ε_i	The signal's error
ρ_ε	The precision of participants' signal error
x_i	The prediction reported by Participant i
m_i	Whether Participant i acquires information
σ_i	Participant i's mixed strategy of information acquisition
c	The cost of information acquisition

A principal wants to forecast the realization of a random variable V. In reality, V could be movie box office revenue, future demand for electricity, or election outcomes. The principal resorts to n participants to obtain an accurate prediction. For ease of exposition, we refer to the principal as "he" and each participant as "she." Before receiving any private information, the principal and the participants share a common prior on the distribution of V, given by:

$$V \sim N(V_0, 1/\rho_V), \tag{2.1}$$

where V_0 is the mean of the normal distribution, and ρ_V is the precision of the prior.

Participants in the prediction market are linked to each other according to a social network, and information is transmitted over the network. The social network $\Gamma = (N, L)$ is given by a finite set of nodes $N = \{1,2,\dots,n\}$ and a set of links $L \subseteq N \times N$. Each node represents a participant in a prediction market. The social connections between the participants are described by an $n \times n$ dimensional matrix denoted by $g \in \{0,1\}^{n \times n}$ such that:

$$g_{ij} = \begin{cases} 1, & \text{if } (i,j) \in L \\ 0, & \text{otherwise} \end{cases}.$$

Let $N_i(g) = \{j \in N: g_{ij} = 1\}$ represent the set of friends of Participant i. The degree of Participant i is the number of Participant i's friends: $k_i(g) = \#N_i(g)$. The principal does not know the social network graph. For simplicity, we assume the network is undirected, but the results also hold for directed networks.

Each participant is risk neutral and can access a private independent information source at a cost c. m_i is a binary variable indicating whether Participant i acquires information. Participants exchange information over the social network: For simplicity, we assume that they can observe their direct friends' information, but not their second-order friends' (friend's friend) information. More precisely, if Participant i acquires information from her private source ($m_i = 1$), she observes a conditionally independent private signal and passes it to her friends:

$$S_i = V + \varepsilon_i, \varepsilon_i \sim N(0,1/\rho_\varepsilon), \tag{2.2}$$

where ρ_ε is the precision of Participant i's information source for $i = 1,2,\dots,n$. The signals' errors $\varepsilon_1,\dots,\varepsilon_n$ are independent across participants and are also independent of V. We assume that the precision of all participants' information sources is equal, which implies that no one is especially well informed, and that the valuable information is not concentrated in a few hands.

The principal designs a quadratic loss function to elicit the private information of participants. A participant's payoff function is given by:

$$w(m_i, x_i, V) = a - b(x_i - V)^2 - m_i c, \tag{2.3}$$

where x_i is the prediction reported by Participant i, and $b(x_i - V)^2$ is a quadratic penalty term for mistakes in the forecast. Notice that the optimal report for Participant i is $x_i^* = E[V|I_i]$, where I_i is the information set of Participant i, which includes both the information she acquires and the information passed to her from the social network Γ. We can also use other strictly proper scoring rules (Fang, Stinchcombe, and Whinston 2010). The qualitative results remain unchanged.

A participant follows a two-step decision procedure. In the first stage, all of the participants decide whether to acquire information simultaneously. In the second stage, a participant makes use of her signal, as well as of the signals of her friends, to report her best prediction.

We first focus on the optimization problem in the second stage. In the second stage, Participant i's best prediction x_i^* depends on whether Participant i and her friends acquire information; thus, x_i^* is a function of m_i and $m_{N_i(g)}$, where $m_{N_i(g)} \in \{0,1\}^{k_i}$ is the action profile of Participant i's friends, and it represents whether Participant i's friends acquire information.

If Participant i acquires information ($m_i = 1$), she forms her private belief from the private signal S_i, as well as from information she obtains from her neighbors, and her payoff is:

$$a - b\left[x_i^*\left(m_i = 1, m_{N_i(g)}\right) - V\right]^2 - c.$$

If the participant has decided not to acquire information ($m_i = 0$), she forms the belief only from her neighbors' signals, and her payoff is:

$$a - b\left[x_i^*\left(m_i = 0, m_{N_i(g)}\right) - V\right]^2.$$

2.3.2 Equilibrium Results

Given the action profile of her friends, Participant i's utility is given by

$$u\left(m_i, m_{N_i(g)}\right) = E_V\left[a - b\left[x_i^*\left(m_i, m_{N_i(g)}\right) - V\right]^2 - m_i c\right], \tag{2.4}$$

where E_V is the expectation with respect to V. The utility $u\left(m_i, m_{N_i(g)}\right)$ depends on whether Participant i and her neighbors acquire information.

Following Galeotti et al. (2010), we assume that each participant observes her own degree k_i, which defines her type, but does not observe the degree or connections of any other participant in the network. For example, people who graduated from the same MBA program might have a good sense of their classmates after graduation, but they do not know who the friends of these classmates are. Another example is that people only pay attention to a subset of their friends in the Facebook and Twitter network, given their limited cognitive resources. They don't know to whom their friends pay attention.

Each participant's belief about the degree of her friends is given by:

$$\Pi(\cdot\,|k_i) \in \Delta\{1, \ldots, k_{max}\}^{k_i},$$

where k_{max} is the maximal possible degree, and $\Delta\{1, \ldots, k_{max}\}^{k_i}$ is the set of probability distribution on $\{1, \ldots, k_{max}\}^{k_i}$. For simplicity, we make an assumption that neighbors' degrees are all stochastically independent, which means that Participant i's degree is independent from the degree of one of her randomly selected friends. This assumption is true for many random networks, such as the Erdös-Rényi random graph (Erdős and Rényi 1960).

A strategy of Participant i is a measurable function $\sigma_i: \{1\ldots, k_{max}\} \rightarrow \Delta\{0,1\}$, where $\Delta\{0,1\}$ is the set of probability distributions on $\{0,1\}$. This strategy simply says that a participant observes her degree k_i, and on the basis of this information she decides whether to acquire information. Notice that $\Delta\{0,1\}$ means that the participant adopts a mixed strategy: She randomizes her actions with some probabilities in $m_i = 1$ and in $m_i = 0$. The strategy profile of Participant i's friends is denoted by $\sigma_{N_i(g)}$.

We focus on symmetric Bayes-Nash equilibria, where all participants follow the same strategy σ. A Bayes-Nash equilibrium is a strategy profile, such that each participant with degree k_i chooses a best response to the strategy profile of her friends. Let $\phi(m_{N_i(g)}, \sigma, k_i)$ be the probability distribution over $m_{N_i(g)}$ induced by $\Pi(\cdot\,|k_i)$. The expected payoff of Participant i with degree k_i and action m_i is equal to:

$$U(m_i, \sigma_{N_i(g)}; k_i) = E_{m_{N_i(g)}} u(m_i, m_{N_i(g)}) =$$
$$\sum_{m_{N_i(g)}} \phi(m_{N_i(g)}, \sigma, k_i) u(m_i, m_{N_i(g)}), \tag{2.5}$$

where $E_{m_{N_i(g)}}$ is the expectation with respect to $m_{N_i(g)}$. We say that Participant i's strategy σ_i is non-increasing if $\sigma_i(k_i)$ dominates $\sigma(k_i')$ in the sense of first-order stochastic dominance (FOSD) for each $k_i' > k_i$. In other words, if the strategy σ_i is non-increasing, high-degree participants randomize their actions with less probability in $m_i = 1$ and thus are less likely to acquire information.

Proposition 2.1 gives us the basic result of the Bayes-Nash equilibrium.

Proposition 2.1. There exists a symmetric Bayes-Nash equilibrium that is non-increasing in degree. There exists some threshold $k^* \in \{0,1,2,\dots\}$, such that the probability of choosing to acquire information satisfies:

$$\sigma(m_i = 1|k_i) = \begin{cases} 1, & \text{for } k_i < k^* \\ 0, & \text{for } k_i > k^*. \\ (0,1], & \text{for } k_i = k^* \end{cases}$$

Furthermore, the expected payoffs are non-decreasing in degree.

The proof is included in the Appendix C. Proposition 2.1 has very clear implications. The participant's equilibrium action is weakly decreasing in her degree. In other words, the more friends she has, the less willing she is to acquire information. Participants can free ride on the actions of their friends. If Participant i has more friends, she is more likely to benefit from the signals passed around by her friends. It should also be emphasized that participants who have more friends earn higher payoffs under the appropriate monotone equilibrium because of the positive externalities. Here, higher degree participants exert lower efforts but earn a higher payoff than do their less connected peers. The non-increasing property of equilibrium actions implies that social connections create personal advantage. In the network game with positive externalities, well-connected participants earn more than poorly connected participants. Note that the threshold degree k^* is a function of parameters such as c, ρ_ε, and ρ_V.

After making the decision on information acquisition, each participant reports the best point estimation. The purpose of prediction markets is to generate fairly accurate predictions of future events by aggregating the private information of a large population. How does the principal aggregate these small bits and pieces of relevant information that exist in the opinions and intuitions of diverse individuals? We assume that the principal adopts a simple averaging rule, and his prediction is $\frac{1}{n}\sum_{i=1}^{n} x_i^*$. Note that the simple averaging rule is optimal only when all the participants' forecasts are independent and equally accurate; however, it is a good operational rule for limited information (e.g., Armstrong 2001). In our networked prediction markets, the principal has limited information: He does not know the social network graph. In this case, the principal cannot propose a weighted averaging rule and simply follows the operational rule of thumb: "Use equal weights unless you have strong evidence to support unequal weighting of forecasts" (Armstrong 2001, p. 422).

2.4 An Experimental Analysis on Network Structure and Forecasting Performance

In this section, we compare the performance of non-networked prediction markets (NNPM) with the performance of social-network-embedded prediction markets (SEPM) using controlled laboratory experiments. We also take into account the network structure in which the participants are embedded. Our experiment demonstrates that network structure has a significant effect on the individual's behavior of information acquisition and the prediction market performance. Eighty undergraduate students were recruited as subjects from a large university, and they had no previous experience in prediction market experiments. There were four experimental sessions, each consisting of five groups. We restricted our attention to the case of four-person networks, so each group consisted of four randomly assigned participants. The average earnings were $8.50 per person, including a $1.50 show-up fee, for a 40-minute session.

2.4.1 Experimental Design

Similar to the setup of the theoretical model, participants were asked to predict a random variable V during the experiment. The common prior is given by equation (2.1) in our model setup, and in the experiment we set $V_0 = 10$ and $\rho_V = 0.5$. Each participant could receive a private signal S_i at a cost c. The signal S_i is given by equation (2.2), and $\rho_\varepsilon = 1$.

The experiment had a 4×2 design: four different treatments of network structures $\times$ two levels of information acquisition cost. The four treatments of network structures include: 1. the baseline treatment, non-networked environment; 2. complete network; 3. star network; and 4. circle network. They are illustrated in Figure 2.1. In all of the treatments, subjects participated in the experiment via the computer system we developed. Throughout the experiment, the subjects were not allowed to communicate in person and could not see others' screens. The only communication channel available to them was to chat via designated Gmail accounts. In the baseline treatment, $N_i(g) = \emptyset$, and each participant was isolated. In a complete network, Participant i was connected to three other participants (we call them Participant i's "friends"). As Figure 2.2 shows, the participant "crecaustin02" could chat with "crecaustin", "crecaustin03", and "crecaustin04" through Gmail. Similarly, the communication networks are given by a star network and a circle network in Treatments 3 and 4, respectively.

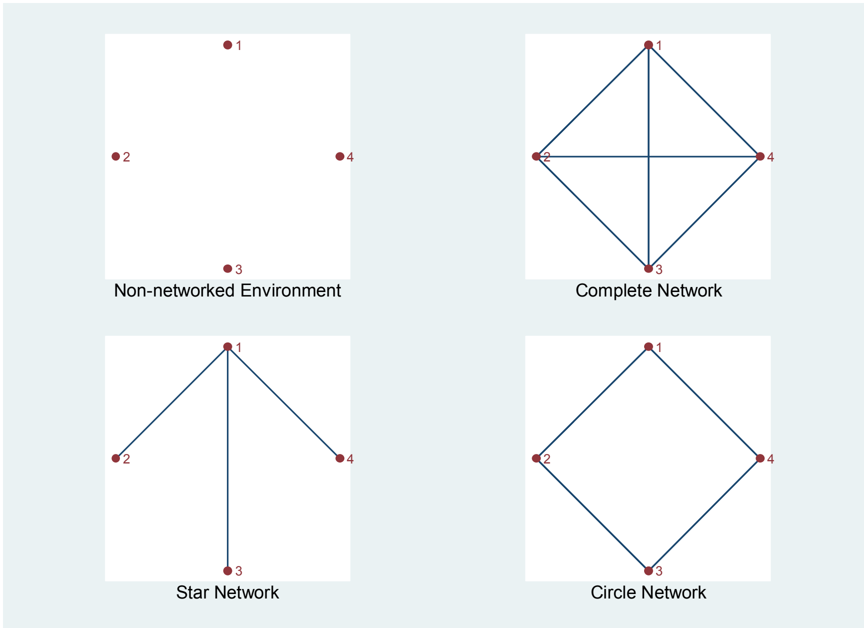

Figure 2.1: Network Structures

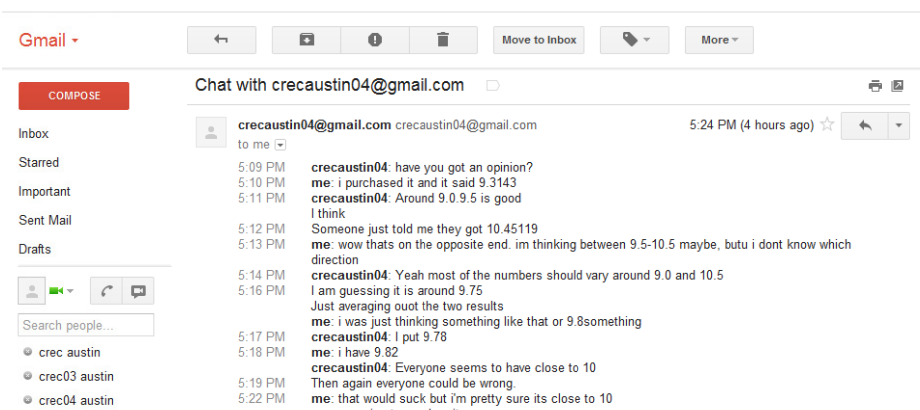

Figure 2.2: A Screenshot of the Communication over a Complete Network

Each treatment was conducted in an experimental session with two independent decision-rounds. In Round 1, the cost of information acquisition was \$0.50. In Round 2, the cost of information acquisition was \$1. The order of the acquisition cost was always low and then high. To minimize the effect of reputation, each round started with the randomly formed groups (four-person networks). Participants in each round followed a two-stage decision process: information acquisition and prediction. Figure 2.3 depicts a flow chart of experiment round t, t = 1, 2 (the only difference between the two rounds is the cost of information acquisition). In the stage of information acquisition, participants made their decisions about whether to purchase a signal from an outside expert. If they paid the cost of information acquisition c, they would receive a private signal. Once all the decisions of information acquisition were made, participants could communicate over the given network under each treatment (After the experiment, we checked the participants' chat history and found that no one misreported the private signal to others). In this stage, every participant chatted with every neighbor at the same time. It means that focal participants might receive information from their second-order friends. After checking the chat history, we found that participants received a substantial amount of information from their first-order friends but less information from their second-order friends. On average, a participant received information from 61.88% of her first-order friends and 4.38% of her second-order friends. This result implies that most participants were willing to exchange their private signals with others but were less willing to tell others the information they got from someone else. Specifically, we find that central participants in a star network only exchanged their own signals with peripheral participants. This information diffusion pattern is consistent with the exchange theory that explains the reciprocity based on the idea of socially embedded behavior (Jackson 2008). Peripheral participants had no other information channels, except for their own private signals and the information from the hub. Thus, central participants exchanged only their private signals, excluding information from others with peripheral nodes according to reciprocity and norms of fairness.

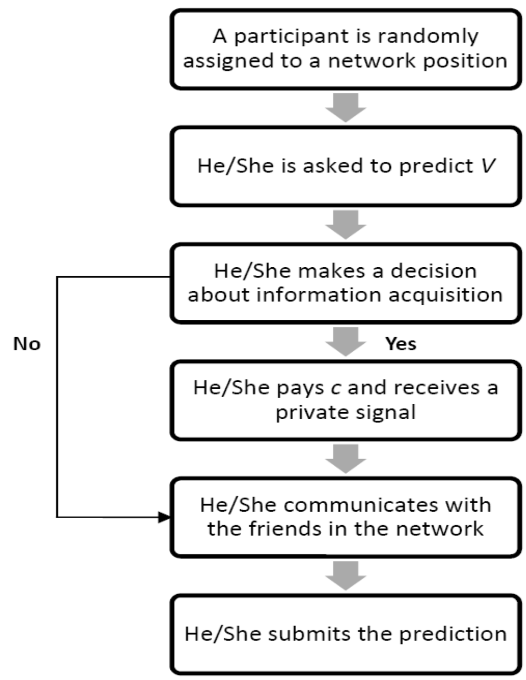

Figure 2.3: The Flow Chart of the Experiment Round t, t = 1, 2

After the experiment, the computer system calculated the total payoff of each participant according to the payoff function (2.3). We set $a = 5$ and $b = 1$. Therefore, the maximum payoff for each round was \$5. We are interested in testing the following four hypotheses. Hypotheses 2.1 and 2.2 are motivated by Proposition 2.1 in the analytical model.

Hypothesis 2.1. Each individual's information acquisition is non-increasing in the participant's degree.

Hypothesis 2.2 The participant's earnings are non-decreasing in the degree.

Hypothesis 2.3 is motivated by the following arguments: Even if participants are isolated in a non-networked environment, individual estimates are no longer independent because of the common prior (public information). The existence of a social network facilitates the dissemination of private information among participants, which effectively puts more weights on private information when participants' predictions are aggregated in the prediction market. Such adjustment is beneficial to the forecasting accuracy because it corrects to a certain extent a possible bias toward the common prior. Social networks need not undermine the wisdom of crowd effect, especially when people share a common prior. On the other hand, when the cost of information acquisition is very high, the existence of a social network can impede information acquisition by the community as a whole because of possible free-riding opportunities, thus lowering the forecasting accuracy of the prediction market.

Hypothesis 2.3. An SEPM outperforms an NNPM when the cost of information acquisition is low.

Hypothesis 2.4 is motivated by a large body of literature on the identification and estimation of peer effects (Aral and Walker 2011). Peer effects are economically important because they are present in many decision domains, such as students' academic performance (Sacerdote 2001), mutual fund managers' portfolio choices (Cohen, Frazzini, and Malloy 2008), and health plan choices (Sorensen 2006). In our experiment, we tested whether the prediction performance of a participant is influenced by the members of the group to which they belong.

Hypothesis 2.4. Peer effects exist in the prediction accuracy among participants.

In a star network, the central participant has an above-average influence. Hypothesis 2.5 is motivated by the following arguments: If the hub has a relatively wrong estimate, the above-average influence exacerbates the problem and hurts the prediction market performance significantly.

Hypothesis 2.5. In a star network, the prediction market performance is positively correlated with the performance of the central participant.

2.4.2 Summary Statistics

Table 2.2 summarizes the statistics of participants' predictions under different network structures. We perform two variance-comparison tests: the Variance ratio test (F test) and the Brown–Forsythe test. Note that the F test relies on the assumption that the samples come from normal distributions, and the Brown–Forsythe test (Brown and Forsythe 1974) provides robustness against many types of non-normal data while retaining good power. By calculating the standard deviations of predictions under different treatments, we find that the standard deviation under a complete network is significantly lower than the standard deviation under a non-networked environment (1.237 vs. 2.186, F test: $p < 0.01$; Brown–Forsythe test: $p < 0.05$), which suggests that communications lead to greater consensus about the true value.

Table 2.2: Descriptive Statistics of the Participants' Predictions

	Mean	The Std. Dev.	Obs
Non-Networked Environment	9.853364	2.186319	40
Complete Network	9.893607	1.237169	40
Star Network	9.916362	2.025045	40
Circle Network	9.616113	1.532874	40

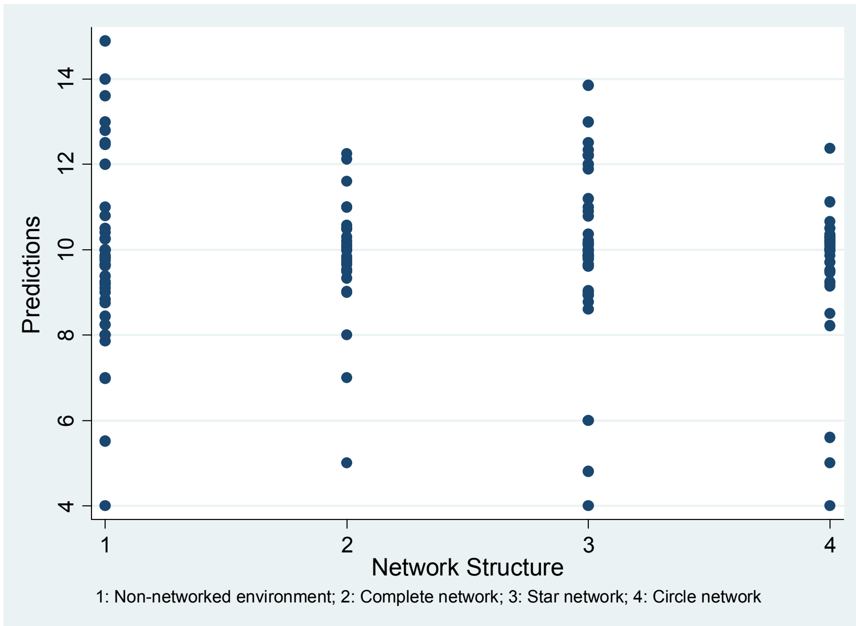

Figure 2.4: Predictions under Different Network Structures

As Table 2.2 and Figure 2.4 show, the variation of the prediction also depends on the network structure. The standard deviation of the predictions under a star network is significantly higher than the standard deviation under a circle network (2.025 vs. 1.533, F test: $p < 0.05$; Brown–Forsythe test: $p < 0.05$), and the standard deviation of the predictions under a circle network is significantly higher than the standard deviation under a complete network (1.533 vs. 1.234, F test, $p < 0.10$; Brown–Forsythe test: $p < 0.10$). The denser the network is, the lower the standard deviation of the predictions (the density of the network: complete > circle > star > non-networked). To address the problem that the underlying observation may not be independent, we also compute the average prediction in each four-person group (essentially removing the within group correlation) and then test the standard deviation under different network structures. The result is robust. The intuition is that participants communicate with each other more effectively in a denser network. Thus, information exchange reduces the variance of the predictions.

2.4.3 Experimental Results: Testing of H1

Do participants play an equilibrium strategy of information acquisition in social networks? To test this hypothesis, we first compute the mean of information acquisition (if Participant i acquires information, $m_i = 1$; otherwise $m_i = 0$) when participants' degree varies. Figure 2.5 shows that the equilibrium strategy of information acquisition is decreasing in the number of connections.

We then run a logistic regression of participants' information acquisition decision on their degree and the cost of information acquisition:

$$\text{logit } E(\text{acquisition}_i|\text{degree}_i, \text{cost}_i, \text{sdummy}_i) = \beta_0 + \beta_1\text{degree}_i + \beta_2\text{cost}_i + \beta_3\text{sdummy}_i, \tag{2.6}$$

where, sdummy, a dummy variable included for a robustness check, indicates whether the participant having three connections is in a star network (because such participants can also be in a complete network). We find that participants' information acquisition behavior is indeed consistent with the equilibrium strategy predicted by the analytical model: A larger number of connections leads to a lower probability of information acquisition. The result is shown in Column 1 of Table 2.3. We find that the probability of participants' acquiring information decreases with the degree and the cost of information acquisition. Roughly speaking, the logit estimates should be divided by four to compare them with the linear probability model estimates (Wooldridge 2002). For example, Column 1 of Table 2.3 shows that adding a degree can reduce the probability of information acquisition by 7.6%.

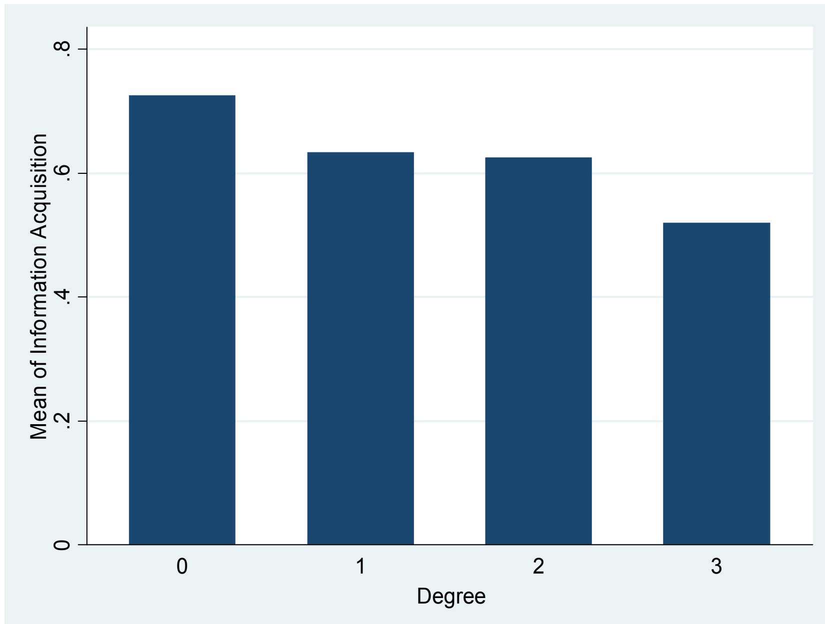

Figure 2.5: Information Acquisition and Participants' Degrees

Column 2 suggests that the result is also robust to the inclusion of sdummy (Note that the P value for the coefficient of degree is 0.064, which is very close to a 5% significance level). Small sample size is a common problem for the experimental method. The validity of z-statistics depends on the asymptotic distribution of large samples. When the sample size is insufficient for straightforward statistical inference, bootstrapping is useful for estimating the distribution of a statistic without using asymptotic theory. In Column 3, we use bootstrapping to compute the standard errors and find that the result is robust (we draw a sample of 160 observations with replacement, and repeat this process 10,000 times to compute the bootstrapped standard errors). To account for the possible unobserved heterogeneity of participants, we control for the subjects' latent characteristics using a random effects model in Column 4, and the result is robust.

Table 2.3: Logistic Regression Analysis of Information Acquisition Using Model (2.6)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Logit	Logit	Bootstrapping	Random effects	Cluster effects	Cluster Bootstrap	Robust Std. Err.
degree	-0.304**	-0.293*	-0.304**	-0.296**	-0.293***	-0.293***	-0.293**
	[-2.010]	[-1.855]	[-2.017]	[-2.201]	[-6.692]	[-3.361]	[-2.092]
cost	-1.302***	-1.302***	-1.302***	-1.317***	-1.302**	-1.302***	-1.302**
	[-3.706]	[-3.706]	[-3.567]	[-3.352]	[-2.492]	[-4.162]	[-3.712]
sdummy		-0.154		-0.156	-0.154	-0.154	-0.154
		[-0.213]		[-0.211]	[-0.313]	[-0.890]	[-0.213]
Constant	1.693***	1.686***	1.693***	1.704***	1.686***	1.686***	1.686***
	[4.403]	[4.374]	[4.393]	[3.882]	[4.191]	[6.333]	[4.560]
Observations	160	160	160	160	160	160	160
R-squared	0.186	0.187	0.186	0.111	0.187	0.187	0.187

z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

As shown in Table 2.2, the standard deviations are not the same under different network structures. Potential problems arise with statistical inference in the presence of clustering effects. Default standard errors that ignore clustering can greatly understate true standard errors (Cameron, Gelbach, and Miller 2008). Wooldridge (2003) provided an econometric approach to analyzing cluster sample. Following his approach, we compute the variance matrices that are robust to arbitrary cluster correlation and unknown heteroskedasticity.[27] In our context, the observations are clustered into different network topologies. Standard errors are adjusted for clusters in Column 5, and the result is similar. A practical limitation of inference with cluster-robust standard errors is the assumption that the number of clusters is large. Cameron, Gelbach, and Miller (2008) show that cluster bootstraps can lead to considerable improved inference when there are few clusters. Column 6 shows that the results of the cluster bootstrap are robust.

[27] Wooldridge's example (2002) is to estimate the salary-benefits tradeoff for elementary school teachers in Michigan. Clusters are school districts. Units are schools within a district.

Because of the strong suspicion of heteroskedasticity, we also compute the heteroskedasticity-robust *t* statistics using the Huber-White sandwich estimators in Column 7 to check the robustness of our results. The robust t statistics can deal with the concerns about the failure to meet standard regression assumptions, such as heteroskedasticity (Wooldridge 2002). Our results are robust to the case when the modeling errors depend on the explanatory variables, such as degree and sdummy. Note that different network topologies can be linearly predicted from the variables degree and sdummy (dummy variables indicating network structures are redundant when we have the two explanatory variables, degree and sdummy, so adding additional dummy variables indicating network structures causes the problem of multicollinearity). Thus, the results in Column 7 are also robust to the case when the modeling errors depend on different network topologies.

2.4.4 Experimental Results: Testing of H2

We also examine the effect of social connections on individuals' earnings. Figure 2.6 shows that the mean of earnings for each round is increasing in the number of connections.

Next, we run an ordinary least squares (OLS) regression of earnings on the degree and the cost of information acquisition:

$$\mathrm{earnings_i} = \beta_0 + \beta_1 \mathrm{degree_i} + \beta_2 \mathrm{cost_i} + \beta_3 \mathrm{sdummy_i} + \beta_4 \mathrm{acquisition_i} + \varepsilon_i. \quad (2.7)$$

Table 2.4 shows that the participants' earnings increase with the degree and decrease with the cost of information acquisition. Being excluded from these connections is thus a handicap for a participant. The basic result remains unchanged when we add a star network dummy variable, *sdummy*, or a dummy variable, acquisition, indicating whether a participant acquires information. Column 4 shows that the result is robust when we use the method of bootstrapping. The result of a random effects model is similar and reported in Column 5. In Column 6, we account for clustering in data. Column 7 reports the results of the cluster bootstrap. We also run a robust regression and compute the robust t statistics in Column 8. Our estimators are shown to be robust to various kinds of misspecification. The experimental results in Tables 2.3 and 2.4 thus support Hypotheses 2.1 and 2.2. Because of the randomization of the network position assignments, our experimental results do not suffer from the identification problem related to the endogenous network structure and reveal causality rather than mere correlation.

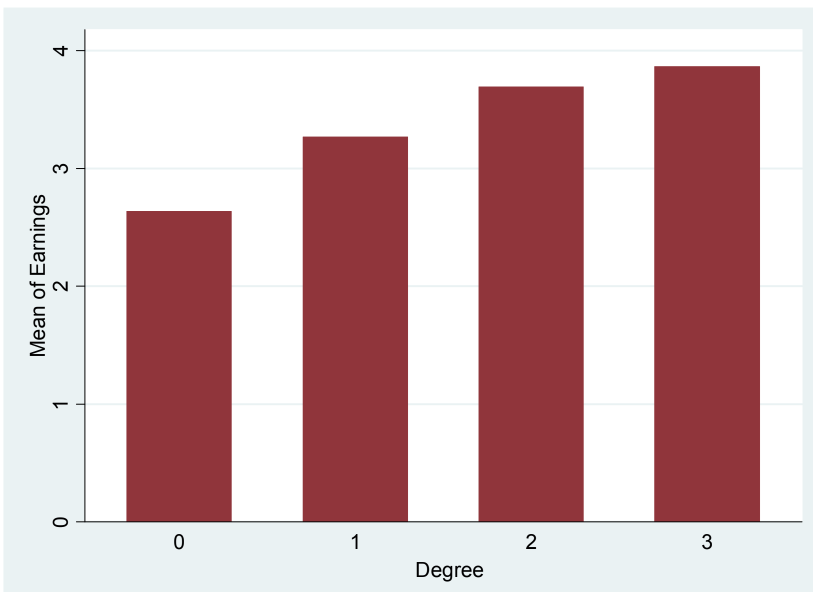

Figure 2.6. Earnings for Each Round and Participants' Degrees

Table 2.4. OLS Regression Analysis of the Participants' Earnings Using Model (2.7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	OLS	OLS	Bootstrapping	Random effects	Cluster effects	Cluster Bootstrap	Robust Std. Err.
degree	0.214**	0.228**	0.179**	0.214**	0.228**	0.228**	0.228**	0.228**
	[2.119]	[2.142]	[2.060]	[2.131]	[2.012]	[2.691]	[2.101]	[2.230]
cost	-0.774***	-0.774***	-1.001***	-0.774***	-0.786***	-0.774**	-0.774***	-0.774***
	[-3.286]	[-3.277]	[-4.161]	[-3.303]	[-3.482]	[-2.232]	[-4.460]	[-3.282]
sdummy		-0.217	-0.246		-0.217	-0.217	-0.217	-0.217
		[-0.424]	[-0.494]		[-0.404]	[-1.224]	[-0.792]	[-0.353]
acquisition			-0.789***					
			[-3.142]					
Constant	3.560***	3.552***	4.234***	3.560***	3.558***	3.552***	3.552***	3.552***
	[15.22]	[15.09]	[13.42]	[16.31]	[14.52]	[47.10]	[19.44]	[16.14]
Observations	160	160	160	160	160	160	160	160
R-squared	0.287	0.287	0.343	0.287	0.187	0.287	0.287	0.287

z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

2.4.5 Experimental Results: Testing of H3

Hypothesis 2.3 predicts that when the cost of information acquisition is low, an SEPM outperforms an NNPM. In our experiment, each group is a prediction market, so we have 20 prediction markets in total. The performance of a prediction market g is measured by forecast accuracy:

$$\mathrm{MAccuracy_g} = 1 - \text{Absolute Percentage Error}_\mathrm{g} = 1 - \frac{|\mathrm{F_g} - \mathrm{V_g}|}{\mathrm{V_g}},$$

where $\mathrm{F_g}$ is the forecast of prediction market g, calculated as the average of all four participants' predictions (the principal's prediction) in that market, and $\mathrm{V_g}$ is the realization of the random variable in market *g*. To test Hypothesis 2.3, we perform *t*-tests and Monte Carlo permutation tests with 10,000 permutations. A *t*-test relies heavily on the asymptotic distributional assumption and may not perform well when the sample size is small. A Monte Carlo permutation test gives a non-parametric way to compute the sampling distribution because no assumption on the sampling distribution is required (for another example, see Jian and Sami (2012) who also compared the performance of different prediction markets using a permutation test).

We find that when the cost of information acquisition is low ($0.50), a complete networked prediction market significantly outperforms an NNPM (t statistics: $p = 0.04$; permutation test: $p = 0.02$). When the cost of information acquisition is high ($1), the performance difference is not significant (t statistics: $p = 0.42$; permutation test: $p = 0.47$). Therefore, the superior forecasting performance of a networked prediction market decreases with the cost of information acquisition. The relative performance of a networked prediction market to a non-networked prediction market depends on the cost of information acquisition.

2.4.6 Experimental Results: Testing of H4 and H5

Hypothesis 2.4 states that participants' prediction accuracy can be affected by the accuracy of other participants in their network. There are several challenges in identifying the peer effects (Manski 1993). First, network formation could be endogenous: Individuals self-select their friends. For example, many social networks exhibit homophily: People are more prone to make friends with those who are similar to themselves. This makes it difficult to disentangle the selection effect and the real peer effects. This challenge is similar to the identification problem in estimating the effects of network structure. In our experiment, the "friends" of a participant were randomly assigned. Random assignment implies that a participant's background characteristics, such as predictive ability, are uncorrelated with their friends' background characteristics. This approach allows us to take care of the first challenge.

Second, Participants *i* and *j* can affect each other simultaneously. This reflection problem (Manski 1993) causes a difficulty in identifying the actual causal effect if we adopt a linear-in-means specification: Participant *i*'s prediction performance is a linear function of the average performance level of his or her friends.

The reflection problem can be overcome by introducing nonlinearities into social interactions (Jackson 2008). The prediction accuracy of Participant *i* is influenced by the maximal accuracy of her friends:

$$\mathrm{Accuracy_i} = \beta_0 + \beta_1 \mathrm{max}_{j \in N_i} \mathrm{Accuracy_j} + \beta_2 \Omega_i + \varepsilon_i. \tag{2.8}$$

$N_i(g) = \{j \in N: g_{ij} = 1\}$ is the set of friends of Participant i, Ω_i represents the control variables, and the prediction accuracy of Participant i is given by:

$$\mathrm{Accuracy_i} = 1 - \mathrm{Absolute\ Percentage\ Error_i} = 1 - \frac{|x_i - V|}{V},$$

where x_i is the prediction of Participant i, and V is the realization of the random variable in the corresponding prediction market. In our experiment, this specification is reasonable because participants with high predictive ability share their "forecasting formula." The performance of a participant directly depends on whether she has a clever friend. For example, as shown in Figure 2.7, a clever participant proposed a useful average rule. As a result, a participant's prediction is influenced by her friends with the best forecasting performance.

Table 2.5 presents the regression results. Again, we control for participants' degree, the cost of information acquisition, and the dummy variable, acquisition. The variable, social influence, represents the maximal accuracy of Participant *i*'s friends. Our interest is the coefficient on social influence, β_1, and we find that the coefficient is significantly positive in Column 1. This result is also robust to a different model specification in Column 2 and the use of bootstrapping. The coefficient implies that a 1% increase in the maximal accuracy of the friends of a focal player is associated with a roughly 0.5% increase in the focal player's prediction accuracy. This coefficient is moderate in size and seems plausible.

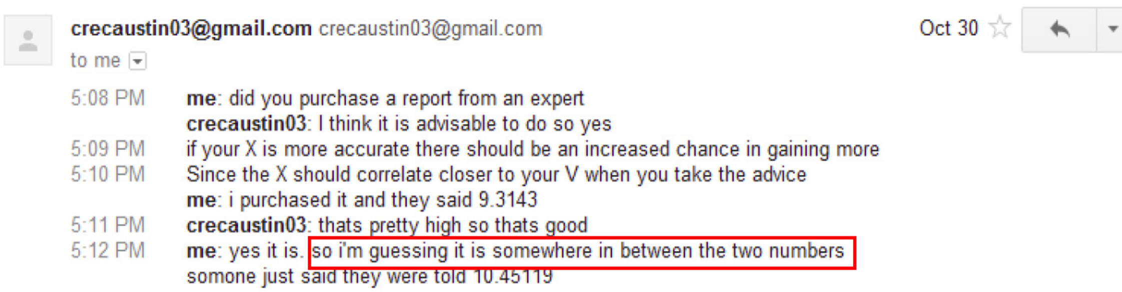

Figure 2.7: A Screenshot of Chats between Two Participants in the Experiment

Table 2.5: Estimation of Peer Effects using the Regression Model in (2.8)

VARIABLES	(1) OLS	(2) OLS	(3) Bootstrapping
social influence	0.460***	0.492***	0.460***
	[6.299]	[6.391]	[2.606]
acquisition	-0.0147	-0.0262	-0.0147
	[-0.362]	[-0.632]	[-0.374]
cost		-0.0387	
		[-1.474]	
degree		-0.2461	
		[-0.601]	
Constant	0.483***	0.483***	0.483***
	[6.874]	[6.874]	[2.853]
Observations	120	120	120
R-squared	0.255	0.271	0.255

z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

Hypothesis 2.5 states that peripheral nodes are influenced by the central participant in a star network, so the prediction market performance is positively associated with the prediction performance of the central participant. To test this hypothesis, we run an OLS regression of the prediction market accuracy of a star network in market g ($\mathrm{MAccuracy_g}$) on the prediction accuracy of the central participant ($\mathrm{Accuracy_g}$), the cost of information acquisition, and the number of participants acquiring information in market g (signal):

$$\mathrm{MAccuracy_g} = \beta_0 + \beta_1 \mathrm{Accuracy_g} + \beta_2 \mathrm{cost} + \beta_3 \mathrm{signal} + \varepsilon_i. \tag{2.9}$$

Table 2.6 shows the regression results. In Column 1, we find that a 1% decrease in the prediction accuracy of the central node is associated with a 0.534% decrease in the prediction market accuracy. When a hub has a relatively wrong estimate, it will cause a serious problem in a star networked prediction market. Column 2 shows that the result is robust after we control for the information acquisition in the market. To address the small sample concern, we do bootstrapping in Column 3, and the positive correlation is still significant.

Table 2.6. Estimation of the Hub Effects using the Regression Model in (2.9)

VARIABLES	(1) OLS	(2) OLS	(3) Bootstrapping
Accuracy	0.534***	0.520***	0.534**
	[7.380]	[6.721]	[2.061]
cost	-0.0828	-0.0775	-0.0828
	[-1.621]	[-1.450]	[-1.282]
signal		-0.0316	
		[-0.733]	
Constant	0.478***	0.559***	0.478*
	[6.882]	[4.242]	[1.893]
Observations	10	10	10
R-squared	0.896	0.904	0.896

z or t-statistics in brackets, *** p<0.01, ** p<0.05, * p<0.1

2.5 Extension

2.5.1 What Happens with a Complex Social Network?

One shortcoming of the controlled experiment approach is that the network structure is relatively simplistic. A natural question is whether our hypotheses are supported when the underlying social network is more complicated. In particular, from a manager's perspective, seeing how well Hypothesis 2.3 is supported with a more complex social network is important. This is because if an SEPM always (weakly) dominates an NNPM, then the manager of a prediction market should always promote the use of social networks among the participants. In this section, we conduct numerical simulations based on the analytical model to further analyze the effects of social networks on the forecast accuracy of prediction markets when the social network is more complex. The simulation results complement our findings from the experiment by demonstrating that a social network is actually a double-edged sword in a prediction market: When the cost of information acquisition is low, a social network can promote forecast efficiency, as suggested by our experimental results, but if the cost of information acquisition is high, it could decrease the prediction performance.

Using our analytical model, we conduct a variety of agent-based simulations in the social-network-embedded prediction markets. In every simulation round, a random social network that includes 100 participants is generated, using a 100×100 dimensional matrix. Following the Erdős–Rényi random graph model, we assume that the link between two participants is formed with independent probability p in our simulation. We set the parameter values for the common prior $V \sim N(V_0, 1/\rho_V) = N(10, 2)$, and the noise of the signal $\varepsilon_i \sim N(0, 1/\rho_\varepsilon) = N(0, 1)$. The results are robust for other parameter values. On the basis of Proposition 2.1, we can compute the fixed point, the threshold degree k^*, and then further compute the prediction by each participant, which enables us to compute the forecasting accuracy of the prediction market.

In the simulation, we use two measures of prediction market performance: the forecast accuracy and the mean squared errors (MSE) of the prediction market. Recall that the forecast of prediction market g, F_g, is the simple average of all 100 participants' predictions (the principal's prediction) in that market.

For each cost level of information acquisition, we run 1,000 simulations for both the SEPM and the NNPM, and then we compute the estimated forecast accuracy and the MSE. Figure 2.8 llustrates the effect of the cost of information acquisition on prediction market performances of the SEPM and the NNPM. The figure is drawn for parameter values n = 100, p = 0.3, V_0 = 10, $\rho_V = 0.5$, $\rho_\epsilon = 1$, and b = 1. $\mathrm{Accuracy0}$ represents the forecast accuracy computed in the NNPM, and $\mathrm{Accuracy1}$ represents the forecast accuracy in the SEPM. The forecast accuracy is defined as:

$$\mathrm{Accuracy_g} = 1 - \text{Mean Absolute Percentage Error}_\mathrm{g} = 1 - \frac{1}{1000}\sum_{j=1}^{1000}\frac{|F_{gj} - V|}{V},$$

$$g = 0,1.$$

Figure 2.8(a) shows that when the cost of information acquisition is low, the SEPM outperforms the NNPM in terms of forecast accuracy, and when the cost is high, the NNPM outperforms the SEPM. In Figure 2.8(b), this result is robust to a different measure of prediction market performance: MSE. $\mathrm{MSE0}$ represents the MSE computed in the NNPM, and $\mathrm{MSE1}$ represents the MSE in the SEPM. When c is small, $\mathrm{MSE0} - \mathrm{MSE1} > 0$, which means that the SEPM outperforms the NNPM. As c increases, $\mathrm{MSE0} - \mathrm{MSE1}$ decreases, and when c is large enough, the NNPM performs better than the SEPM.

(a) Forecast Accuracy (b) MSE

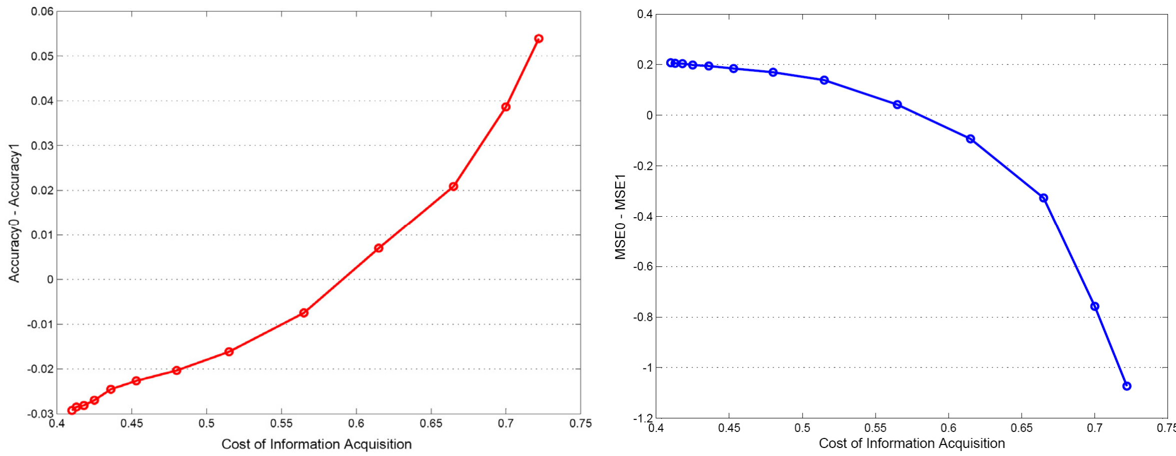

Figure 2.8: A Comparison between the Performances of the SEPM and the NNPM (Erdős–Rényi random graph)

The Erdős–Rényi random graph may be inappropriate for modeling some real-life phenomena. Typical real-world social networks possess additional structure that is absent in the Erdős–Rényi random graph. For example, the Erdős–Rényi random graph does not exhibit power laws. Using the similar simulation approach, we can also study the prediction performance under more realistic social networks, such as the Preferential Attachment graph (Jackson 2008). In the Preferential Attachment graph, two participants are more likely to be socially connected if they have a common acquaintance. Note that the Preferential Attachment graph has two parameters: the number of participants n and the total number of edges in the graph e. To compare the Preferential Attachment graph with the Erdős–Rényi random graph we already discussed, we calculate the expected number of edges in the Erdős–Rényi random graph ($n = 100$, $p = 0.3$): $[n(n-1)p]/2 = 1485$ (corresponding to the mean degree 29.7). Thus, we do a robustness check on the

Preferential Attachment graph for parameter values n = 100, e = 1485, V_0 = 10, ρ_V = 0.5, ρ_ϵ = 1, and b = 1. Figure 2.9 shows that the results are robust.

(a) Forecast Accuracy (b) MSE

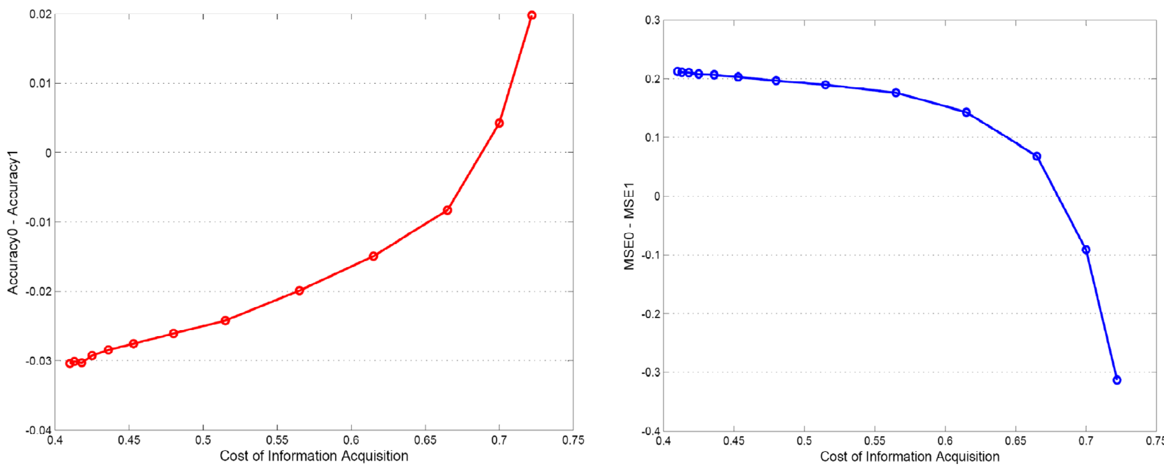

Figure 2.9: A Comparison between the Performances of the SEPM and the NNPM (Preferential Attachment graph)

This simulation analysis suggests the following results.

Simulation Result: The performance of an SEPM increases compared to an NNPM with decreasing information acquisition costs.

There are two implications of this result: First, when the cost of information acquisition is low, a social network can enhance forecast accuracy in prediction markets. Second, a social network also has a negative effect on the forecast accuracy of a prediction market when the cost of information acquisition is high. The second implication is driven by the fact that in our analytical model, social networks could reduce people's incentive to acquire information and could then be detrimental to the forecast accuracy of the prediction market as a whole. Our result depends crucially on the cost of information acquisition. Coval and Moskowitz (2001) show that investors prefer to hold local firms rather than distant ones, because the cost of acquiring information about companies located near investor is lower.[28] Similarly, if a prediction market is created for forecasting the performance of a firm, participants have easier access to private information and have the lower travel, time, and research costs associated with obtaining private information.[29] If participants in the United States are trying to predict the performance of a Chinese company, the cost of acquiring private information is extremely high.[30]

These implications are critical to understanding how to use social networks to improve the performance of prediction markets. Our present results suggest the following guidance for the business practice of prediction markets: When the predicted event is simple, which is interpreted as a low information acquisition cost, we recommend a social-network-based prediction market. When the predicted event involves complicated issues, which can be interpreted as a high cost of information acquisition, the traditional non-networked prediction market is preferred. For example, it is rather difficult for people to know some information about the event, "Hugo Chavez to no longer be the President of Venezuela before midnight ET 31 Dec 2012" (Intrade Prediction Market). However, it is relatively easy to have some ideas about the Twilight movie box office

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[28] The "Home bias puzzle" has been widely studied in the finance literature (Coval and Moskowitz 2001). Investment managers exhibit a strong preference for domestic equities.

[29] Local participants can visit the firm's operations, talk to employees, managers, and suppliers of the firm, and assess the local market conditions in which the firm operates. They may have close personal ties with local executives (e.g., run in the same circles, belong to the same country club).

[30] That is why Muddy Waters Research Group is especially known for its keen eye in spotting fraudulent accounting practices at Chinese companies. See http://blogs.wsj.com/deals/2012/11/28/examining-muddy-waters-track-record/.

(Iowa Electronic Markets). Whether to use social networks in prediction markets depends on the cost of information acquisition.

2.5.2 What Happens When the Signals Are Misleading?

In the previous analysis, we assume that the private signals in the market are informative. However, under some circumstances, the signals may be misleading or systematically biased. For example, stocks plunged sharply on April 23, 2013, after a hacker accessed a newswire's account and tweeted about a false White House emergency.[31] The erroneous tweet, which was posted around 1:07 p.m. ET, said "BREAKING: Two Explosions in the White House and Barack Obama is injured." This tweet sent shock waves through the stock market and caused the market to tumble.

What would happen when the signals in the markets are systematically biased? More formally, we modify equation (2.2) and assume that the signal is misleading in the sense that $S_i = V + d + \varepsilon_i$, where $d > 0$ or $d < 0$. The absolute value of d measures the systematic bias of the signal. The underlying social network is the Erdős–Rényi random graph. In Figure 2.10, we redo the simulation analysis when the signal is misleading.

Accuracy0 represents the forecast accuracy computed in the NNPM, and Accuracy1 represents the forecast accuracy in the SEPM. In Figure 2.10(a), we find that when the systematic bias is small (i.e., the absolute value of d is 1), the result is similar: The performance of an SEPM increases compared to an NNPM with decreasing information acquisition costs. However, when the systematic bias is sufficiently large (the absolute value of d is 3, 5, or 10), the result is the opposite (Figure 2.10(b)). Note that because our problem is symmetric, the simulation results when $d = y$ are the same as

[31] See http://buzz.money.cnn.com/2013/04/23/ap-tweet-fake-white-house/?iid=EL.

the results when d = - y, y = 1, 3, 5, 10. The intuition is that when the bias is large, receiving more signals is misleading rather than beneficial (the role of signals is just the opposite). When the cost of information acquisition is small, a social network between participants exacerbates the spread of misleading signals. Instead of improving the market performance, the dissemination of information is detrimental in this case. When the cost is high, the existence of a social network impedes the acquisition of biased information because of possible free-riding opportunities. Thus, an SEPM outperforms an NNPM.

(a) Small-Bias Signal (b) Large-Bias Signal

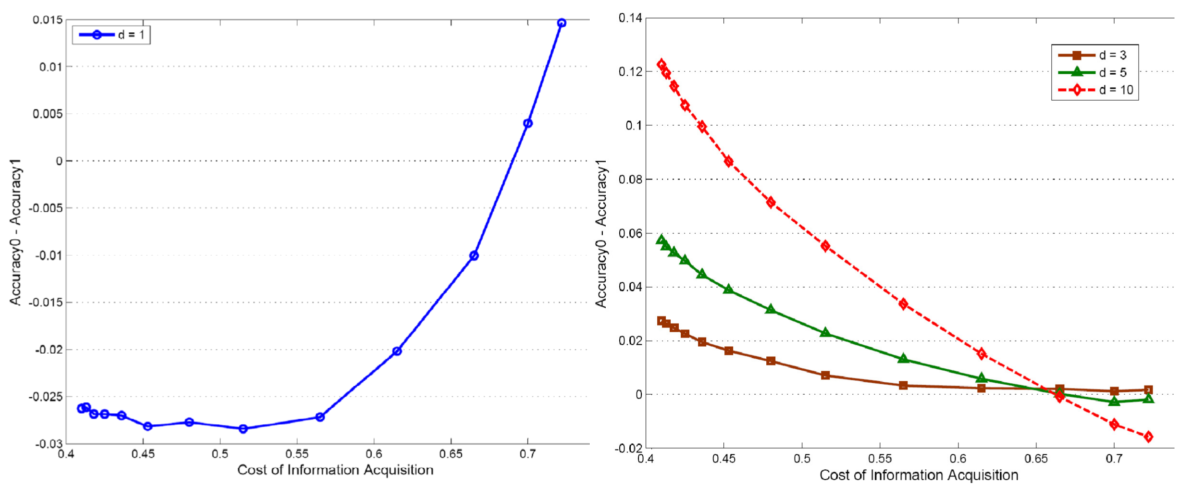

Figure 2.10: A Comparison between the Performances of the SEPM and the NNPM When the Signals are Systematically Biased

2.5.3 What Happens When Participants Can Observe Their Friends' degrees?

In our theoretical model, we assume that each participant observes her own degree, but does not observe the degrees of her friends. In many situations, a participant has a good forecast of her own degree, but has incomplete information about the degrees of others (Galeotti et al. 2010). However, this is a strong assumption when we talk about social media, such as Facebook and LinkedIn. In this section, we extend our analytical model and relax this assumption by allowing each participant to observe her friends' degrees in the four networks shown in Figure 2.1. The model setup in this section is similar to the setup in the previous theoretical analysis, except that the social networks are topologies in Figure 2.1 instead of random graphs. It is a complete information game in the sense that each participant has perfect knowledge about her friends' degrees, so the equilibrium concept is a Nash equilibrium rather than a Bayes-Nash equilibrium. In this section, we show that a non-increasing strategy in information acquisition is also a Nash equilibrium strategy (it might not be the unique equilibrium strategy). In other words, the basic result in Proposition 2.1 is also valid when each participant can observe the degrees of her friends.

For simplicity, let's consider sixteen participants in total, and each network structure consists of four participants (four network structures). Participant *i*'s net benefit of acquiring information when k_a (k_a= 0, 1, 2, or 3) of her friends acquire information is:

$$NB_{k_a} = u(m_i' = 1, m_{N_i(g)}) - u(m_i = 0, m_{N_i(g)}) = b\left(\frac{1}{k_a\rho_\varepsilon+\rho_V} - \frac{1}{(k_a+1)\rho_\varepsilon+\rho_V}\right) - c,$$

and for vector $m_{N_i(g)}$, there are k_a elements of 1 and $k_i - k_a$ elements of 0. Note that NB_{k_a} is decreasing in k_a, so we have five possible cases:

(1) $NB_3 < NB_2 < NB_1 < NB_0 \leq 0$.

In this case, the cost of information acquisition is too high, and $m_i = 0$ is a Nash equilibrium strategy for all sixteen participants in the four networks. It is trivial to show that the equilibrium strategy is non-increasing in degree.

(2) $NB_3 < NB_2 < NB_1 \leq 0 < NB_0$.

In Case 2, a Nash equilibrium strategy for all four participants in the non-networked environment is $m_i = 1$, because the net benefit of acquiring information when $k_a = 0$ is positive. A Nash equilibrium strategy for participants in the complete network is that one participant acquires information and the other three participants do not acquire information. For participants in the star network, a Nash equilibrium strategy is that the central participant does not acquire information and the other three participants acquire information. A Nash equilibrium strategy for participants in the circle network is that Participants 1 and 3 in Figure 2.1 acquire information and the other two participants do not acquire information. Summarizing all the equilibrium strategies, we find that 100% of participants with degree 0 acquire information, 100% of participants with degree 1 acquire information, 50% of participants with degree 2 acquire information, and 20% of participants with degree 3 acquire information. Thus, the equilibrium strategy is non-increasing in degree.

(3) $\mathrm{NB}_3 < NB_2 \leq 0 < NB_1 < NB_0$.

Similarly, in Case 3, Nash equilibrium strategies for participants in the non-networked environment, the star network, and the circle network are the same as the strategies in Case 2. For participants in the complete network, a Nash equilibrium strategy is that two participants acquire information and the other two participants do not acquire information. We find that 100% of participants with degree 0 acquire information, 100% of participants with degree 1 acquire information, 50% of participants with degree 2 acquire information, and 40% of participants with degree 3 acquire information. Thus, the equilibrium strategy is non-increasing in degree.

(4) $\mathrm{NB}_3 \leq 0 < NB_2 < NB_1 < NB_0$.

In Case 4, Nash equilibrium strategies for participants in the non-networked environment and the star network are the same as the strategies in case (2). For participants in the complete network, a Nash equilibrium strategy is that three participants acquire information and the other one participant does not acquire information. A Nash equilibrium strategy for participants in the circle network is that all of them acquire information. We find that 100% of participants with degree 0 acquire information, 100% of participants with degree 1 acquire information, 100% of participants with degree 2 acquire information, and 60% of participants with degree 3 acquire information. Thus, the equilibrium strategy is non-increasing in degree.

(5) $0 < NB_3 < NB_2 < NB_1 < NB_0$.

In Case 5, the cost of information is low, and the net benefit of acquiring information when $k_a = 3$ is positive. All participants in the four networks acquire information. The equilibrium strategy is trivially non-increasing in degree.

2.6 Conclusions

In this paper, we designed and carried out a laboratory experiment to examine the effect of a social network on the performance of a prediction market, as well as on the behavior of its participants. Through randomization in the controlled experiment, we were able to identify the causal relationship between the network degrees of players and their performance in the prediction market as well as their strategic decisions regarding whether to acquire costly information. More importantly, we tested the hypotheses that social-network-embedded prediction markets outperform prediction markets without social network in terms of prediction accuracy, and we found the difference to be significant when the cost of information acquisition is low but insignificant when the cost of information acquisition is high. Further numerical simulations suggest that the existence of a social network in a prediction market lowers the forecasting accuracy when the cost of information acquisition is high. This has a direct managerial implication for the business practice of prediction markets: When the predicted event is simple, promoting social networking among participants is beneficial, whereas if the predicted event involves complicated issues, a social network among participants should be discouraged.

In the past few years, many large firms, such as Google, Microsoft, and HP, have experimented with internal prediction markets to improve business decisions (Chen and Plott 2002). The primary goal of these markets is to generate predictions that efficiently aggregate many employees' information. It is easier for employees to gain access to private information about the company. Compared to outsiders, the cost of information acquisition is lower for internal employees. In this context of corporate prediction markets, the implication of our results is that an SEPM outperforms an NNPM when participants are internal employees.

Our experiment results also suggest that network structure matters when it comes to the performance of social-network-embedded prediction markets. An important future research direction is to extend our static model to further investigate exactly how the network structure affects prediction market performance as well as the performance and behavior of each participant over time. It would be interesting to create some social network measures that can help explain the variation of performances of prediction markets with different social network structures. Another interesting future research direction is to examine the incentives to share information in a social network through a laboratory experiment. Do participants exchange information according to reciprocity and norms of fairness? Studying the incentives for sharing information or the sale of information in social-network-embedded prediction markets remains an open question.

Chapter 3: Learning from Your Friends' Repeated Check-Ins: An Empirical Study of Location-Based Social Networks

3.1 Introduction

The most famous example of herd behavior is a sequential decision model in Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992): people make their decisions on whether or not to dine on the basis of how many consumers are already in a restaurant. In the current practice, however, people tend to seek information available on location-based social networking applications for decision making (e.g., Foursquare, Facebook Place, or Google Latitude).[32] The location-sensing mobile devices offer geolocation capabilities to share the users' location information with their friends. People "check in" at restaurants using a mobile website, text messaging, or a device-specific application in order to have their check-ins posted on their social network accounts. As technology evolves, the emerging location-based service makes us rethink the classical theory of herding and observational learning and try to upgrade it to a 2.0 version embedded with social media features.

The location information adds an important social network dimension to prior herding literature. People can observe the choices made by their Foursquare or Facebook friends without having to physically visit the restaurants to observe. As a result of these new technologies, a striking difference has arisen: In the previous herding story, people arrive at the restaurants in a sequence, and they can observe all of the choices made by people before them, including many anonymous consumers. In the current practice, people are connected by a Foursquare or a Facebook network, and they can observe only

[32] As of December 19, 2013, Foursquare has 45 million users and 60 million locations. Locations consist of restaurants, theaters, bars, museums, or schools. See http://expandedramblings.com/index.php/by-the-numbers-interesting-foursquare-user-stats/#.U0GFrvldVIE.

their friends' choices.[33] Such features change the way people find what they want online. Searching the web is the traditional way that people discover contents, and people can read online comments of anonymous consumers by searching the web. However, as location-based social networks become increasingly important in information exchange and transmission, friends start to direct each to interesting content. People actively share their check-ins to interact with their friends, family, and colleagues, and provide social recommendations (Lindqvist et al. 2011). Therefore, the study of the herd behavior in location-based social networks is both interesting and important.

In prior literature, observational learning means that individual's decisions are affected by the observation of others' choices because of its informational content. Despite the intuitive appeal of observational learning, the estimation of the effects of observational learning is complicated by a plausible confounding mechanism: the saliency effects, an aspect of a stimulus that stands out from the rest (Cai et al. 2009).

In this study, we aim to take a step further to examine these confounding mechanisms and estimate observational learning and the saliency effect in a structural model of location-based social networks. In our context, observational learning means "check-ins" made by friends to help users learn the quality information of a venue; the saliency effect refers to the fact that check-ins leads some of the uninformed consumers to discover a new venue. Both effects are theoretically plausible and need to be empirically examined.

The recent growth of location-based social networks provides an ideal environment to study observational learning. First, the well-known reflection problem (Manski 1993) arises when there is a circularity of cause and effect: Person i's choice is

[33] Although users can also observe anonymous people's check-ins on Foursquare, they only receive push check-in notification from their friends. We argue that this push technology makes friends' check-ins stand out from all check-ins on Foursquare because of users' limited attention.

influenced by the mean of peer behavior, which reflects person i's behavior. Social interactions models can fail to be fully identified for this interdependency in behaviors. In our context, the problem does not occur because of the rich data: we can observe the chronological sequence of users' check-in behavior. Later check-in behavior is influenced by early check-in behavior, but not vice versa.

Second, social network platforms are prone to abusive use and manipulations from strategic parties.[34] Without a proper verification mechanism to filter out opinion spam, firms can manipulate the process of observational learning by deploying spam bots and leaving fake messages to deceive consumers. It is difficult to identify the real effect of observational learning in an environment where firms deliberately manipulate public beliefs by exploiting spamming techniques to create information cascades (such as Yelp and TripAdvisor reviews). Recently, there are more concerns about the authenticity of restaurant reviews. For example, only diners who have booked and honored a reservation through OpenTable.com are able to submit ratings and reviews.[35] In contrast with other social network platforms, location-based service is less susceptible to these types of contamination by integrating location-based information which can be used for additional verification (Lindqvist et al. 2011). A check-in using the location-sensing mobile devices requires verification of users' GPS data, so it represents a real visit. When a focal user's friends check in at venues, the push notification service uses push technology[36] through a constantly open IP connection to forward notifications from the servers of the location-based application to the focal user's mobile devices.

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[34] For example, Yelp allows its users to sign up free and post reviews under a made-up "screen name." The Federal Trade Commission has received more than 2,046 complaints filed about Yelp from 2008. Most of the complaints are from small businesses that claim to have received unfair or fraudulent reviews. See http://online.wsj.com/news/articles/SB10001424052702303847804579477633444768964.

[35] See http://support.opentable.com/app/answers/detail/a_id/152/kw/rr/related/1.

[36] See http://en.wikipedia.org/wiki/Push_technology.

Third, in the classical story of observational learning (Banerjee 1992), a consumer is not allowed to visit a restaurant repeatedly. However, we observe a pattern of repeated check-ins in location-based social networks. To motivate our analysis, consider the following example. Assume that Mr. A observes that his friend Miss. B checked in at Restaurant C once one month ago, and after that Miss B has never visited again. Mr. A also observes that Miss B has checked in Restaurant D four times in the past month. What then could Mr. A conclude? He might believe that Miss B's repeated visits signal the suitability and quality of Restaurant D. Differing from the classical observational learning theory, one check-in during a long time period could be a bad signal for Restaurant C in contrast with Restaurant D. Location-based service allows us to offer insights into real-world observational learning in social networks.

Using a unique dataset from a major location-based social networking website in China, we estimate a structural model of observational learning. A tight integration of structural modeling and location-based technology allows us to identify the parameters of the underlying individual choice model and conduct counterfactual analysis. Our structural model goes beyond location-based service, and applies to other experience goods where observational learning occurs in social networks. For example, Amazon allows consumers to socially-share their purchases across Facebook, Twitter and e-mail.[37]

3.2 Literature Review

This present study adds to prior research by offering a new perspective on location-based services. Xu et al. (2010) address the privacy concerns in location-based networks. They differentiate three privacy intervention approaches --- compensation,

[37] See http://www.amazon.com/gp/feature.html?docId=1001426011.

industry self-regulation, and government regulation --- and examine their impacts on the privacy calculus. Xu et al. (2012) conduct an experimental study to further explore the effects of these three approaches on control perceptions and privacy concerns. In the present study, we focus on answering a different question about location-based networks: Given that consumers check in at restaurants using location-based services, how does observational learning (friends' check-ins) affect the focal consumer's decision?

Our present work also contributes to existing literature on network effects. Most prior research focuses on payoff externalities of network effects: The value of the service directly depends on the consumption choices made by some other consumers, irrespective of their reasons for the choices. Pang and Etzion (2012) analyze the optimal pricing of the online service when a firm sells a product and can offer a complementary online service that displays network effects. Kauffman et al. (2000) empirically examine the impact of network externalities on the adoption of networks. Oestreicher-Singer and Zalmanson (2013) show that consumers' willingness to pay is strongly linked to community participation using the data from the online music website Last.fm. These studies share a similar feature: payoff externalities. Similar to their models, in our structural model of location-based networks, a customer's dining decision is also affected by the decisions of other consumers. However, our study focuses on information externalities instead of payoff externalities: A customer's utility does not directly depend on other people's prior dining decisions. She makes an inference about the restaurant quality by observing other people's choices. The decisions of her friends are useful signals that extract more information about the quality.

Herd behavior and information cascade have been widely studied in the literature (Banerjee 1992; Bikhchandani, Hirshleifer, and Welch 1992). In the canonical model of observational learning, agents make decisions sequentially after having observed their predecessors' choices. In a sequential decision making setup, they show that at some point, people follow the decisions of their predecessors regardless of their private information. Smith and Sørensen (2000) further generalize the model by allowing taste diversity and find that herding is not the only possible long run outcome: there exists an informational pooling equilibrium where everyone must rely on her private signal. In these models, people can observe the decisions of all their predecessors. This is not an appropriate assumption in location-based networks. People have limited attention and tend to be worried about letting strangers know where they are. Acemoglu et al. (2011) study a theoretical observational learning model over a general social network. In their model, people observe only subsets of their predecessors. Golub and Jackson (2010) examine how network structure influences learning and the diffusion of information. In our structural model, we assume that a customer can observe only her friends' decisions, which fits the important feature of location-based social networks.

A handful of empirical research has examined the mechanism of observational learning in reality. Duan, Gu, and Whinston (2009) empirically examine herd behavior and informational cascades in the context of online software adoption. Zhang (2010) study observational learning in the U.S. kidney market. Chen, Wang, and Xie (2011) disentangle if consumers' purchase decisions can be influenced by others' opinions (word of mouth) or others' actions (observational learning) using a natural experiment from Amazon. Hendricks, Sorensen, and Wiseman (2012) develop a model of social learning in which consumers observe only the aggregate purchase history and test the model using the data from a controlled laboratory experiment. In our present study, we use a structural approach to empirically estimate parameters of an observational learning model in location-based social networks.

Our work is also related to social influence models that can fail to be fully identified for a variety of reasons. Manski (1993) discusses the econometric challenge of identifying social effects: Is a person's behavior caused by his social reference group, or does it simply reflect the same movement in his reference group? The observation that individuals belonging to the same group tend to behave similarly might result from social contagion, exogenous contextual effects, or homophily. Failure to account for contextual effects or homophily — the tendency of individuals to associate with similar others, might lead to an overestimation of the effect of social effects. These confounding effects are difficult to distinguish, and the identification of social effects often requires strong parametric assumption or rich data collection. Aral, Muchnik, and Sundararajan (2009) distinguish influence-based contagion from homophily-driven diffusion using a dynamic matched sample of global instant messaging users. Iyengar et al. (2011) distinguish social contagion from homophily and exogenous contextual effects in prescribing behavior among networks of doctors. Shi and Whinston (2013) use the nonnegative matrix factorization technique to solve the problem of correlated unobserved heterogeneity and identify the real social effects. In our context of location-based networks, homophily (correlated unobserved taste) may also provide useful information to help people make inference about the quality of venues. Thus, we do not formally differentiate real social effects and homophily, and the estimate in our study is an upper bound of social learning.

It is also instructive to contrast our model with the diffusion model in marketing literature, especially the repeat purchase diffusion model (Rao and Yamada 1988). Different types of social learning are at work under different circumstances. Word of mouth has been studied widely in the previous literature, but there have been very few attempts to examine the effects of observational learning in location-based networks. Several studies have shown the presence of diffusion in new product adoption and the role of word of mouth (e.g., Godes and Mayzlin 2009; Goldenberg et al. 2009). In our study, social learning also plays a critical role in location-based networks, but the diffusion mechanism is different. Our model captures the feature of observational learning, which is different from word of mouth. People can infer the quality of venues by observing the choices of their friends: their check-ins.

3.3 Data

The dataset comes from a major location-based social networking website (a foursquare-like website) in China. As of July 2013, it has 5 million users. Users can check in at a venue to say that they are currently there using this location-based mobile application. It also lets users connect to their friends, which are equivalent to the concept of friends on Facebook. Users can observe their network friends' check-ins through the mobile application like Figure 3.1.[38] Users can choose to have their check-ins synchronized to their other social-network accounts, such as Twitter, Sina Weibo, and Tencent Weibo (see Figure 3.2).

[38] The screenshot is actually from a U.S. location-based app: Foursquare, however, the Chinese location-based social networking website described in our paper is highly similar to Foursquare and is frequently called the Foursquare of China.

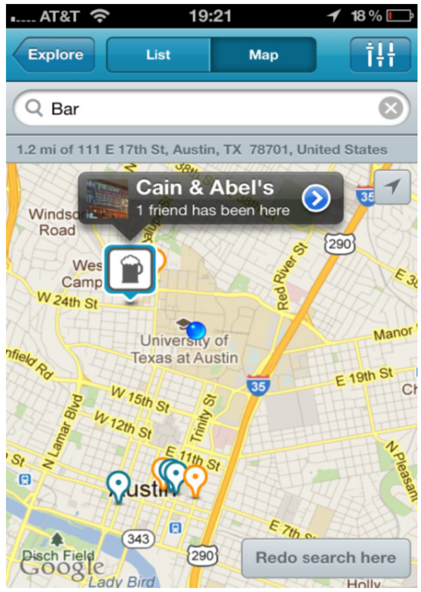

Figure 3.1: A Screenshot from a Location-Based App

Figure 3.2: A Screenshot of Check-in Synchronization

Our data includes restaurant check-in information and the users' social network. The first part of the data is a complete history of check-ins of 50 restaurants in Shanghai, China. The period of check-in history is from May, 2010 – Jan, 2013. We can observe when who checked-in and where. The total number of users is 138,972, and the total number of check-ins is 391,767. Figure 3.3 depicts the frequency histogram of the check-ins of restaurants, and Figure 3.4 is the frequency histogram of the unique customers of restaurants. The other part of our data is the undirected friendship network. The social network is recorded as of February 15, 2011. Table 3.1 summarizes the descriptive statistics by a user. It shows that on average each user has approximately 35 friends and makes 3 check-ins in the sampling time period.

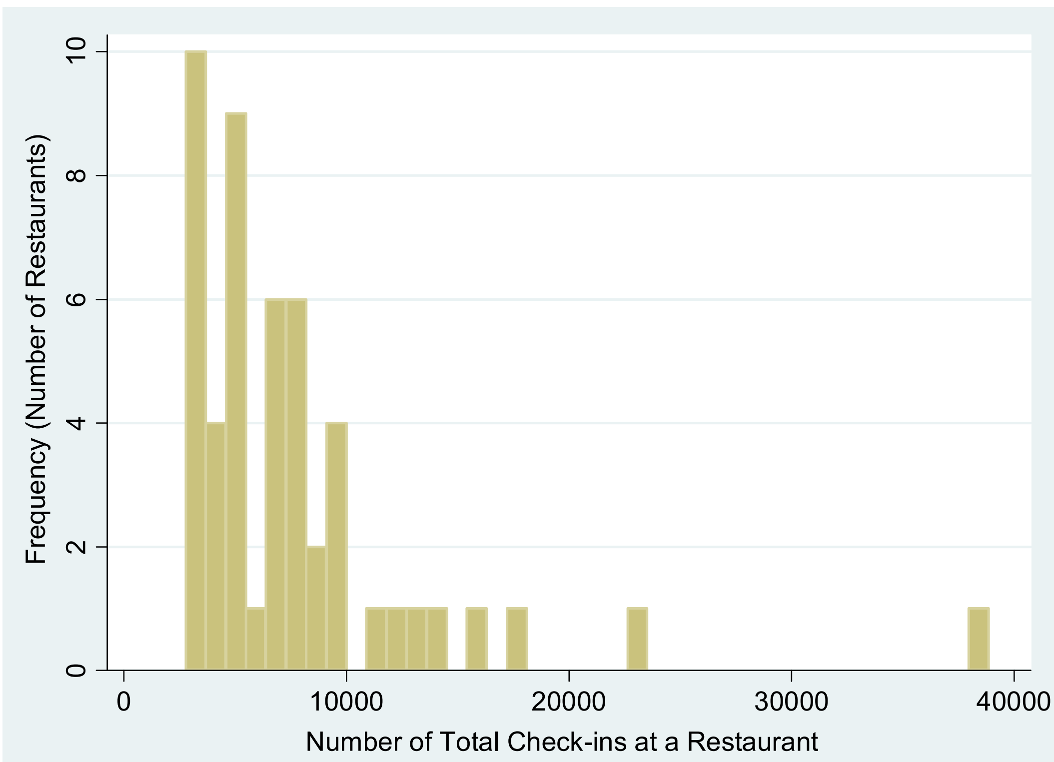

Figure 3.3: Histogram of the Check-ins of Restaurants

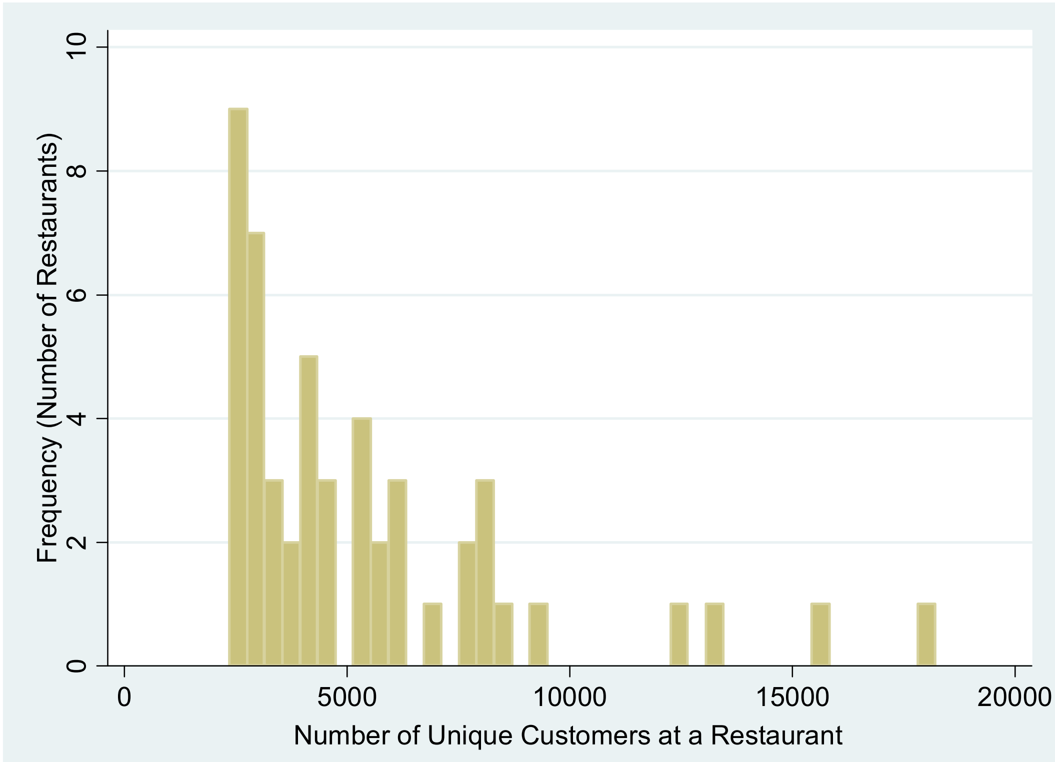

Figure 3.4: Histogram of the Unique Customers of Restaurants

Table 3.1: Descriptive Statistics of Location-Based Service Users

	Mean	The Std. Dev.	Max	Min	Obs
The number of check-ins	2.819	6.839	817	1	138,972
The number of friends	34.639	529.883	5,461	0	138,972

In our dataset, a user may observe two types of check-ins within a time period: a friend's first time check-in (see Figure 3.5) or her repeated check-ins (see Figure 3.6). The role of these two types of check-ins is different. When a user checks in at venue, a check-in notification is by default pushed to her friends in location-based networks. Therefore, the first time check-in can help the user discover a new restaurant. Although technically a user can observe all recent check-ins made by the location-based application, an extensive empirical literature on limited attention shows that attention is a scarce resource and people have limited cognitive abilities to process information (Lacetera, Pope, and Sydnor 2012). The push notification technology makes the friends' check-ins more salient to the focal user than other anonymous check-ins.

Repeated friends' check-ins do not add additional information about the existence of a new restaurant. However, your friends' repeated visits show that they are satisfied with the restaurant food and service. Repeated check-ins imply that the ex-post utility is higher than the reservation utility and further signal the quality of the restaurant. To some extent, a first time check-in might also signal the restaurant quality: It shows that a consumer's ex-ante utility from visiting a venue is higher than her reservation utility. However, in contrast with repeated check-ins, the main role of a first-time check-in is the awareness effect.

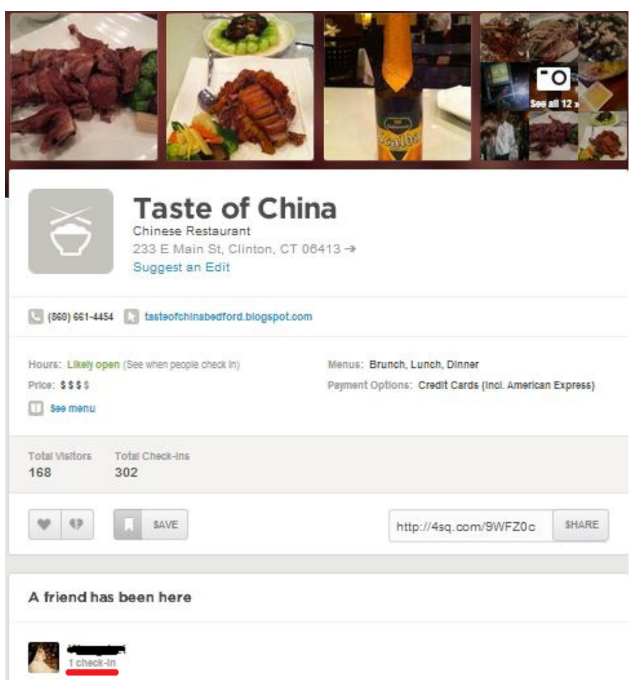

Figure 3.5: A First Check-in at a Restaurant

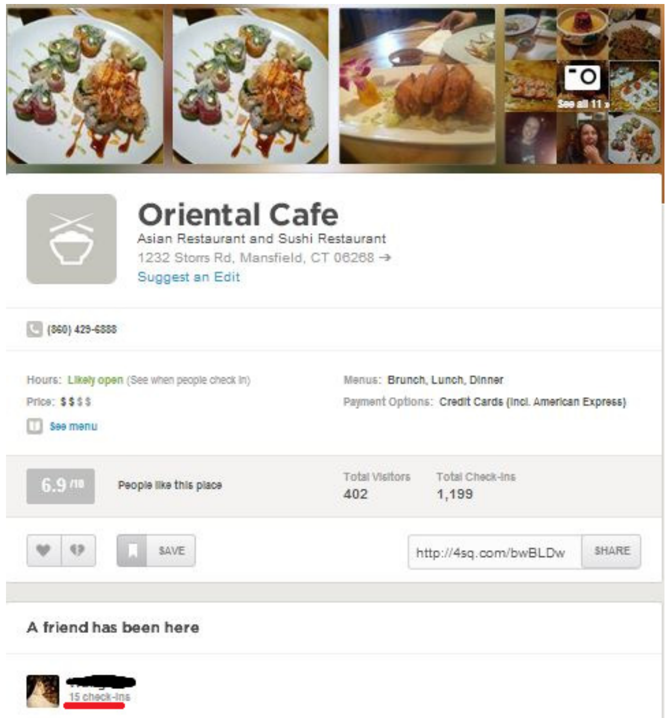

Figure 3.6: Repeated Check-ins at a Restaurant

3.4 A Structural Model of Learning in Location-Based Networks

In this section, we develop and estimate a model of restaurant discovery and quality learning. Following Hendricks and Sorensen (2009), the probability that a consumer visits a venue is the product of two probabilities: the probability that she likes the venue conditional on discovering the venue and the probability that she discovers the venue. It's important to consider the awareness probability in restaurant discovery. Note that neither of these two probabilities is directly observable in the data. We estimate them from a structural model.

We outline the sequence of events in period t as follows (the process proceeds in a similar manner in period $t + 1$):

Stage 1: Consumers become aware of a restaurant j in period t. Following Hendricks and Sorensen (2009), we specify a functional form for the conditional probability that an uninformed consumer discovers venue j in period t:

$$\Pr(D_{ijt} = 1) = \frac{p_j e^{b_j f_{ijt-1}}}{(1-p_j)+p_j e^{b_j f_{ijt-1}}}, \tag{3.1}$$

where D_{ijt} denotes a binary variable that is equal to one if consumer i learns about venue j in period t (conditional on not having learned in any prior period), and f_{ijt-1} is the number of first time check-ins of consumer i's friends in period $t-1$. In this specification, the number of unique friends' check-ins can increase the awareness probability in the first stage. A friend may check in a restaurant several times in a period, and we assume that only the first check-in matters in terms of awareness probability. Repeated check-ins may increase the focal consumer's expectation about the quality of a restaurant, but they do not add new information about the existence of the restaurant. In location-based social networks, the focal consumer becomes aware of a restaurant via the first time check-in.

If the number of first time check-ins (unique friends' check-ins) is zero ($f_{ijt-1} = 0$), then the default awareness probability is: $\Pr(D_{ijt} = 1) = p_j$. Without a location-based social network, a consumer can still discover a new restaurant by searching on Yelp, TripAdvisor, and other sources of public information. As the number of first time check-ins gets very large, the probability converges to one, at a rate that depends on the parameter b_j, which measures the saliency effect of first time check-ins.

Note that we are not trying to answer the question why people would like to check in using location-based services when they visit a venue in this study.[39] Instead, we assume

[39] Lindqvist et al. (2011) find that people actively use location-based service mainly because of pro-social motivations. Some restaurants and bars also reward consumers (typically in the form of discounts) when they check in using the mobile application.

that active users always check in at a venue using their smart phones if they visit the venue. In future research, this assumption can be relaxed in a more complete structural model considering the check-in incentives based on a trade-off between check-in deals and privacy concerns for friends.

The unconditional probability that an uninformed consumer discovers venue j in period t:

$$q_{ijt} = q_{ijt-1} + (1 - q_{ijt-1})\Pr\big(D_{ijt} = 1\big). \tag{3.2}$$

We set $q_{ij0} = q_{j0}$. q_{j0} is interpreted as the baseline awareness of venue j. q_{ijt} can be interpreted as the proportion of informed consumers for venue *j* in period *t*, and the proportion accumulates over time. Unlike purchasing durable goods (Berry, Levinsohn, and Pakes 1995), consumers can repeatedly visit a venue in different time periods in our context.

Stage 2: Conditional on that they are aware of the restaurant, consumers make a decision on whether to go to this restaurant.

The utility function for consumer i conditional on having learned venue j

$$U_{ijt} = E\big(Q_j \big| R_{ijt-1}, \alpha_j\big) + \varepsilon_{ijt}, \varepsilon_{ijt} \sim N(0, \sigma^2), \tag{3.3}$$

where $E\big(Q_j \big| R_{ijt-1}, \alpha_j\big) = \alpha_j + \gamma_j R_{ijt-1}$. The reservation utility $\overline{U}$ is normalized to zero. $\mathrm{R_{ijt-1}}$ is the number of friends' total repeated check-ins at venue j up until period *t* - 1. The parameter $\mathrm{\alpha_j}$ is the heterogeneity of restaurants. Consumers interpret their friends repeated check-ins as more credible signals of the suitability and quality of restaurants. Yan, Wang, and Chau (2013) empirically show that the higher satisfaction a restaurant delivers, the higher the possibility that consumers will revisit. Following the test of herding proposed in Zhang and Liu (2012), the coefficient on R_{ijt-1} measures the effect of observational learning. In our study, we focus on the learning effect of repeated check-ins and assume that the restaurant quality is exogenously given and cannot be changed over time. In reality, the positive effect of repeat purchases on quality can mitigate the lemons problem (Riordan 1986): A restaurant has an incentive to provide higher quality in order to retain repeat purchases. ε_{ijt} represents individual taste heterogeneity and is i.id. distributed. Note that in equation (3.3), we do not directly model the process of Bayesian learning in networks because the decision rules used in perfect Bayesian equilibria are complicated and the analytic solution requires strong assumptions on network topology (Acemoglu et al. 2011; Qiu and Whinston 2012).

Conditional on discovering the venue, if the utility of visiting restaurant *j* in period *t*, U_{ijt}, is greater than the reservation utility, consumer *i* will go to restaurant *j* in period *t*. The probability that consumer i visits venue j in period t conditional on discovering the venue is given by $E\left[1\left(U_{ijt} \geq \overline{U}\right)\right]$.[40] The probability that a consumer visits a venue in period t is the product of two probabilities: $q_{ijt} \cdot E\left[1\left(U_{ijt} \geq \overline{U}\right)\right]$. Let's consider the benchmark case: In the absence of a location-based social network, the probability that consumer *i* visits a venue in period 1 is $[q_{j0} + (1 - q_{j0})p_j]\Pr\left(\alpha_j + \varepsilon_{ij1} \geq 0\right)$. Note that in this model, we do not consider the strategic behavior of delaying the decision making process to obtain more information about restaurant quality.[41] This assumption is appropriate in our context because the dining choice is not a critical decision, in contrast with the purchase of durable goods, such as automobiles. When the product is purchased repeatedly and is relatively unimportant, consumers tend to apply very simple choice rules that provide a satisfactory choice to make a quick decision (Hoyer 1984). It is also important to note that in Berry, Levinsohn, and Pakes (1995), a consumer can only choose one from several brands available in the automobile market. In contrast with the

[40] Each time people check in, they show the restaurants and bars they like to their friends. Because of this reputation concern, some consumers may only check in at a restaurant when they truly like it. In the present study, we do not consider the heterogeneity of individual's reservation utility.

[41] Similarly in the behavioral literature, preference uncertainty may lead to choice deferral when no single alternative has a decisive advantage (Dhar 1997). We also do not consider this situation.

durable good market discussed in Berry, Levinsohn, and Pakes (1995), our setup allows a consumer to visit several different venues during one time period. We think this is more realistic for non-durable goods, such as restaurant dining.

We construct the likelihood function to estimate the empirical model:

$$\log L(\theta) = \log \prod_{t=1}^{T} \prod_{j=1}^{J} \prod_{i=1}^{N} \left[q_{ijt} \cdot \Pr\left(U_{ijt} \geq 0\right)\right]^{Y_{ijt}} \left[1 - q_{ijt} \cdot \Pr\left(U_{ijt} \geq 0\right)\right]^{1-Y_{ijt}}$$

$$= \sum_{t=1}^{T} \sum_{j=1}^{J} \sum_{i=1}^{N} \left[Y_{ijt} \log \frac{q_{ijt} \cdot Pr\left(U_{ijt} \geq 0\right)}{1 - q_{ijt} \cdot Pr\left(U_{ijt} \geq 0\right)} + \log\left(1 - q_{ijt} \cdot \Pr\left(U_{ijt} \geq 0\right)\right)\right],$$

where Y_{ijt} is an indicator for whether consumer i visits venue j in period t from the real data. In the estimation, we use one month as the time unit of analysis. T is the number of time periods (T = 32), J is the number of venues (J = 50), and N is the number of consumers (N = 138,972). Note that if $Y_{ijt} = 1$, then $\Pr(D_{ijm} = 1) = 1$, for $m = t, t+1, \ldots, T$.

Our estimates of the parameters are chosen to satisfy:

$$\hat{\theta} = (\widehat{\alpha_j}, \widehat{\gamma_j}, \widehat{p_j}, \widehat{b_j}, \hat{q}_{j0}) = \underset{\alpha_j, \gamma_j, p_j, b_j, q_{j0}}{\operatorname{argmax}} \log L(\theta) \tag{3.4}$$

To summarize, the parameters to estimate include the observational learning effect γ_j, restaurant heterogeneity α_j, the default awareness probability p_j, the saliency/awareness effect b_j, and the baseline awareness q_{j0}.

The saliency/awareness parameters p_j, b_j, and q_{j0} are identified from the variation in first time check-ins of focal user's friends and the functional form of conditional awareness probability specified in equation (3.1). The observational learning effect γ_j, and restaurant heterogeneity α_j together shape the second stage of consumers' decision process. Note that they cannot separately identified from the variance of individual taste heterogeneity σ^2. Therefore, we normalize the variance σ^2 to be one, and estimate γ_j and α_j as free parameters. In the present study, we do not use the fixed effect method because in general our two-stage model is not linear although in the second stage, equation (3.3) is linear.

The estimation of our model is different from the generalized method of moments (GMM) algorithm used by Berry, Levinsohn, and Pakes (1995). Because we have a richer individual level dataset, we don't need to match the calculated market shares with the observed market shares. In contrast with the structural models in cereal industry (Nevo 2001) and hotel industry (Ghose, Ipeirotis, and Li 2012), we propose and estimate a two-stage individual decision model considering new restaurant discovery in the first stage and quality learning in the second stage. Following Erdem, Keane, and Sun (2007), we can also construct R_{ijt-1} as an exponentially smoothed weighted average of friends' repeated check-ins, and the estimation results are similar.

3.5 Empirical Results

In this section, we present the empirical results estimated from equation (3.4). Figure 3.7 shows the estimated γ_j for each restaurant in equation (3.3). We can also see the heterogeneity of observational learning effects in Figure 3.7. This might be driven by the heterogeneity of restaurant characteristics. For example, a restaurant in a downtown area might be more affected by observational learning effects than a roadside restaurant on a highway: The business of the first restaurant relies heavily on repeat purchases.

Figure 3.8 show that b_j is significantly positive for some restaurants, but insignificant for some other restaurants. This implies that for some restaurants, the saliency effect may not exist in location-based social networks. As the number of first time check-ins gets larger, the probability of discovering a new restaurant converges to one, at a rate that depends on the parameter b_j. It would be interesting to compare our estimates with Hendricks and Sorensen (2009): the awareness rate b = 0.065 in their estimation.

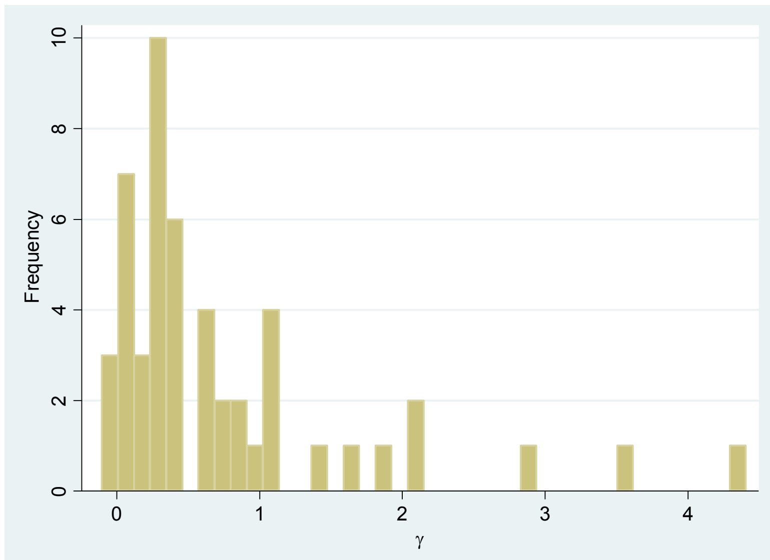

Figure 3.7: Histogram of the Effect of Repeated Check-ins

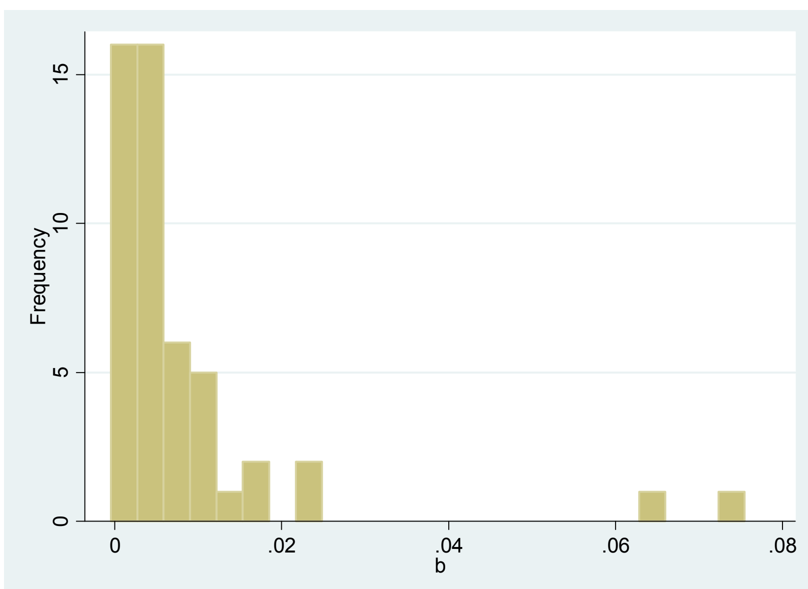

Figure 3.8: Histogram of the Effect of First Time Check-in

Figure 3.9 depicts the estimation results of the default learning probability. If the number of first time check-ins is zero, then the conditional probability that an uninformed consumer discovers venue j in period t is p_j. For most restaurants, p_j is less than 0.5%. The result indicates that the location-based social network could play a great role in increasing the initial awareness of restaurants. Figure 3.10 shows the estimated baseline awareness in the initial period. For most restaurants, q_{j0} is less than 5%. Figure 3.11 depicts the estimated restaurant heterogeneity, α_j.

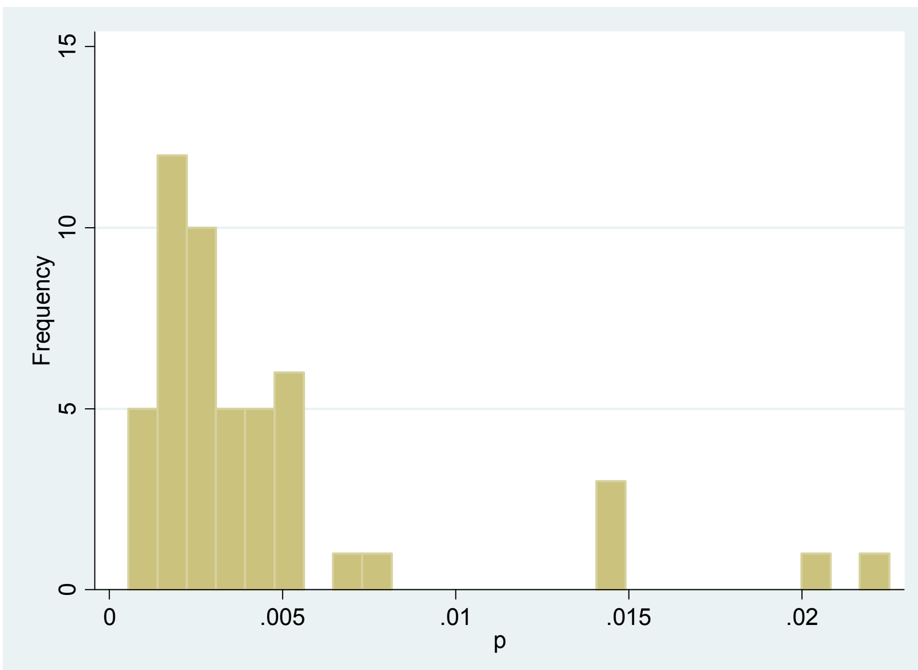

Figure 3.9: Histogram of the Default Learning Probability

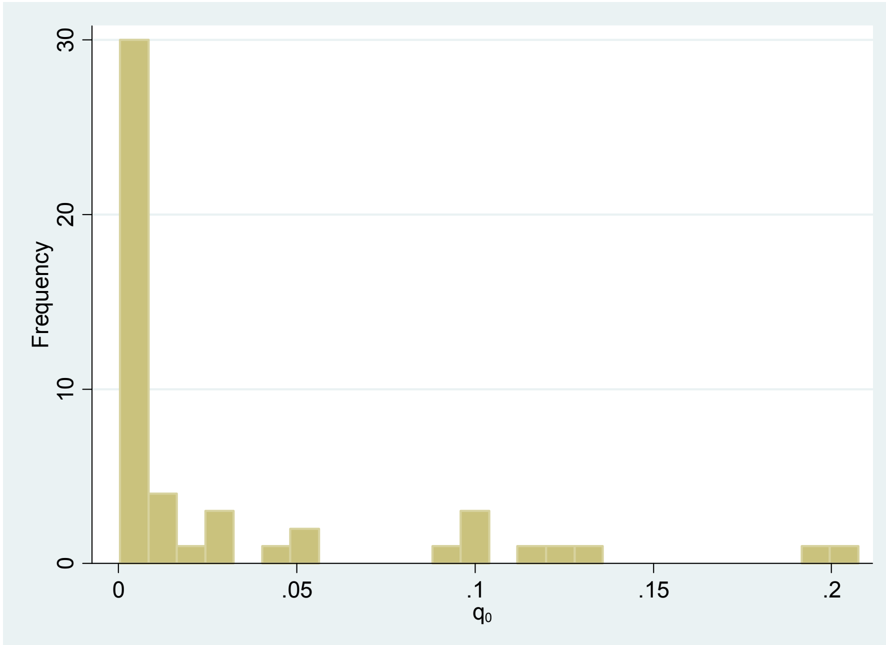

Figure 3.10: Histogram of the Baseline Awareness

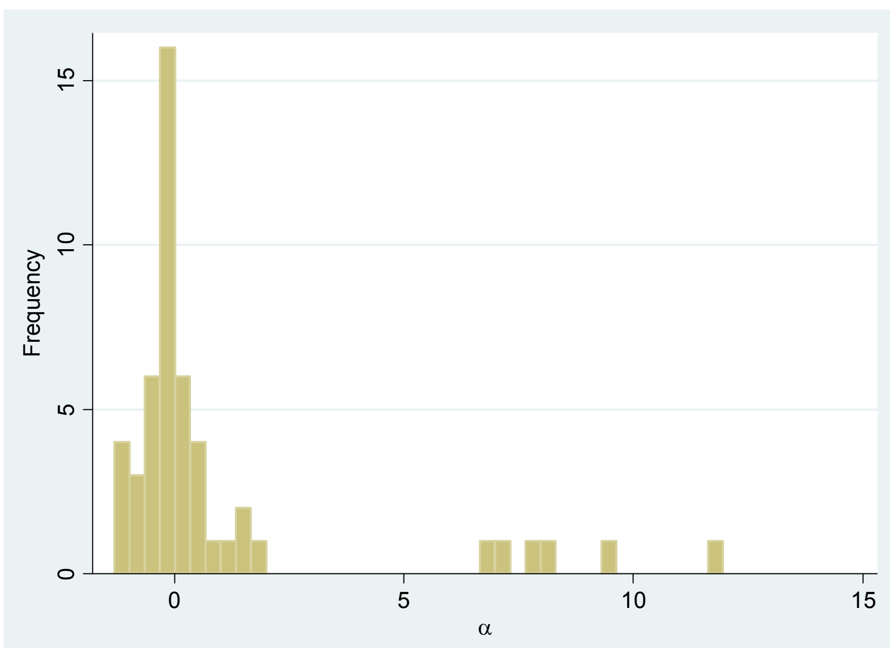

Figure 3.11: Histogram of the Restaurant Heterogeneity

3.6 The Strength of Strong Ties

In this section, we further examine the strength of social ties on observational learning in location-based networks. The role of social ties has been extensively examined in literature (Shriver, Nair, and Hofstetter 2013). The strand of research on social ties originates from the "strength of weak ties" hypothesis proposed by Granovetter (1973). The gist of the hypothesis is that we always get truly new information from acquaintances, rather than from our close friends. The groups with which we have strong ties, although they are filled with people eager to help, are also filled with people who know roughly the same things we do. Thus, strong ties usually result in informational redundancy. Weak ties, meanwhile, are much more valuable in terms of contributing genuinely new information.

However, when we consider observational learning in location-based social networks, our estimation in this section shows the strength of strong ties: Strong ties were more likely to be activated for observational learning. In other words, a "closer" friend's check-in would play a more important role in the focal consumer's decision making.

The strength of social ties between consumer i and her friend, consumer j, is measured by the number of their common friends, adjusted by the number of consumers who are friends of either consumer i and consumer j. More formally,

$$s_{ij} = s_{ji} = \frac{G(i) \cap G(j)}{G(i) \cup G(j)}, \tag{3.5}$$

where $G(i)$ represents the set of friends of consumer i. This measure is widely used in the literature (Shi and Whinston 2013). We divide a consumer' friends into two equally sized groups depending on the tie strength: The group of close friends include consumer i's friends who have the highest 50% of the level of s_{ij}. The left is the group of ordinary friends. Let $C(i)$ represent the set of close friends of consumer i, and $O(i)$ represent the set of ordinary friends of consumer i.

We modify the structural model to investigate the role that tie strength plays in the process of observational learning. The awareness stage (the first stage) remains unchanged, and we focus on the observational learning stage (the second stage). The equation (3.3) is modified to the following utility function:

$$U_{ijt} = \alpha_j + \beta_j V_{ijt-1} + \gamma_j^c R_{ijt-1}^c + \gamma_j^o R_{ijt-1}^o + \varepsilon_{ijt}, \varepsilon_{ijt} \sim N(0, \sigma_j^2). \quad (3.6)$$

where R_{ijt-1}^c is the number of close friends' total repeated check-ins at venue j up until time period t - 1, and R_{ijt-1}^o is the number of ordinary friends' total repeated check-ins at venue j up until period t - 1. The parameter γ_j^c measures the observational learning effect of strong ties, and γ_j^o measures the observational learning effect of weak ties.

The strength of strong ties could be driven by two reasons. First, close friends' check-ins can be a more credible signal because of trust and reputation based on repeated interactions. People tend to trust information from close trusted sources more. A recommendation from a close friend is more reliable than an acquaintance who may have an incentive to mislead the focal consumer. Forman, Ghose, and Wiesenfeld (2008) show that identity and reputation of online review authors are often factored when consumers make purchase decisions and evaluate the helpfulness of online reviews. Online community members rate reviews containing identity-descriptive information more positively.

Second, homophily caused by close friendship might accelerate the speed of observational learning. Homophily refers to the fact that people are more prone to maintain friendship with people who are similar to themselves. It has profound implications for the spread of information (Jackson 2008) and the speed of opinion convergence and learning (Golub and Jackson 2012). In our context, a close friend's check-in could be more informationally valuable because it reflects both the quality of the restaurant and the correlated taste. In the present study, we do not formalize homophily in the structural model, and it could be a future extension of our work.

Note that in both specifications (3.3) and (3.6), we find a significant observational learning effect in location-based social networks. It shows that our estimates are more likely driven by credible sources of identification in the data rather than functional forms.

3.7 Counterfactual Analysis: the Engineering of Observational Learning

A major advantage of the structural approach is that it allows for interesting counterfactual analysis that is simply not possible with reduced form regressions by recovering fundamental structural parameters (Nevo and Whinston 2010). If observational learning can provide consumers with useful quality information when they purchase experience goods, we would like to know the value of observational learning. We may also want to evaluate the effectiveness of different seeding strategies that can strengthen the awareness effect and induce consumers' observational learning. Seeding is the process of allocating marketing to specific customers. In our context, seeding refers to the fact that restaurants reward specific consumers in the form of discounts (check-in deals) when they check in using location-based services to stimulate observational learning. In order to compute such values, we need to be able to adjust optimal consumer behavior when observational learning is amplified (by different seeding strategies). With a structural model a managerial recommendation is possible, unlike reduced form regressions that would suffer from a lack of external validity to predict responses to not-yet-observed changes when past evidence is not rich enough to provide exogenous sources of variation to accurately identify treatment effects (Nevo and Whinston 2010).[42]

[42] It is also important to note that when exogenous variations have occurred before and we have a rich set of directly observable controls, a reduced form model (based on treatment effects) has its own advantages

In the present study, we allow the heterogeneity of structural parameters across different firms, and therefore can more precisely predict consumers' responses to different seeding strategies. Our firm-specific counterfactual analysis could expand the business model of location-based service and has profound implications for local business to engage with consumers in experience good markets.

In our context, restaurants must consider three critical factors that can affect the success of seeding strategies:

(1) The initial set of targeted consumers (the portion of targeted consumers x);

(2) The length of the viral marketing campaign periods, w;

(3) Seeding effort, e.

Note that for (1) the initial set of targeted consumers, restaurants could collaborate with location-based networks and seed to well-connected consumers in terms of degree centrality. (3) seeding effort is measured by the number of additional check-ins made by each consumer in the initial targeted set. If restaurants provide a higher reward in the forms of check-in deals (high seeding efforts), they may induce a larger number of consumers' check-ins within a certain time period. For example, a new restaurant might attract more check-ins by the deal "free lunch special on your 8th visit this month" than the deal "free jamaica iced tea on your 4th visit this month."

Let's consider the following seeding strategy: seeding to 5% well-connected consumers (in terms of degree centrality) and induce each of them to make four more check-ins in period 0. In this case, $e = 4$, $w = 1$, and $x = 5\%$. Figure 3.15 is an illustrating example and shows the effect of the seeding strategy on the number of consumers dining in a specific restaurant. We can observe a similar pattern when we examine different

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and can "trace a shorter route from facts to findings" (Angrist and Pischke 2010). For example, Aral and Walker (2011) examine how to engineer social contagion using a randomized field experiment.

restaurants. The triangle markers represent the growth of the number of consumers dining in the restaurant from real data, and the circle markers represent the counterfactual growth patterns when the restaurant uses the seeding strategy. The counterfactual analysis based on the estimates from equation (3.4) demonstrates that the seeding strategy can significantly increase the number of future consumers. This result is consistent with the findings in the prior literature showing that seeding tends to be more cost efficient than traditional mass media advertising (Hinz et al. 2011). Aral and Walker (2011) econometrically identify the effect of different viral product features on social contagion. In their paper, the passive-broadcast viral feature is the automated broadcast notifications that are passively triggered by user activity. For example, Facebook notifies friends automatically when a user adopts a new application. Actually, this passive-broadcast viral feature also induces consumers' observational learning. They find that designing products with passive-broadcast viral messaging capabilities generates a significant (246%) increase in local peer influence and social contagion. Dou, Niculescu, and Wu (2013) explore how a monopolistic firm can strategically engineer the strength of network effects via social media with the right market seeding strategies.

Through the counterfactual policy simulations, we quantify the value of check-in deals offered by the collaboration between location based platforms and local business. In contrast with the business model of online coupon websites, such as Groupon, the business model of location-based service could be more sustainable because of the positive effect of observational learning induced by friends' check-ins.

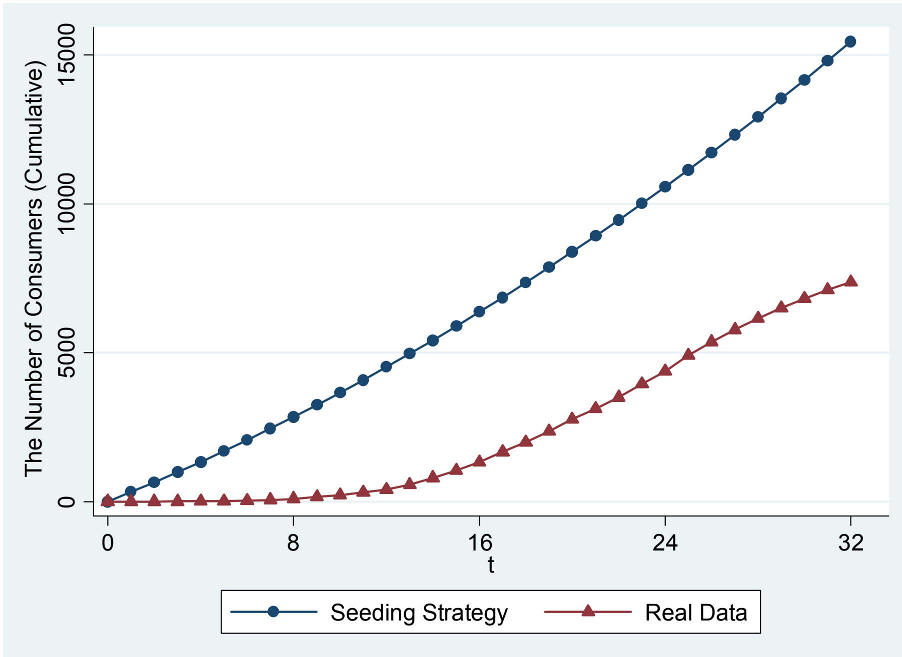

Figure 3.12: The Effect of Seeding Strategies

It is believed that one of the major advantages of the business model of Groupon is that Groupon's offerings create Word-of-Mouth and buzz for new products and services, helping them reach the "tipping point." The theory is that even though local business would lose money on the coupons, they can attract long-term customers for listing the deal. However, in practice, local merchants already have their doubts about the effectiveness of daily deals: they find their customer volume falls off after the deals are done and they are not much better off than before they offered the coupon.[43] In our study, we find that consumers' observational learning is particularly important for local business, considering its limited advertising campaigns. Check-in deals targeting well-connected consumers could be a more effective seeding strategy to help local business reach the

[43] See http://www.usnews.com/news/blogs/rick-newman/2013/03/01/maybe-groupons-problem-isnt-its-ceo. Groupon's stock has plunged from $20 in 2011 to around $7 in 2014. The shrinking profit margins make future earnings and revenue growth unsustainable.

tipping point of customer volume.

3.8 Conclusions

In this paper, we estimated a structural model of social learning in location-based networks using data from a Foursquare-like website in China. Through estimating a model of restaurant discovery and quality learning, we were able to identify observational learning and the saliency effects in location-based social networks.

The present study has several limitations. We did not differentiate real social effects and homophily. Although these mechanisms lead to similar empirical outcome, their implications are vastly different (Aral, Muchnik, and Sundararajan 2009). It would be interesting to allow correlated unobserved tastes in the estimation of our structural model. Like Hinz et al. (2011), we also assumed that the location-based social network remains fixed for the duration of our study. This assumption ignores the effects of dynamic network formation in real-world social networks.

The business model of location-based service relies on the active online sharing of check-ins. However, personally identifiable check-in data can place the user at unexpected risk.[44] People who highly value privacy can be less willing to share their check-ins when they visit venues.[45] In reality, people may choose not to check in when they visit venues because of privacy concerns. Real-time location sharing could be used for criminal purposes, ranging from spying and stalking to theft.[46] A site known as

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[44] See http://www.huffingtonpost.com/christopher-burgess/the-double-edged-sword-of_b_643178.html.

[45] This might cause a selection bias problem in sampling (Heckman 1979). However, As Lindqvist et al. (2011) shows, privacy concerns have not kept user from experimenting with and adopting location-based service. Restaurants and bars are fairly popular places to check-in at. Therefore, we believe the selection bias is small.

[46] In 2012 Foursquare blocked an app called 'Girls Around Me' which highlighted the locations of young women using Foursquare in the area. See http://bits.blogs.nytimes.com/2012/03/30/girls-around-me-ios-app-takes-creepy-to-a-new-level/?_php=true&_type=blogs&_r=0.

"Please Rob Me" raises awareness about the privacy concerns of location sharing. The site scrapes data from public Twitter messages that have been pushed through Foursquare to list people who were not at home. The positive effect of observational learning in social networks would be weakened as a result of privacy concerns. For example, Blippy was a social networking site for users to post and follow each other's updates about their credit card purchases of goods and services. The purchase sharing service was shut down as of May 2011 because it is risky to share online purchases with friends on the web: Several credit card transactions shared on Blippy have been exposed — with full credit card numbers included — in Google search results.[47] Studying the effect of privacy concerns on observational learning in social networks remains an open question.

Another future research direction is to examine welfare implications of location-based services using structural estimations. When changes in consume welfare is unobserved, estimation of classical treatment effects is not possible, but inferences about underlying parameters drawn from observed behavior using structural modeling can allow us to predict these welfare changes (Nevo and Whinston 2010). Another issue is related to big data and sampling strategies. In very large samples, *p*-values could go quickly to zero, and they are not reliable for statistical significance. Our estimation results are robust when we draw a smaller sample and use different sampling strategies.

[47] See http://techcrunch.com/2011/05/19/the-end-of-blippy-as-we-know-it/.

Appendix A: Proof of Results in Chapter 1

Proof of Proposition 1.1

Proof. Suppose that the bidding strategy of all other hotspots is $Q^*(\theta)$, and let's consider hotspot i's expected profit. If $Q^*(\theta)$ is also an optimal strategy for hotspot i, hotspot i should have no incentive to pretend that the cost parameter is $\tilde{\theta}$ when the true cost parameter is θ_i. Let $v(\tilde{\theta}, \theta_i)$ be hotspot i's expected profit if he bids $Q(\tilde{\theta})$ while his true cost parameter is θ_i:

$$v(\tilde{\theta}, \theta_i) = \left[1 - F(\tilde{\theta})\right]^{n-1} \left[B\left(Q(\tilde{\theta})\right) - C\left(Q(\tilde{\theta}), \theta_i\right)\right]. \tag{A.1}$$

For $v(\tilde{\theta}, \theta_i)$ to be maximized at $\tilde{\theta} = \theta_i$, we need $\partial v(\tilde{\theta}, \theta_i)/\, \partial\tilde{\theta}|_{\tilde{\theta}=\theta_i} = 0$:

$$\begin{aligned} &[1 - F(\theta_i)]^{n-1}\left[B'(Q(\theta_i))Q'(\theta_i) - C_Q(Q(\theta_i), \theta_i)Q'(\theta_i)\right] \qquad \text{(A.2)} \\ &= [B(Q(\theta_i)) - C(Q(\theta_i), \theta_i)](n-1)[1 - F(\theta_i)]^{n-2}F'(\theta_i). \end{aligned}$$

Let $v(\theta_i) = v(\theta_i, \theta_i)$. Plugging (A.2) into the expression of $v'(\theta_i)$, we can obtain that $v'(\theta_i) = -[1 - F(\theta_i)]^{n-1}C_\theta(Q(\theta_i), \theta_i)$, and

$$v(\theta_i) = \int_{\theta_i}^{\theta^*} [1 - F(x)]^{n-1}C_\theta(Q(x), x)dx. \tag{A.3}$$

On the other hand, the hotspot with the lowest θ always wins the auction, so the sum of the expected profits of the cellular service provider and the hotspots is

$$n\int_{\underline{\theta}}^{\theta^*} \left(1 - F(\theta)\right)^{n-1}F'(\theta)[V(Q) - C(Q, \theta)]d\theta,$$

where n is the number of hotspots and $n\left(1 - F(\theta)\right)^{n-1}F'(\theta)$ is the density of the lowest θ. The cellular service provider's expected profit is given by

$$n\int_{\underline{\theta}}^{\theta^*} \left(1 - F(\theta)\right)^{n-1}F'(\theta)[V(Q) - C(Q, \theta)]d\theta - nE[v(\theta_i)],$$

where $nE[v(\theta_i)]$ is the sum of the expected profits of all hotspots because the hotspots are ex-ante symmetric. After integration by parts, the equation above reduces to:

$$n\int_{\underline{\theta}}^{\theta^*} \left(1 - F(\theta)\right)^{n-1}F'(\theta)[V(Q) - C(Q, \theta) - C_\theta(Q, \theta)H(\theta)]d\theta.$$

Let $Q^*(\theta)$ be determined by the following first-order condition:

$$V'(Q^*(\theta)) = C_Q(Q^*(\theta),\theta) + C_{Q\theta}(Q^*(\theta),\theta)H(\theta).$$

Because $V(\cdot)$ is strictly concave and $H(\cdot)$ is increasing, we can easily show that $Q^*(\theta)$ is decreasing in θ. In addition, $Q^*(\theta)$ clearly maximizes the cellular service provider's expected profit. We need to further show that $Q^*(\theta)$ is an equilibrium bidding strategy for the hotspots. Suppose that $Q^*(\theta)$ is the equilibrium bidding strategy. From (A.1), we have

$$v(\theta_i,\theta_i) = [1 - F(\theta_i)]^{n-1}[B(Q(\theta_i)) - C(Q(\theta_i),\theta_i)].$$

Combining this equation with (A.3), we can obtain:

$$B\big(Q^*(\theta)\big) = C(Q^*(\theta),\theta) + \frac{\int_{\theta}^{\theta^*} \big(1 - F(x)\big)^{n-1} C_\theta(Q^*(x),x)dx}{\big(1 - F(\theta)\big)^{n-1}},$$

and then we can verify that under $B(\cdot)$, $Q^*(\theta)$ is indeed an equilibrium bidding strategy.

Proof of Proposition 1.2

Proof. This proof is similar to the proof of Proposition 1.1. For a multiple region auction, the cellular service provider's expected profit is

$$E\left[\hat{V}\left(\sum_{i=1}^{n} q_i\right) - \sum_{i=1}^{n} C(q_i,\theta_i) - \sum_{i=1}^{n} C_\theta(q_i,\theta_i)H(\theta_i)\right].$$

Because the hotspots' congestion cost functions are convex, the virtual marginal costs are equalized across hotspots:

$$\hat{V}'\left(\textstyle\sum_{i=1}^{n} q_i\right) = c(q_i,\theta_i) + c_\theta(q_i,\theta_i)H(\theta_i). \tag{A.4}$$

for $i = 1,2,\ldots n$. The bandwidth allocation schedule $q_i = Q(\theta_i,\theta_{-i})$ satisfying (A.4) maximizes the cellular service provider's expected profit. Using arguments analogous to those in Proposition 1.1, we can show that $Q(\theta_i,\theta_{-i})$ is decreasing in θ_i and that $Q(\theta_i,\theta_{-i})$ is an equilibrium bidding strategy for the hotspots.

Proof of Proposition 1.3

Proof. We first show that the cellular service provider does not have incentive to misreport the demand vector when $\mathrm{M} = 1$. The proof for the case that $\mathrm{M} > 1$ is similar.

If the cellular service provider purchases Y_1 units of bandwidth in region 1, then given the realization of the demand, $\widetilde{\mathrm{X}}$, the expected reduction of congestion cost for the cellular service provider is:

$$U(Y_1) = C_0(\tilde{X} - X_B) - C_0(\tilde{X} - X_B - Y_1).$$

$\mathrm{U}(\mathrm{Y}_1)$ is strictly increasing and strictly concave, and

$$U'(Y_1) = C_0'(\tilde{X} - X_B - Y_1).$$

Lemma A.1 If $\mathrm{X}_\mathrm{a} = \widetilde{\mathrm{X}}$, the optimal bidding strategy $\mathrm{Q}^*(\theta, \widetilde{\mathrm{X}})$ is strictly increasing in $\widetilde{\mathrm{X}}$.

Proof: The bidding strategy $\mathrm{Q}^*(\theta, \widetilde{\mathrm{X}})$ is determined by the following first order condition:

$$U'(Q^*, \tilde{X}) = C_Q(Q^*, \theta) + C_{Q\theta}(Q^*, \theta)H(\theta).$$

Using the implicit function theorem, we can obtain:

$$\frac{\partial Q^*}{\partial \tilde{X}} = \frac{-C_0''(\tilde{X} - Q^*)}{-C_0''(\tilde{X} - Q^*) - C_{QQ}(Q^*, \theta) - C_{QQ\theta}(Q^*, \theta)H(\theta)} > 0. \quad \textit{Q.E.D.}$$

Let $\mathrm{U}_\mathrm{a}(\mathrm{Z}_1) = \mathrm{C}_0(\mathrm{X}_\mathrm{a}) - \mathrm{C}_0(\mathrm{X}_\mathrm{a} - \mathrm{Z}_1)$. If $\mathrm{X}_\mathrm{a} \neq \widetilde{\mathrm{X}}$, the cellular service provider should pretend that the demand is X_a. Under the payment-bandwidth schedule B, the bidding strategy for a hotspot is $\mathrm{Q}^*(\theta, \mathrm{X}_\mathrm{a})$, which is given by:

$$U_a'(Q) = C_Q(Q, \theta) + C_{Q\theta}(Q, \theta)H(\theta).$$

However, the cellular service provider's expected profit is

$$n\int_{\underline{\theta}}^{\theta^*} \big(1 - F(\theta)\big)^{n-1} F'(\theta)[U(Q) - C(Q, \theta) - C_\theta(Q, \theta)H(\theta)]d\theta$$

The bidding strategy $Q^*(\theta, X)$ maximizes the cellular service provider's expected profit. Because $X_a \neq \widetilde{X}$, and by Lemma A.1, $Q^*(\theta, X)$ is strictly increasing in X, $Q^*(\theta, X_a)$ cannot maximize the cellular service provider's expected profit. Thus, the cellular service provider does not have incentive to misreport the demand information.

Proof of Proposition 1.4

Proof. The proof is straightforward from the proof of Proposition 1.2.

Proof of Proposition 1.5

Proof. First, we need to show that hotspot i does not have an incentive to misreport its type under the mechanism $(P_i^{**}, q_i^{**}, \lambda_m^{**})$. Let's define

$$q_i^{**} = Q^{**}\left(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m^{**}(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right),$$
$$Q' = Q^{**}\left(\hat{\theta}_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m^{**}(\hat{\theta}_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right),$$

where $\hat{\theta}_i \neq \theta_i$. Without loss of generality, we assume $\hat{\theta}_i > \theta_i$. It is easy to show that $Q^{**}\left(\theta_i, \theta_{-i}, \widetilde{X}_1, \widetilde{X}_2, \lambda_m^{**}(\theta_i, \theta_{-i}, \widetilde{X}_1, \widetilde{X}_2)\right)$ is nonincreasing in θ_i (A higher reported type results in less bandwidth purchased from this hotspot). Given that other hotspots report their types truthfully, the gain of hotspot i if it reports its true type θ_i is:

$$\begin{aligned}
&P_i^*(\theta_i, \theta_{-i}) - C(Q^*(\theta_i, \theta_{-i}), \theta_i) \\
&= \int_{\theta_i}^{\theta^*} C_\theta\left(Q^{**}\left(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m^{**}(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right), \theta\right) d\theta \\
&= \int_{\theta_i}^{\hat{\theta}_i} C_\theta\left(Q^{**}\left(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m^{**}(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right), \theta\right) d\theta \\
&+ \int_{\hat{\theta}_i}^{\theta^*} C_\theta\left(Q^{**}\left(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m^{**}(\theta, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right), \theta\right) d\theta \\
&\geq \int_{\theta_i}^{\hat{\theta}_i} C_\theta\left(Q^{**}\left(\hat{\theta}_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \lambda_m^{**}(\hat{\theta}_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2)\right), \theta\right) d\theta
\end{aligned}$$

$$+\int_{\hat{\theta}_i}^{\theta^*} C_\theta\left(Q^{**}\left(\theta,\theta_{-i},\tilde{X}_1,\tilde{X}_2,\lambda_m^{**}(\theta,\theta_{-i},\tilde{X}_1,\tilde{X}_2)\right),\theta\right)d\theta$$

$$= C(Q',\hat{\theta}_i) - C(Q',\theta_i)$$

$$+\int_{\hat{\theta}_i}^{\theta^*} C_\theta\left(Q^{**}\left(\theta,\theta_{-i},\tilde{X}_1,\tilde{X}_2,\lambda_m^{**}(\theta,\theta_{-i},\tilde{X}_1,\tilde{X}_2)\right),\theta\right)d\theta,$$

where the inequality comes from the fact that $Q^{**}\left(\theta_i,\theta_{-i},\tilde{X}_1,\tilde{X}_2,\lambda_m^{**}(\theta_i,\theta_{-i},\tilde{X}_1,\tilde{X}_2)\right)$ is nonincreasing in θ_i and the assumption $c_\theta \geq 0$. Therefore, hotspot i does not have an incentive to report $\hat{\theta}_i$ when its true type is θ_i.

Then we need to show the proposed mechanism is optimal for the cellular service provider. If $0 \leq y_m^{**} \leq X_B$, we have:

$$\lambda_m^{**}X_B = y_m^{**} = (\tilde{X}_m - \bar{X}) - (Y_m - \bar{Y}).$$

The expected payment from the cellular service provider to hotspot i is

$$\int_{\underline{\theta}}^{\theta^*}\left[C(q_i^{**},\theta_i) + \int_{\theta_i}^{\theta^*} C_\theta(q_i^{**},\theta)d\theta\right]F'(\theta_i)d\theta_i = \int_{\underline{\theta}}^{\theta^*} C(q_i^{**},\theta_i)F'(\theta_i)d\theta_i$$

$$+\int_{\underline{\theta}}^{\theta^*}\left[\int_{\theta_i}^{\theta^*} C_\theta\left(Q^{**}\left(\theta,\theta_{-i},\tilde{X}_1,\tilde{X}_2,\lambda_m^{**}(\theta,\theta_{-i},\tilde{X}_1,\tilde{X}_2)\right),\theta\right)d\theta\right]F'(\theta_i)d\theta_i.$$

After integration by parts (the second term), this reduces to

$$\int_{\underline{\theta}}^{\theta^*}[C(q_i^{**},\theta_i) + C_\theta(q_i^{**},\theta_i)H(\theta_i)]dF(\theta_i).$$

We can show that the expected payment under the proposed mechanism is the same as the payment characterized in Proposition 1.4 if $0 \leq y_m^{**} \leq X_B$. Because the mechanism described in Proposition 1.4 is optimal for the cellular service provider when $0 \leq y_m^{**} \leq X_B$, the proposed mechanism is also optimal when $0 \leq y_m^{**} \leq X_B$. If $y_m^{**} < 0$, or $y_m^{**} > X_B$, then we have $\lambda_m^{**} = 0$ or 1. Without loss of generality, we assume that $\lambda_1^{**} = 1$, and $\lambda_2^{**} = 0$. In this case, an optimal mechanism is to allocate all cellular resource to region 1, and then organize two separate local auctions. This result is given by the following lemma:

Lemma A.2 If the feasibility condition is not satisfied, then it is optimal for the cellular service provider to organize two local auctions with

$$\lambda_m^{**}(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2) = \begin{cases} 0, \text{if } y_m^{**} < 0 \\ 1, \text{if } y_m^{**} > X_B \end{cases}, m = 1,2.$$

Proof: Under the contingent procurement auction, we need to solve the following optimization problem under each demand contingency:

$$\min_{y_1, y_2} \sum_{m=1}^{2} C_0(\tilde{X}_m - Y_m - y_m)$$

$$s.t. \sum_{m=1}^{M} y_m = X_B, y_m \geq 0.$$

Because the feasibility ratio is 0, the constraint is always binding for all (θ_i, θ_{-i}). Thus the optimal solution is $y_1^* = X_B$, $y_2^* = 0$, or $y_1^* = 0$, $y_2^* = X_B$. Without loss of generality, we assume that $y_1^* = X_B$, and $y_2^* = 0$.

The expected reduction of congestion cost for the cellular service provider is given by

$$U(Y_1, Y_2) = \max_{y_1, y_2} \sum_{m=1}^{2} C_0(\tilde{X}_m) - \sum_{m=1}^{2} C_0(\tilde{X}_m - Y_m - y_m).$$

According to the Envelope Theorem, we have:

$$U_{Y_1}(Y_1, Y_2) = C_0(\tilde{X}_1 - Y_1 - X_B) = C_0[(\tilde{X}_1 - X_B) - Y_1],$$

$$U_{Y_2}(Y_1, Y_2) = C_0(\tilde{X}_2 - Y_2).$$

Thus, the cellular service provider can implement the optimal allocation by two independent local auctions with $\lambda_1^{**} = 1$ and $\lambda_2^{**} = 0$. *Q.E.D.*

According to Lemma A.2, we need to show that the expected payment from the cellular service provider under the proposed mechanism is the same as the payment under two separate local auctions. In our proposed mechanism, the bandwidth allocation is given by:

$$C_0'\left(\tilde{X}_m - \lambda_m^{**} X_B - \sum_{i \in \Psi_m} q_i\right) \tag{A.5}$$
$$= c(q_i, \theta_i) + c_\theta(q_i, \theta_i) H(\theta_i), \qquad \text{for } i \in \Psi_m.$$

This bandwidth allocation is the same as the allocation generated by two separate local auctions. Under the proposed mechanism, the expected payment from the cellular service provider to hotspot i, $i \in \Psi_m$ is:

$$\int_{\underline{\theta}}^{\theta^*} P_i^{**} F'(\theta_i) d\theta_i$$
$$= \int_{\underline{\theta}}^{\theta^*} \left[C(Q^{**}(\theta_i, \theta_{-i}, \tilde{X}_m, \lambda_m^{**}), \theta_i) + \int_{\theta_i}^{\theta^*} C_\theta(Q^{**}(\theta, \theta_{-i}, \tilde{X}_m, \lambda_m^{**}), \theta) d\theta \right] F'(\theta_i) d\theta_i$$
$$= \int_{\underline{\theta}}^{\theta^*} \left[C(Q^{**}(\theta_i, \theta_{-i}, \tilde{X}_m, \lambda_m^{**}), \theta_i) + C_\theta(Q^{**}(\theta_i, \theta_{-i}, \tilde{X}_m, \lambda_m^{**}), \theta_i) H(\theta_i) \right] dF(\theta_i),$$

where P_i^{**} is given by equation (1.13) and $Q^{**}(\theta_i, \theta_{-i}, \tilde{X}_m, \lambda_m^{**})$ is the solution to equation (A.5). We compare this with the expected payment under two separate local auctions and find that they are equal.

Proof of Proposition 1.6

Proof. Let R_k^+ be the set of m such that $y_{mk} \geq 0$, and R_k^- be the set of m such that $y_{mk} < 0$. We have the following lemma:

Lemma A.3 If region $m \in R_k^-$, then $m \notin R_{k-1}^+$, for $k = 2,3,\ldots,M$.

Proof: If the cardinality of the set $|R_k^-| = 1$, it is trivial to show that $m \notin R_{k-1}^+$. Thus, we focus on the non-trivial case: $|R_k^-| \geq 2$. Without loss of generality, we assume that $y_{kk} < 0$, and $m \neq k$. Let's consider a k-region procurement auction. According to equation (1.10), the optimal bandwidth allocation schedule $q_i = Q^*(\theta_i, \theta_{-i}, \tilde{X}_1, \tilde{X}_2, \cdots, \tilde{X}_M)$ is given by:

$$C_0'(\bar{X} - \bar{Y}) = c(q_i, \theta_i) + c_\theta(q_i, \theta_i)H(\theta_i), \text{ for } i \in \cup_{j=1}^{k} \Psi_j, \tag{A.6}$$

where $\bar{X} = \frac{\tilde{X}_1 + \tilde{X}_2 + \cdots + \tilde{X}_k - X_B}{k}$, and $\bar{Y} = \frac{1}{k}\sum_{i \in \cup_{j=1}^{k} \Psi_j} q_i$. The allocation of cellular resource across regions in a k-region procurement auction is $y_{mk} = (\tilde{X}_m - \bar{X}) - (Y_m - \bar{Y})$. In the next iteration, the optimal bandwidth allocation schedule under an auction with $k-1$ regions, q_i', is given by the following equation:

$$C_0'(\bar{X}' - \bar{Y}') = c(q_i', \theta_i) + c_\theta(q_i', \theta_i)H(\theta_i), \text{ for } i \in \cup_{j=1}^{k-1} \Psi_j, \tag{A.7}$$

where $\bar{X}' = \frac{\tilde{X}_1 + \tilde{X}_2 + \cdots + \tilde{X}_{k-1} - X_B}{k-1}$, and $\bar{Y}' = \frac{1}{k-1}\sum_{i \in \cup_{j=1}^{k} \Psi_j} q_i{}'$. We show that there exists $i \in \cup_{j=1}^{k-1} \Psi_j$, such that $q_i' \geq q_i$, by contradiction. Suppose that $q_i' < q_i$ for all $i \in \cup_{j=1}^{k-1} \Psi_j$. By equation (A.6) and (A.7), $\bar{X}' - \bar{Y}' < \bar{X} - \bar{Y}$. Let the allocation of cellular resource across regions in a $k-1$-region procurement auction be $y_{m,k-1}$, and we have

$$\begin{aligned} y_{m,k-1} &= (\tilde{X}_m - \bar{X}') - (Y_m' - \bar{Y}') \\ &> (\tilde{X}_m - \bar{X}) - (Y_m - \bar{Y}) = y_{mk}, \qquad \text{for } m = 1,2,\ldots,k-1. \end{aligned}$$

where $Y_m' = \sum_{i \in \Psi m} q_i'$. Because $\sum_{m=1}^{k} y_{mk} = X_B$, and $y_{kk} < 0$, $\sum_{m=1}^{k-1} y_{m,k-1} > \sum_{m=1}^{k-1} y_{mk} > X_B$, which contradicts $\sum_{m=1}^{k-1} y_{m,k-1} = X_B$ in an auction with $k-1$ regions. Therefore, $\bar{X}' - \bar{Y}' \geq \bar{X} - \bar{Y}$, and then we can obtain that $y_{m,k-1} \leq y_{mk}$. $Q.E.D$

Our iteration process in Proposition 1.6 is essentially an iterated elimination of the regions with $y_{mk} < 0$. This lemma says that if $y_{mk} < 0$ in the iteration step k, the allocation of cellular resource in this region will be less than zero in the iteration step $k+1$. Therefore, the regions with $y_{mk} < 0$ will eventually be eliminated. The implication is important in the sense that the order of elimination does not matter, so in each iteration, we eliminate the region with the smallest y_{mk} if the smallest $y_{mk} < 0$.

Now we can show the optimality of the iterated process. If $y_{MM} \geq 0$, the feasibility condition 1.8 is satisfied, and the cellular resource and bandwidth allocation is the same as the allocation in Proposition 1.4. If $y_{MM} < 0$, we generate two new regions: $i \in \cup_{j=1}^{M-1} \Psi_j$ or Ψ_M. Using Proposition 1.5, we can show that $\lambda_M^{**} = 0$. Then, we continue to consider the iterated process: for $i \in \cup_{j=1}^{M-2} \Psi_j$ or $i \in \Psi_{M-1}$, if $y_{M-1,M-1} \geq 0$, the feasibility condition is satisfied when we consider a procurement auction such that the participating hotspot $i \in \cup_{j=1}^{M-1} \Psi_j$. Therefore, the optimal bandwidth allocation for hotspot $i = 1,2,\ldots,M-1$ is given by equation (1.10) when the participating hotspot $i \in \cup_{j=1}^{M-1} \Psi_j$. If $y_{M-1,M-1} < 0$, we use Proposition 1.5 again, and $\lambda_{M-1}^{**} = 0$. We complete the proof by iterating this process.

Appendix B: The Procedure of Computing the Optimal Mechanism

• Invite each of the n hotspots to report its cost parameter θ. Denote the submitted cost parameters as $\{\theta_1, \theta_2, \cdots, \theta_n\}$.

• Define the map $q: \Theta^n \to R^n$ as follows:

- For each $i = 1,2,\cdots,n$ and $x \geq 0$, let $\phi_i(x)$ be the implicit function satisfying the following equation

$$c(\phi_i(x), \theta_i) + c_\theta(\phi_i(x), \theta_i)H(\theta_i) = x.$$

Because the left-hand-side of the equation is increasing in $\phi_i(x)$, given a value of x, $\phi_i(x)$ can be easily solved using bisection in the interval $[0, \bar{q}_i]$ where $\bar{q}_i$ is a positive number large enough so that the value of left-hand-side exceeds x.

- From equation (1.9), $\hat{V}'(q)$ can be written as

$$\hat{V}'(q) = \int_{\bar{Y}}^{1} c_0(\bar{X} - \bar{Y})d\bar{G}(\bar{X}) = \int_{q/M}^{1} c_0(\bar{X} - q/M)d\bar{G}(\bar{X}).$$

Let q^* be the solution to the following equation:

$$\sum_{i=1}^{n} \phi_i(\hat{V}'(q)) = q.$$

Again, because the left-hand-side is decreasing in q, we can easily solve for q^* using bisection in the interval $[0, M]$.[48]

- Let

$$q \equiv (q_1, q_2, \cdots, q_m) \equiv \left(\phi_1(\hat{V}'(q^*)), \phi_2(\hat{V}'(q^*)), \cdots, \phi_m(\hat{V}'(q^*))\right).$$

• Define payment plan P_i as

$$P_i \equiv P_i(\theta_1, \cdots, \theta_m) \equiv C(q_i, \theta_i) + \int_{\theta_i}^{\theta^*} C_\theta(q_i(\theta, \theta_{-i}), \theta)d\theta,$$

where θ^* is a threshold cost parameter to be determined.

---

[48] When $q = 0$, the left-hand-side is positive. When $q = M$, the left-hand-side is nonpositive. More generally, q^* can be found in the interval $[0, M\bar{\bar{X}}]$ where $\bar{\bar{X}}$ is the upper bound of $\bar{X}$.

• Hotspot i will provide capacity q_i and receive payment P_i. The capacity allocation and payment schedule (q_i, P_i) consist of the optimal feasible mechanism with the choice of θ^*.[49] The expected profit of each hotspot before the auction is:

$$\Pi_i(\theta_i) = \int_{\theta_i}^{\theta^*} E_{-i}[C_\theta(q_i(\theta, \theta_{-i}), \theta)]d\theta.$$

• The expected gain of the cellular service provider before the auction is

$$W(\theta^*) = E\left[\hat{V}(q^*) - \sum_{i=1}^{n} C(q_i, \theta_i) - \sum_{i=1}^{n} C_\theta(q_i, \theta_i)H(\theta_i)\right]$$

• The optimal procurement auction can be obtained by searching over $[\underline{\theta}, \bar{\theta}]$ for the optimal threshold value θ^* that yields the highest value of $W(\theta^*)$.

[49] The payment schedule P and the non-increasing property of the $q_i(\theta_i; \theta_{-i})$ guarantee incentive compatibility. The design of q_i guarantees optimality from the cellular network's perspective.

Appendix C: Proof of Results in Chapter 2

Proof of Proposition 2.1

Proof. We say that a function u exhibits strategic substitutes if an increase in others' actions lowers the marginal returns from one's own actions: For all $m_i' > m_i$ and $m'_{N_i(g)} \geq m_{N_i(g)}$,

$$u(m_i', m'_{N_i(g)}) - u(m_i, m'_{N_i(g)}) \leq u(m_i', m_{N_i(g)}) - u(m_i, m_{N_i(g)}).$$

When u exhibits strategic substitutes, a participant's incentive to take a given action decreases as more friends take that action.

Lemma C.1. If the payoff is a quadratic loss function, then $u(m_i, m_{N_i(g)})$ exhibits strategic substitutes.

Proof: A participant's utility maximization problem given m_i and $m_{N_i(g)}$ is equivalent to a predictor error minimization problem. We can obtain the best mean square predictor of V based on S_i:

$$E[V|S_i] = \frac{\rho_V}{\rho_\varepsilon + \rho_V} V_0 + \frac{\rho_\varepsilon}{\rho_\varepsilon + \rho_V} S_i.$$

Similarly, we can obtain the best mean square predictor of V based on other information sets. Assume that for $m_{N_i(g)}$, there are k_a of Participant i's friends (among the total number k_i) who acquire information. In other words, for vector $m_{N_i(g)}$, there are k_a elements of 1 and $k_i - k_a$ elements of 0. Let $A_{N_i(g)}$ be the set of friends who acquire information. If Participant i acquires information, the best mean square predictor is:

$$\frac{\rho_V}{(k_a+1)\rho_\varepsilon + \rho_V} V_0 + \frac{\rho_\varepsilon}{(k_a+1)\rho_\varepsilon + \rho_V} \left(\sum_{i \in A_{N_i(g)}} S_i \right).$$

For Participant i's action, $m_i = 0$, and $m_i' = 1$:

$$u(m_i, m_{N_i(g)}) = a - b\left[\frac{\rho_V^2}{(k_a\rho_\varepsilon + \rho_V)^2}\frac{1}{\rho_V} + \frac{\rho_\varepsilon^2}{(k_a\rho_\varepsilon + \rho_V)^2}\frac{k_a}{\rho_\varepsilon}\right] = a - b\left(\frac{1}{k_a\rho_\varepsilon + \rho_V}\right),$$

And $u(m_i', m_{N_i(g)}) - u(m_i, m_{N_i(g)}) = -b\left(\frac{1}{(k_a+1)\rho_\varepsilon+\rho_V} - \frac{1}{k_a\rho_\varepsilon+\rho_V}\right) - c.$

From here, obtaining the following equation is straightforward:

$$\frac{\partial}{\partial k_a}\left[u(m_i', m_{N_i(g)}) - u(m_i, m_{N_i(g)})\right] = -\frac{\rho_\varepsilon}{(k_a\rho_\varepsilon+\rho_V)^2} + \frac{\rho_\varepsilon}{[(k_a+1)\rho_\varepsilon+\rho_V]^2} < 0.$$

Therefore, u exhibits strategic substitutes. *Q.E.D.*

If the payoff function exhibits strategic substitutes, then for $m_i' > m_i$ and $k_i' > k_i$,

$$\begin{aligned}
&U(m_i', \sigma; k_i) - U(m_i, \sigma; k_i) \\
&= \sum_{k_{N_i(g)}} P(k_{N_i(g)}|k_i)\left[u(m_i', \sigma_{N_i(g)}) - u(m_i, \sigma_{N_i(g)})\right] \\
&= \sum_{k_{N_i(g)}} P(k_{N_i(g)}|k_i)\left[u\left(m_i', (\sigma_{N_i(g)}, 0)\right) - u\left(m_i, (\sigma_{N_i(g)}, 0)\right)\right] \\
&= \sum_{k_{N_i(g)}} P(k_{N_i(g)}|k_i')\left[u\left(m_i', (\sigma_{N_i(g)}, 0)\right) - u\left(m_i, (\sigma_{N_i(g)}, 0)\right)\right] \\
&> \sum_{k_{N_i(g)}} P(k_{N_i(g)}|k_i')\left[u\left(m_i', (\sigma_{N_i(g)}, m_{k+1})\right) - u\left(m_i, (\sigma_{N_i(g)}, m_{k+1})\right)\right] \\
&= U(m_i', \sigma; k_i') - U(m_i, \sigma; k_i'),
\end{aligned} \tag{C.1}$$

where the third equality follows from the assumption that neighbors' degrees are all stochastically independent, and the first inequality follows from strategic substitutes. Then, we show the existence of a decreasing symmetric equilibrium by using two steps: (1) There exists a symmetric equilibrium; and (2) every symmetric equilibrium is non-increasing in degree. First, we want to show a symmetric equilibrium exists (we allow mixed-strategy equilibrium). Our game is a standard symmetric incomplete information game because all participants have identical action sets of information acquisition $\Delta\{0,1\}$; the quadratic payoff functions are also the same; and participant's beliefs concerning networks are ex-ante symmetric. Given that the action set $\Delta\{0,1\}$ is compact, and the payoff function is continuous, then a symmetric mixed strategy Bayes-Nash equilibrium exists according to the fixed-point theorem.

Next, we show that every symmetric equilibrium is non-increasing. Let σ_k be a symmetric equilibrium strategy for the participant with degree k. If σ_k is a strategy with all degrees choosing action 1 with probability 1, the equilibrium is obviously non-increasing. Thus, we focus on the non-trivial case. If σ_k is not a trivial strategy, then let $m_k = \min[\text{supp}(\sigma_k)]$, where $\text{supp}(\sigma_k)$ is the support of the mixed strategy σ_k. In our context, the support can be $\{0\}$, $\{1\}$, or $\{0,1\}$. If $m_k = 1$, it is easy to show that $m_{k'} \leq m_k$ for all $m_{k'} \in \text{supp}(\sigma_{k'})$ with $k' > k$. If $m_k = 0$, then for any $m > m_k$, we have the following inequality by equation (C.1):

$$U(m,\sigma;k) - U(m_k,\sigma;k) > U(m,\sigma;k+1) - U(m_k,\sigma;k+1).$$

Note that $m_k \in \text{supp}(\sigma_k)$, so we have: $U(m,\sigma;k) - U(m_k,\sigma;k) \leq 0$. Thus, $U(m,\sigma;k+1) - U(m_k,\sigma;k+1) < 0$, for all $m > m_k$. This implies that if $m_{k+1} \in \text{supp}(\sigma_{k+1})$ then $m_{k+1} \leq m_k$. Therefore, σ_k FOSD σ_{k+1}. The conclusion follows by iterating this process.

Now let's show that the non-increasing strategy is actually a threshold strategy. Suppose that for degree k_i participant, there is a positive probability of acquiring information, we can prove that $\sigma(m_i = 1|\hat{k}) = 1$, for all $\hat{k} < k_i$, by the decreasing difference of $U(m_i, \sigma; k_i)$. Similarly, we can show that if for degree k_i participant, there is positive probability of not acquiring information, then $\sigma(m_i = 1|\hat{k}) = 0$, for all $\hat{k} < k_i$. Then the equilibrium strategy is a threshold strategy.

We make a few more remarks here. Because all participants adopt a threshold strategy, Participant i believes that the probability for a randomly chosen neighbor to acquire information is $\theta = \Pr(k_j \leq k^*)$, $j \in N_i(g)$. Participant i's belief about the number of informed neighbors thus follows a binomial distribution given by:

$$f(k_a;k_i,\theta) = \binom{k_i}{k_a}\theta^{k_a}(1-\theta)^{k_i-k_a},$$

where k_a is the number of participants who acquire information, and $f(k_a; k_i, \theta)$ is the density function of the binomial distribution. Knowing the belief of Participant i, we can obtain the expected payoff $U(m_i, \sigma_{N_i(g)}; k_i)$. Because k^* is a threshold, it is determined by the following inequalities:

$$U(m_i = 1, \sigma_{N_i(g)}; k^*) \leq U(m_i = 0, \sigma_{N_i(g)}; k^*),$$
$$U(m_i = 1, \sigma_{N_i(g)}; k^* + 1) > U(m_i = 0, \sigma_{N_i(g)}; k^* + 1).$$

These inequalities simply mean that the participant with degree k^* is better off to acquire information, and the participant with degree $k^* + 1$ is better off not to acquire information.

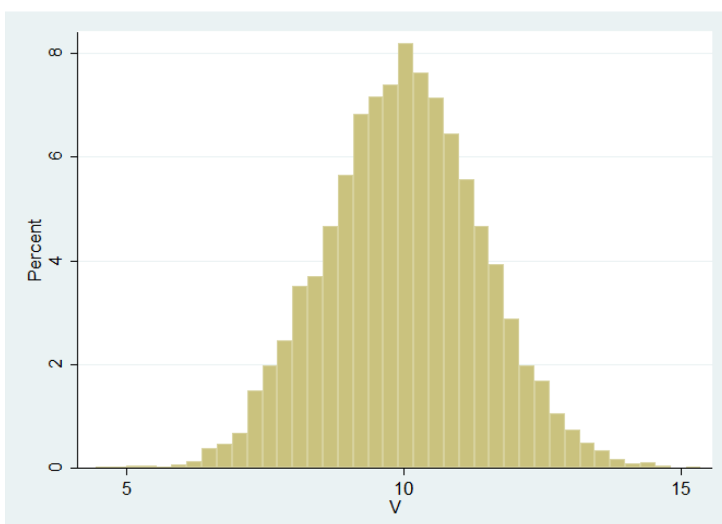
Appendix D: Experimental Instructions

The following are the experimental instructions for an SEPM. The guidelines for an NNPM are similar except that the participants are not allowed to communicate with others.

General Guideline: This is an economic experiment so it is conducted with Real Money! Your profit is a direct result of your prediction performance during the experiment. The experiment has 2 rounds. The highest cash payoff for you to earn is $5*2=$10! In order to maximize your profits, you need to read the instructions carefully and use your information wisely. The experiment has 2 rounds. Your total payoff is the sum of the payoff in each round.

Experiment Description

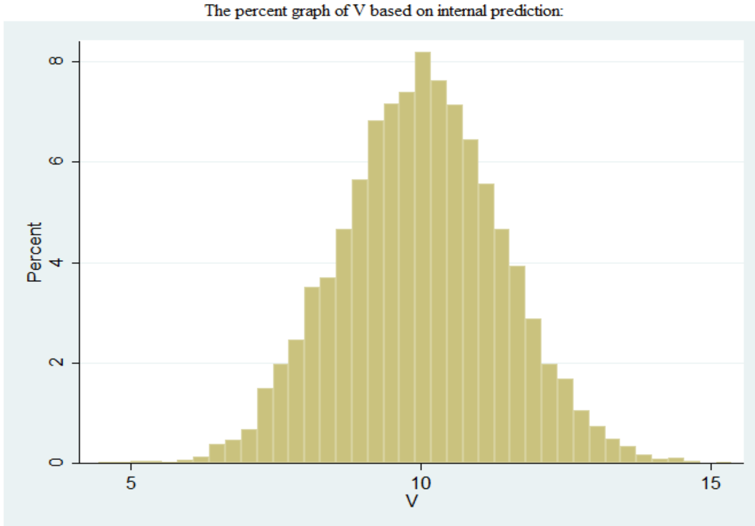
CREC (Central Real Estate Company) needs to predict the size of the rental market, V, in a large metropolitan area. The internal estimation predicted by employees within the company suggests that the market size, V, is probably around $10 millions. Below is the percent graph of the employees' predictions: Most of them think that the market size V is around 10.



As the head of the marketing department of CREC, you can also consider purchasing an evaluation of the market size from one of several outside experts. Your experience tells you that each expert's prediction is twice as accurate as the internal prediction. Obtaining the prediction of an outside expert will cost you money in this experiment. If you choose to purchase an expert's opinion, you can combine the internal estimation from employees with the expert prediction to get a more precise estimate. The actual market size, V, in million USD, will be announced right after the experiment (Note that the true value of V in round 1 is different from the value in round 2). Suppose that your prediction is x million USD, if you do not purchase expert opinions, your payoff in this round is: $\$ 5 - (x - V)^2$. If you choose to purchase an expert's opinion, you have to pay a cost c = \$1 in this experiment and your payoff in the first round is $\$ 5 - (x - V)^2 - c$.

Apparently, the more precise your estimate is, the higher the payoff you will get. You are free to communicate with other experiment participants on your designated Gmail account after making a decision about whether to purchase an expert's signal. You can discuss with the other group members through Gtalk. If your group members purchase evaluations from outside experts, they may provide useful information to you. After reading the guidelines, you need to make a decision about whether to purchase a signal.

The percent graph of V based on internal prediction:



Do you want to purchase a signal at cost $1 ?

Yes

No

Then, you can submit your predictions on the basis of the prior and your signal.

Prior: 10

Signal: 10.8575

Submit

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