The Sound of Silence

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Abstract

When choosing between alternatives of uncertain quality, one can learn from other decision-makers either through communicating with them about the reasons underlying their choices, or through simply observing their choices. The former way of learning has been extensively studied in the word-of-mouth (WOM) literature, while the latter way, labelled silent word-of-mouth (SWOM), has received less attention. This paper is the first individual-level empirical study to structurally model how SWOM influences choices. I consider a setting where a group of individuals sequentially decide whether to adopt a product of unknown quality. Each individual is equipped with a private quality signal. Under WOM, one incorporates her predecessors' signals, as well as her own signal, in her quality evaluation. Under SWOM, she observes her predecessors' decisions, infers what their signals have been, and updates her quality evaluation. I show that WOM and SWOM can lead to distinct choice patterns in the marketplace in that decisions are more likely to be imitated under SWOM.

The model is applied to a high-stake decision environment where patients on a transplant waiting list must choose whether to accept a kidney for transplantation. This data is desirable to study the SWOM effect because (1) decisions are sequential, (2) all previous decisions are observed, and (3) privacy concerns make WOM impractical, which helps to isolate the SWOM effect. An interesting puzzle in the data is that, other things equal, patients towards the back of the queue are less likely to accept a kidney. SWOM explains this phenomenon: A patient lowers her quality evaluation about a kidney once it is previously refused and becomes more inclined to reject as well. Her refusal in turn lowers the quality evaluation for subsequent patients, triggering more refusals down the queue. In this way, refusals are self-reproductive. Indeed, policy experiments show that kidney acceptance rate would have been substantially higher if there were WOM communication, or if there were no social learning at all. The competing explanation of unobservable (to the researcher) public quality information is ruled out.

This paper contributes to the understanding of how social imitation originates and propagates with observations of others' choices. It highlights for marketing managers the importance of (1) first-impression management by building a strong initial customer base and by enhancing the visibility of early adopters, and (2) tipping-point management by targeting the marginal customer segment.

Keywords: Silent Word-of-Mouth, Word-of-Mouth, Social Learning, Observational Learning, Bayesian Inference, Kidney Transplantation

1 Introduction

People frequently make choices between alternatives of uncertainty quality. To evaluate such choice options, one may seek information from themselves through, for example, past consumption experience (e.g., Nelson 1970, Erdem and Keane 1996). In addition, one may learn from other people faced with similar decisions. Learning from others, or social learning, plays a crucial role in determining the patterns of product adoption. It is well documented that consumers belonging to the same social network often make closely related product choices (e.g., Yang and Allenby 2003). Various diffusion models (e.g., Bass 1969, Horsky and Simon 1983) where imitators follow the choices of early adopters have successfully predicted the sales of a new product from its introduction and initial customer base.

Despite the advances in diffusion studies, the various behavioral mechanisms of imitation in product adoption decisions remain disentangled. In particular, a consumer can learn from others through what they say and through what they do. The vast literature on word-of-mouth (Katz and Lazarsfeld 1955, Coleman, Katz, and Menzel 1966, Gladwell 2000, and numerous others) has studied how communications among individual decision-makers influence choices. Alternatively, one may learn by observing other people's actions. Examples are widely found in life: Lots of people favor restaurants with a descent line waiting outside, choose movies with great box-office performances, and, more generally, go for fashion. In these situations choices are influenced even in the absence of direct communication. I label this effect *silent word-of-mouth.* Word-of-mouth and silent word-of-mouth are often intertwined in practice, with the combined effect studied at an aggregate level. It is therefore not clear how each effect is driving sales, and to what extent. The goal of this paper is to empirically model the leaning process underlying silent word-of-mouth and show that it may lead to a distinct choice pattern than word-of-mouth.

This paper contributes to the social learning literature by being the first individual-level empirical study of observational learning (i.e., learning through observations of other people's actions). Theoretical works in observational learning are pioneered by Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992). They demonstrate that informational cascade and herd behavior may arise in a sequential decision context, where individuals repeat their predecessors' actions regardless of their own information.[2] Gale (1996), Bikhchandani, Hirshleifer and Welch (1998) provide reviews of the early research in this direction. Recent studies by Smith and Sorensen (2000), Gale and Kariv (2003), and Çelen and Kariv (2004a) extend the observational learning literature by incorporating heterogeneous preferences, social networks and imperfect observation. However, empirical studies in observational learning have either remained at the aggregate level (e.g., Golder and Tellis 2004), or relied on lab experiments (e.g., Çelen and Kariv 2004a, b). There has been no study to date that examines observational learning at the individual decision-maker level with field data. This paper is the first attempt in such direction and develops a structural behavioral framework to model individual choices that (1) immediately translates to product adoption decisions, (2) is flexible to accommodate different permutations of the decision sequence, (3) allows for a rich set of policy experiments, and (4) embraces individual heterogeneity in valuation and in learning.

I consider a setting where consumers sequentially decide whether to adopt a product of uncertain quality. Besides the commonly observed product attributes, each consumer also receives a private signal (e.g., experience, judgment, feeling) about the uncertain product quality. Under word-of-mouth, a consumer is able to access her predecessors' private signals and incorporate them in her quality inference. Under silent word-of-mouth, one only observes previous decisions, and therefore only knows the possible range that the previous signals have fallen in. For instance, if a previous consumer has adopted/rejected a product, her private signal must have been above/below a certain threshold value. A consumer then uses the information about the range of previous signals to update her quality inference by applying Bayes' rule.

A unique prediction of silent word-of-mouth is that adoption/rejection will always increase/decrease subsequent decision-makers' quality evaluation. In contrast, under word-of-mouth one's quality evaluation might go in the opposite direction of the decisions of her predecessors. To see this, imagine a consumer who makes her adoption decision after an extremely selective person who has rejected the product despite the great signal

[2]Strictly saying, informational cascade refers to the convergence of belief, while herd behavior pertains to the convergence of actions.

received. Under silent word-of-mouth, the consumer sees this previous rejection as a negative sign, or uninformative at the best if she knows her predecessor's high standards. However, through word-of-mouth communication with her predecessor, the consumer is able to see through the apparent rejection and find the great signal behind. She might thus view the product more positively. In other words, under word-of-mouth communication the factor driving choices is what previous people *think*, not what they *do*. If private signals are unbiased, when more and more signals come in, quality evaluation will eventually converge to its true value, and individual choices converge to efficiency. On the other hand, in the world of silent word-of-mouth, once a choice is initiated, it tends to be imitated by the population and to become the social trend. Individuals may end up with a choice contrary to what aggregate information would have suggested.

The model is applied to data from the United Network for Organ Sharing (UNOS) and the United States Renal Data System (USRDS), where patients on a transplant waiting list must choose whether to accept a kidney for transplantation. This data is attractive to study the silent word-of-mouth effect because: (1) Decisions are sequential. (2) All previous decisions are observed. The fact that a patient is ever offered a kidney implies that the same kidney has been rejected by all patients before her. (3) Privacy concerns, size of the waiting list and promptness of the decision make word-of-mouth impractical, which helps to isolate the silent word-of-mouth effect. An interesting puzzle in the data is that, other things equal, patients towards the back of the queue are less likely to accept a kidney. Silent word-of-mouth explains this phenomenon: A patient lowers her quality perception about a kidney once it is previously refused and becomes more inclined to reject as well. Her refusal in turn lowers the quality perception for subsequent patients, triggering more refusals down the queue. In this way, refusals breeds refusals. Indeed, policy experiments show that kidney acceptance rate would be substantially higher if there were word-of-mouth communication, or if there were no social learning. The competing explanation of unobservable (to the researcher) public quality information is ruled out.

The empirical findings have immediate policy implications. UNOS has been challenged with a significant shortage of kidneys supply for transplantation, while most of the refused kidneys are of acceptable clinical value. This study suggests two potential solutions to this problem. One is to facilitate information sharing (i.e., word-of-mouth communication) among patients. Another is to suppress social learning either by not releasing the queue position information, or by offering a kidney simultaneously to all eligible patients and then assigning priority among those who have expressed their willingness to accept the kidney.

The message to marketing managers is that actions can speak louder than words. In some markets direct conversation occurs less frequently than observation of actual choices. Massive social imitation can be triggered by the choices of a few consumers. It is thus essential to manage the direction of the social trend by building a strong customer base from the introduction of the product. Moreover, marketing efforts spent on the marginal customers could bring huge returns.

The rest of the paper is organized as follows. Section 2 presents a choice model of silent word-of-mouth where individuals decide whether to adopt a product of uncertain quality after observing other people's choices. Section 3 discusses the application of the model to patients waiting for kidney transplant, and provides the background information on kidney transplantation in the United States. Section 4 describes the data and summarizes the empirical regularities. In section 5, I estimate the silent word-of-mouth model together with four alternative models (i.e., a model without quality uncertainty, a model without social learning, a model of public quality information, and a model of word-of-mouth). Section 6 presents the policy experiments. Section 7 concludes the paper and discusses future research.

2 A Choice Model of Silent Word-of-Mouth

2.1 Consumers' Utility Function

In this section, I model consumers' decision of whether to adopt a product with uncertain quality. Consumers act as risk-neutral utility-maximizing economic agents. Assume that for each product consumers make their adoption decisions sequentially, that each consumer knows her position in the sequence, and that everyone observes all the preceding decisions regarding this product.

Let U_{ij} denote the utility of consumer i in adopting product j, where i means that she is the i^{th} consumer to make the adoption decision:

$$U_{ij} = X_{ij}\beta + \alpha\theta_j + \epsilon_{ij} \tag{2.1}$$

ϵ_{ij} denotes the idiosyncratic utility shock encountered by consumer i when evaluating product j. X_{ij} contains a constant term, the attributes of product j and the individual characteristics of consumer i which affect her utility of adoption. β consists of the utility weight parameters associated with X_{ij}.

Product quality is often known to consumers with uncertainty. Let θ_j represent the unobservable quality component of product j and α be the associated utility weight. Consumers do not observe θ_j directly. Instead, they know the distribution of θ_j across products, which is assumed to be i.i.d. normal with mean μ and variance σ_θ^2:

$$\theta_j \sim N(\mu, \sigma_\theta^2)$$

Although consumers do not know θ_j with certainty, they may each be equipped with some private information regarding θ_j. For example, a consumer may judge the desirability of a product from her past experience. Let s_{ij} denote the private signal that the i^{th} consumer receives regarding the unobservable quality of product j. Assume the private signals to be unbiased about the true product quality, although the actual signals may vary across consumers. In other words, given a true θ_j, the private signals are assumed to be i.i.d. normal:

$$s_{ij}|\theta_j \sim N(\theta_j, \sigma_s^2)$$

Without the private signals, consumers' expected θ_j is equal to the prior mean μ. Consumers may update this expectation based on the private signals they possess. Additionally, word-of-mouth conveys information when consumers also observe some other people's signals. Alternatively, consumers may update their quality inference based on other people's adoption decisions, even in the absence of word-of-mouth communication. Figure 1 classifies learning into three categories based on the sources of quality information—whether it is the decision-maker herself or others, and whether it is based on the signal or the decision outcome. There is no social learning when one's information set only contains her private signal. In the word-of-mouth case, one's information set contains the private signals of her predecessors, as well as her own signal. In the case of silent word-of-mouth, one's information set contains the decisions of all predecessors, together with her own signal.

Let I_{ij} denote the information set that consumer i possesses when deciding whether to adopt product j. Her expected utility from adopting product j is

$$E(U_{ij}|I_{ij}) = X_{ij}\beta + \alpha E(\theta_j|I_{ij}) + \epsilon_{ij} \tag{2.2}$$

Instead of adopting product j, consumer i can keep the *status quo* and receive utility U_{io}:

$$U_{io} = Z_i\gamma + \epsilon_{io}$$

where Z_i contains consumer i^{th} personal characteristics and γ is the associated utility parameters. This formulation captures the idea that the *status quo* utility, or outside opportunity, is more often an individual-specific measure and is invariant to the particular product currently available.[3] It follows that consumer i would accept product j if and only if

$$X_{ij}\beta - Z_i\gamma + \alpha E(\theta_j|I_{ij}) + \epsilon_{ij} - \epsilon_{io} \geq 0 \tag{2.3}$$

The following sections will discuss the quality inference processes in the scenarios of no social learning, learning through word-of-mouth, and learning through silent word-of-mouth respectively.

2.2 Quality Inference Without Social Learning

In the absence of social learning, decision-makers either do not observe or ignore previous people's signals and decisions. Consequently, each individual behaves as if she is the first

[3] It is possible that the current product offering may alter consumers' *status quo* utility by, for example, changing their reference points. I leave the modelling of this dynamics to future research.

person in the sequence to decide. Consumer i's information set when deciding whether to choose product j is

$$I_{ij}^{NoSocialLearning} = \{s_{ij}\}$$

According to the Bayes' rule (DeGroot 1970), the posterior expectation about θ_j is a weighted average of the prior mean μ and the private signal:

$$E(\theta_j | I_{ij}^{NoSocialLearning}) = \frac{\sigma_\theta^2 s_{ij} + \sigma_s^2 \mu}{\sigma_\theta^2 + \sigma_s^2} \tag{2.4}$$

where the more noisy the private signal is, the more weight is assigned to the prior quality perception.

2.3 Quality Inference from Word-of-Mouth

Under perfect word-of-mouth communication, every consumer knows the private signals of all people who have made decisions before her. The information set in this scenario is

$$I_{ij}^{WOM} = \{s_{1j}, \cdots, s_{ij}\}$$

The posterior expectation about θ_j is a weighted average of the prior mean μ and the sample average of signals:

$$E(\theta_j | I_{ij}^{WOM}) = \frac{\sigma_\theta^2 \sum_{t=1}^{i} s_{tj} + \sigma_s^2 \mu}{i \cdot \sigma_\theta^2 + \sigma_s^2} \tag{2.5}$$

It can be seen from equation (2.5) that the weight given to signals increases in i. In other words, the early adopters rely more on the prior perception about a product, while the late adopters heed more to actual signals. When i approaches infinity, the influence from the prior disappears, while the posterior expectation of θ_j equals the average of all observed signals, which, by the Law of Large Numbers, will converge to the true value of θ_j.

2.4 Quality Inference from Silent Word-of-Mouth

In certain situations communication can be costly. However, other people's choice itself may still be informative. In order to isolate this effect, the following model assumes a world of silence where people only observe others choices but not their private signals. Put differently, a consumer sees other people's choices, but does not know the exact reason for choosing. Let d_{ij} be a dummy variable which equals 1 if the i^{th} consumer adopts product j and 0 otherwise. The information set in this case of silent word-of-mouth is

$$I_{ij}^{SWOM} = \{d_{1j}, \cdots, d_{i-1,j}, s_{ij}\}$$

2.4.1 The First Consumer

The first consumer to make the adoption decision infers the value of θ_j based on her own signal s_{1j}. Her posterior expectation about θ_j is

$$E(\theta_j|s_{1j}) = \frac{\sigma_\theta^2 s_{1j} + \sigma_s^2 \mu}{\sigma_\theta^2 + \sigma_s^2}$$

Note that the smaller s_{1j} is, the lower perceived mean quality of the product, and therefore the less likely the first consumer is to adopt the product. Indeed, the first consumer adopts product j if and only if $s_{1j} \geq B_{1j}$, where B_{1j} is the cutoff signal that solves the indifference condition:

$$X_{1j}\beta - Z_1\gamma + \alpha E(\theta_j|B_{1j}) + \epsilon_{1j} - \epsilon_{1o} = 0$$

2.4.2 The Second Consumer

The second patient makes inference about θ_j based on two pieces of information: the decision of the first person d_{1j}, and her private signal s_{2j}. By Bayes' Rule, the posterior density of θ_j is proportional to the product of the conditional (on θ_j) density of the observed data and the prior density of θ_j:

$$p(\theta_j|d_{1j}, s_{2j}) \quad \propto \quad p(d_{1j}, s_{2j}|\theta_j)\ p(\theta_j)$$

The first consumer's cutoff B_{1j} is only stochastically known to the second consumer, since she is uncertain about the first consumer's personal characteristics in X_{1j} and Z_1 and her idiosyncratic utility terms ϵ_{1j} and ϵ_{1o}. Assume that the second consumer knows $G(B_{1j})$, the distribution of B_{1j}. This is equivalent to assuming that the second consumer knows the joint distribution of X_{1j}, Z_1, ϵ_{ij}, and ϵ_{io}. It follows that

$$p(d_{1j}, s_{2j}|\theta_j) = \int p(s_{1j} \geq B_{1j}, s_{2j}|\theta_j)^{d_{1j}} \; p(s_{1j} < B_{1j}, s_{2j}|\theta_j)^{1-d_{1j}} \; dG(B_{1j})$$

Since the private signals s_{1j} and s_{2j} are conditionally (on θ_j) independent, the conditional probability of the joint event that the first signal is below B_{1j} and the second event equals s_{2j} is the product of the conditional probabilities of these two events:

$$\begin{aligned} p(s_{1j} < B_{1j}, s_{2j}|\theta_j) &= p(s_{1j} < B_{1j}|\theta_j) \; p(s_{2j}|\theta_j) \\ &= \Phi(\tfrac{B_{1j}-\theta_j}{\sigma_s}) \; p(s_{2j}|\theta_j) \end{aligned}$$

where $\Phi(\cdot)$ is the c.d.f. of the standard normal. Consequently, the posterior density of θ_j can be written as

$$p(\theta_j|d_{1j}, s_{2j}) \;\; \propto \;\; \int (1 - \Phi(\frac{B_{1j} - \theta_j}{\sigma_s}))^{d_{1j}} \; \Phi(\frac{B_{1j} - \theta_j}{\sigma_s})^{1-d_{1j}} \; dG(B_{1j}) \; p(s_{2j}|\theta_j) \; p(\theta_j)$$

Additionally, because the distribution of θ_j and the conditional distribution of signals are both normal, the last two terms on the right-hand side can be simplified as

$$\begin{aligned} p(s_{2j}|\theta_j) \; p(\theta_j) &\propto e^{-\frac{(s_{2j}-\theta_j)^2}{2\sigma_s^2}} \; e^{-\frac{(\theta_j-\mu)^2}{2\sigma_\theta^2}} \\ &\propto e^{-\frac{(\theta_j-m_{2j})^2}{2\Sigma}} \end{aligned}$$

where $m_{2j} = \frac{\sigma_\theta^2 s_{2j} + \sigma_s^2 \mu}{\sigma_\theta^2 + \sigma_s^2}$, and $\Sigma = \frac{\sigma_\theta^2 \sigma_s^2}{\sigma_\theta^2 + \sigma_s^2}$. Collecting terms, the posterior density of θ_j is

$$p(\theta_j|d_{1j}, s_{2j}) \;\; \propto \;\; \int (1 - \Phi(\frac{B_{1j} - \theta_j}{\sigma_s}))^{d_{1j}} \; \Phi(\frac{B_{1j} - \theta_j}{\sigma_s})^{1-d_{1j}} \; dG(B_{1j}) e^{-\frac{(\theta_j - m_{2j})^2}{2\Sigma}} \quad (2.6)$$

It follows that the posterior mean quality of product j perceived by the second consumer is

$$E(\theta_j|d_{1j}, s_{2j}) = \frac{1}{D} \int \int (1 - \Phi(\frac{B_{1j} - \theta_j}{\sigma_s}))^{d_{1j}} \; \Phi(\frac{B_{1j} - \theta_j}{\sigma_s})^{1-d_{1j}} \; dG(B_{1j}) e^{-\frac{(\theta_j - m_{2j})^2}{2\Sigma}} \; \theta_j d\theta_j$$

where D is the normalizing factor to ensure that the posterior density of θ_j integrates to one:

$$D = \int\int (1-\Phi(\frac{B_{1j}-\theta_j}{\sigma_s}))^{d_{1j}}\ \Phi(\frac{B_{1j}-\theta_j}{\sigma_s})^{1-d_{1j}}\ dG(B_{1j})e^{-\frac{(\theta_j-m_{2j})^2}{2\Sigma}}\ d\theta_j$$

Other things equal, the higher s_{2j}, and the lower $G(B_{1j})$ (in the sense of first-order stochastic dominance), the higher the second consumer's expected quality of product j. This can be seen by examining equation (2.6): Both a larger B_{1j} and a larger s_{2j} shift more weights to θ_j values towards the upper tail of its posterior distribution. The intuition is that the second consumer will infer higher product quality when she receives a more favorable private signal, and when she knows that the first consumer has adopted (rejected) the product despite (due to) her stringent standard. Since $E(\theta_j|d_{1j}, s_{2j})$ increases in s_{2j}, the second consumer's decision rule can also be characterized by a cutoff strategy: She adopts the product if and only if $s_{2j} \geq B_{2j}$, where B_{2j} is the private signal value that makes her just indifferent between acceptance and rejection:

$$X_{2j}\beta - Z_2\gamma + \alpha E(\theta_j|d_{1j}, B_{2j}) + \epsilon_{2j} - \epsilon_{2o} = 0$$

2.4.3 A Generic Consumer

The adoption decision of a generic consumer i can be modelled in the same way as for the second consumer. After observing the $i-1$ previous decisions and her own signal, consumer i's posterior inference about θ_j is

$$E(\theta_j|d_{1j},\cdots,d_{i-1,j},s_{ij}) = \frac{1}{D}\int\cdots\int\prod_{t=1}^{i-1}(1-\Phi(\frac{B_{tj}-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}-\theta_j}{\sigma_s})^{1-d_{tj}}dG(B_{1j},\cdots,B_{i-1,j})e^{-\frac{(\theta_j-m_{ij})^2}{2\Sigma}}\ \theta_j d\theta_j \tag{2.7}$$

where

$$D = \int\cdots\int\prod_{t=1}^{i-1}(1-\Phi(\frac{B_{tj}-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}-\theta_j}{\sigma_s})^{1-d_{tj}}dG(B_{1j},\cdots,B_{i-1,j})e^{-\frac{(\theta_j-m_{ij})^2}{2\Sigma}}\ d\theta_j$$

$$m_{ij} = \frac{\sigma_\theta^2 s_{ij} + \sigma_s^2\mu}{\sigma_\theta^2+\sigma_s^2}, \qquad \Sigma = \frac{\sigma_\theta^2\sigma_s^2}{\sigma_\theta^2+\sigma_s^2}$$

Consumer i adopts product j if and only if $s_{ij} \geq B_{ij}$, where B_{ij} solves the indifference condition

$$X_{ij}\beta - Z_i\gamma + \alpha E(\theta_j|d_{1j}, \cdots, d_{i-1,j}, B_{ij}) + \epsilon_{ij} - \epsilon_{io} = 0 \tag{2.8}$$

Use $h_{ij}(G(\cdot), d_{1j}, \cdots, d_{i-1,j}, s_{ij}, \Delta)$ to denote $E(\theta_j|d_{1j}, \cdots, d_{i-1,j}, s_{ij})$, where Δ is the collection of parameters β, γ, α, μ, σ_θ, and σ_s. The function h_{ij} has the following properties:

Property 1 $\frac{\partial\ h_{ij}}{\partial\ s_{ij}} \geq 0$. *The higher the private signal, the higher the expected quality.*

Property 2 $\frac{\partial\ h_{ij}}{\partial\ G} \leq 0$. *The higher the previous consumers' adoption standard, the higher the expected quality.*

Property 3 *If* $s_{ij} = s_{i+1,j}$, *then* $d_{ij} = 0 \Rightarrow h_{ij} \geq h_{i+1,j}$, *and* $d_{ij} = 1 \Rightarrow h_{ij} \leq h_{i+1,j}$. *Other things equal, a consumer's rejection (adoption) weakly decreases (increases) her follower's expected quality.*

The first two properties can be shown as discussed before. To see the third property, notice that $p(\theta_j|d_{1j}, \cdots, d_{i-1,j}, s_{ij}) \propto \int \prod_{t=1}^{i-1}(1 - \Phi(\frac{B_{tj}-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}-\theta_j}{\sigma_s})^{1-d_{tj}} e^{-\frac{(\theta_j - m_{ij})^2}{2\Sigma}}$ $dG(B_{1j}, \cdots, B_{i-1,j})$. When $s_{ij} = s_{i+1,j}$, in the integrand $p(\theta_j|d_{1j}, \cdots, d_{i,j}, s_{i+1,j})$ differs from $p(\theta_j|d_{1j}, \cdots, d_{i-1,j}, s_{ij})$ by $(1 - \Phi(\frac{B_{ij}-\theta_j}{\sigma_s}))^{d_{ij}}\ \Phi(\frac{B_{ij}-\theta_j}{\sigma_s})^{1-d_{ij}}$, which gives more weight to higher (lower) values of θ_j if d_{ij} equals 1 (equals 0). Therefore, $h_{i+1,j}$ goes above (below) h_{ij} if consumer i adopts (rejects) product j. The intuition is that both consumers have witnessed the $i-1$ previous decisions, while the extra adoption (rejection) seen by patient $i+1$ can only increase (decrease) her expected quality of the product unless she receives a sufficiently unfavorable (favorable) private signal. This is true for all values of B_{ij}. In other words, a previous adoption (rejection) will always lead to more positive (negative) quality inference no matter how open (stringent) the standard has been.

2.4.4 Discussion

The above properties highlight a key difference between learning through word-of-mouth and learning through silent word-of-mouth. Suppose a consumer has formed a certain level of quality inference based on her own signal. Now she is informed that another consumer before her has rejected the same product. In the case of silent word-of-mouth, her quality inference can only be lowered. However, if word-of-mouth communication is allowed, she knows the previous consumer's exact signal. Her quality inference then becomes a weighted average of both signals together with the prior mean quality (equation 2.5), which might exceed the inferred quality obtained without social learning if the previous signal has been high enough. In other words, with word-of-mouth communication a rejection decision does not always lower the expected quality of subsequent decision-makers. In situations where early consumers do receive good signals but still reject the product due to their strict requirement, word-of-mouth communication may actually raise later consumers' inferred quality.

Another implication of silent word-of-mouth is that the marginal consumers can be crucial in determining the pattern of subsequent adoption decisions. This is because although each individual consumer's quality inference is continuous in her own signal, it is *discontinuous* (except when $B_{ij} = \theta_j$) in her predecessors' signals under silent word-of-mouth. This break in continuity comes from the discrete nature of the choice and the unobservability of previous signals. Imagine a marginal consumer who is indifferent between adoption and rejection but chooses to reject. Suppose there is an infinitesimal increase in her private signal such that she now favors adoption, with only infinitesimal increase in her own utility. However, her followers' guess about the possible region of her signal now flips to the upper part of the distribution, which leads to a jump in their quality expectation. Consequently, a distinct path of inference and choice might ensue. In contrast, under word-of-mouth, such "pivotal" marginal consumers do not exist because all signals enter into a later consumer's quality evaluation continuously.

2.5 Choice Probabilities

Assume that the idiosyncratic utility components ϵ_{ij} and ϵ_{io} are distributed i.i.d. Gumbel. Given the history of decisions regarding product j, and her private signal s_{ij}, the probability of consumer i adopting product j is

$$Pr(d_{ij} = 1 | d_{1j}, \cdots, d_{i-1,j}, s_{ij}) = \frac{e^{X_{ij}\beta - Z_i\gamma + \alpha h_{ij}(G(B_{1j},\cdots,B_{i-1,j}), d_{1j},\cdots,d_{i-1,j}, s_{ij}, \Delta)}}{1 + e^{X_{ij}\beta - Z_i\gamma + \alpha h_{ij}(G(B_{1j},\cdots,B_{i-1,j}), d_{1j},\cdots,d_{i-1,j}, s_{ij}, \Delta)}} \quad (2.9)$$

Since the private signals are observed by consumers but not the researcher, they need to be integrated out to evaluate the adoption probabilities of a product. Given quality θ_j, signals about product j are conditionally independent, so are individual consumers' adoption probabilities for product j. Let I_j denote the total number of consumers making adoption decisions about product j. The probability that product j of true unobservable quality θ_j having a choice history of $\{d_{1j}, \cdots, d_{I_j,j}\}$ is

$$P_j(\theta_j) = \prod_{i=1}^{I_j} \int \frac{e^{[X_{ij}\beta - Z_i\gamma + \alpha h_{ij}(G(B_{1j},\cdots,B_{i-1,j}),d_{1j},\cdots,d_{i-1,j},s_{ij},\Delta)]\cdot d_{ij}}}{1 + e^{X_{ij}\beta - Z_i\gamma + \alpha h_{ij}(G(B_{1j},\cdots,B_{i-1,j}),d_{1j},\cdots,d_{i-1,j},s_{ij},\Delta)}} \; f_{s|\theta}(s_{ij}|\theta_j) \; ds_{ij} \quad (2.10)$$

where $f_{s|\theta}(s_{ij}|\theta_j)$ is the p.d.f. of s_{ij} conditional on θ_j, which is a normal density with mean θ_j and variance σ_s^2.

Meanwhile, the true unobservable quality θ_j is not known to either the consumers or the researcher. Therefore, the unconditional probability of product j having a sequence of adoption decisions indicated by $\{d_{1j}, \cdots, d_{I_j,j}\}$ is

$$P_j = \int P_j(\theta_j) \; f_\theta(\theta_j) \; d\theta_j \quad (2.11)$$

where $f_\theta(\theta_j)$ is the p.d.f of θ_j, a normal density with mean μ and variance σ_θ^2.

2.6 Identification

Since a constant term is included in the matrix X, the corresponding element in β (i.e., the intercept) cannot be separately identified from μ, the prior mean unobservable quality. Therefore, I set μ to zero. In other words, I assume the mean value of the product to be captured by its observable attributes, while the unobservable quality adds on to fluctuations around this mean. At the same time, one cannot identify α, σ_θ and σ_s simultaneously. The intuition is that the inference process is determined by the ratio of σ_s over σ_θ, while α captures the remaining scaling effect. Therefore, I restrict σ_θ to be 1 and estimate α and σ_s. It follows that the set of parameters to be estimated reduces to $\Delta = \{\beta, \gamma, \alpha, \sigma_s\}$.

2.7 Public Quality Information

Extra caution should be exerted in establishing the causal relationships in socially correlated choices. Individuals may end up with the same choice either through social contagion, or due to common contextual factors. If such contextual effects are not observed to the researcher and are not accounted for, then the conformity in choices might be spuriously attributed to social contagion. For example, Van den Bulte and Lilien (2001) reanalyze the classic diffusion study *Medical Innovation* (Coleman, Katz, and Menzel 1966) and find that the adoption of the drug tetracycline turns out to be driven by marketing efforts rather than social contagion as previously speculated.

In the framework of this study, one need to identify social learning from quality information which is publicly known to individual decision-makers but is unobserved by the researcher. This can be done by testing a set of parameter values of the model. Indeed, different values of α and σ_s can imply distinct underlying behaviors. Specifically, $\alpha = 0$ (or equivalently, $\sigma_\theta = 0$) means that consumers do not care about the unobserved product quality (or there is no uncertainty about product quality). When $\alpha \neq 0$ (or equivalently, $\sigma_\theta \neq 0$), variation in unobservable quality exists and matters. At the same time, if $\sigma_s = 0$, each consumer perfectly knows the exact value of θ_j with no need for social learning, and the story becomes one of unobservable (to the researcher) public information. Therefore, the full choice model nests the case of public quality information. On the other hand, if $\alpha \neq 0$ and $\sigma_s \neq 0$, individual decision makers do not perfectly know the unobserved product quality, and have to learn it from other decision-makers. In short, the test of whether $\alpha = 0$ and $\sigma_s = 0$ can help distinguish between the often confounded cases of unobservable public information and social learning.

2.8 The Estimation Procedure

Let $LL_j(\Delta)$ be the log-likelihood associated with product j as a function of the parameter vector Δ:

$$LL_j(\Delta) = \ln P_j(\Delta) \tag{2.12}$$

where $P_j(\Delta)$ is given by equation (2.11). The log-likelihood function is

$$LL(\Delta) = \sum_{j=1}^{J} LL_j(\Delta) \tag{2.13}$$

where J is the total number of products offered.

The log-likelihood function involves high dimensional integrals. First of all, the cutoff sequence $\{B_{ij}\}$ is only stochastically known to subsequent consumers, and the term $\int \cdots \int \prod_{t=1}^{i-1}(1-\Phi(\frac{B_{tj}-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}-\theta_j}{\sigma_s})^{1-d_{tj}} dG(B_{1j},\cdots,B_{i-1,j})$ in the formulation of h_{ij} is an integration over the joint distribution of $B_{1j},\cdots,B_{i-1,j}$. I approximate this integral by taking R random draws from the joint distribution of $B_{1j},\cdots,B_{i-1,j}$, evaluating the integrand at these draws, and averaging them:

$$\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{i-1}(1-\Phi(\frac{B_{tj}^r-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}^r-\theta_j}{\sigma_s})^{1-d_{tj}}$$

where B_{tj}^r is solved by taking an r^{th} draw from the joint distribution of X_{tj}, Z_t, ϵ_{tj} and ϵ_{to}. (Please see Appendix for the detailed procedure). Note that the cutoff sequence $\{B_{ij}\}$ only depends on the joint distribution of consumer characteristics and their idiosyncratic utility shocks, but not on the actual signals. Therefore, $\{B_{ij}\}$ itself can be solved recursively independent of $\{s_{ij}\}$. This property enhances the modularity of the simulation process: increasing the number of signal draws when simulating the log-likelihood need not be accompanied by a larger number of draws from the cutoff distribution.

Given the random cutoff draws, the posterior quality expectation h_{ij} can be approximated as

$$\hat{h}_{ij}(d_{1j},\cdots,d_{i-1,j},s_{ij},\Delta) = \frac{1}{D}\int \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{i-1}(1-\Phi(\frac{B_{tj}^r-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}^r-\theta_j}{\sigma_s})^{1-d_{tj}} e^{-\frac{(\theta_j-m_{ij})^2}{2\Sigma}}\ \theta_j d\theta_j$$

where

$$D = \int \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{i-1}(1-\Phi(\frac{B_{tj}^r-\theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}^r-\theta_j}{\sigma_s})^{1-d_{tj}} e^{-\frac{(\theta_j-m_{ij})^2}{2\Sigma}}\ d\theta_j$$

$$m_{ij} = \frac{\sigma_\theta^2 s_{ij}+\sigma_s^2\mu}{\sigma_\theta^2+\sigma_s^2} \quad and \quad \Sigma = \frac{\sigma_\theta^2\sigma_s^2}{\sigma_\theta^2+\sigma_s^2}$$

Evaluating $\hat{h}_{ij}(d_{1j}, \cdots, d_{i-1,j}, s_{ij}, \Delta)$ involves one-dimensional integration over θ_j, which is numerically implemented using Gaussian quadratures.

Lastly, consumers' private signals need to be simulated to evaluate $P_j(\Delta)$:

$$\hat{P}_j(\Delta) = \frac{1}{L}\sum_{l=1}^{L}\prod_{i=1}^{I_j}\frac{1}{M}\sum_{m=1}^{M}\frac{e^{[X_{ij}\beta - Z_i\gamma + \alpha\hat{h}_{ij}(d_{1j},\cdots,d_{i-1,j},s_{ij}^{lm},\Delta)]\cdot d_{ij}}}{1+e^{X_{ij}\beta - Z_i\gamma + \alpha\hat{h}_{ij}(d_{1j},\cdots,d_{i-1,j},s_{ij}^{lm},\Delta)}} \tag{2.14}$$

The idea is that for each product j, make L random draws from the distribution of θ_j. Label the l^{th} draw θ_j^l. Given each θ_j^l, the private signals are conditionally independent. Let e_{ij} denote the deviation of actual signal s_{ij} from θ_j^l. e_{ij} is distributed i.i.d. normal with mean 0 and variance σ_s^2. Make M draws from the distribution of e_{ij} and label the m^{th} draw e_{ij}^m. It follows that $s_{ij}^{lm} = \theta_j^l + e_{ij}^m$. This procedure maintains the correlation among signals for the same product.

Finally, the simulated log-likelihood function to maximize is

$$\hat{LL}(\Delta) = \sum_{j=1}^{J}\ln\hat{P}_j(\Delta) \tag{2.15}$$

3 Application to Kidney Acceptance Decisions

The silent word-of-mouth model can be applied to the U.S. kidney transplant waiting list. The individual decision makers are End-Stage Renal Diseases (ESRD) patients waiting for kidney transplantation. The "products" correspond to kidneys that arrive over time, and the adoption decision is whether to accept a kidney for transplantation. Specifically, when a kidney arrives, eligible patients are ordered based on a certain point system. If the patient in the first position decides to accept the kidney, she takes the transplant and the rest of the patients are not asked. Otherwise the kidney is offered to the next patient. This process goes on.

The quality of a kidney offer is often associated with uncertainty. A patient may assess this quality with the aid of her own observations, which can be either objective or subjective. For example, objective quality measures include the attributes of the kidney and the patient's own medical conditions. At the same time, a patient may have subjective input into her valuation process. For example, doctor recommendation (e.g., based on past experience) could be a major source of such information. Although the organ sharing societies in the United States have published certain policies guiding the kidney allocation process, they have also stated that "this policy, however, does not nullify the physician's responsibility to use appropriate medical judgment"(UNOS 2002 Annual Report). Additionally, patients can draw information from their predecessors' decisions. The fact that a patient in position i is ever offered a kidney means that the same kidney has been rejected by $i-1$ people before her.

To see how previous rejections can be informative, consider the following scenario. The first patient in the queue may reject a kidney offer for three reasons: First, the kidney is deficient in certain observable attributes. Second, the patient's personal characteristics are such that she has less to gain from the transplant. For example, the patient might be too young or might have poor tissue match with the donor. Third, the patient or her doctor has negative views regarding this kidney. When the same kidney is offered to the second patient, she learns whether the first reason holds by examining the kidney attributes. Meanwhile, she can form her believe about how much role reason two and reason three have each played, and update her quality assessment accordingly. For example, if she holds the view that "they must have found something bad about the kidney", her own judgment would be negatively influenced as well. In this way, the first rejection of a kidney lowers its chance of acceptance down the queue.

Kidney acceptance decision provides an attractive setting to test the silent word-of-mouth effect. The reasons are: First, decisions are sequential and each decision maker knows her position in the sequence. Second, all previous decisions (rejections) regarding the same offer are observed by the decision maker. Third, the order of decision is exogenously determined, hence self-selection is less of an issue. Fourth, due to the size of the waiting list and privacy concerns, conversation within the queue for a certain kidney is limited, if not impossible. This fact provides excellent control for the confounding effects from word-of-mouth communication. Last but not least, the nature of kidney transplantation helps rule out the other three primary mechanisms underlying uniform social behavior, namely, sanctions of deviants, network effects, and conformity preference (Bikhchandani, Hirshleifer, and Welch 1992).

The rest of this section presents an overview of kidney transplantation in the United States.

3.1 Overview of Kidney Transplantation

Each year more than 40,000 people in the United States develop End-Stage Renal Diseases (ESRD) or chronic kidney failure. The two major treatments of chronic kidney failure are dialysis and kidney transplantation. Dialysis requires at least 9 to 12 hours of treatment at a dialysis center each week. Kidney transplantation, on the other hand, frees patients from the inconveniences of dialysis and, if successful, offers patients a life quality comparable to people without kidney disease. The ideal kidney for transplantation is from a living-related donor. However, the number of kidneys donated from a living relative is small in the United States. In fact, more than 70 percent of kidneys are obtained from cadaveric (i.e., deceased) donors. Patients waiting for cadaveric-donor kidneys are referred by their nephrologists to a local transplant center and are placed on a waiting list.

The United Network for Organ Sharing (UNOS) administers the allocation of organs to transplant candidates. When a kidney arrives, eligible patients are ordered based on criteria established by the UNOS Point System. (Please refer to the Appendix for details on how the order is decided). The kidney is offered to the first patient in the queue. If it is refused, it is passed on to the next patient. During the search for transplant recipients, kidneys are kept frozen and accumulate cold ischemia time, which may lead to inferior transplant outcome. Kidney are normally discarded if not accepted within 48 hours.

There has been an acute shortage of cadaveric kidney supply in the United States. In 2002, there were 23,328 new chronic kidney failure patients, while only 11,860 cadaveric kidneys were procured. Between 1992 and 2002, the number of people on the national waiting list for kidney transplant grew from 22,063 to 51,144, and the median waiting time increased from 624 days to 1,144 days (UNOS 2002 Annual Report).[4] Despite the significant shortage of kidney supply, each year more than 10% of cadaveric kidneys are

[4]As of May 26, 2005, the number of national waiting list candidates has reached 61,896 (http://www.optn.org).

discarded after being repeatedly refused by transplant candidates. While the kidney transplant waiting list is rapidly expanding, the percentage of discarded kidneys keeps rising too, reaching 12.6% in 2001 (OPTN 2003 Annual Report). The most common reason for kidney refusal is that the current offer is seen to be of marginal quality and that the patients choose to wait for a better organ (UNOS 2002 Annual Report).

The alarming contrast between kidney shortage and high refusal rate has attracted substantial attention both in the kidney transplantation community and in the academia. Various studies have proposed explanations for the inefficiencies of the current kidney allocation system, and have suggested new allocation schemes to improve social welfare. For example, David and Yechiali (1985) applied the sequential stochastic assignment model to the case of kidney allocation, analyzing the patients' problem of deciding whether to accept a kidney offer drawn from a random stream. Roth, Sönmez, and Ünver (2004) examined issues of patient choice in kidney allocation using matching models. Su, Zenios and Chertow (2004) find that incorporating patient choice in kidney transplantation improves equity, efficiency and the quality-adjusted life expectancy of the end-stage renal disease population. Su and Zenios (2004) studied the role of the queueing discipline in kidney allocation. They showed that the first-come-first-served queueing system amplifies patients' desire to refuse offers of marginal quality and generates excessive organ wastage. On the other hand, the last-come-first-served queue achieves optimal organ utilization, while at the cost of social equity. Different from extant studies in this direction, I propose an observational social learning explanation to the low acceptance rate of kidneys, and recommends solutions to the kidney wastage problem.

4 Data

UNOS launched a database system called UNet^{sm} in 1999. This system contains data regarding every organ donation and transplant event which occurred in the United States since 1986. In particular, UNOS provided data on the national waiting list for kidney transplant, including the date each patient enters the waiting list, and the date each transplant is performed. Meanwhile, the United States Renal Data System (USRDS) provided data on cadaveric kidney transplants performed between March 1964 and

June 2000. This dataset includes detailed information on patient characteristics and donor/kidney characteristics. Both UNOS and USRDS keep track of patient records using the unique USRDS patient identification number.

4.1 Variables

The variables that explain patients' kidney acceptance decisions fall into three categories: (1) Attributes of the kidney offer which directly affects the utility of transplantation (X_{ij}); (2) Variables that determine patients' outside opportunity (Z_i); and (3) The inferred unobservable kidney quality h_{ij}. This section presents details of the first two categories, while the inference about the unobservable quality h_{ij} has been discussed in previous sections.

4.1.1 Attributes of the Kidney Offer

The factors that could directly affect the transplant outcome include patient-specific characteristics, kidney characteristics, and donor-patient match measures. Patient-specific characteristics are either demographic (age, gender, race) or clinical (blood type, number of years on dialysis, etc.[5]) Kidney-specific characteristics include the donor's age, gender, race, blood type, body surface area, and donor's cause of death.

The most important donor-patient match measure is the tissue match. The dummy variable "0 Mismatch" is equal to 1 if the patient has no tissue mismatch with the donor at all six loci (i.e., perfect tissue match). Similarly, "0 Mismatch at DR" is equal to 1 if there is no mismatch at DR but there is mismatch at some other loci (i.e., the second-best tissue match). "1 Mismatch at DR" equals 1 if there is one mismatch at the DR loci (i.e.,

[5] Other clinical measures include body surface area, dialysis modality (hemodialysis, peritoneal, hemodialysis followed by peritoneal, or peritoneal followed by hemodialysis), and comorbidities (hypertension, diabetes, unstable angina pectoris, stroke, peripheral vascular disease, pulmonary embolism, malignancy, chronic obstructive pulmonary disease, peptic ulcer disease, or cachexia). For simplicity of presentation, I will not report the summary statistics and parameter estimates associated with all clinical measures, which are available upon request.

the third-best).[6] Another important factor is the cold ischemia time of the kidney at the moment the patient decides whether to accept it. The cold time variable captures the possible deterioration of kidney quality during the process it is passed down the queue.

4.1.2 Operationalize the *Status Quo* Utility

Since kidneys are arriving over time, accepting a kidney offer today means forfeiting future kidney offers. A patient's decision rule under such dynamic setting would involve a cutoff strategy. She accepts a kidney as long as it offers a utility greater than U_{io}, the *status quo* utility, which is determined by two factors: expected future utilities, and costs of waiting.

Patient's expected future utilities depend on their forecasted chance for future kidney offers. In particular, if the qualities of kidneys are evenly distributed over time, or are perceived to be, then U_{io} would depend on where the patient will be in the queue for future kidney offers. According to the UNOS point system, the queue ordering in the US kidney transplant waiting list is determined by four factors: (1) how long a patient has been on the waiting list; (2) whether the patient's PRA (peak panel reactive antibody) exceeds 80%, where a higher PRA may lead to higher risk of graft failure; (3) whether the patient is younger than 11, or is between 11 and 18; and (4) the tissue match between the patient and the kidney. However, *ex ante* patients have approximately the same chance for good tissue match with the upcoming kidneys. Therefore, the first three criteria matter the most to patients' forecasted chance of future offers .[7] The following variables capture the forecast effect: number of days waiting, "PRA>80%" which equals 1 if the patient's PRA exceeds 80% and 0 otherwise, "Patient Below 11" which equals 1 if the patient is younger than 11 and 0 otherwise, and "Patient Between 11 and 18" which equals 1 if the patient is between 11 and 18 and 0 otherwise.

By rejecting a current kidney offer, patients incur costs of waiting, which may be

[6] Please refer to the Appendix for details on tissue match.

[7] Zhang (2005) has shown that such forecast in a queue environment only relies on an individual's "permanent position", which is defined as her position in a queue ordered by offer-invariant factors. The permanent position of patients on the kidney waiting list is determined by factors (1), (2) and (3) of the UNOS point system.

affected by health-related factors such as number of years on dialysis. Meanwhile, opportunity cost of time may vary with demographic variables such as income and employment status. Additionally, I include the number of previous offers to account for state dependence.

In sum, the *status quo* utility is operationalized as $U_{io} = Z_i\gamma$ where Z_i contains the above described variables. It should be pointed out, however, that in practice X_{ij} and Z_i may overlap as some variables may affect both current utility and future utility. For example, other things equal, patients of high PRA have lower current utility from accepting a kidney due to higher risk at transplantation. Moreover, high-PRA patients are privileged by the UNOS point system and therefore will have the same priority to choose at the next kidney offer. Both factors can lead to a low acceptance rate of kidneys from high-PRA patients, while one cannot identify which factor is in effect without further investigation. In this study I only aim to capture the overall effect of the observable explanatory variables, while focusing on the learning process.

4.2 Summary Statistics

This study uses the national waiting list data as of UNOS 2002 Annual Report, and the transplant data from USRDS 2001 Annual Data Report. The national waiting list for kidney transplant contains records of 135,736 patients. I focus on the TXGC OPO, one major OPO in Texas, which contains 2,217 patients. Since the UNOS points system is not in effect until 1995, in the analysis I will only consider kidneys accepted by patients entering after 1995. Meanwhile, waiting lists for kidneys of different blood type can exhibit distinct behaviors due to different demand-supply situations. In this study I present the results on waiting list for blood-type A kidneys.[8] According to this selection criterion, the sample contains 9,384 observations (each observation defined as one decision occasion), including 338 patients and 275 accepted kidneys. Patients' dates of entry to the waiting list range from January 1987 to June 1998. Transplant dates range from March 1995 to October 1999. The average number of days waiting at the time of transplant is 209, with minimum of 1 and a maximum of 1272. On average, at the time of transplant

[8] Statistics about other blood types are available upon request.

a patient would have rejected 15 previous kidney offers. Meanwhile, a kidney needs to travel through an average of 34 patients till it is accepted, when it has accumulated 18 hours cold time. Table 1 presents the variable summary statistics.

4.3 Empirical Regularities

The lower line in Figure 2 corresponds to the actual kidney acceptance rate plot against patient's position in the queue. About 10% patients at the top of the queue accept the kidney offer. However, patients near the top of the queue (approximately from position 2 to position 12) almost always reject. The acceptance rate then increases a bit, remains flat for most part of the queue, and rises sharply at the end.

As a direct way to see how patients' position in the queue influences their decisions, a reduced-form logit model is estimated where the dependent variable is the dummy variable indicating acceptance, and the independent variables include a patient's position in the queue for a kidney, its squared term, as well as the observable attributes contained in X and Z. The coefficient of position is negative and significant, which means that after the observable attributes are controlled for, the more a patient is towards the back of the queue, the less likely she will accept a kidney.

Figure 2 shows an alarming divergence between the actual acceptance rate and the acceptance rate predicted by the observable attributes. The average predicted acceptance rate is 31.42%, compared with 2.92% from the data. Moreover, the gap between the two curves increases from approximately position 12 to position 68, a region that includes 70.36% of all decision occasions (in comparison, 29.07% observations fall between position 1 and 11, and 0.67% above position 68). Put differently, after the observable attributes are controlled for, kidney acceptance rate declines along the queue. This observation is consistent with the prediction from the silent word-of-mouth model that an initial rejection lowers subsequent decision-makers' quality perception and acceptance rate.

5 Model Estimation

In addition to silent word-of-mouth, four other models are also estimated for comparison purpose. First, I look at the basic case where decisions only rely on observable attributes. This is equivalent to restricting $\alpha = 0$ (and σ_s would not be estimable either). I label this model "No Quality Uncertainty". The second model restricts σ_s to 0, meaning that the quality term θ_j is publicly known to all decision makers, but only unobserved by the researcher. I name this model "Public Information". The third is a "No Social Learning" model, where individuals make decisions based on their own private signals as well as the observable attributes. Lastly, I estimate the word-of-mouth model by allowing each individual to know the signals of all predecessors. These four models are estimated by maximum likelihood using quasi-Newton methods.

5.1 Goodness of Fit and Model Selection

Table 2 reports the parameter estimates and log-likelihood values. The "No Quality Uncertainty" model yields the worst fit. Indeed, the estimates of α in all other models differ from 0 at the .05 level. The message is that quality uncertainty of the kidney offers does affect patients' decisions. The "Public Information", "No Social Learning", and "Word-of-Mouth" models perform approximately the same, while the "Silent Word-of-Mouth" model fits better than all four alternatives. The estimated σ_s under silent word-of-mouth is significantly different from 0, thus ruling out the competing explanation of public information. In other words, patients' private signals vary substantially around the true unobservable quality. Therefore, it is impossible to pin down the uncertain quality in a single shot by simply observing one's own signal, and she has to learn from others. The estimate of α in the silent word-of-mouth model is statistically significant and is quantitatively larger than in the other three models. This happens because α is the utility weight associated with the expected unobservable quality. The quality inference processes specified in the silent word-of-mouth is more consistent with the data, and hence assumes more explanatory power.

5.2 Parameter Estimates

All five models yield relatively similar parameter estimates for the observable attributes. In particular, older patients are more likely to accept a kidney offer. However, donor age has no significant effect. Gender and race of neither the patient nor the donor are significant. Patients with higher income are less likely to accept a kidney. Unemployed patients also accept less, though the effect is not as significant. State dependence is not obvious from the data: Patients' decisions are not sensitive to the number of previous kidney offers they have received, or the number of years on dialysis.

As expected, good tissue match increases the chance of acceptance. Patients are remarkably more likely to accept a kidney when there is zero mismatch at all six loci. Surprisingly, a longer cold time turns out to be associated with more acceptance. One possible reason is that patients take longer time to decide whether to accept a good kidney, while they are able to reject those obviously poor kidneys right away.

The longer a patient has been on the waiting list, the less likely she will accept a kidney. This finding is consistent with the fact that patients who have accumulated more time on the waiting list are given more priority in the queue and thus have better chance for future offers. However, one should be cautious interpreting the causality between waiting and acceptance. It might be that due to some factors not captured in the model, certain patients are less prone to take transplant and therefore stay on the waiting list longer. Finally, patients with high PRA tend to refuse more often, as expected.

Figure 3 illustrates how quality inference evolves along the queue of decision-makers. I take one kidney as an example, fix the true value of the unobservable quality at zero, draw random signals and calculate each patient's expected unobservable quality using the parameters estimates from the silent word-of-mouth model. In the absence of social learning, the expected values of the unobservable quality fluctuate with the actual private signals, only with less variance. This is because the existence of prior quality perception makes each decision-maker less responsive to her actual private signal. Where this is word-of-mouth communication, the expected values of the unobservable quality quickly converge to the true quality level zero. The more interesting case is that of silent word-of-mouth, where the expected values of the unobservable quality still vary with the actual signals, but demonstrate a declining trend along the queue as the same kidney has been repeated refused.

Figure 4 shows the average expected unobservable quality across patients' positions in the queue. Overall, the inferred quality declines along the queue, as people at the back witness more refusals. Figure 4 and Figure 5 together illustrate how quality inference and acceptance standards interact with each other, and how heterogeneity in the observable attributes leads to heterogeneous speed of learning. Specifically, people in the top positions of the queue have longer waiting time, and are able to keep their priority in the queue at the next offer. Therefore, they tend to hold for "the ideal kidney" by setting a very high cutoff value, and their rejection reveals little information about their private signals. Therefore, the inferred quality does no differ much from the prior perception for patients towards the top of the line. Moving down the queue, as the cutoffs drop sharply, the rejections conveys more negative message. Therefore, the inferred quality also decreases quickly, which in turn slows down the decrease in the cutoff values in Figure 5: The cumulated doubt about the kidney quality needs to be compensated by a good enough private signal for a patient to be willing to accept. Finally, as people near the end of the queue reject because everyone before them has already rejected, their own rejections become less informative. Consequently, the curve of inferred quality becomes flatter near the end.

The interaction between acceptance standards and quality inference calls for reconsideration of the conventional need-basis allocation mechanism for kidneys (and various scarce resources). By first assigning the kidney to people who need it the most, the efficiency *conditional on acceptance* is enhanced. However, in cases where those people turn down the kidney, the remaining crowd can receive such an enormous negative shock in their quality perception that nobody else is willing to take the offer either. In this sense, silent word-of-mouth puts the need-basis allocation system into the risk of wasting the scarce resources, as already evidenced by the alarming number of rejected kidneys in the United States. The next section suggests two solutions to the kidney wastage problem.

6 Policy Experiments

6.1 Increase Kidney Acceptance Rate

Using parameter estimates obtained from the silent word-of-mouth model, I simulate the kidney acceptance rates under two counterfactual scenarios: One is if there were word-of-mouth communication among patients, the other is if there were no social learning and each patient only followed her private signal. As can be seen in Figure 6, under both scenarios the kidney acceptance rates are substantially higher than under silent word-of-mouth, especially for people further back in the queue. In fact, under word-of-mouth the average predicted kidney acceptance rate is 27.56%, and under no-social-learning 25.99%, compared with the average predicted acceptance rate of 2.92% under silent word-of-mouth. In other words, under word-of-mouth and no-social-learning, a kidney is accepted by the 4^{th} patient on average, while it needs to travel through 34 patients to find a transplant candidate under silent word-of-mouth.

One of the current imperatives of organ allocation organizations in the U.S. is to improve the kidney acceptance rate. The above counterfactual experiments show that this goal can be achieved by controlling social imitation among patients. One solution would be to facilitate information sharing among patients, that is, to encourage word-of-mouth communication. In this way, patients are able to understand the reason why a kidney has been previously refused, rather than guessing that "something must be wrong". However, this solution is at odds with patients' confidentiality concerns. A second solution avoids observational learning by breaking the sequentiality in the decision processes. For instance, organ allocation organizations can choose not to release the information of patients' position on the waiting list. However, this policy might meet resistance from patients who prefer to have control over the pace. Alternatively, upon its arrival a kidney can be offered to all eligible patients. Among those who declare their willingness of acceptance, the final recipient is then determined by the UNOS point system. In this way, no "previous rejection" ever happens and patients make decisions based on their own private signals. The downside of this solution is that patients may incur enormous cognitive and emotional costs by making frequent decisions while the availability of the kidney is not guaranteed. Eventually, policy makers need to make a careful tradeoff between efficiency and other social values and concerns.

6.2 First Impression Management

Figure 7 illustrates the differences in the returns to first impression management among three markets: a market without social learning, a market where word-of-mouth prevails, and a market dominated by silent word-of-mouth. I focus on the queue for a particular kidney, and plot patients' net utility from accepting this kidney using the estimated parameter values. A patient will accept the kidney if and only if her net utility from acceptance is positive. In order to match the more general situations where the supply of a product is not limited to one, I assume in this illustration that the kidney can be accepted multiple times along the queue.

Before first impression management, out of 77 patients on the queue, 29 would accept the kidney under no-social-learning, 25 under word-of-mouth, and 5 under silent word-of-mouth. To improve the first impression of the kidney, firms can invest in increasing the private signal of the first individual in the queue. In this example, the first patient will become willing to accept the kidney after her private signal is increased by 6 times the standard deviation of the signals. When there is no social learning, the acceptance rate on the rest of the queue is not affected by this change because each patient only follows her private signal. When there is word-of-mouth, the increase in the first patient's signal passes on to subsequent patients through communication and increases their quality evaluation as well, while the effect is diluted by the arrival of more signals and diminishes along the queue. The more interesting case is where there is silent word-of-mouth: The first patient's conversion to acceptance triggers a jump in the quality evaluation of almost all followers. In fact, after enhancing the first impression, out of 77 patients, 30 accept under no-social-learning, 34 accept under word-of-mouth, and 64 accept under silent word-of-mouth.

The message of the above illustration is that, in markets without social learning and in markets driven by word-of-mouth communication, firms cannot sustain the boost in sales by simply encouraging early adoption of the product. On the contrary, in markets where consumers more often just observe the choices of other people rather than engage in direct communication, first impression management could bring enormous returns. Firms operating in such markets would want to build strong initial customer base by, for example, encouraging early adoption and by enhancing the visibility of early adopters.

6.3 Tipping Point Management

In markets where silent word-of-mouth prevails, social choices can be fragile because the decisions of a few individuals can dramatically alter the choice pattern among the followers. Figure 8 illustrates the effect from such "tipping point management" by targeting the marginal customers. I use the same example as for Figure 7. In the market of silent word-of-mouth, originally only 5 patient out of 77 is willing to accept the kidney, but several patients are close to indifference. For example, the 30^{th} patient's net utility from accepting the kidney is only slightly below zero. Indeed, this patient would convert to acceptance after a small marketing effort of increasing her private signal by 0.2 times its standard deviation. However, winning this particular patient turns out to totally flip the quality inference on the rest of the queue, with the number of accepting patients dramatically increased to 45. The point is that in markets driven by silent word-of-mouth, the marketing efforts spent on marginal customers may be extremely rewarding by starting a stream of social imitation after her. In contrast, the return to such efforts is limited in markets without social learning and markets characterized by word-of-mouth communication.

7 Concluding Remarks

This paper has studied how an individual decision-maker learns the uncertain quality of a product by observing the choice outcome of other decision-makers. A structural choice model is developed where individuals sequentially decide whether to adopt a product of uncertainty quality. Each decision-maker incorporates her predecessors' choices in her quality inference by Bayes' rule. Without word-of-mouth communication about the reasons underlying the decision, an adoption/rejection decision will always increase/decrease the subsequent individuals' quality evaluation. Consequently, choices can be socially reproductive, and individuals may conform to a choice different from what aggregate information would have suggested. In contrast, with word-of-mouth communication, not only the choices, but the exact signals are known to subsequent individuals. Decisions then depend on the actual signals and are less sensitive to the history of choices.

The model is applied to the kidney transplant waiting list in the United States where patients sequentially decide whether to accept a kidney for transplantation. Without direct communication, a patient only witnesses the decisions of people before her in the queue. An initial refusal of a kidney makes subsequent patients view the kidney quality more negatively, and therefore lowers its chance of acceptance down the queue. In fact, after the observable attributes of kidney offers are controlled for, the more a patient is towards the back of the queue, the more likely she is to turn down the kidney. The completing explanation of unobservable (to the researcher) public information about kidney quality is ruled out, while evidence is found for substantial learning. I simulate the choice patterns in counterfactual markets where there is no social learning or where there is word-of-mouth communication. In both markets the kidney acceptance rates are substantially higher. This finding suggests two potential solutions to the kidney shortage problem in the United States, namely, to facilitate communication among patients, and to suppress social learning. The message to marketing managers is that social trend can stem from the choices of a few individuals. Therefore, in order to successfully launch a new product, especially in categories where conversation is less often than direct observation of the choice outcome, first impression management and tipping point management can be crucial. Building a strong initial customer base can boost sales in the long run. At the same time, targeting the segment of marginal consumers can be especially rewarding.

One may raise the question regarding the normative value of observational learning. It is individually rational for each decision-maker to make inference from other people's choices. However, each choice imposes informational externality upon subsequent decision-makers. Inefficiency arises whenever a decision is repeated, as the imitator reveals less to her followers what her private information has been. Therefore, the imitator's decision will be relatively discounted later, although her private information may be of equal quality. From a social planner's perspective, individuals can over-imiate relative to the efficient level. In this way, individual rationality can aggregate into erroneous and seemingly irrational mass behavior (and hence the notion "private truth, public lies"). In comparison, such aggregate inefficiency is absent under word-of-mouth communications: Decisions confers no informational externality since the private signals are also known by the subsequent decision-makers. Put differently, no information is lost in the discreteness of choices. The social planner's goal is not to discourage observational learning itself, but to guide it in the socially efficient way. For example, appropriate release of public information can rapidly lead the trend into the correct direction. At the same time, incentives can be provided to individuals to internalize the informational externality and make socially responsible decisions.

Several paths of future research are possible. In more general situations, word-of-mouth and silent word-of-mouth often coexist. It could be interesting to study how the two forces interact with each other. Meanwhile, previous decisions are not always observed. One may not be able to tell whether a consumer is unaware of the product or has already rejected it. Also, the timing of the decisions matter. Refusals followed by initial adoptions means a different path of inference than the reverse. One direction is to study the learning process in these cases by allowing a stochastically more flexible model.

This study has focused on the demand side. It would be interesting to model supplier strategies of "trend management". Moreover, intriguing questions will emerge if we put the current model into a competitive setting. For example, firms may compete severely in the introduction stage of a product and may both want to target the switcher segment. Analyzing these scenarios would provide great insight into the dynamics of the product life cycle.

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8 Appendix

8.1 Computing the Cutoff Sequence

The sequence of cutoff signals $\{B_{ij}\}$ is computed recursively following the procedure below:

(1) Partition X_{ij} into $[X_i, X_j]$. X_j contains the product-specific attributes in X_{ij}, which is observed by all consumers of product j, hence for each given product there is no need to make random draws from X_j. X_i contains the remaining variables in X_{ij}. Find the empirical joint distribution of X_i and Z_i across i.

(2) Take an r^{th} draw from the above joint distribution, labelled as $\{X_1^r, \cdots, X_I^r, Z_1^r, \cdots, Z_I^r\}$, where $I = \max I_j$. At the same time, for each product j take $2I_j$ random draws from the i.i.d. Gumbel density, labelled as $\{\epsilon_{1j}^r, \cdots, \epsilon_{I_j j}^r, \epsilon_{1o}^r, \cdots, \epsilon_{I_j o}^r\}$.

(3) Given $\{X_1^r, Z_1^r, \epsilon_{1j}^r, \epsilon_{1o}^r\}$, B_{1j}^r is computed by solving

$$[X_1^r, X_j]\ \beta - Z_1^r\gamma + \alpha\frac{\sigma_\theta^2 B_{1j}^r + \sigma_s^2\mu}{\sigma_\theta^2 + \sigma_s^2} + \epsilon_{1j}^r - \epsilon_{1o}^r = 0$$

Repeating this procedure for $r = 1, \cdots, R$ generates $B_{1j}^1, \cdots, B_{1j}^R$.

(4) For a generic consumer $i \geq 2$, given $\{X_i^r, Z_i^r, \epsilon_{ij}^r, \epsilon_{io}^r\}$, B_{ij}^r is computed by solving

$$[X_i^r, X_j]\ \beta - Z_i^r\gamma + \alpha\hat{E}(\theta_j|d_{1j}, \cdots, d_{i-1,j}, B_{ij}^r) + \epsilon_{ij}^r - \epsilon_{io}^r = 0$$

where

$$\hat{E}(\theta_j|d_{1j}, \cdots, d_{i-1,j}, B_{ij}^r) = \frac{1}{D}\int \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{i-1}(1 - \Phi(\frac{B_{tj}^r - \theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}^r - \theta_j}{\sigma_s})^{1-d_{tj}}\ e^{-\frac{(\theta_j - m_{ij})^2}{2\Sigma}}\ \theta_j d\theta_j$$

$$D = \int \frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{i-1}(1 - \Phi(\frac{B_{tj}^r - \theta_j}{\sigma_s}))^{d_{tj}}\ \Phi(\frac{B_{tj}^r - \theta_j}{\sigma_s})^{1-d_{tj}}\ e^{-\frac{(\theta_j - m_{ij})^2}{2\Sigma}}\ d\theta_j$$

and

$$m_{ij} = \frac{\sigma_\theta^2 B_{ij}^r + \sigma_s^2\mu}{\sigma_\theta^2 + \sigma_s^2}, \qquad \Sigma = \frac{\sigma_\theta^2\sigma_s^2}{\sigma_\theta^2 + \sigma_s^2}$$

The integration over θ_j is evaluated by Gaussian quadrature. Repeating this procedure for $r = 1, \cdots, R$ generates $B_{ij}^1, \cdots, B_{ij}^R$.

Note that the cutoffs $B_{1j}^1, \cdots, B_{1j}^R$ obtained from step (3) are used in computing the set of the second cutoffs $B_{2j}^1, \cdots, B_{2j}^R$. These $2R$ cutoffs in turn are used together in solving for $B_{3j}^1, \cdots, B_{3j}^R$. This goes on for the subsequent consumers. The idea is to recursively make use of the previous cutoffs already solved for, while the potential correlation among cutoffs across i are maintained by the fact that each r^{th} draw has come from the joint distribution of individual consumer characteristics over i.

8.2 How the Order of The Queue is Determined

UNOS oversees 90 organ procurement organizations (OPO's) throughout the United States. An OPO is an organization which concentrates its organ procurement efforts within a geographic territory. When a kidney is procured by an OPO, blood-type compatible[9] patients on the waiting list within this OPO [10] are selected into in a queue for that particular kidney.

UNOS attempts to improve transplant outcomes by providing the OPO's with specific organ allocation guidelines. In particular, UNOS launched a point system in August 1995 that determines the queue ordering for each kidney based on the following four factors: First, more priority is given to patients with longer waiting time. A patient receives 1 point for each year on the waiting list. Second, the points system favors those patients who have better tissue match with the kidney donor. The tissue type consists of six proteins at six loci, namely, A1, A2, B1, B2, DR1 and DR2. The protein at each locus may be one of approximately thirty types. A "mismatch" occurs at a locus if the patient and the donor have different protein types at the locus. A patient is given infinite points

[9]Kidneys from a blood type B/O/AB donor are to be allocated only to blood type B/O/AB patients, and kidneys from a blood type A donor are to be allocated only to blood type A or AB patients, with the exception for zero tissue mismatched patients.

[10]There are, however, a small fraction of patients who register at multiple OPO's. Per UNOS 2002 report, 5.74% of the patients on the national waiting list sign up with two OPO's, 0.30% sign up with three, 0.02% four, and none above four. In this study I do not model such behavior, and treat each OPO as one separate waiting list.

if there is no mismatch at all six loci. In that case, the patient has absolute priority over the others. Otherwise if there is no mismatch at the DR loci, the patient receives 2 points. If there is one mismatch at the DR loci, the patient gets 1 point. Third, the points system favors patients with higher peak panel reactive antibody (PRA) measure, who have higher risk of graft failure. Patient peak PRA takes the value between 0 and 1. 4 points are given to patients whose peak PRA is greater than 80%. Four, patients below 18 years old have higher risk of graft failure and are given priority by the points system. Patients below 11 years old receive 4 points, and those between 11 and 18 get 3 points. When a kidney arrives, eligible patients on the waiting list are assigned points according to the four criteria. The total points determine the queue ordering: The patient with the highest total point ranks first in the queue. In practice, due to the continued shortage of kidneys and the associated explosion in waiting times, and because the percentages of patients satisfying the last three criteria are small,[11] the UNOS point system is converging to the first-come-first-served basis (Su and Zenios 2004).

[11]For example, in the TXGC OPO, 40.6% of all eligible patients have one mismatch at the DR loci with the corresponding kidney. 3.8% of patients have no mismatch at DR but have some mismatch at other loci. Only 0.35% of patients have no mismatch at all loci. 1.8% of patients have peak PRA greater than 80%. 1.8% of patients are younger than 11, and another 1.8% are aged between 11 and 18.

Table 1: Summary Statistics

Patient-Specific Variables **(N=338)**

Variable	Mean	Std. Dev.	Min	Max
Patient Age	47.059	14.342	4	79
Patient Below 11*	0.018	0.132	0	1
Patient Between 11 and 18*	0.018	0.132	0	1
Patient_Female*	0.340	0.474	0	1
Patient_Asian*	0.024	0.152	0	1
Patient_Black*	0.175	0.380	0	1
Patient_White*	0.790	0.408	0	1
Patient_Unemployed*	0.559	0.497	0	1
Income ($1,000)	30.733	11.789	6.399	86.254
PRA > 80%*	0.018	0.132	0	1
# Years on Dialysis	1.649	2.025	0	13

Kidney-Specific Variables **(N=275)**

Variable	Mean	Std. Dev.	Min	Max
Donor Age	32.186	15.483	0	73
Donor_Female*	0.447	0.498	0	1
Donor_Asian*	0.007	0.085	0	1
Donor_Black*	0.098	0.298	0	1
Donor_White*	0.895	0.308	0	1
# Eligible Patients	73.669	17.872	7	170
Rank of Accepting Patient	34.124	19.406	1	77
# Previous Offers at Transplant	15.455	23.994	0	166
# Days Waiting at Transplant	209.440	206.311	1	1272

Kidney-Patient-Interactive Variables **(N=9384)**

Variable	Mean	Std. Dev.	Min	Max
Accept*	0.029	0.169	0	1
0 Mismatch*	0.004	0.059	0	1
0 Mismatch at DR*	0.038	0.190	0	1
1 Mismatch at DR*	0.406	0.491	0	1
Cold Time	8.877	7.034	0.016	43

* dummy variable

Table 2: Estimation Results

Parameters	No Quality Uncertainty ($\alpha = 0$)		Public Information ($\sigma_s = 0$)		No Social Learning		Word-of-Mouth		Silent Word-of-Mouth	
Intercept	-1.473		-1.486		-1.542		-1.556		1.421	**
Patient Age	0.015	**	0.015	**	0.015	**	0.015	**	0.014	**
Patient_Female	0.022		0.025		0.019		0.025		0.005	
Patient_Asian	0.325		0.289		0.306		0.275		0.161	
Patient_Black	-0.715		-0.728		-0.714		-0.727		-0.653	
Patient_White	-0.926		-0.950		-0.934		-0.950		-0.891	
Patient_Unemployed	-0.228		-0.224		-0.227		-0.224		-0.246	
PRA > 80%	-0.997		-1.236		-1.225		-1.244		-3.311	**
Patient Below 11	0.177		-0.034		-0.026		-0.036		-2.088	
Patient Bw 11 and 18	0.326		0.117		0.124		0.089		-1.496	
# Years on Dialysis	-0.052		-0.051		-0.052		-0.051		-0.040	
# Previous Offers	-0.008		-0.007		-0.007		-0.006		-0.001	
Patient Income	-0.017	**	-0.017	**	-0.017	**	-0.017	**	-0.015	**
Donor Age	-0.005		-0.004		-0.003		-0.003		-0.004	
Donor_Female	0.021		0.054		0.053		0.057		0.073	
Donor_Black	-1.202		-1.177		-1.158		-1.122		-1.019	
Donor_White	-1.336		-1.314		-1.292		-1.256		-1.165	
Cold Time	0.100	****	0.112	****	0.112	****	0.113	****	0.100	****
# Days Waiting	-0.002	*	-0.003	*	-0.003	*	-0.003	*	-0.005	*
0 Mismatch	5.962	****	6.003	****	6.011	****	5.964	****	4.446	***
0 Mismatch at DR	1.042	****	0.875	***	0.873	***	0.864	***	-0.466	**
1 Mismatch at DR	-0.145		-0.272		-0.274		-0.284		-0.733	*
α	----		0.455	**	0.510	**	0.495	**	7.700	****
σ_s	----		----		0.342		1.166		0.663	****
LL	-871.901		-868.901		-868.428		-868.534		-859.840	

* P < 0.10
** P < 0.05
*** P < 0.01
**** P < 0.001

Figure 1: Sources of Information When Making Choices Under Uncertainty

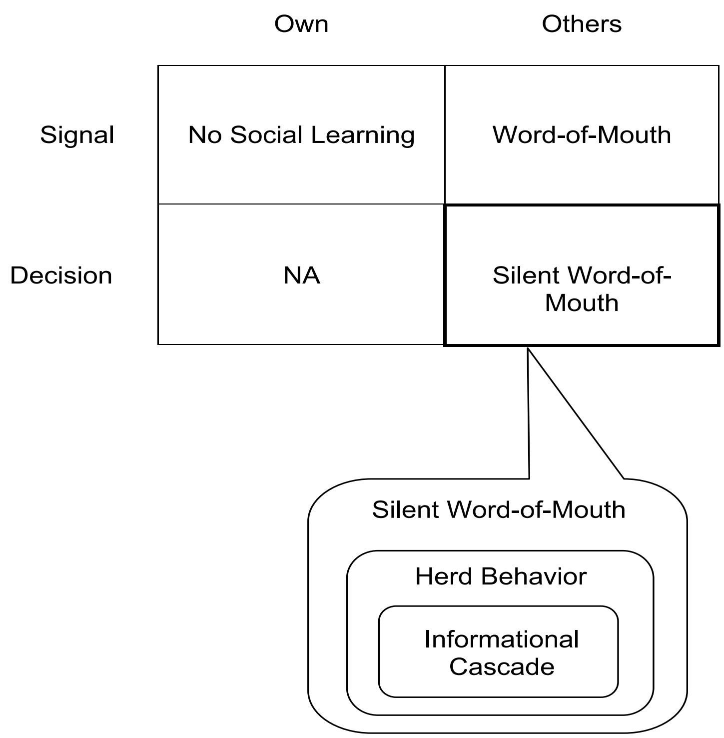


Figure 2: Empirical Regularities

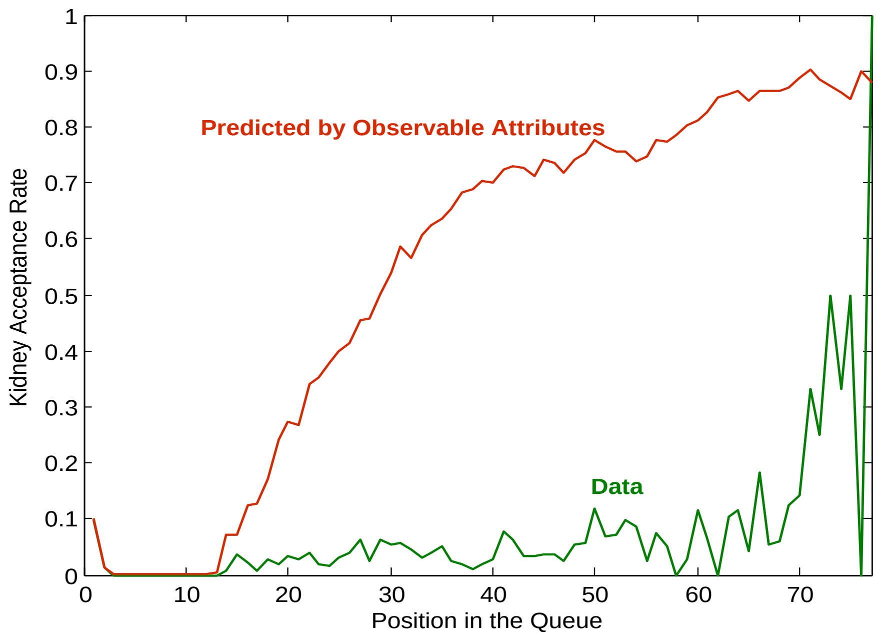


Figure 3: Expected Unobservable Quality (h)—Example of One Kidney

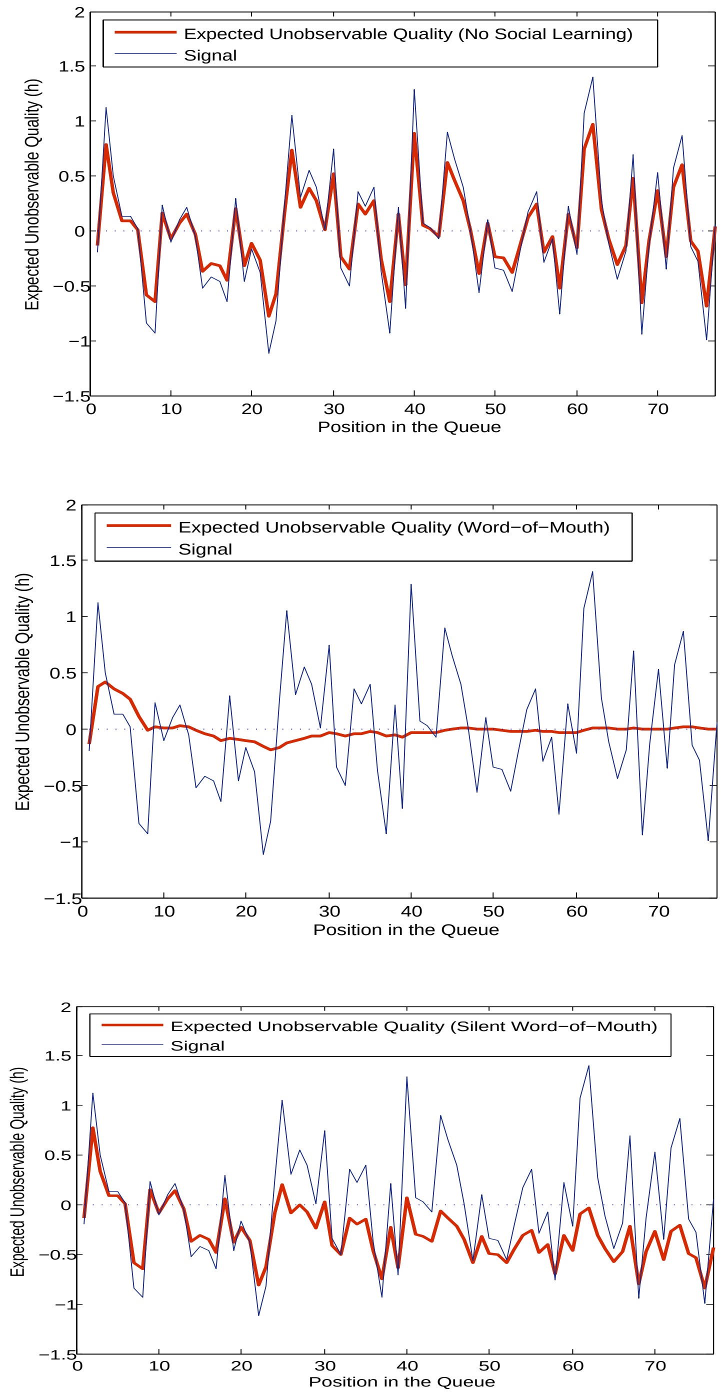


Figure 4: Expected Unobservable Quality (h)—Aggregate

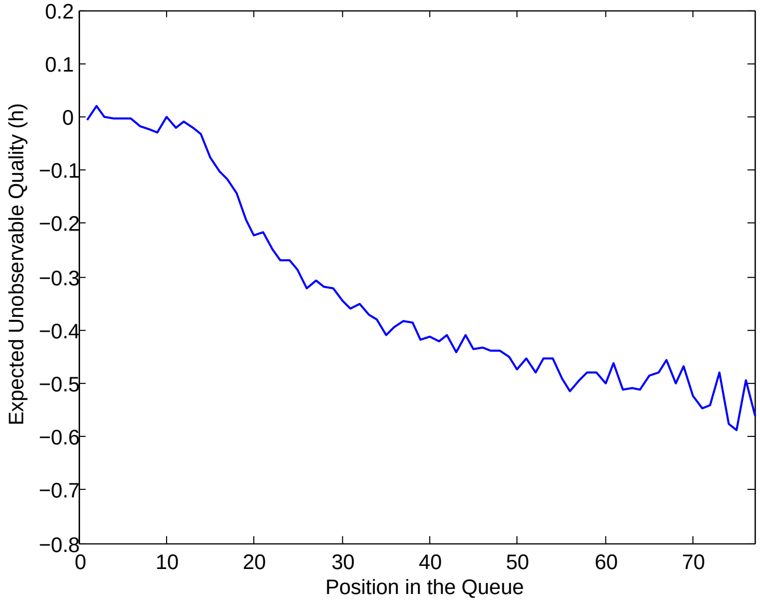


Figure 5: Cutoff Signals (B)—Aggregate

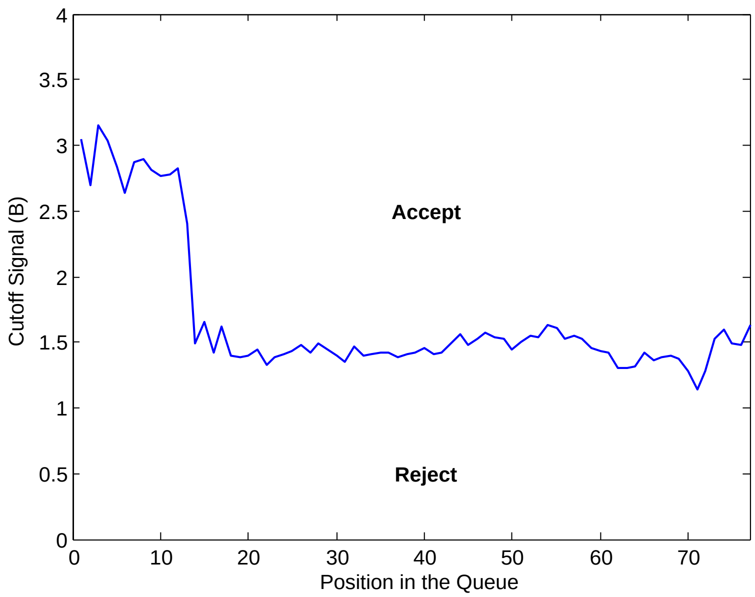


Figure 6: Policy Experiments

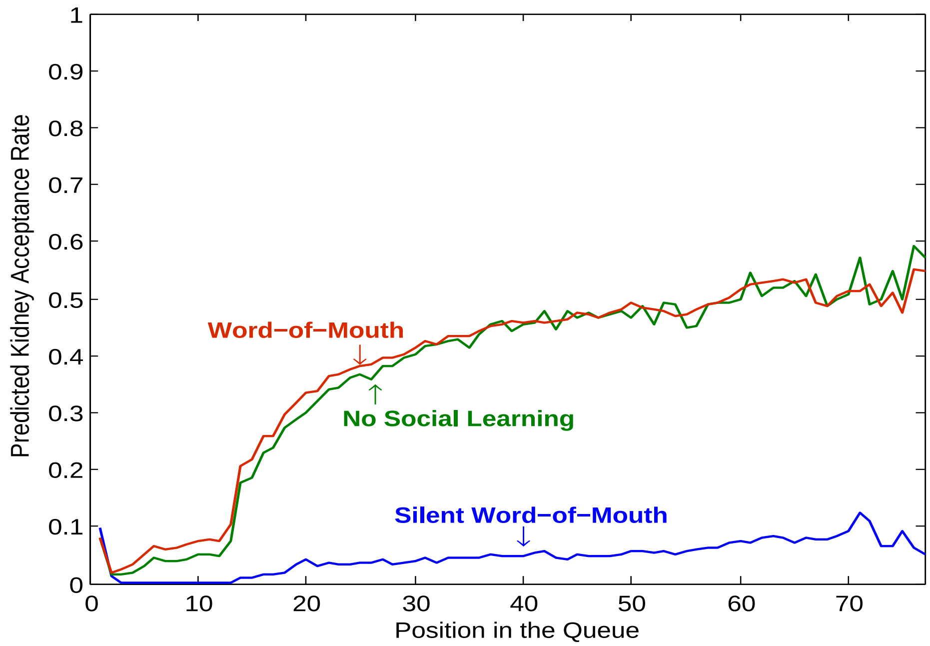
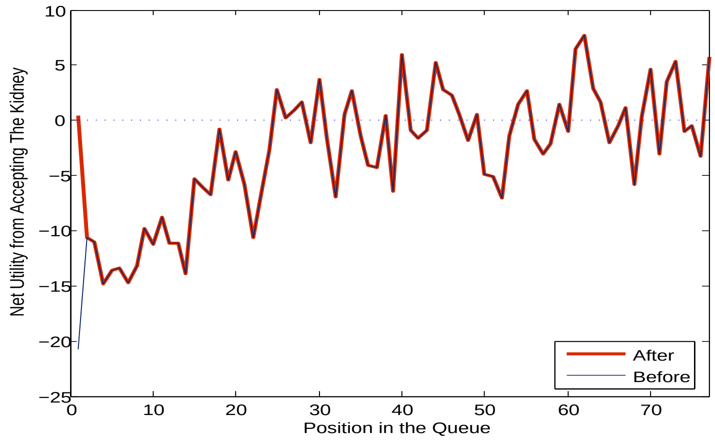
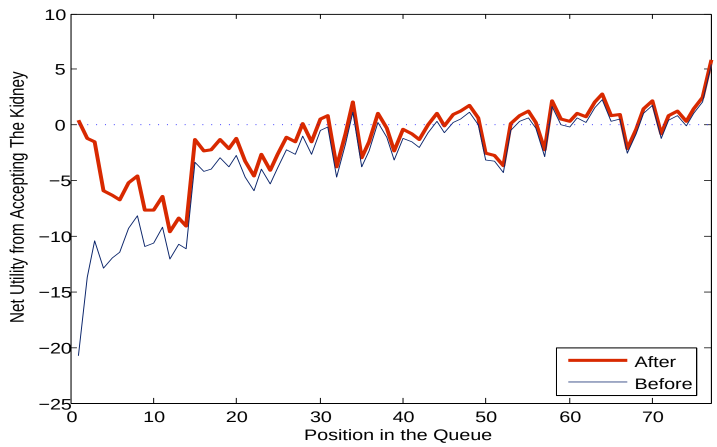


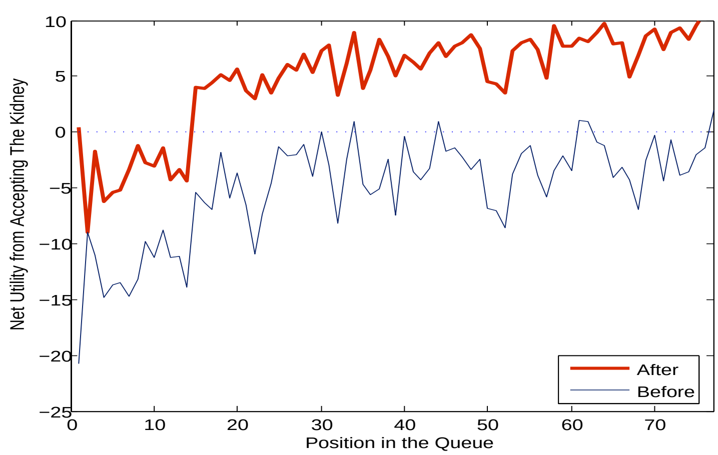
Figure 7: First Impression Management



No Social Learning

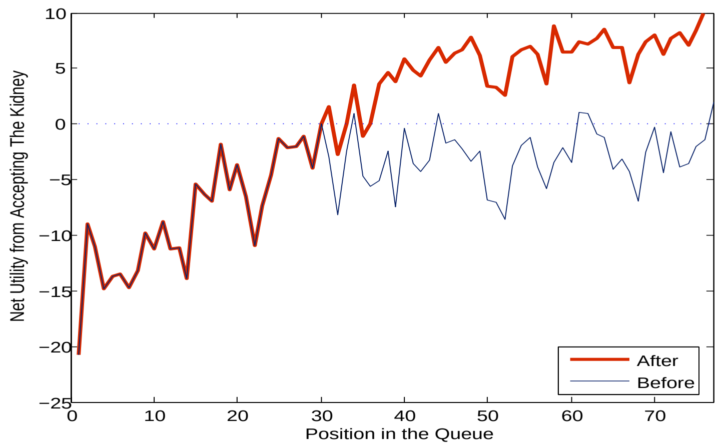


Word-of-Mouth

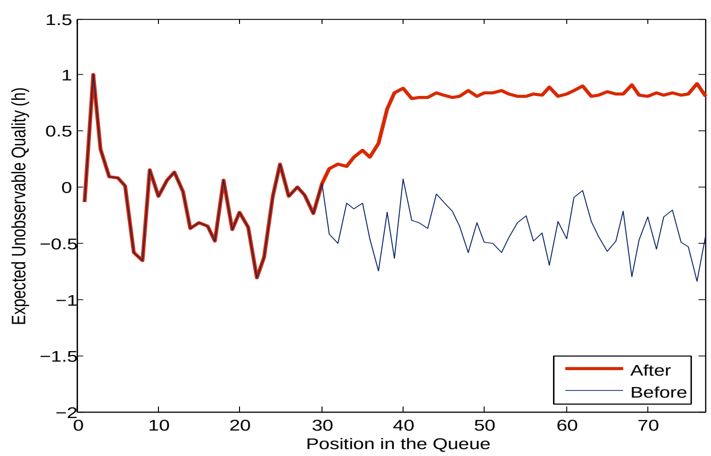


Silent Word-of-Mouth

Figure 8: Tipping Point Management



Net Utility from Accepting the Kidney (Silent Word-of-Mouth)



Expected Unobservable Quality (Silent Word-of-Mouth)