ESSAYS ON DECISION MAKING

by

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ABSTRACT OF THE DISSERTATION
Essays on Decision Making

By George Joseph

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The three essays in this dissertation examine individual decision making from a behavioral economics perspective. The first two essays report the results of an experiment that examine bidding behavior and belief formation in market-like environments with common values. In the first essay, using elicited beliefs of bidders on the value of the object at different stages of bidding, I examine whether information cascades and rational herding can be credited for the occurrence of the 'winners' curse' I find that the role of information cascades in the occurrence of the winner's curse is marginal and bidders tend to give more weight to private information in making the bidding decisions.. The winner's curse is caused primarily by herding due to disconfirmation bias and conservatism in updating beliefs.

In the second essay, I extend the analysis to understand heuristics and biases like confirmation bias, disconfirmation bias, conservatism and overreaction exhibited by decision makers in the formation of subjective beliefs. The results show hardly any evidence for Bayesian updating by the bidders. Confirmation bias, disconfirmation bias and heuristics like conservatism and are observed in the formation of beliefs but are sensitive to treatment conditions. Non-optimal belief formation due to upwardly biased prior beliefs and conservatism in updating beliefs are responsible for overbidding in markets with sequential bids and common values. Another important finding is that

Perfect Bayesian equilibrium behavior is consistent with the presence of biases and heuristics.

The third essay estimates a series of random parameter logit models of the college-to-work migration decisions of technology graduates and holders of doctorates within the United States. I employ detailed information on the migration-relevant characteristics of individuals, as well as on their actual origins and destinations at the metropolitan scale. The results demonstrate that science and technology graduates migrate to better educated places, other things equal; that PhD graduates pay greater attention to amenity characteristics than other degree holders; and that foreign students from some immigrant groups migrate to places where those groups are concentrated.

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To my Parents

Smt.Thankamma Joseph

&

Sri.P.J. Joseph

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Chapter 1 Introduction

Individual decision making has been a subject of intense research in various disciplines including economics and psychology. In most of the models in modern economic theory, the individual is the primary decision making unit who makes the best possible choice given the available alternatives. Models involving individual decisions such as saving, working, occupational choice, marriage and fertility have been constructed with strong assumptions on individual behavior. These assumptions presume that individuals are rational maximizers endowed with unlimited time and cognitive powers in making the best possible decisions. Developments in psychology and the cross fertilization of such ideas into economics have raised doubts on the prevailing dominant paradigm of ‘homo-economicus’. Several field studies and laboratory based experiments have unraveled systematic departures in human behavior from the normative prescriptions of perfect rationality, common knowledge of rationality and Bayesian updating of beliefs. Introduction of uncertainties on the possible states of the world demonstrated further problems with the normative prescriptions of behavior. Individuals have been found to exhibit inconsistent preferences, anomalies in inter-temporal choice and probability judgments.

The three essays in the dissertation examine various aspects of individual decision making from a behavioral economics perspective. The second and the third chapters in the dissertation study individual bidding behavior and the underlying subjective beliefs using laboratory experiments. The third chapter, in a more applied context, examines the determinants of destination choice decisions made by graduates and PhD degree holders within the United States.

The first two essays are based on experiments in markets with sequential bids, thus providing a strategically richer environment wherein individuals make bids on an object with uncertain value. Herd behavior occurs when individuals make identical decisions in a sequence and is widely observed in financial markets and in many social phenomena like fashions and fads. Chapter 2 reports the results of an experiment that examines herd behavior in market environments with common values. In markets where bidders bid in a sequence, information cascades due to rational herding is credited as one of the important reasons for 'the winners' curse situations where the winning bidder makes loses when the actual value of the object is announced. Apart from examining whether rational herding is responsible for the winners' curse, the essay also looks into other possible behavioral strategies that bidders employ in making their bidding decisions. In the essay, I distinguish between equilibrium and non equilibrium cascades so as to relax the strong assumptions of common knowledge of rationality and Bayesian updating. Also, a generalized decision weight model is estimated to study the respective weights that the decision makers place on various sources of information when the bidders have both informative private signal and public information.

In Chapter 3, I turn my attention to the formation of subjective beliefs by bidders in an attempt to understand whether non optimal belief formation due to the violation of Bayesian updating can explain overbidding in common value environments. In particular, using our rich experimental data on subjective beliefs at different stages of the bidding process, I examine heuristics and biases exhibited by decision makers in the formation of beliefs. While an individual makes decisions under uncertainty in real life situations, it is important to know how far detached is the standard prescription of Bayesian updating from the observed behavior. Two possible explanations have been suggested on how people update their prior beliefs when faced with cognitive limitations on computational ability. First, as pointed out in most of the literature on cognitive biases, the prior beliefs that people hold before they receive their signal has a strong influence on how they interpret and use the new evidence. Departures from Bayesian behavior often occurs when individuals have strong prior beliefs before they receive their private signal and interpret the new evidence as confirming or disconfirming their prior beliefs leading to confirmation bias and disconfirmation bias respectively. Second, it is also possible that in uncertain situations, irrespective of their prior beliefs, individuals follow their private information and make updates on their prior beliefs in the direction of the signal. This is particularly true in strategically richer environments where decision errors have costly consequences for the decision maker. In both cases, Bayesian updating of beliefs is violated. The essay provides a richer analytical framework and econometric to examine biases and heuristics in the formation of beliefs. Apart from being an addition to the literature on herd behavior and learning in common value auctions, the results of this experiment as discussed in Chapter 2 and Chapter 3 have obvious implications on the design and analysis of online auctions and in financial markets.

Chapter 4 of the dissertation examines individual decision making in a more applied context by focusing on the destination choice decisions of graduates and PhD holders within the United States. Apart from the decision making aspect inherent in this issue, the essay addresses a major policy issue in regional economic development with regard to attracting and retaining people with high levels of human capital. The chapter attempts to answer the following questions. First, I look into the widely debated issue of whether economic opportunities are more important than amenities and lifestyle factors in the migration decisions. Second, I examine how the location decisions of doctorate holders differ from those of other graduates. Third, I investigate whether there is a remarkable difference in the decision to stay or leave by local and out of state or international students. This has obvious policy implications for the design of scholarship schemes and tuition policies at the state level. As against conditional logit models which are traditionally used in migration studies, I have used the random parameter logit (RPL) models which overcome many limitations including the independence of irrelevant alternatives (IIA). Random Parameter Logit models also provide more insight on behavioral parameters underlying the decision problem. Since the mean and standard deviation of a given parameter are estimated, I am able to make statements about the distribution of preference weights in the population for attributes of interest. This chapter differs from previous works, however, in the detail with which it specifies personal characteristics (especially country of birth), the characteristics of origins and destinations below the level of the state, and interactions between personal and place characteristics. I have also developed a particularly rich set of data on international students in order to explore affinity grouping. It is also the first major study of the college to-work migration behavior of PhDs working outside of academia.

Chapter 2 Information Processing in Strategic Environments: Herds and Cascades in Markets with Sequential Bids. An Experimental Analysis

2. 1 Introduction

"*Everything is vague to a degree you do not realize till you have tried to make it precise.*"

Bertrand Russell

Most individual decision making has to do with resolving the uncertainty in the state of the world. Individuals form subjective beliefs on the state of the world prior to making their decisions. In the presence of uncertainty, the formation of such beliefs is complicated as it involves the use of different sources of information available to the decision maker. Also, individuals make different inferences from the available information to form subjective beliefs. It is often rational for decision makers to follow the decisions made by others as demonstrated in the herding and information cascades literature. Most experimental studies are set in simple decision-making environments with limited scope for strategic behavior. Most social learning, on the other hand, takes place in more complex environments. In this experimental study, I examine sequential decision making in market-like environments with common values. In the chapter, I attempt to analyze the prevalence of herd behavior and information cascades in a market where participants bid in a sequence. I also examine whether the winner's curse events can be explained by the formation of information cascades.

The present study is motivated by the increasing predominance of online auctions in Business to Business and Business to Consumers transactions both in terms of magnitude and volume.[1] Most of the online auction sites—including eBay, Amazon and Yahoo—can be broadly characterized as having a sequential nature where the bidders place their bids in a sequence after typically observing the history of previous bids. Bidders can be thought of as having private information on the value of the object from different sources including the manufacturers' sites.[2] On the basis of private information and the observed history of bids, a typical bidder forms an individual estimate of the value of the object and makes her bid. Strategic behavior in online auctions is evident in the shading of bids as well as the time at which a major proportion of the bids are placed (Bajari and Hortascu (2002), Roth and Ockenfels (2000)).[3] Though there have been several studies that have documented the strategic aspects of bidding and the extent of the winner's curse in online auctions, no serious attempt has been made to understand the various aspects of social learning taking place in online auctions that are responsible for aggressive bidding.

The present chapter is an addition to the literature in the following sense. First, like numerous other experimental studies, I am able to replicate information cascades and herds in a laboratory setting. Second, this is one of the first papers to examine information cascades and herd behavior in a strategic context.[4] Experimental analysis of

[1] See, for instance, Bajari and Hortascu (2002) on the increasing volume of sales in eBay auctions.
[2] Kelley's Blue Book is an example in the case of second hand cars.
[3] The practice of sniping is reported by Bajari and Hortascu (2002) and Roth and Ockenfels (2000).
[4] Drehmann, Oechssler and Roider (AER Dec 2005) and Cipriani and Guarino (2001) examine herd and cascade behavior in financial markets.

the prevalence and consequences of cascade behavior in a sequential auction context has not been undertaken so far. Previous studies have been set in simple decision-making environments with a limited role for strategic interaction. Third, I explicitly collect information on beliefs at various stages of decision making in order to analyze how bidders process information at different stages of bidding and how they form subjective expectations. Choice data alone do not enable the researcher to infer expectations that the bidders would hold (Manski (2004)). The data also help us to examine whether bidders update their beliefs as they receive additional information in a Bayesian fashion, as prescribed by the theory. Fourth, with the stated beliefs elicited at different stages of the bidding process, I develop a more accurate private-information variable free from the specifications of the model. This enables me to estimate the respective weights that bidders ascribe to different sources of information available at the time of bidding. Fifth, I distinguish between equilibrium and non-equilibrium cascades and examine the validity of the generally held assumption of common knowledge of rationality in a sequential bidding context. Sixth, in this experiment, informational externalities and payoff externalities are credited as the reason for strategic behavior. This enables us to examine the winner's curse in this context. I also examine the explanatory power of information cascades with respect to the winner's curse phenomenon.

Since the seminal papers by Banerjee (1991) and Bikchandani, Hirschlifer and Welch (1991), individuals making a binary decision in a sequential manner have been studied extensively in the herding and information cascades literature.[5] Decision makers

[5] See http://welch.econ.brown.edu/cascades/ for a detailed list of the different strands of the literature.

typically learn by observing the behavior of others and making inferences on the information upon which the previous decisions are made. The Rational herding literature demonstrates that when decision makers have perfect information about the decisions made by others, including the inferences they would make regarding their own signal and others' bids, everyone will eventually make the same decision when faced with the same decision problem regardless of their private information (Chamley (2004)). Information cascades occur when, after some finite time, all decision makers make the same decision, ignoring their private information. Herd behavior occurs when decision makers make the same decision, though not necessarily ignoring their private information. Hence an information cascade implies a herd, but herd behavior is not necessarily the result of an information cascade (Celen and Kariv (2003)).

Previous experiments on informational cascades and herding have focused on the realization of cascades in a laboratory environment (Anderson and Holt (1996), Celen and Kariv (2000, 2001), Alisop and Hey (2001), Hung and Dominitz (2003), Kubler and Weizsacker (2004), Hung and Plott (2004) and Drehmann, Oechssler and Roider (2005)). It has been observed that as the probability of receiving a signal and the precision of the signal increases, there is a tendency toward herding (Alisop and Hey (2000)). Attempts to study the underlying beliefs responsible for individual decisions have been undertaken by measuring cut-off beliefs (Celen and Kariv (2000, 2001)) and explicitly eliciting stated beliefs (Hung and Dominitz (2003)). All these experiments are based on the assertion that bidders exhibit Bayes' rational behavior both on and off the equilibrium paths as the game is played.[6]

The essay introduces an auction context to provide a strategically richer environment in which to examine information processing when people make decisions in a sequential manner.[7] In an auction context, the seller is uncertain about the value the buyer places on the object being sold. The buyer's private information is the main factor affecting strategic behavior (Wilson (1992)). In typical common value auctions, the ex-post value of the object is the same for all bidders, but different bidders have different estimates about the underlying value. The winners' curse occurs where the winning bidder ignores the informational consequences of winning.[8] If this problem of adverse selection is not accounted for in formulating the bidding strategy, it will result in winning bids that produce below normal or negative profits.

The main results of the chapter are that the winner's curse is highly pervasive in sequential auction experimental settings. Cascades on the equilibrium path are clearly visible in the early stages of bidding, but are short and fragile. However, a majority of observed events of herd behavior is not a consequence of cascades. Bidders update their beliefs, but mostly in a non-Bayesian fashion. Private signals that bidders receive are the

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[6] An exception is Dominitz and Hung (2003) where play off the equilibrium path is explicitly analyzed in order to understand the divergence of beliefs and the convergence of actions.

[7] For an exhaustive discussion of experimental evidence on common value auctions, see Roth and Levin (2003). Contrary to most of the previous experimental work on common value auctions, our motive is to analyze bidding decisions as well as the impact of herds and cascade formation on bidding decisions and the winner's curse.

[8] See Clapp and Cambell (1971) who first reported observing the winner's curse in field data.

single most important determinant of bidding decisions. Herd behavior due to confirmatory bias and conservatism in beliefs could be credited for the occurrence of the winner's curse. Cascades can hardly explain the observed phenomena of the winner's curse.

The chapter is structured as follows. In the next section I present the theoretical model on the basis of which I conduct the experiment. I examine whether the theoretical predictions of the model are actually observed in the laboratory. I also propose possible behavioral models of decision making that assume less strict notions of rationality in order to examine their empirical validity. In the third section, the experimental set up is presented. In the fourth section the results are analyzed on the basis of theoretical predictions and possible departures from rationality. The fifth section concludes with a brief discussion of the results.

2.2 Theoretical Set Up

We consider a variant of the model by Neeman and Orosel (1999) in which the seller sequentially obtains bids for an object from a finite number of bidders. All of the bidders have the same ex-post valuation of the object. They differ only in their estimates of this value. The basic structure of the model is similar to the one considered by the herding literature.

2.2.1 The Basic Model

The seller solicits bids from a finite number of buyers $i = 2....N$. It is common knowledge to the bidders that the object is of high quality q_H or of a low quality q_L with equal ex-ante probability. Also, $v(q_H) > v(q_L)$ ensures that an object of high quality is worth more than an object of a low quality. It is common knowledge that an object is of high quality with a positive probability, i.e. $0 < \Pr(q_H) < 1$. The seller's reservation value is zero. Bidding occurs at each point in time, $t \in \{1,2,...T\}$, in a sequential manner. The order of bidding is exogenously decided by seller. The bidders receive a private signal, high or low, $S^b \in \{H, L\}$, which is conditionally independent from the value. The signal is private information to the buyers. The signals are such that

$$0 < \Pr(S^b = H | q_L) < \Pr(S^b = H | q_H) < 1.$$

In the present set up, I examine a case of identically distributed signals. The bidder, when approached by the seller, has to make a bid $b(h_t)$ after observing the previous history of bids h_t and receiving her private signal. The bid $b(h_t)$ has to be greater than or equal to all the previous bids or a zero bid. If she makes a zero bid, she becomes an inactive bidder. The seller can re-approach the active bidders in later rounds.

The seller can decline to offer the object to the highest bidder in which case she has a payoff of zero. The payoff to the seller by selling the object at a price p is p. The payoff to the buyer from purchasing the object at a price p is the value of the object less the bid which given by $\pi(b^1) = v(q) - p$.

2.2.2 Formation of Beliefs by the Bidder

One of our important concerns in the experiment is the formation of subjective beliefs regarding the value of the object. It is on the basis of these subjective beliefs that the bidders form subjective expectations about the value of the object. The bidders form prior beliefs about the actions of other bidders and update the prior into posterior beliefs as they receive their private signal. A prior belief for bidder i is given by a function $\Gamma : \mathrm{H} \to \cup_{t\geq 1}[0,1]^t$ that maps every history $h_t \in \mathrm{H}$ into a vector of probabilities $(\gamma_1^i......\gamma_t^i)$. The posterior beliefs $\mu^i(q = q_H | s_t, h_t)$ are the prior beliefs $\gamma^i(q = q_H | h_t)$ updated on the basis of the signal. Here, $\mu^i(q = q_H | s_t, h_t) = \Pr(q = q_H | s_t, h_t)$ represents the belief the bidder forms as to whether the object is of a high value prior to placing her bid. Therefore, the belief captures the uncertainty and the strategic content before the decision is made.

2.2.3 The Bidder's Problem and the Threshold Rule

The bidder's problem can be reduced to the following binary decision problem. Conditional on her signal and observed history, she forms beliefs μ^i. On the basis of these subjective beliefs, she decides whether or not to bid up the price, assuming that all subsequent bidders receive a low signal. In other words, the bidder will bid high conditional on her beliefs, μ^i, if the respective bid will maximize her payoffs, i.e. if

$$E(\pi(b^{\mathrm{H}})) \geq E(\pi(b^L)).$$

That is, she will form a threshold value of belief τ that the object is of a high value: $\mu^i \geq \tau$. The expected utility maximizer employs a threshold rule and announces b^H if her posterior probability that the object is of a high value exceeds a threshold $\tau = 0.5$. If the posterior probability is less than 0.5, she will announce b^L. In the case of indifference, I assume that the bidder weakly favors the signal.

2.2.4 Information Cascades and Herding

The formation of posterior beliefs plays a critical role in determining the subjective expectations that the bidders form regarding the value of the object. In markets where bidding takes place sequentially, with perfect rationality and common knowledge, all available information including private information gets aggregated. But with information cascades present, the aggregation of information is not complete. An information cascade is said to occur at time T, if no information about the quality of the object is revealed at time T or after. The individual announcement of bids is invariant to the realization of the bidder's private signal. That is, an individual who makes her decision in period t has a posterior probability, μ^i, such that

$$\mu^i < \tau \text{ or } \mu^i > \tau \text{ for all } s_t \in \{H, L\}.$$

A cascade may arise despite the fact that signals may lead to revisions of the posterior beliefs:

$$\mu^i(q|s_t = H, h_t) > \gamma^i(h_t) > \mu^i(q|s_t = L, h_t).$$

If such a cascade begins in period t, the bidder's announcement of her bid in period t reveals no additional information to the bidder in period $t+1$. That is

$$\mu^{i+1}(q = q_H|s_{t+1}, h_{t+1}) = \mu^i(q = q_H|s_{t+1}, h_t).$$

So once a cascade is begun, it is not possible to infer the bidders' private signals from their announcements. That is

$$\mu(q = q_H | s_t = H, h_t, h_{t+1}, \ldots . h_{t+k}) = \mu(q = q_H | h_{t-1})$$

with the cascade lasting for k periods. Hence, even with perfect rationality and common knowledge, I have insufficient aggregation of information under rational herding.

Herd behavior as widely discussed in fashions, fads, and financial markets and emphasizes only identical actions by a sequence of decision makers. Herding occurs if all buyers, if and when approached, follow the actions of the predecessor at time T or after. That is, if a herd sets in period t, then bid, $b = b_H$ or $b = b_L$ for $t, t+1, \ldots, t+k$ with the herd lasting for k periods. Herds occurring due to cascade formation are rational herds for which no additional information is revealed to the bidder after the cascade has begun. Herding can occur due to reasons other than cascades. Therefore, cascades will cause herds but not all herds are cascades.

2.2.5 Conditional Expected Value and the Winner's Curse

Profit or loss in each market that the winner receives depends on others' bids and the ex-post value of the object. This introduction of payoff externality along with the information externality in similar sequential games helps us to examine the widely discussed problem of the winner's curse. The problem that the seller faces is to get the bidders to bid up the expected value of the object, conditional on the public information and private signal. The buyer i at time t who considers bidding up the price to $E(v(q_t)|s, h_t)$ expects that the seller would subsequently approach a new buyer in $t+1$. If the new buyer observes a high signal, she would outbid buyer i since the posterior beliefs are revised upward upon receiving a high signal and the conditional expected value of the object $E(v(q_{t+1})|s,h_{t+1})$ will be higher than $E(v(q_t)|s,h_t)$. If she observes a low signal, she would decline to bid up the price. This is because, since an additional low signal has been observed, the updated conditional expected value $E(v(q_{t+1})|s,h_{t+1})$ is lower than $E(v(q_t)|s,h_t)$. Therefore, being the highest bidder in a market could mean that the subsequent bidders have observed low signals and have a low conditional expected value of the object. Consequently, the object is worth less in expectation than the price paid for it, and the winners will suffer from below normal or negative profits. If the bidders fall into a cascade, they will not be able to draw the correct information from previous bids and update their beliefs accordingly. In the absence of information aggregation, the winner's curse is further accentuated.

2.2.6 Equilibrium Behavior and Prediction of Actions

We rely on Perfect Bayesian Equilibrium (PBE) for the solution of this sequential game. A profile of strategies and beliefs is a Perfect Bayesian Equilibrium for this game if: a) for every possible history h_t the seller's strategy maximizes the seller's expected revenue given her beliefs and the buyer's strategies; b) for every possible history h_t buyer i's strategy maximizes her expected payoffs conditional on her beliefs and the strategies of the seller and other buyers; and c) whenever possible, beliefs are updated using the Bayes' rule. I now turn our attention to the actions of the bidders.

2.2.6.1 Perfect Bayesians

The Perfect Bayesian Equilibrium of the game predicts that the bidders update their posterior beliefs in a Bayesian fashion and believe that others are rational and follow the same. With a symmetric ex-ante prior belief on the value of the object, the first bidder will follow her signal, bid high if she gets a high signal and bid low if she gets a low signal. Bidder two will follow if she receives a confirming signal. But if she receives a contrary signal she will announce her signal.[9] A cascade will begin with the third bidder if she has observed two identical announcements. If she has observed two contrary announcements, then they both will cancel out and the third bidder's decision problem will be identical to that of the first bidder, where she follows her signal as described earlier. The equilibrium predictions of actions of the subsequent players can be inferred in a similar fashion. Depending upon prior probabilities and the precision of the signal, the onset of a cascade depends on the net number of high and low signals. If the posterior probability of the object being of a high value or a low value is equal, then the bidder will bid on the basis of her signal. If there is an imbalance in one of the bids favoring high or low, then the bidder will behave as the second bidder, weakly favoring her signal. If there is an imbalance of two or more bids favoring high or low, then all the subsequent bidders will fall into a cascade. Off the equilibrium path, the formation of beliefs is uncertain and I do not venture into that in the present chapter .[10]

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[9] In the case of indifference there are two possibilities. Bikchandani, Hircshlifer and Welch (1992) assume that the players will randomize with a probability 0.5. Anderson and Holt (1997) and Drehmann, Oechssler and Roider (2005) assume that the players will follow her signal with probability 1. In our experiment I will make use of the second assumption for sharper predictions.

[10] For a detailed discussion, see Dominitz and Hung (2003).

2.2.6.2 Other Behavioral Strategies

The theoretical predictions of the PBE are based on perfect rationality, Bayesian updating and common knowledge of rationality, which the bidders are bound to follow. If the common knowledge of rationality is relaxed, inferences that bidders would make on the history of previous bids becomes uncertain. I propose two other candidates for these behavioral strategies. One extreme candidate is the bidder following OWN SIGNAL, departing from rationality, Bayesian updating and common knowledge of rationality completely. The second candidate is rational under imputed history of signals (RUIHS). Here the bidders are assumed to impute a history of signals from the observed history of actions and update their beliefs in a Bayesian fashion as they receive their private signal (Hung and Plott (2001), Dominitz and Hung (2003) and Drehmann, Oechssler and Roider (2005)).[11] On the equilibrium path the predictions of the RUIHS are identical to the predictions on actions generated by the PBE of the game. But RUIHS can act as an intermediate step between the PBE and OWN SIGNAL strategies in that RUIHS retains Bayesian updating but relaxes the common knowledge of rationality. The introduction of RUIHS is intended to capture some off-the-equilibrium actions.[12] To any bidder, off the equilibrium behavior by the predecessor could be treated as if the predecessor is following her own signal rather than being undefined.

[11] The notion of RUIHS is similar to the idea of naïve Bayesians by Hung and Plott (2001) and Dominitz and Hung (2003) and the idea of ruck by Drehmann, Oechssler and Roider (2005).

[12] For example, a low bid after three consecutive high bids can be classified as an off-the-equilibrium behavior under PBE. The successors can either a) ignore the decisions of the third bidder and form any beliefs (Banarjee (1992)) or b) assume that the third bidder has followed her own signal and form beliefs in a Bayesian fashion (Bikcahndani, Hircshlifer and Welch (1992)). RUIHS follows the second option and is, therefore, an intermediate level of rationality with a more behavioral meaning.

2.2.7 Generalized Decision Weight Model

It is important to understand whether the bidders rely more on public or private information when they make bidding decisions. Before announcing their bid, a bidder has two sources of information: her private signal and the history of all previous bids. The generalized decision weight model (Grether (1980), Hung and Plott (2002) and Dominitz and Hung (2003)) is constructed on the premise that a bidding decision is based on these two sets of information. Given a pattern of bids, the model allocates weight that a bidder places on the history of bids relative to the weight she places on her signal in making her bidding decision. Let q_H be the event that the true value of the object is high and q_L be the event that the true value of the object is low. The relative subjective odds for each bidder in favor of q_H before she makes her bid can be expressed as

$$\frac{P(q_H)}{1-P(q_H)} = \frac{P(q_H)}{P(q_L)}.$$

These relative odds depend on the information available at the time the bidding decision is made. Let $I_{it}(h_{it}, s_{it})$ be the information available to the bidder at time t, where h_{it} be the history of all previous bids (public information) and s_{it} is the private signal (private information) that she receives. For a Bayesian individual i who makes her decision at period t,

$$\frac{P(q_H|I_{it})}{P(q_L|I_{it})} = \frac{P(I_{it}|q_H)P(q_H)/P(I_{it})}{P(I_{it}|q_L)P(q_L)/P(I_{it})} = \frac{P(I_{it}|q_H)P(q_H)}{P(I_{it})|q_L P(q_L)}.$$

If h_{it} and s_{it} are independent then bidders form subjective odds in favor of q_H as

$$\frac{P(q_H|I_{it})}{P(q_L|I_{it})}=\frac{P(I_{it}|q_H)P(q_H)}{P(I_{it}|q_L)P(q_L)}=\frac{P(H_{it}|q_H)P(s_{it}|q_H)P(q_H)}{P(H_{it}|q_L)P(s_{it}|q_L)P(q_L)}.$$

Generalizing after taking logs,

$$Y_{it}=\alpha+\beta\ln\left[\frac{P(H_{it-1}|q_H)}{P(H_{it-1}|q_L)}\right]+\eta\ln\left[\frac{P(s_{it}|q_H)}{P(s_{it}|q_L)}\right]+\delta\ln\left[\frac{P(q_H)}{P(q_L)}\right]+u_{it}.$$[13]

The model can be rewritten as,

$$Y_{it}=\alpha+\beta\ln\left[\frac{P(H_{it-1}|q_H)}{P(H_{it-1}|q_L)}\right]+\eta\ln\left[\frac{P(s_{it}|q_H)}{P(s_{it}|q_L)}\right]+u_{it}$$

where $Y_{it}=\ln\left[\frac{P(q_H|I_{it})}{P(q_L|I_{it})}\right]$; α, β, η and δ are constants; and u_{it} is a random and distributed logistic.[14] I define an indicator variable Y_{it}^*, which takes the value 1 if the bidder decides to bid high and 0 otherwise. That is $Y_{it}^*=1$, the underlying log odds Y_{it} is positive, or $Y_{it}^*=0$ if Y_{it} is negative.

For each bidder at the time of bidding, the private information variable, the variable associated with the coefficient η, can be calculated using the prior $\gamma^i(q=q_H|h_t)$

[13] $\ln\left[\frac{P(q_H|I_{it})}{P(q_L|I_{it})}\right]=\ln\left[\frac{P(H_{it}|q_H)}{P(H_{it}|q_L)}\right]+\ln\left[\frac{P(s_{it}|q_H)}{P(s_{it}|q_L)}\right]+\ln\left[\frac{P(q_H)}{P(q_L)}\right].$

[14] Since the prior odds are fixed throughout the experiment δ is not identified. Since $\ln\left[\frac{P(q_H)}{P(q_L)}\right]=0$, this term drops out of the equation.

and posterior $\mu^i(q = q_H | s_t, h_t)$ elicited from the bidder.[15] This is an improvement over the previous approaches (Hung and Plott (2001) and Dominitz and Hung (2003)) because the private information available to the bidder at the time of bidding is revealed from his own stated beliefs. In previous studies this variable is assumed to be known to her and fixed throughout each market. The public information variable captures the information the bidder draws from the observed history of bids.[16]

We can use the signs, magnitude and ratio of the coefficients of the model to understand how individuals use their information in making the bidding decision. In terms of the decision weight model, individuals are *private information revealers* if β is not significantly different from zero. If η is not significantly different from zero, individuals are following the actions of others, thus acting as *public information revealers*. If $\frac{\beta}{\eta} > 1$, individuals place more weight on public information than on private information. I expect this situation when I consider the cascades alone where the private information gets swamped by the public information. When the bidders are strategic in an auction context, they will place more weight on the private information than on public

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[15] Let $P^i(s_{it} | q_H) = \frac{\mu^i(\gamma^i - 1)}{[(2\mu^i\gamma^i) - \mu^i - \gamma^i]} = k$. With γ^i and μ^i elicited from the bidder,

$$\ln\left[\frac{P(s_{it} | q_H)}{P(s_{it} | q_L)}\right] = \ln\left[\frac{k}{(1-k)}\right].$$

[16] The public information variable is calculated using the following formula: if n is the number of high bids and M is the number of low bids that individual i has heard when she is called upon to make her bid, then

$$\ln\left[\frac{P(H_{it-1} | q_H)}{P(H_{it-1} | q_L)}\right] = \ln\left[\frac{(2_{it}^{n})}{(2_{it}^{m})}\right] = (n_{it} - m_{it})\ln 2.$$

information and hence $\frac{\beta}{\eta} < 1$.[17] This is because the bidders consider that with a positive probability the previous bidders could have made some errors in their announcements and those other bidders, too, are acting strategically. Since herds can occur due to reasons other than cascades it could reveal the strategic behavior of bidders. But when I consider the herds alone I expect more weight on public information such that $\frac{\beta}{\eta} < 1$ but with a larger magnitude for this fraction than all bids taken together. Bidders are said to be RUIHS if they place equal weight on both public and private information so that $\frac{\beta}{\eta} = 1$. Here I will not be able to reject the hypothesis that $\beta = \eta$.

2.3 Experimental Set Up

The experiment consists of 13 sessions with 190 markets. In each session there are markets in which six bidders bid for the value of the object. The value is high or low with equal ex-ante probability of 0.5, and this is common knowledge to all bidders. The high value is 100 and the low value is 0 in terms of the experimental currency unit franc. Ten francs are equal to 1 rupee. The seller's reservation price is 0. The conditional probability of the signal being correct is always more than 0.5 and is common knowledge to all participants. The seller, if she decides to, can re-approach the active bidders in the next round of bidding.

[17] The buyer's private information is the main factor affecting strategic behavior (Wilson (1992)).

One important feature of this experiment is the elicitation of beliefs at different stages of bidding process. Beliefs of bidders are elicited through a quadratic scoring rule such that it is their best interest to reveal their true beliefs (Sonnemans and Offerman (2001)).[18] Belief elicitation by providing financial incentives to participants has been used in several experimental studies to report the truth (Nyarko and Shorter (2002) and Nyarko, Shorter and Sopher (2001)).[19] Since measuring subjective expectations is a difficult task, I elicit subjective beliefs from the bidder as she receives additional information (Manski (2004)). At various stages of the bidding, each bidder is asked to state her beliefs on the probability of the object being of high value. Once her turn to bid comes, the bidder has to state the probability of the object being of high value after observing all previous bids (prior). Then she is asked to state the probability that her immediate predecessor had received a high signal. After she receives her own signal, she is again prompted to state the probability that the object is of a high value (posterior).[20] These stated beliefs are highly informative in understanding how the bidders update their belief as new information is revealed.

Among others, the experiment is also intended to understand whether the precision of signals has an effect on herd and cascade formation (Alisop and Hey (2001)). Therefore, the precision of signal is set at a high of 0.8 and a low of 0.66. At the

[18] Among the different scoring rules, the quadratic scoring rule has the property that it is incentive compatible for the participants to reveal their true beliefs. For some experiments and discussions on scoring rules and their relative strengths and weaknesses, see Sonnemans and Offerman (2001).

[19] There are various views on whether belief elicitation would affect the behavior of decision makers. For a discussion on this, see Rustrom and Wilcox (2004) and Dominitz and Hung (2003). In our experiment, I do not intend to examine these possibilities.

[20] The detailed instruction given to each participant (bidder) is given at the end of the chapter . At the beginning of each session the instructions were read aloud and the participants were given a copy of the instructions.

beginning of each market, the following information was announced and also exhibited on the blackboard regarding the precision of signal. For example, if the precision was high, it was announced and exhibited that, "the probability of receiving a high signal when the real value of the object being high is 0.8 and the probability of receiving a low signal when the real value of the object being low is 0.2." At the beginning of the experiment, I provided information on how to interpret this announcement and made sure that the participants understood it clearly. It is important to point out that the low precision treatment is also intended for comparison with other studies like Anderson and Holt (1997) and Dominitz and Hung (2003) who have used similar parameterization for the precision of the signal. Also, I assigned the value of the object to be high or low in each market in a predetermined order. Signals that the bidders receive also are random to them but predetermined to ensure maximum cell counts.

Table 2.1 Treatments and Number of Markets

	Precision	
	High Precision (0.8)	Low Precision (0.66)
High value	48	40
Low value	50	52

In short, as shown in Table 2.1, I have high value treatments with the true value of the object being high and low value treatments with the true value of the object being low. Also in each treatment, I have two regimes with high and low precision of signal, hence I can analyze four treatments in the experiment: 1) Treatment I - high value treatment with a high precision of signal. 2) Treatment II - high value treatment with a low precision of signal, 3) Treatment III - low value treatment with high precision of signal, and 4) Treatment IV - low value treatment with a low precision of signal.

The experiments were conducted at Jawaharlal Nehru University and at the Indian Statistical Institute, New Delhi. Since the experiments required participants to state probabilities, I recruited graduate students from statistics and economics. The rest of the participant pool consisted of master's level students with training in mathematics, statistics or physics.

At the end of each session the participants were paid in cash. The payment included the profit or loss for winning, remuneration for stated probabilities, along with a participation fee of Rs.50. Participants, on average, earned a sum of Rs.250.00. This is approximately equivalent to 40 percent of monthly expenses on food for a student in these residential universities.

2.4 Results

For proper evaluation and discussion of the outcome of the experiment I will discuss the results in several steps. I first begin by examining how far the theoretical predictions of PBE and other behavioral strategies can explain bidding decisions. I examine whether herds and cascades could be replicated in our experiments like other sequential decision experiments. Then I proceed to examine whether the observed herds and cascades are responsible for the winner's curse. In the fourth subsection, I utilize the results of the Generalized Decision Weight Model to estimate the informational content behind observed patterns of behavior

Before I proceed, it is useful to collect together our theoretical hypotheses on the basis of our discussions in Section 2. 1) Bidders make their bid on the basis of the posterior beliefs they form regarding the value of the object and follow a threshold rule for posterior beliefs to make bidding decision. 2) Bidders revise their prior beliefs upward upon receiving a high signal and downward upon receiving a low signal. If bidders are perfect Bayesians, they update their beliefs in a Bayesian fashion and follow the PBE strategies as prescribed by the theory. 3) If bidders are following PBE, then *average PBE* is equal to1, indicating complete validation of the theory.[21] On the other hand, if the bidders follow their private signal, *average OWN* is equal to 1. In case bidders show an intermediate level of rationality, as discussed earlier, *average RUIHS* is equal to 1. 4) Under PBE, I expect the empirical probability of cascades to be equal to 1 for respective events of interest. 5) Under PBE, the empirical probability of non-equilibrium cascade events is equal to zero. 6) In the Generalized Decision Weight model, I expect the bidders to be strategic such that $\frac{\beta}{\eta} < 1$. In order to further validate the robustness of the model I will examine herd events and cascade events separately. When I estimate the model with cascade events alone, I expect $\frac{\beta}{\eta} > 1$. 7) If bidders are following PBE strategies, I anticipate a significant number of cases of winner's curse due to equilibrium cascades. In the following discussion, I will examine each of these hypotheses in further detail.

[21] Average PBE, average OWN and average RUIHS represent the fraction of actual decisions that follow PBE, OWN and RUIHS, respectively.

2.4.1 Posterior Beliefs, Threshold Rule and the Bidding Decision

One of the important propositions that underlie our analysis is that bidders form posterior beliefs on the value of the object before they make their bidding decision. Also, I maintain that bidders follow a threshold rule to bid high if the posterior is greater than 0.5 and bid low otherwise.

Table 2.2 Posterior, Threshold Beliefs and Bids

Signal	Posterior > 0.5		Posterior = 0.5		Posterior <0.5		Total
	High bid	Low bid	High bid	Low bid	High bid	Low bid	
High	391	77	27	25	17	23	560
Low	45	68	19	56	46	346	580
Total	436	145	46	81	63	369	1140

As shown in Table 2.2, our data indicates that 75% of all bidders whose posterior is greater than the threshold level made a high bid. In addition, more than 85% of bidders made a low bid, when their posterior belief was below the threshold value. As mentioned in Section 2, the decision of bidders when the posterior is equal to the threshold is ambiguous. But I observe that more than half of the bidders with posterior equal to 0.5 follow their signal as a tie-breaking rule.

2.4.2 Updating Beliefs

It is interesting to see whether the bidders respond to signals in forming their beliefs on the value of the object. In our experiment, bidders form their beliefs in two steps. They observe the previous history of bids and form a prior belief. Then they receive their private signal on the basis of which they update their beliefs and form posterior beliefs.

Table 2.3 Updating Beliefs

Signal	Posterior > Prior	Posterior = Prior	Posterior < Prior	Total
High	432	87	41	560
Low	61	97	422	580
Total	493	184	463	1140

As shown in Table 2.3, upon receiving a high signal, 77 percent of the bidders revised their prior beliefs upward while around 16 percent maintained their original level of prior beliefs. Similarly, approximately 73 percent of the bidders made a downward revision of their beliefs once they received a low signal and around 16 percent of bidders remained at their original level of prior beliefs without revising it downward. I can conclude that overall, nearly 93 percent of bidders responded to their signal and revised their beliefs as the theory predicts.

It is also interesting to examine whether the bidders update their beliefs in a Bayesian fashion as the theory predicts. I examine the stated prior and posterior beliefs and compare them with equilibrium beliefs as predicted by PBE.

[Insert Figure 2.2 here]

Figure 2.2 shows the prior beliefs and equilibrium prior beliefs of six bidders in the first round of bidding. It is important to recall that the prior is formed by the bidder by observing the previous history of bids. In both high precision treatments, there is a considerable and increasing divergence of prior and equilibrium prior beliefs. On the other hand, in both the low precision treatments, the prior and equilibrium prior are close and follow the same trend. It is interesting to note that in both high precision and low precision treatment, bidders appear as conservative in forming their beliefs (Grether

(1990) and Griffin and Tversky (1992)). In low precision treatments on the other hand equilibrium prior is lower than stated prior on the average. In both low value treatments, the bidders are more optimistic on the value of the object than they should be from observing the history.

[Insert Figure. 2. 3 Here]

A similar pattern is visible when I examine the posterior and equilibrium posterior. Figure 2.3 shows the posterior and equilibrium posterior in all four cases. In the high precision treatments, the posterior and equilibrium posterior show an increasing divergence as I move from the first to the sixth bidder. In low precision treatments, they are closer and follow the same trend. It is important to point out that in all cases except low value high precision treatments, as the equilibrium posterior moves to the extreme, the movement of posterior is less extreme. In other words, the bidders on the average exhibit conservatism in their beliefs than the theory predicts. This could be traced as one of the important reasons for winner's curse in low value treatments. In short I can conclude that though the bidders on the average update their beliefs in the direction of the signal, they are not Bayesian but show considerable amount of conservatism in the formation of beliefs. (Grether (1990) and Griffin and Tversky (1992))

2.4.3 Prediction of Actions

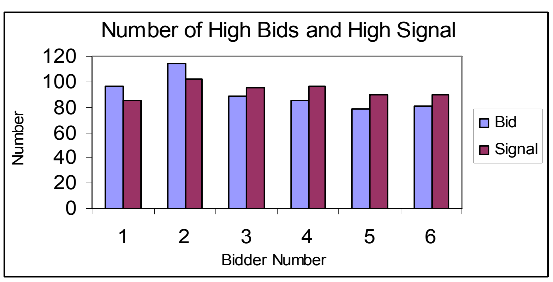
So far, I have been examining the beliefs that the bidders form before they make the bid. I begin our discussion of the bidding behavior by examining whether the bidders behave as the theory predicts. I examine events of interest of the first three bidders in Table 4, with the empirical probability of bids against their theoretical probability.

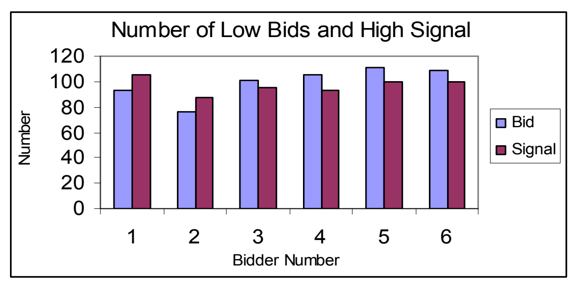
[Insert Table 2.13 Here]

As shown in Table 2.13, I examine the bidding decisions of the first three bidders after observing the history of bids and private signal. As per the theory, the first bidder follows her signal, bidding high when she gets a high signal (88 percent) and bidding low when she gets a low signal (78 percent).

The second bidder, when she gets a confirming signal should follow the signal. But I observe an overwhelming preference to bid high than to bid low in response to a confirming signal. That is 84 percent bid high upon receiving a high signal and 57 percent bid low upon receiving a low signal. In case of a contrary signal, the bidders should follow the signal, 93 percent bid high and 82 percent bid low.

Figure 2.1 Number of Bids and Number of Signals





This general tendency to bid high and thus behaving in a contrarian manner to their signal is visible in Figure 2.1. For the first two bidders, the number of decisions to bid high is more than the number of high signals. Bidders from position three and after show the opposite trend.

2.4.3.1 PBE, OWN Signal and RUIHS

As discussed in section 2, I utilize three possible types of behavior that could characterize the individual decisions in a sequential environment. The variable PBE is meant to capture how well the theory explains data. Bidders will follow PBE if they follow Perfect Bayesian play of the game. As discussed earlier, PBE strategies rely heavily on the common knowledge of rationality and Bayesian updating of beliefs. In a sequential bidding context, making inferences from the actions of the predecessors is a difficult issue. The inferences that different bidders will draw from the same set of information can be different as well. RUIHS is introduced to see how far the bidders can impute signals from the predecessor's actions and then make their bids. Bidders in a strategic setting will rely on their private information by following OWN SIGNAL if they find the public information less reliable or in other words the predecessors are prone to make mistakes. It is also possible that following own signal is rational as discussed in Section 2. I will focus on the fraction of decisions that followed each of these strategies. A*verage PBE* represents the fraction of decisions that follow PBE strategies as prescribed by the theory. On the other extreme, *averages OWN* represents the fraction of decisions that follow private signal. At the intermediate level, *average RUIHS* denotes the fraction of decisions that are rational under the imputed history of signals

Table 2.4 Behavioral Explanation: Average over all markets

	PBE	OWN Signal	RUIHS
All Markets	0.7	0.76	0.74
High Precision	0.83	0.81	0.77
Low Precision	0.75	0.71	0.72

As shown in Table 2.4, *average OWN*, best explains the bidding behavior. More than 76% of bidding decisions are identical to decisions had bidders followed own signal. The other two candidates also fair high in explaining the observed decisions. Actions that are characterized as PBE are the lowest among the three, indicating that equilibrium strategies are less common than others. In high precision treatment, average OWN, average RUIHS and average PBE are higher than the low precision treatment.

2.4.3.2 Herds and Information Cascades

Herd behavior is said to occur in a market with sequential bids if the bidders follow the bidding decisions of the predecessors.

Table 2.5 Herds and Information Cascades

Treatment	Herds	Cascades
All Markets	908 (79.65)	127 (9.21)
High Precision	501 (84.34)	55 (8.01)
Low Precision	407 (74.54)	72 (10.40)

In our experiment, I could successfully replicate herds in the laboratory. As shown in Table 2.5, when all markets are taken together, I find herd behavior in about 80% of decisions. Also herd behavior is more pervasive in markets with high precision of signals. 84.3% of decisions in high precision treatment and 74.5% of decisions in low precision treatment can be treated as herds. This confirms the findings of Alisop and Hey (2001) that as precision of signal increases there is an increasing tendency towards herding.

Cascades occur when a bidder ignores her signal and follows the predecessor's action. Therefore once a cascade sets in, the subsequent bidders cannot infer any information. In our experiment, only 9.3 percent of all decisions can be classified as cascades. But as evident from Table 2.5, cascades are more common in low precision treatments. As I discussed in Section 2, not all herds are due to cascades. Approximately, 14% of herds are due to cascade behavior where the bidders show contrarian behavior with regard to their signal and follow the decision of the predecessor.

In order to check rigorously whether the bidders try to imitate the predecessors in their bidding decisions, I conduct a logit regression analysis with the decision to bid high as the dependent variable of interest. I run four separate regressions with different specifications that underlie our hypotheses about how the bidders behave.

Table 2.6 Logit Regressions - Decision to Bid High in All Markets

	(1)	(2)	(3)	(4)
High signal	2.69*** (16.37)	2.66*** (16.79)	2.45*** (12.00)	2.42*** (10.47)
Number of Previous High Bids	-0.01(0.15)			
Net Number of Previous High Bids		0.20*** (4.21)		
High bid (immediate predecessor)			1.25*** (6.67)	1.21*** (5.59)
High bid (second immediate predecessor)			0.20 (1.05)	0.26 (1.17)
High bid (third immediate predecessor)				0.06 (0.30)
Constant	-1.43*** (10.6)	-1.44*** (13.1)	-2.27*** (11.4)	-2.32*** (9.84)
Number of observations	1140	1140	760	570
Log Likelihood	-580.44	-572.03	-372.05	-270.65
Pseudo R2	0.26	0.28	0.29	0.31

Robust z statistics in parentheses, * Significant at 10%, ** significant at 5%, *** significant at 1%

The independent variables used in the regressions are a dummy variable that takes the value one if the signal is high and zero otherwise, number of previous high bids, net number of previous high bids, and dummy variables that take the value one if the immediate predecessors (first second and third) made a high bid. The two variables, number of high bids and net number of previous high bids are used to capture two different behavioral assumptions regarding whether the bidders consider total number of previous high bids or net number of previous high bids to make their decision. I find, as expected, high signal unambiguously has a positive and significant impact on the decision to bid high. Bidders consider net number of high bids rather than simply the total number of previous high bids suggesting the presence of strategic reasoning by the bidders. There is evidence of imitation behavior as seen from the positive and significant effect of the high bid made by the immediate predecessor. The effect of second and third predecessor is statistically not significant pointing to the possibility of rather short horizons of sequential reasoning and non-equilibrium cascades.

Since I anticipate short horizons of sequential reasoning, I will proceed to distinguish between equilibrium and non-equilibrium cascades. I have already found that there are substantial number of decisions that deviate from PBE but could be explained by RUIHS and OWN. Equilibrium cascades occur, when the bidders following PBE strategies find it rational to ignore their private signal and follow their predecessor. When a bidder shows contrarian behavior with respect to her signal and follow the predecessor regardless of the past history, I can observe non-equilibrium cascades. Non-equilibrium cascades exhibit sharp departures from common knowledge of rationality and Bayesian updating.

Table 2.7 Equilibrium and Non-Equilibrium Cascade

Treatment	Cascade	Equilibrium Cascade	Non-equilibrium Cascade
All Markets	127	35(27.56)	92(72.44)
High Precision	55	15(27.27)	40(72.72)
Low Precision	72	20(27, 78)	52(72.22)

As shown in Table 2.7, about 27.56 percent of all cascades can be classified as equilibrium cascades and the rest 72.44 percent of cascades can be treated as non-equilibrium cascades. So I can infer that not all observed cascades are caused due to rational herding behavior.

[Insert Table 2.14 Here]

Now I look at the empirical probability of equilibrium cascade events as prescribed by the theory. In Table 2.14, I present the events of interest, theoretical probability of events, and their empirical probability. I will look at the bidders from position three onwards where I expect equilibrium cascades. One third of bidders in the third position follow their predecessors ignoring their signals. From fourth position onwards the empirical probability of cascades are positive but relatively lower than the theoretical probability. So I conclude that the fractions of players falling into a cascade due to equilibrium play are positive but significantly lower than the theoretical predictions.

[Insert Table 2.15 Here]

Table 2.15 shows the empirical probability of non-equilibrium cascades against their theoretical probability. I can observe substantial amount of contrarian behavior off the equilibrium path. I notice two important features of the bidding behavior. There exists positive empirical probability of non-equilibrium cascades at all bidding positions. Also there is an observable tendency to bid high behaving contrary to private signal for the bidders in the second and third position.

2.4.3.3 Winner's curse

Now I will turn our attention to the winner's curse. As mentioned earlier, in our experiment I observe the winner's curse in all 102 markets with a low value treatment where the winning bidder suffers from losses when the value of the object is revealed at the end of the market. One important question to ask is whether the market aggregates all available information. Full information bid in each market shows the bid at the end of the market had all the bidders acted rationally on the basis of their information.[22] I compare the winning bid and ending bid in each market to the full information bid to understand the how strongly bids are distorted with respect to the full information bid.

Table 2.8 Average Winning Bid, Ending Bid and Full Information Bid

Treatment	Winning Bid	Ending Bid	Full Information Bid	Profit
High value high precision	83.89	81.99	99.61	16.12
High value low precision	81.95	81.06	80.48	18.05
Low value high precision	54.86	31.24	0.39	-54.86
Low value low precision	66.96	43.04	19.52	-66.96

In Table 2.8, I present the average winning bid, full information bid and ending bid in all the four treatments. Except in high value high precision treatment, the winning bid is lower than the full information bid. One important reason for this behavior is apparent conservatism in beliefs as discussed earlier. The bidders tend to follow the market, but less aggressively (Drehmann, Oechssler and Roider (2005)). Also I observe positive profits in the high value treatments and losses in the low value treatments, suggesting to

[22] This is analogous to the bid at the end of the market that a market maker who has observed all signals would make.

the winner's curse in low value markets. Average ending bid is lower than the winning bid pointing to the fact that as bidding proceeds the bidders tend to be more conservative. This also highlights that as bidding proceeds, more information gets aggregated but less than that would lead to a full information decision.

We have now found that in all the markets with low value treatment, there is insufficient aggregation of information and hence winning bids tend to be higher than the full information bid leading to the winner's curse. Now I need to examine whether the observed events of the 'winner's curse are due to the formation of cascades. Rational herding literature explains winner's curse in markets with sequential bids as a result of cascade formation. When a bidder falls into a cascade she is unable to make inferences about the previous bidders signal. So the information aggregation is imperfect leading to the bidders making mistakes.

Table 2.9 Winning Bidders, Herds and Cascades

Treatment	Number of Winners	Herd	Equilibrium Cascade	Non-equilibrium Cascade
All Markets	281	186	6	13
High Precision	137	93	3	9
Low Precision	144	93	3	4

But, as seen in Table 2.9, only 0.06 percent of the wins are due to cascades. When I examine winner's curse specifically, I find that only 0.05 percent of the winners facing loses could be explained by cascades. However, more than 66 percent of winners can be identified as falling into a herd. About 64 percent of winner's curse can be accounted to as a result of herd behavior. Equilibrium cascade behavior is a rather insignificant determinant of the winner's curse. Even non-equilibrium cascades have a minor role in causing the winner's curse. But herding can explain a majority of events of winner's curse. Herding in the absence of cascade formation implies that bidders upon receiving a confirming signal follow the signal. In low value treatments this tends to high bids and hence the winner's curse.

2.4.4 Generalized Decision Weight Model

So far I have seen that the bidders exhibit a significant amount of herd behavior in all treatments. Equilibrium cascade behavior on the other hand is significantly less than the theoretical predictions of the PBE. Also I found that non-equilibrium cascade behavior is also present. The bidding decisions could be described by different behavioral strategies followed by the bidders, but none of them can explain the informational content behind the decisions. In this section, I report the results of Generalized Decision Weight Model discussed earlier to understand the weights the bidders place on the two sources of information available to them at the time of bidding. As discussed earlier, I have constructed a more accurate private information variable that captures the private information available to each bidder using the stated prior and posterior beliefs.

Table 2.10 Estimates of Generalized Decision Weight Model - All Bids

	All Markets	High Precision	Low Precision
Public Information	0.32*** (5.56)	0.54*** (6.28)	0.05 (0.56)
Private Information	0.78*** (8.71)	0.84*** (6.37)	0.68*** (5.53)
Intercept	-0.12*(1.93)	-0.04 (0.47)	-0.23** (2.50)
Log Likelihood	-660.72	-316.28	-335.609
Pseudo R2	0.16	0.23	0.11
Number of Observations	1140	594	546

Robust z statistics in parentheses, * Significant at 10%, ** significant at 5%, *** significant at 1%

In Table 2.10, the results of the General Decision Weight Model for all markets and the two treatments are presented.[23] I focus on the ratio of the slope coefficient estimates to examine the relative weights placed on public and private information. In all treatments pooled together and each of them separately, I find that the coefficient of public information is significantly smaller in magnitude than the coefficient of private information. In the pooled case, the former is only 41 percent of the latter. This finding confirms the results obtained in other cascade experiments (Anderson and Holt (1997), Hung and Plott (2001) and Dominitz and Hung (2003)) that the bidders on the average exhibit strategic behavior.[24] Our belief that the bidders will give more weight to public information, if the signals are less precise is contradicted by the results. In the high precision treatment, the weight placed on public information is 64 percent of the latter while in the low precision treatment, the coefficient on public information is not statistically different from zero indicating that the bidders place all the weight on private information. One possible explanation for this is that with imprecise signals, the bidders' belief in the rationality of the predecessors is lower, leading them to follow ones own signal. In other words, with confirming signals, bidders place more weight on public information and with disconfirming signals the bidders follow their own signals.

[23] I have used Huber-White Sandwich estimator for deriving the standard errors in the logistic regression to control for the repeated observation of individuals.

[24] The ratio of slope coefficients is 0.43 in Anderson and Holt (1997), 0.37 in Hung and Plott (2001) and 0.39 in Dominitz and Hung (2003).

Table 2.11 Estimates of Generalized Decision Weight Model- Herds Only

	All Markets	High Precision	Low Precision
Public Information	0.67*** (7.67)	0.88*** (6.96)	0.41*** (3.22)
Private Information	0.88*** (7.66)	0.94*** (5.05)	0.77*** (5.52)
Intercept	-0.17** (1.98)	-0.02 (0.17)	-0.36*** (2.85)
Log Likelihood	-481.57	-236.92	-237.84
Pseudo R2	0.23	0.32	0.14
Number of Observations	908	501	407

Robust z statistics in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%

Now I will examine the herd and cascade events separately. When I examine the herds as given in Table 2.11, the ratio of the coefficients is 0.76 in the pooled data indicating that the bidders assign more weight to public information but significantly less than private information Therefore observed herd behavior is due to the use of both private and public information with a greater weight assigned to the former. Also I find the ratio of coefficients higher in the high precision treatments than the low precision treatments, 0.93 and 0.53 respectively. This indicates that in high precision treatments, herd behavior is due to an increased reliance on public information.

Table 2.12 Estimates of the Generalized Decision Weight Model –Cascades only

	All Markets	High Precision	Low Precision
Public Information	1.94*** (5.82)	1.34*** (3.21)	3.03*** (3.87)
Private Information	-0.56** (2.20)	-0.59** (2.38)	-0.23 (0.63)
Intercept	-0.17 (0.66)	0.44 (1.18)	-1.4118
Log Likelihood	-54.06	-26.62	-22.65
Pseudo R2	0.38	0.26	0.51
Number of Observations	127	55	72

Robust z statistics in parentheses. * Significant at 10%, ** significant at 5%, *** significant at 1%

In order to examine whether the model is robust, I estimate the decision weight model for the cascade events alone. In both treatments and the pooled results I find that coefficients on public information are positive and substantially larger in magnitude. The coefficients on private information show negative sign indicating that private information is more than offset by public information in cascade situations. Therefore our results indicate that cascades events occur due to the swamping of public information by public information as held by the theory (Neeman and Orosel (2001)).

2.5 Summary and Conclusions

In situations where individuals make decisions in a sequential manner, information cascades and herd behavior are widely prevalent. In the chapter, I introduced a strategic environment where I examined bidding decisions in markets with sequential bids. I look at herd behavior and information cascades as the reason behind widely observed phenomenon of the winner's curse. I collect information on the beliefs that bidders form at different stages of bidding providing financial incentives to reveal the truth.

I find that bidders form beliefs on the basis of which they make their bidding decisions. There is evidence to learn that bidders update their beliefs on the basis of the private signal, but not necessarily in the Bayesian fashion. From the bidding decisions I observe that both herds and cascades are present though cascades on the equilibrium path are considerably less. Due to departures from common knowledge and perfect rationality, cascades off the equilibrium path are also prevalent. I have found that the winner's curse is quite pervasive in the experimental markets with sequential bids. However, herd behavior more than cascades could be credited to the occurrence of the winner's curse. Conservatism in beliefs and apparent disconfirmation bias could be credited to the winner's curse.

In order to explain the information processing and information content behind the bidding decisions, I estimate Generalized Decision Weight Model that allocates weights to the public and private information behind decisions. I find that in a strategic environment, bidders place more weight on private information than on public information. Herds are caused due to the use of both private and public information. In the case of cascade events, private information gets swamped by public information.

Table 2.13 Some Events of Interest

Bidder Number	Event of Interest	Theoretical Probability	Empirical Probability		
			All	High Precision	Low Precision
1	$b_1^H \mid s_H$	1	0.88 (85)	0.88 (42)	0.86 (43)
	$b_1^H \mid s_L$	0	0.22 (105)	0.16 (57)	0.29 (48)
	$b_1^L \mid s_L$	1	0.78 (105)	0.84 (57)	0.71 (48)
	$b_1^L \mid s_H$	0	0.13 (85)	0.12 (42)	0.14 (43)
2	$b_2^H \mid s_H, b_1^H$	1	0.84 (32)	0.90 (20)	0.75(12)
	$b_2^L \mid s_L, b_1^H$	0	0.82 (65)	0.73 (26)	0.87 (39)
	$b_2^L \mid s_H, b_1^H$	0	0.16 (32)	0.10 (20)	0.25 (12)
	$b_2^L \mid s_L, b_1^L$	1	0.57 (23)	0.47 (15)	0.75 (8)
	$b_2^H \mid s_H, b_1^L$	1	0.93 (70)	0.90 (38)	0.97 (32)
	$b_2^L \mid s_H, b_1^L$	0	0.07 (70)	0.11 (38)	0.03 (32)
	$b_2^H \mid s_L, b_1^L$	0	0.44 (23)	0.53 (15)	0.25 (8)
3	$b_3^H \mid s_L, b_1^L, b_2^L$	0	0.33 (6)	0.33 (3)	0.33 (3)
	$b_3^H \mid s_H, b_1^L, b_2^L$	0	0.67 (12)	0.75 (8)	0.50 (4)
	$b_3^L \mid s_L, b_1^H, b_2^H$	0	0.68 (22)	0.69 (16)	0.67 (6)
	$b_3^L \mid s_H, b_1^H, b_2^H$	0	0.06 (17)	0.00 (9)	0.13 (8)
	$b_3^L \mid s_H, b_1^L, b_2^L$	1	0.33 (12)	0.25 (8)	0.50 (4)

Table 2.14 Empirical Conditional Probability of Actions- Equilibrium Cascades

Bidder Number	Event of Interest	Theoretical Probability	Empirical Probability		
			All	High Precision	Low Precision
3	$b_3^H \mid s_L, b_1^H, b_2^H$	1.00	0.32 (22)	0.32 (16)	0.33 (6)
	$b_3^L \mid s_H, b_1^L, b_2^L$	1.00	0.33 (12)	0.25 (8)	0.5 (4)
4	$b_4^H \mid s_L, b_1^H, b_2^H, b_3^H$	1.00	0.38 (8)	1.00 (3)	0.00(5)
	$b_4^L \mid s_H, b_1^L, b_2^L, b_3^L$	1.00	0.25 (4)	0.00 (2)	0.50 (2)
5	$b_5^H \mid s_L, b_1^H, b_2^H, b_3^H, b_4^H$	1.00	0.20 (5)	0.00 (2)	0.33 (3)
	$b_5^L \mid s_H, b_1^L, b_2^L, b_3^L, b_4^L$	1.00	0.50 (2)	0.00 (0)	0.50 (2)
	$b_5^H \mid s_L, b_1^H, b_2^H, b_3^L, b_4^H$	1.00	0.00 (2)	0.00 (0)	0.00 (2)
	$b_5^L \mid s_H, b_1^L, b_2^L, b_3^H, b_4^L$	1.00	0.00 (1)	0.00 (0)	0.00 (1)
	$b_5^H \mid s_L, b_1^H, b_2^L, b_3^H, b_4^H$	1.00	1.00 (3)	0.00 (0)	1.00 (3)
	$b_5^L \mid s_H, b_1^L, b_2^H, b_3^L, b_4^L$	1.00	0.43 (7)	1.00 (1)	0.33 (6)
	$b_5^H \mid s_L, b_1^L, b_2^H, b_3^H, b_4^H$	1.00	0.25 (8)	0.50 (4)	0.00 (4)
	$b_5^L \mid s_H, b_1^H, b_2^L, b_3^L, b_4^L$	1.00	0.46 (11)	0.00 (1)	0.50(10)
6	$b_6^H \mid s_L, b_1^H, b_2^H, b_3^H, b_4^H, b_5^H$	1.00	0.00 (1)	0.00 (0)	0.00 (1)
	$b_6^L \mid s_H, b_1^L, b_2^L, b_3^L, b_4^L, b_5^L$	1.00	0.00 (1)	0.00 (0)	0.00 (1)
	$b_6^H \mid s_L, b_1^H, b_2^H, b_3^H, b_4^L, b_5^H$	1.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^L \mid s_H, b_1^L, b_2^L, b_3^L, b_4^H, b_5^L$	1.00	0.50 (2)	0.00 (1)	1.00 (1)
	$b_6^H \mid s_L, b_1^H, b_2^H, b_3^L, b_4^H, b_5^H$	1.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^L \mid s_H, b_1^L, b_2^L, b_3^H, b_4^L, b_5^L$	1.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^H, b_2^L, b_3^H, b_4^H, b_5^H$	1.00	0 00 (3)	0.00 (0)	0.00 (3)
	$b_6^L \mid s_H, b_1^L, b_2^H, b_3^L, b_4^L, b_5^L$	1.00	0.33 (3)	1.00 (1)	0.00 (2)
	$b_6^H \mid s_L, b_1^L, b_2^H, b_3^H, b_4^H, b_5^H$	1.00	0.50 (2)	0.50 (2)	0.00 (0)
	$b_6^L \mid s_H, b_1^H, b_2^L, b_3^L, b_4^L, b_5^L$	1.00	0.50 (4)	0.00 (0)	0.50 (4)

Table 2.15 Empirical Probability of Actions-Non Equilibrium Cascades

Bidder Number	Event of Interest	Theoretical Probability	Empirical Probability: All	Empirical Probability: High Precision	Empirical Probability: Low Precision
2	$b_2^H \mid s_L, b_1^H$	0.00	0.19(65)	0.27 (26)	0.13 (39)
3	$b_3^H \mid s_L, b_1^L, b_2^H$	0.00	0.22 (41)	0.28 (18)	0.17 (23)
4	$b_4^H \mid s_L, b_1^L, b_2^L, b_3^H$	0.00	0.13 (8)	0.17 (6)	0.00 (2)
	$b_4^H \mid s_L, b_1^L, b_2^H, b_3^H$	0.00	0.31 (16)	0.4 (10)	0.17 (6)
	$b_4^H \mid s_L, b_1^H, b_2^L, b_3^H$	0.00	0.38 (13)	0.00 (2)	0.45 (11)
5	$b_5^H \mid s_L, b_1^L, b_2^H, b_3^L, b_4^H$	0.00	0.25 (4)	1.00 (1)	0.00 (3)
	$b_5^H \mid s_L, b_1^H, b_2^L, b_3^L, b_4^H$	0.00	0.00 (2)	0.00 (0)	0.00 (2)
	$b_5^H \mid s_L, b_1^L, b_2^L, b_3^H, b_4^H$	0.00	0.00 (1)	0.00 (1)	0.00 (0)
	$b_5^H \mid s_L, b_1^L, b_2^L, b_3^L, b_4^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^L, b_2^L, b_3^L, b_4^L, b_5^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
6	$b_6^H \mid s_L, b_1^H, b_2^L, b_3^L, b_4^L, b_5^H$	0.00	0.00 (1)	0.00 (0)	0.00 (1)
	$b_6^H \mid s_L, b_1^L, b_2^H, b_3^L, b_4^L, b_5^H$	0.00	0.00 (5)	0.00 (2)	0.00 (3)
	$b_6^H \mid s_L, b_1^L, b_2^L, b_3^H, b_4^L, b_5^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^L, b_2^L, b_3^L, b_4^H, b_5^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^H, b_2^H, b_3^L, b_4^L, b_5^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^L, b_2^H, b_3^H, b_4^L, b_5^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^L, b_2^L, b_3^H, b_4^H, b_5^H$	0.00	0.00 (0)	0.00 (0)	0.00 (0)
	$b_6^H \mid s_L, b_1^H, b_2^L, b_3^H, b_4^L, b_5^H$	0.00	1.00 (1)	0.00 (0)	1.00 (1)
	$b_6^H \mid s_L, b_1^L, b_2^H, b_3^L, b_4^H, b_5^H$	0.00	0.00 (1)	0.00 (1)	0.00 (0)
	$b_6^H \mid s_L, b_1^H, b_2^L, b_3^L, b_4^H, b_5^H$	0.00	0.00 (1)	0.00 (0)	0.00 (0)

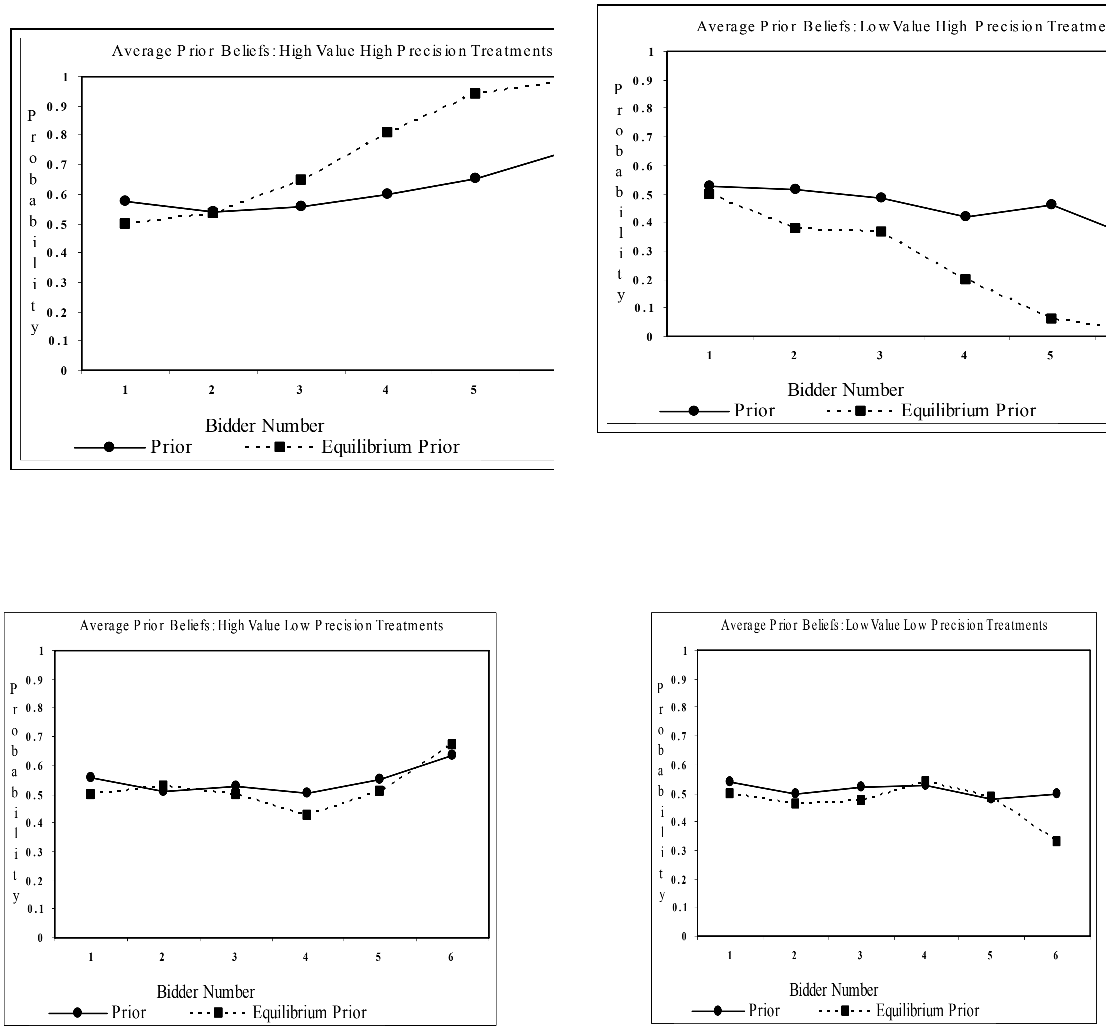


Figure 2.2Average Prior and Equilibrium Prior

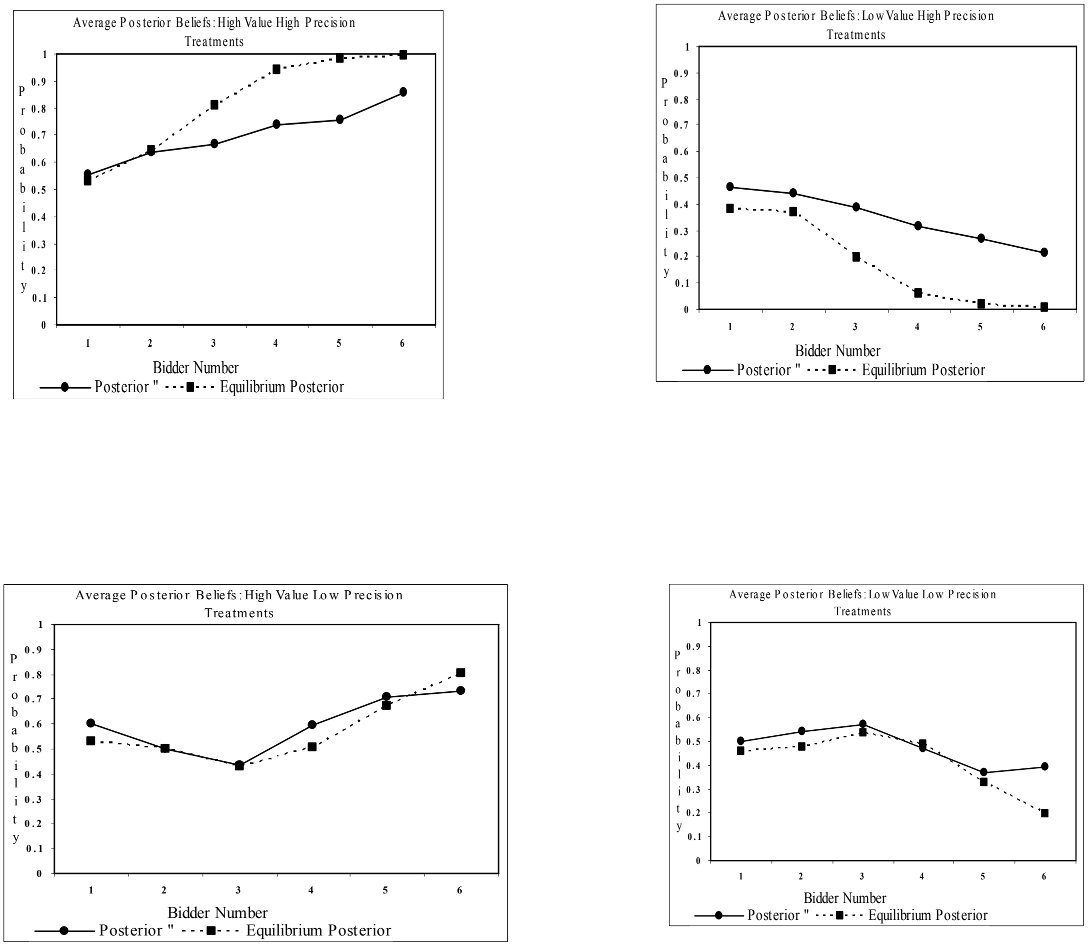


Figure 2.3 Average Posterior and Equilibrium Posterior

Chapter 3 Heuristics and Biases in the Formation of Beliefs: An Experiment in Markets with Sequential Bids

3.1. Introduction

In environments with imperfect information, individuals have to form judgments about the uncertain state of the world in order to evaluate alternate state contingent actions and their consequences. But due to cognitive limitations on computational ability, decision makers tend to use simplified procedures or heuristics that causes systematic biases in problem solving, judgment and choice (Tversky and Kahneman (1982), Kagel and Roth (1995) and Camerer (2003)). In this paper, I examine whether one such bias, confirmation bias and its mirror image disconfirmation bias, lead to systematic errors in the formation of beliefs by bidders in markets with sequential bids. In particular, I attempt to understand whether errors in the formation of beliefs can explain the observed overbidding in common value auction environments[25].

In the literature on common value auctions, overbidding has been credited to risk aversion (Lind and Plott (1991)) and winners' curse (Holt and Sherman (2000)). Very few attempts have been made to explain overbidding when the bidders experience 'the joy of winning '(Goeree and Offerman (2003)) or when the bidders deviate from the equilibrium notions of belief formation. When bidders experience some non pecuniary utility by being the winner in an auction, there is a tendency for the bidders to start with strong prior beliefs that the value is high for the object being auctioned and interpret any

[25] Overbidding in common value auctions have been widely documented in the empirical literature (Capen et al. (1971), Roll (1986), McAfee and McMillan (1987), Thaler (1988), Ashenfelter and Genesove (1992) and Kagel (1995). Several laboratory experiments have also provided convincing evidence of overbidding in common value environments (Kagel (1995)).

new evidence as confirming or disconfirming their previously held beliefs. Thus confirmation bias and disconfirmation bias can be understood as the tendency exhibited by bidders to use new information as confirming or disconfirming their previously held beliefs. These biases in the formation of beliefs and the use of heuristics like conservatism causes deviations form Bayesian behavior. Non equilibrium beliefs thus formed can in turn result in overbidding by bidders in common value auction environments.

This paper differs from the previous experimental work on decision making and auctions on the following grounds. First, I introduce a strategically richer economic environment to study biases and heuristics in the formation of beliefs. Second, I examine whether these deviations from Bayesian behavior can explain observed overbidding in markets with common values. Third, I use the rich experimental data on subjective beliefs and actions to study whether equilibrium belief formation is a prerequisite for observed equilibrium actions. Despite biases in the formation of beliefs, many a times, decisions that are taken based on biased subjective beliefs are consistent with the theoretical predictions (Gigerenzer and Goldstein (1996)). In other words, I attempt to understand whether decision makers eventually make optimal decisions with biased beliefs.

I introduce a strategic environment in which individuals bid in a sequence for an object whose value can be high or low at the end of the period.   Each bidder receives a private signal on the value of the object which is more likely to be true than false. Each bidder has two sources of information: the history of previous bids that she observes and an informative private signal. I elicit beliefs at different stages of the bidding process which helps us to draw conclusions on the process of belief updating and the factors underlying that process.

Analysis of the experimental data reveals that there exists hardly any evidence of Bayesian updating of beliefs for the bidders as a whole. Our results indicate the presence of heuristics and biases in the formation of subjective beliefs by the bidders. In high value treatments, I find evidence for confirmation bias and conservatism while in low value treatments, disconfirmation bias and conservatism are prevalent. Moreover, overbidding in low value treatments can be explained by conservative belief updates. But in both high value and low value treatments, bidders consistently follow their signal and update their beliefs in the direction of the signal. One of the important results is that Perfect Bayesian Equilibrium behavior is consistent with the presence of heuristics and biases in belief formation.

This paper is divided into six sections. In the second section, I briefly explain the biases and heuristics discussed in the literatures which are considered to inhibit Bayesian behavior. The third section introduces the economic environment and experimental set up. In the fourth section, I discuss the analytical framework and the econometric model, which are intended to develop a test for confirmation bias, disconfirmation bias and other heuristics discussed in the third section. The fifth section briefly discusses the results and the sixth section concludes.

3.2. Departures from Bayesian Behavior

In this section, I will outline some of the relevant literature on various heuristics that have been advanced to explain departures from Bayesian updating. I then introduce the presence of confirmation bias and disconfirmation bias as the reason for the reported simultaneous occurrence of some of these heuristics in the aggregate data.

3.2.1. Confirmation Bias, Disconfirmation Bias and Other Heuristics

In most of modern economic theory, individuals are assumed to be rational utility maximizers given the constraints. In situations where judgments have to be made under uncertainty, the standard view is as follows. Individuals form a set of prior beliefs on the uncertain state of the world given the available information. As they receive additional information or signals, they update their beliefs using the Bayes' rule to form posterior beliefs. The posterior beliefs thus formed, motivate individual decisions that maximize the optimization objectives.

Computing probabilities using Byes' rule is complicated in real life situations and hence people use simple heuristics in updating their beliefs when they receive new information (Kahneman, Slovic and Tversky (1982)). When decision makers use heuristics like 'base rate ignorance' and representativeness' they tend to ignore the base rates and overweight new information. (Kahneman and Tversky (1972). In an abstract experimental setting, Grether (1980) and Grether (1991) show that financially motivated subjects underweighted base rates less than the likelihoods as representativeness predicts, but not entirely. Another heuristic that is used in updating beliefs relative to the Bays' rule is 'conservatism' wherein the subjects underweight likelihood information and thus all new information is insufficiently weighted. On the other hand, 'overreaction' is said to occur if all new information is over-weighted. McKelvey and Page (1990) observe conservatism in the updating of probabilities in an experiment similar to Grether (1980). Eger and Dickhaut (1982) found some conservatism when accounting students simply reported probabilities, but it reduced in an environment that penalized Bayesian errors. Camerer (1987) investigates and documents several judgment biases like representativeness, base rate ignorance, conservatism and overreaction jointly in a double auction experimental environment where subjects were engaged in asset trades. Bayesian predictions are rejected and market experience tends to reduce the biases but not eliminate them completely. El Gamal and Grether (1995) formulate a procedure in which the rules of thumb actually used by the subjects can be identified. Their results indicate that subjects use Bayes' rule, reprsentativenss and conservatism in that order of importance.

Though base rate neglect and conservatism are conflicting on first glance, it can be argued that they are both two sides of the same coin (Griffin and Tversky (1992)). Both these phenomena result from individuals overemphasizing the strength of evidence and underemphasizing its weight. Conservatism is a kind of under-confidence that results when individuals under-emphasize the large size (weight) of a sample of weak evidence. Base rate neglect occurs when people overemphasize strong evidence (Camerer (1995)). Therefore, in understanding deviations from Bayesian baseline behavior, it is important to consider the strength of the prior beliefs and how the new information is perceived in the light of prior beliefs. It is in this context that I introduce cognitive biases like confirmation bias and disconfirmation bias which explain the bias in perceiving new information in the light of already existing beliefs.

Confirmation bias is defined as the tendency of individuals to update their beliefs in the light of new information in a manner more likely to confirm and less likely to disconfirm their previously held beliefs relative to a Bayesian observer (Dave and Wolfe (2003)). The opposite bias is the disconfirmation bias where the decision makers tend to interpret the new evidence in a manner to disconfirm their previously held beliefs. Confirmation bias and disconfirmation bias can lead to the use of both conservatism and overreaction as heuristics by underweighting or over-weighting base rates. Also, the presence of these biases can lead to the use of representativeness heuristic as well by overweighting sample in favor of the existing belief or against the existing belief. Thus, confirmation bias and disconfirmation bias understands deviations from the Bayesian behavior with respect to the prior beliefs held by the decision maker as the reference point As I have noted, in several experimental investigations like Camerer (1987) and El Gamal and Grether (1995), several or all of the heuristics have been used by decision makers depending on the environment. Introduction of confirmation bias and disconfirmation bias in this sense explains the simultaneous occurrence of the use of these heuristics in the aggregate data.

Various suggestions have been put forth by the psychological literature on the cognitive processes that give rise to confirmation bias ((Manktelow and Over (1993); Oaksford and Chater (1994); Cheng and Holyoak (1989)). First, as suggested in Wason

(1968), individuals tend to seek evidence that can confirm a hypothesis than that can disconfirm it. In this experiment, subjects engaged in a card selection task in which two sided cards could be turned over or not to conform or disconfirm a rule that the cards were supposed to follow[26]. The results showed that majority of decisions exhibited confirmation bias. Subjects would turn over those cards that could confirm the rule and not the cards that could disconfirm it. Jones and Sudgen (2002) modified the Wason Selection Task by placing it within a Bayesian decision theory framework where costs, benefits and prior probabilities of acquiring information were made explicit. They found evidence for confirmation bias when subjects purchased information and when they used it for decision making. Also, it was observed that the bias persisted even after the subjects repeatedly engaged in the selection task.

Second, individuals tend to make mistakes in perceiving signals or interpreting evidence in such a way that they support their hypothesis. Ambiguous evidence can be interpreted by two individuals with opposing beliefs to support their hypothesis (Lord, Lepper and Ross (1979) and Plous (1991). From the behavioral economics perspective, within a signal extraction framework, Rabin and Schrag (1999) provides a theoretical model in which agents suffering from confirmation bias are shown to be overconfident relative to a Bayesian observer. The model shows that this leads to failure in learning despite infinite amount of information available.

[26] Four cards were shown marked E, K, 4 and 7. Each had a letter on one side and a number on the other. The following rule was given-each card with a vowel on one side had an even number on the other side. The task is to state which cards are to be turned over to test whether the rule is true or false.

To summarize, the cognitive processes underlying confirmation bias relative to Bayesian updating involves two components. If the decision task involves seeking new information, agents tend to seek confirmatory evidence. If the task does not involve information seeking, agents misperceive information to support their existing beliefs. The second aspect has been demonstrated by Dave and Wolfe (2003) in simple non strategic environments. In this paper, I develop a strategically richer environment for testing confirmation bias due to subjects misperceiving information.

3.2.2. Equilibrium Actions with Biased Beliefs

Despite the apparent complexities in Bayesian updating and presence of biases in the formation of beliefs, people do not seem to make mistakes in their actions almost all the time. Recent approaches to decision making have argued that emphasis on speed and frugality replaces the methods of classical rationality with ‘‘simple, plausible psychological mechanisms of inference that a mind can actually carry out under limited time and knowledge’’ (Gigerenzer and Goldstein (1996)). The fast and frugal approach to judgment and decision making has achieved recent wide popularity ((Gigerenzer (2000), Gigerenzer and Goldstein (1996), Gigerenzer and Selten (2001) and Gigerenzer and Todd (1999)). According to this view, individuals use simple heuristics in decision making to save time and reduce computational complexity on the one hand and reduce informational requirements on the other. In the absence of information on beliefs held by the decision makers, observed Bayesian Equilibrium behavior is often regarded as a result of equilibrium or ‘correct’ formation of beliefs. In such cases, Bayesian actions are defined as one to one mapping from equilibrium beliefs to equilibrium actions. Instead, according to the fast and frugal framework, equilibrium actions are defined as a many to one mapping from beliefs to equilibrium actions. In such situations, even with biased or incorrect beliefs, decision makers can end up in equilibrium actions. With our rich experimental data on beliefs at different stages of the bidding process, I examine whether PBE behavior is consistent with the presence of heuristics and biases in decision making. In other words, I attempt to answer the question as to whether with the use of heuristics and with the presence of biases in the formation of beliefs; people are able to approximate PBE decisions.

3.3. Experimental Set Up

We consider a variant of the model by Neeman and Orosel (1999) in which the seller sequentially obtains bids for an object from a finite number of bidders. All the bidders have the same ex-post valuation of the object. They differ only in their estimates of this value. Similar to the card selection task, bidders have to decide whether to make a high bid or low bid, depending on their subjective beliefs on the value of the object. So a bidder in each market starts with a subjective prior belief on the value of the object on the basis of the available information she has which is the history of previous bids that she observes. Then she is provided an informative costless private signal on the basis of which she updates the subjective prior beliefs to form subjective posterior beliefs. The signal is more likely to be correct than wrong and it is common knowledge to all bidders. Also at the beginning of each market, the precision of the signal or the probability of getting a correct signal is announced[27]. Finally on the basis of the subjective posterior beliefs, she makes her bid on the object. The problem of the bidder in this context is to decide on the basis of her posterior beliefs whether to bid high or remain inactive. The

[27] Please refer to the experimental instructions for details.

sequential nature of the task and the inferences to be made on other bidders' beliefs and actions, typical to an auction context, adds the strategic content to the decision making process. Along with the assumptions of rationality and common knowledge of rationality, the Bayes' Nash equilibrium play of the game ensure that the bidders form correct beliefs on the basis of the Bayes' rule whenever possible. It is this formation of beliefs that is the focus of our investigation in this paper.

The experiment consists of 13 sessions with 190 markets. In each session there are markets in which six bidders bid for the value of the object. The value is high or low with equal ex-ante probability of 0.5, and this is common knowledge to all bidders. The high value is 100 and the low value is 0 in terms of the experimental currency unit franc. Ten francs are equal to 1 rupee. The seller's reservation price is 0. The conditional probability of the signal being correct is always more than 0.5 and is common knowledge to all participants. The seller, if she decides to, can re-approach the active bidders in the next round of bidding.

One important feature of our experiment is the elicitation of beliefs at different stages of bidding process. Beliefs of bidders are elicited through a quadratic scoring rule such that it is their best interest to reveal their true beliefs (Sonnemans and Offerman (2001)).[28] Belief elicitation by providing financial incentives to participants has been used in several experimental studies to report the truth (Nyarko and Shorter (2002) and

[28] Among the different scoring rules, the quadratic scoring rule has the property that it is incentive compatible for the participants to reveal their true beliefs. For some experiments and discussions on scoring rules and their relative strengths and weaknesses, see Sonnemans and Offerman (2001).

Nyarko, Shorter and Sopher (2001)).[29] Since measuring subjective expectations is a difficult task, I elicit subjective beliefs from the bidder as she receives additional information (Manski (2004)). At various stages of the bidding, each bidder is asked to state her beliefs on the probability of the object being of high value. Once her turn to bid comes, the bidder has to state the probability of the object being of high value after observing all previous bids (prior). Then she is asked to state the probability that her immediate predecessor had received a high signal. After she receives her own signal, she is again prompted to state the probability that the object is of a high value (posterior).[30] These stated beliefs are highly informative in understanding how the bidders update their belief as new information is revealed.

Among others, the experiment is also intended to understand whether the precision of signals has an effect on belief formation. Therefore, the precision of signal is set at a high of 0.8 and a low of 0.66. At the beginning of each market, the following information was announced and also exhibited on the blackboard regarding the precision of signal. For example, if the precision was high, it was announced and exhibited that, "the probability of receiving a high signal when the real value of the object being high is 0.8 and the probability of receiving a high signal when the real value of the object being low is 0.2." At the beginning of the experiment, I provided information on how to interpret this announcement and made sure that the participants understood it clearly. Also, I

[29] There are various views on whether belief elicitation would affect the behavior of decision makers. For a discussion on this, see Rustrom and Wilcox (2004) and Dominitz and Hung (2003). In our experiment, I do not intend to examine these possibilities.

[30] The detailed instruction given to each participant (bidder) is given at the end of the paper. At the beginning of each session the instructions were read aloud and the participants were given a copy of the instructions.

assigned the value of the object to be high or low in each market in a predetermined order. Signals that the bidders receive also are random to them but predetermined to ensure maximum cell counts.

Table 3.1 Treatments and Number of Markets

	Precision	
Treatment	High Precision (0.8)	Low Precision (0.66)
High Value	48	40
Low Value	50	52

In short, as shown in Table 3.1, I have high value treatments with the true value of the object being high and low value treatments with the true value of the object being low. Also in each treatment, I have two regimes with high and low precision of signal, hence I can analyze four treatments in the experiment: 1) Treatment I - high value treatment with a high precision of signal. 2) Treatment II - high value treatment with a low precision of signal, 3) Treatment III - low value treatment with high precision of signal, and 4) Treatment IV - low value treatment with a low precision of signal.

The experiments were conducted at Jawaharlal Nehru University and at the Indian Statistical Institute, New Delhi. Since the experiments required participants to state probabilities, I recruited graduate students from statistics and economics programs. The rest of the participant pool consisted of master's level students with training in mathematics, statistics or physics.

At the end of each session the participants were paid in cash. The payment included the profit or loss for winning, remuneration for stated probabilities, along with a participation fee of Rs.50. Participants, on average, earned a sum of Rs.250.00. This is approximately equivalent to 40 percent of monthly expenses on food for a student in these residential universities.

3.4. Analytical Framework

In this section, I present a simple analytic framework to understand the determinants of belief updating process by the bidders in the experiment. As noted earlier, I have collected information on the signal received by each bidder. The subjects reported their prior beliefs, (γ_{ij}), that is probability that the object is of high value before receiving their signal and posterior beliefs, μ_{ij}, that is probability that the object is of high value after receiving their private signal. Using this information, I can calculate the log odds of prior beliefs, $(\delta_{ij} = \ln(\frac{\gamma_{ij}}{1-\gamma_{ij}}))$ and the log odds of posterior beliefs. $(\omega_{ij} = \ln(\frac{\mu_{ij}}{1-\mu_{ij}})$ The log odds ratio of prior beliefs can be thought of as the strength of beliefs .held by each bidder regarding the value of the object before she gets her signal.

3.4.1. Bayesian Behavior

In this paper, our main objective is to identify confirmation bias and disconfirmation bias exhibited by the bidders relative to a hypothetical Bayesian. With the assumptions of rationality and common knowledge of rationality for all bidders, a typical Bayesian will be able to infer the signals previous bidders have received from the history of previous bids. Let the history of previous bids be h_t Let the number of high signals that can be inferred from previous bids by bidder i at t be nh and the number of low signals that can be inferred from previous bids by bidder i at t be nl A hypothetical Bayesian, who estimates the prior beliefs, (γ_{ij}) correctly will calculate the posterior (μ_{ij}) in the following manner.

$$\mu_{it}(h_t, s) = \frac{\theta^{(nh-nl)}}{\theta^{(nh-nl)} + (1-\theta)^{(nh-nl)}}$$

where θ is the probability of getting a high signal when the value is high or in other words, the precision of the signal. As mentioned earlier, before the beginning of each market this information is announced.[31] It is important to note that for the Bayesian, the order in which the signals evolve does not matter since she cares only about the number of high signals and the number of low signals. Each time she sees a new signal, the quantity $(nh-nl)$ increases or decreases by one. Therefore, the log odds of the posterior beliefs, $\omega_i(h_t, s) = (nh-nl)\ln(\frac{\theta}{(1\text{-}\theta)})$ It is evident that the log odds ratio is linear in the net number of signals. Therefore, in the high value high precision treatment (where $\theta = 0.8$, $\omega_i = (nh-nl)\,x1.39$ for each bidder. Therefore after receiving the signal each bidder will update the prior by ± 1.39 if she follows Bayesian behavior. Similarly in the high value low precision treatment, each bidder will update the prior by ± 0.69. In the low value high precision and low value low precision the updates will be ± -1.39 and ± -0.69 respectively. Therefore if the subjects deviate from the Bayesian behavior due to conservatism, smaller updates are observed and if the deviations are due to overreaction larger updates are observed.

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[31] Please refer to the experimental instructions for details.

A bidder is said to have confirmation bias if she perceives and uses new information depending on whether it confirms her previously held belief. In our experiment, I can verify whether new information is confirming or disconfirming to the bidder by comparing it with the prior beliefs. If $\delta_{ij} > 0$, then a high signal is treated as confirming signal and a low signal will be treated as disconfirming signal. Similarly, if $\delta_{ij} < 0$ a low signal is treated as confirming evidence and a high signal will be treated as disconfirming evidence. If $\delta_{ij} = 0$ then the bidder is neutral with respect to her prior beliefs and both high signals and low signal treated identically with respect to the prior beliefs. In short, with the introduction of confirmation bias and disconfirmation bias, the same signal will be interpreted differently by different bidders depending upon their prior beliefs.

3.4.2 Model Specification and Interpretation

First as mentioned earlier, I compute the log odds of prior beliefs, (δ_{ij}) and the log odds of posterior beliefs, (ω_{ij}), from the reported prior and posterior. I also calculate the following variables to be used in the estimation equation. First, I compute the belief updates, on the basis of the signal.

$$y_{ij} = \begin{cases} \omega_{ij} - \delta_{ij} \text{ if } S_{ij} = \mathrm{s_H} \\ \delta_{ij} - \omega_{ij} \text{if } S_{ij} = \mathrm{s_L} \end{cases}$$

A confirming signal dummy is computed,

$$x_{ij}^{C} = \begin{cases} 1 \quad \text{if } \delta_{ij} > 0 \text{ and } S_{ij} = \mathrm{s_H} \\ \qquad \delta_{ij} < 0 \text{ and } S_{ij} = \mathrm{s_L} \\ 0 \quad \text{otherwise} \end{cases}$$

Similarly, a disconfirming dummy is calculated,

$$x_{ij}^{D} = \begin{cases} 1 & \text{if } \delta_{ij} > 0 \text{ and } S_{ij} = \mathrm{s_L} \\ & \delta_{ij} < 0 \text{ and } S_{ij} = \mathrm{s_H} \\ 0 & \text{otherwise} \end{cases}$$

Three interaction terms: signal strength ($x_{ij}^{S} = (s_{ij} \times \delta_{ij})$) confirming strength ($x_{ij}^{CS} = (x_{ij}^{C} \times \delta_{ij})$) and disconfirming strength ($x_{ij}^{DS} = (x_{ij}^{D} \times \delta_{ij})$ are also calculated.

I test two models using the variables I have constructed to throw more light into the process of updating beliefs. I first estimate a general model to test whether the updates are sensitive to the signal alone.

$$y_{ij} = \alpha_0 + \alpha_1 s_{ij} + \alpha_2 x_{ij}^{S} + \xi_{ij} \tag{1}$$

The error term ξ_{ij} can be decomposed into individual fixed effects, ν_{ij} and an idiosyncratic error term. μ_{ij}.

Then, I proceed to estimate the following model to test the presence of confirmation bias and disconfirmation bias in updating beliefs.

$$y_{ij} = \beta_0 + \beta_1 x_{ij}^{C} + \beta_2 x_{ij}^{D} + \beta_3 x_{ij}^{CS} + \beta_4 x_{ij}^{DS} + \varepsilon_{ij} \tag{2}$$

here, as before, the error term ε_{ij} can be decomposed into individual fixed effects, υ_{ij} and an idiosyncratic error term . ς_{ij}. (1) is estimated to examine whether bidders exhibit a tendency to follow their own signal regardless of their prior beliefs as a starting point for our analysis. It can be considered that (2) is nested in (1) since in (2) I split the signal into confirming signal and disconfirming signal and the signal strength into confirming signal strength and disconfirming signal strength to isolate the effect of biases and heuristics as described earlier.

By estimating (1), I can test hypotheses regarding the relationship between belief updates, signal and the strength of beliefs. Also given equation (2), I can test several hypotheses on the prevalence of Bayesian updating, conservatism, confirmation bias, and disconfirmation bias. I also test whether Perfect Bayesian Equilibrium actions are consistent with any of the biases and heuristics above. A graphical illustration of (2), our main regression equation, is presented in Figure 3.1. In both high value treatments, the Bayesian baseline behavior is presented as horizontal lines parallel to the X axis above zero with an intercept of $\ln(\frac{\theta}{(1-\theta)})$ and slope of zero. In both low value treatments, the Bayesian baseline behavior is depicted as horizontal lines parallel to the X axis below zero, with an intercept of $-\ln(\frac{\theta}{(1-\theta)})$ and a slope of zero. If the bidders on the average exhibit conservatism, the estimated regression lines should lie between the Bayesian lines. On the other hand, if the bidders exhibit overreaction on the average, the estimated regression lines should be outside the two baseline Bayesian lines. In the case of confirmation bias or disconfirmation bias, the regression lines will have a slope different from zero. Now, I begin with a description of the hypotheses that I are interested in.

Hypothesis 1: Bayesian updating

Since $\Pr(S_H | V_H)$ and $\Pr(S_L | V_L)$ are announced at the beginning of each market, if the bidders follow Bayesian updating, I will have the following testable hypothesis for (1)

$\hat{\alpha}_0 = \ln(\frac{0.8}{0.2}) = 1.39$ and $\hat{\alpha}_1 = \hat{\alpha}_2 = 0$ in Treatment I

$\hat{\alpha}_0 = \ln(\frac{0.66}{0.33}) = 0.69$ and $\hat{\alpha}_1 = \hat{\alpha}_2 = 0$ in Treatment II

$\hat{\alpha}_0 = \ln(\frac{0.2}{0.8}) = -1.39$ and $\hat{\alpha}_1 = \hat{\alpha}_2 = 0$ in Treatment III

$\hat{\alpha}_0 = \ln(\frac{0.33}{0.66}) = -0.69$ and $\hat{\alpha}_1 = \hat{\alpha}_2 = 0$ in Treatment IV

And for (2), we can test the following hypthesis on Bayesian updating of beliefs.

$\hat{\beta}_0 = \ln(\frac{0.8}{0.2}) = 1.39$ and $\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_2 = \hat{\beta}_4 = 0$ in Treatment I

$\hat{\beta}_0 = \ln(\frac{0.66}{0.33}) = 0.69$ and $\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_2 = \hat{\beta}_4 = 0$ in Treatment II

$\hat{\beta}_0 = \ln(\frac{0.2}{0.8}) = -1.39$ and $\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_2 = \hat{\beta}_4 = 0$ in Treatment III

$\hat{\beta}_0 = \ln(\frac{0.33}{0.66}) = -0.69$ and $\hat{\beta}_1 = \hat{\beta}_2 = \hat{\beta}_2 = \hat{\beta}_4 = 0$ in Treatment IV

As described before, here for the Bayesian behavior to hold, I test whether estimated regression lines are horizontal to the X axis with a specified intercept.

Hypothesis 2: Conservatism and overreaction

We can test the following hypothesis on whether the bidders employ conservatism heuristic by testing the following hypothesis on (2)

$$\hat{\alpha}_0 < 1.39 \text{ in Treatment I}$$

$$\hat{\alpha}_0 < 0.69 \text{ in Treatment II}$$

$$\hat{\alpha}_0 > -1.39 \text{ in Treatment III}$$

$$\hat{\alpha}_0 > -0.69 \text{ in Treatment IV}$$

A similar hypothesis on the use of overreaction heuristic can be tested in (2) also.

$$\hat{\beta}_0 > 1.39 \text{ in Treatment I}$$

$$\hat{\beta}_0 > 0.69 \text{ in Treatment II}$$

$$\hat{\beta}_0 < -1.39 \text{ in Treatment III}$$

$$\hat{\beta}_0 < -0.69 \text{ in Treatment IV}$$

(2) is essentially meant to test hypotheses on whether bidders exhibit confirmation bias and disconfirmation bias in all the four treatments.

Hypothesis 3: Confirmation Bias

$$\hat{\beta}_1 > 0 \text{ and/or } \hat{\beta}_3 \neq 0 \text{ in all the four treatments.}$$

Hypothesis 4 Disconfirmation Bias

$$\hat{\beta}_2 < 0 \text{ and/or } \hat{\beta}_4 \neq 0 \text{ in all the four treatments.}$$

3.5. Results and discussion

[Insert Figure 3.2, Figure 3.3 Figure 3.4 and Figure 3.5 here]

Figure 3.2, Figure 3.3, Figure 3.4 and Figure 3.5 illustrate the average strength of beliefs, average updates, and average prior and average posterior in each treatment. Though a clear correlation between strength of beliefs and updates are visible in treatment I and treatment III (both treatments are with high precision of signals), no clear pattern is discernable in the other low precision treatments. In general, I can conclude that when the precision of signals is higher regarding the value of the object, strength of beliefs and update are closely related.

[Insert Table 3.2, Table 3. 3, Table 3.4 and Table 3.5]

3.5.1 Following private signal

Here I look at the estimates of (1) in all four treatments. It is clear that bidders consistently follow their signal in updating their beliefs in all four treatments. But in the low value treatments, the strength of prior beliefs has no statistically significant effect on the updates. As I hypothesized earlier, in strategic environments, where decision errors have costly consequences for the bidders, and where common knowledge of rationality is not presumed, I can see on the aggregate why bidders tend to give more weight to their private signal given the information that the signals are more likely to be correct than wrong. In order to understand whether the bidders perceive identical signals differently depending upon their prior beliefs, I turn out attention to the estimates of (2) in all four treatments.

3.5.2 Bayesian Updating, conservatism and overreaction

It is evident from the constant terms in (2) in all four treatments that there is no evidence for Bayesian updating. Bidders exhibit conservatism heuristic and make updates of their beliefs less than a Bayesian decision maker. Figure 3.6, Figure 3.7, Figure 3.8 and Figure 3.9 illustrate the estimated regression lines and the Bayesian benchmark in the respective treatments. As pointed out before, the estimated regression lines in Figure 3.6 and Figure 3.7 lie below the Bayesian benchmark in the high value treatments. Similarly, the estimated regression lines in Figure 3.8 and Figure 3.9 lie above the Bayesian benchmark in the low value treatments, providing further evidence for the use of conservatism heuristic in the aggregate data.

3.5.3 Confirmation bias and Disconfirmation bias

Confirmation bias and disconfirmation bias can be identified from the coefficients in (2) on the confirmation signal dummy, disconfirmation signal dummy, confirmation belief strength and disconfirmation belief strength. In both high value treatments, bidders exhibit confirmation bias as evident from the coefficient on the confirming belief strength. Though the coefficient on the confirming signal is not statistically significant, the coefficients on the confirming belief strength points to the fact that bidders treat confirming signals differently from disconfirming signals. As shown in Figure 3.6 and Figure 3.7, in both high value treatments, the estimated regression lines are below the Bayesian baseline and with a negative slope suggesting the presence of both conservatism and confirmation bias in the aggregate data. I also need to also examine why I observe confirmation bias in high value treatments. In auction like environments, bidders typically start with a high prior belief that the value of the object being sold is high. According to our set up, the bidders are more likely to receive high signals than low signals and they are informed at the beginning of each market that the signal is more likely to be correct than wrong, with the exact value of the precision of the signal known. With this information, due to confirmation bias, bidders tend to perceive high signals differently than low signals treating high signals with a higher weight than low signals.

In the low value treatments, I observe that the coefficient on the both the disconfirmation signal and disconfirmation signal strength are statistically significant in treatment III. Along with this, statistically significant coefficient on the disconfirmation belief strength in treatment IV suggests that the bidders on the average show disconfirmation bias. In short, in both low value treatments, I observe disconfirmation bias. Figure 3.8 and Figure 3.9 show that the estimated regression lines in both low value treatments are above the Bayesian baseline with a positive slope. This further confirms that in the aggregate date in the low value treatments, bidders exhibit conservatism and disconfirmation bias. As in the high value treatments, bidders start with a high prior belief that the value of the object being sold is high and they are more likely to observe low signals than high signals. Also they are aware of the precision of the signal and that the signal is more likely to be correct. Therefore, the bidders tend to revise their prior as the signal suggests giving more weight to the low signals, thus disconfirming their prior beliefs. Our data shows that, the bidders tend to treat low signals differently from high signals, due to disconfirmation bias.

3.5.4 Overbidding in markets with common values

Two aspects of bidding behavior in the low value treatments- starting with a high prior belief and conservatism in making belief updates- together provide an explanation for why overbidding occurs in common value treatments due to non-optimal beliefs. A closer look at the estimated regression lines of updates in Figure 3.8 and Figure 3.9 for treatment III and Treatment IV respectively shows that the updates are on the average well above what they should be in equilibrium.[32] Despite the presence of disconfirmation bias in the low value treatments, since the bidders show conservatism in updating beliefs, they fail to make downward revision of beliefs as equilibrium behavior suggests. This

[32] Note that overbidding occurs only in the low value treatments in our experiment. This is because in the high value treatments, the true value of the object and the maximum allowed bid are set as 100. In the low value treatments, the true value of the object is 0 , but the bidders can bid up to a maximum of 100.

leads to posterior beliefs higher than equilibrium posterior beliefs and hence overbidding occurs in common value environments when the value is low.

3.5.5 PBE behavior in the presence of heuristics and bias

As discussed earlier, one of the important concerns in the literature on 'fast and frugal' heuristics is whether the decision makers should hold Bayesian beliefs for implementing Bayesian actions. Table 3.2, Table 3.3, Table 3.4 and Table 3.5 show the estimation results of (1) and (2) on actions which are identical to someone with Perfect Equilibrium beliefs on the equilibrium path. I find that in the estimates of (2) in the high value treatments, bidders show conservatism and confirmation bias. Similarly, the estimates of (2) in the low value treatments on PBE actions show the presence of conservatism and disconfirmation bias. These results suggest that bidders need not necessarily hold Bayesian beliefs on the equilibrium path to generate equilibrium actions.

In summary, I find no support for Bayesian updating of beliefs by the bidders in our experimental data. Though some previous studies have found evidence for Bayesian updating in simple decision making environments (El Gamal and Grether (1995)), in a strategically richer and computationally challenging environment, bidders use simple heuristics in updating their beliefs. The prevalence of overbidding in common value auctions can be understood on the basis of these non optimal beliefs Even Perfect Bayesian Equilibrium decisions are characterized by underlying biased beliefs which are formed by the use of heuristics. This provides further support to the idea that even if people use heuristics and are prone to biases in complex decision making environments; they are able to make the theoretically predicted correct decisions. In the high value treatments, bidders exhibit confirmation bias and conservatism and in the low value treatments, bidders are prone to disconfirmation bias and conservatism. This highlights the apparent sensitivity of biases in belief formation to the environment and treatment conditions. But I find that in our more general specification, bidders tend to follow their private signal in updating their beliefs which can be generalized in both the high value and low value treatments.

3.6. Conclusion

In this paper, I introduced a strategically richer environment as against the previous studies on decision making to examine the formation of beliefs by decision makers. In particular, I attempted to test whether heuristics and biases were used by the bidders in experimental markets with sequential bids. I found hardly any evidence of Bayesian updating. Instead, bidders use conservatism heuristic in forming their subjective beliefs before they make their bids. Both confirmation bias and disconfirmation bias are present in the formation of beliefs in high value and low value treatments respectively. But in both the high value and low value treatments, bidders tend to update their beliefs in the direction of their signal. Our results, therefore, point out that though systematic biases are observed in updating beliefs, they are highly sensitive to treatment conditions and the environment in which the decision process is set. In strategic environments, bidders, in general, follow their private information and confirmation bias and disconfirmation bias cannot be generalized across treatments. It is the high prior beliefs that the bidders start with and the overwhelming tendency to follow their own signal that give rise to these biases. Moreover, non-optimal posterior beliefs due to upwardly biased prior beliefs and conservatism in updating beliefs can be advanced as a plausible explanation for overbidding in common value auction environments. Perfect Bayesian Equilibrium actions are consistent with the presence of heuristics and biases in belief formation, suggesting that equilibrium actions need not necessarily be a result of equilibrium beliefs.

Figure 3.1 Bayesian behavior, conservatism and overreaction: A Diagrammatic Illustration

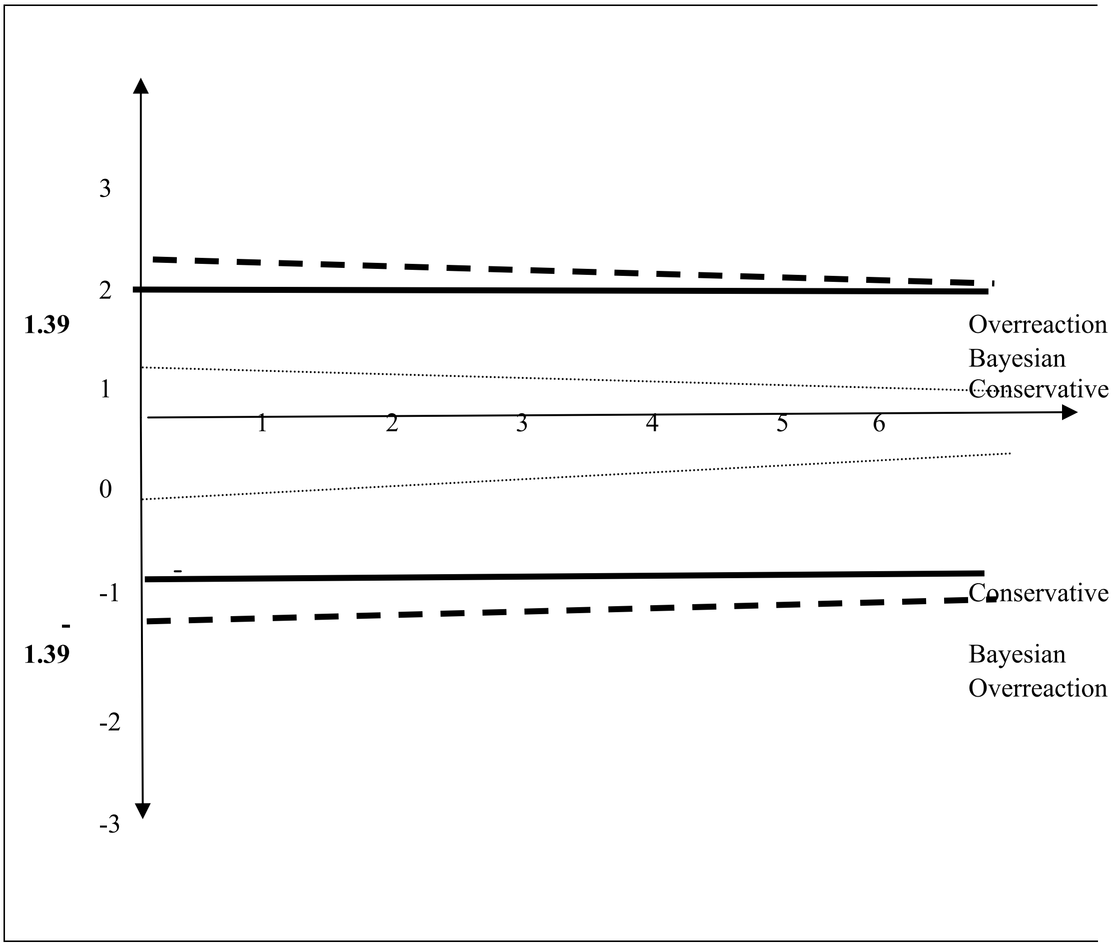

Figure 3.2 Treatment 1: Average Strength of Belief and Average Update

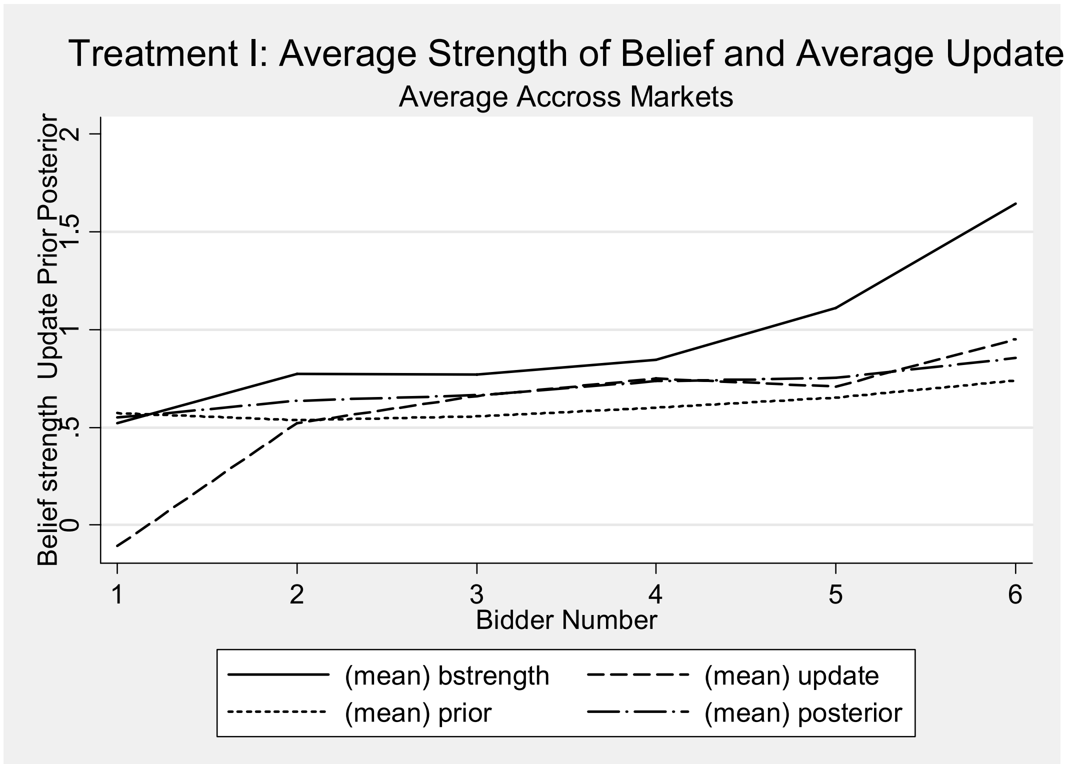

Figure 3.3 Treatment 2: Average Strength of Belief and Average Update

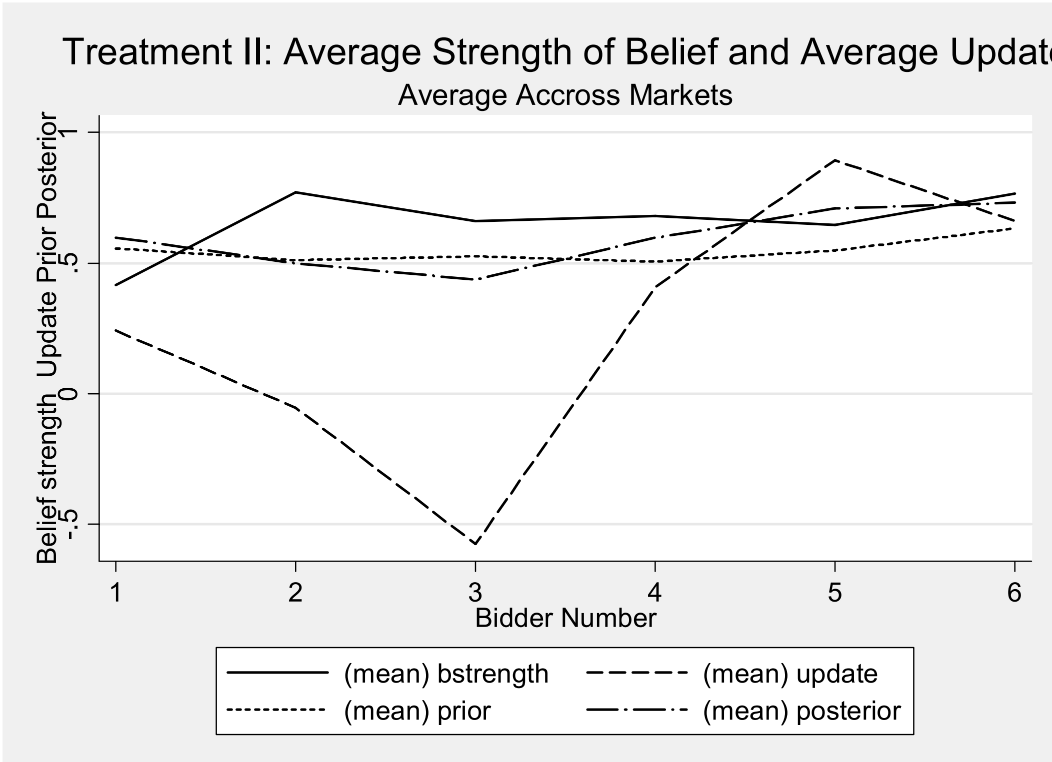

Figure 3.4Treatment 3: Average Strength of Belief and Average Update

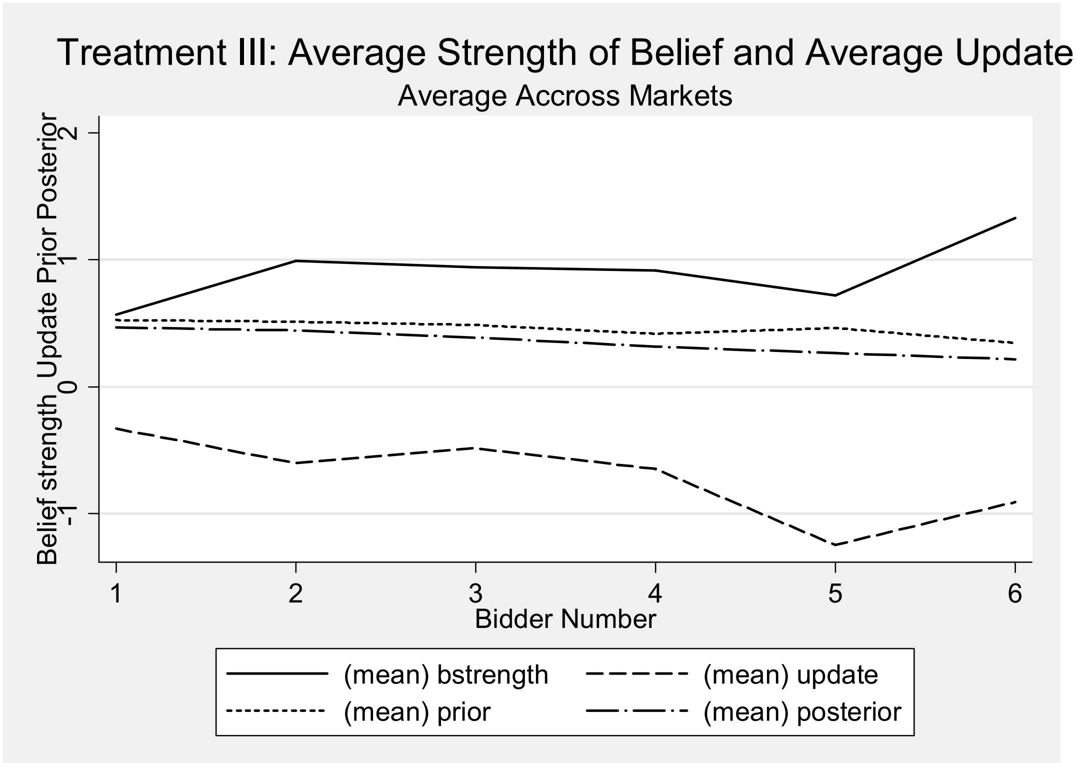

Figure 3.5 Treatment 4: Average Strength of Belief and Average Update

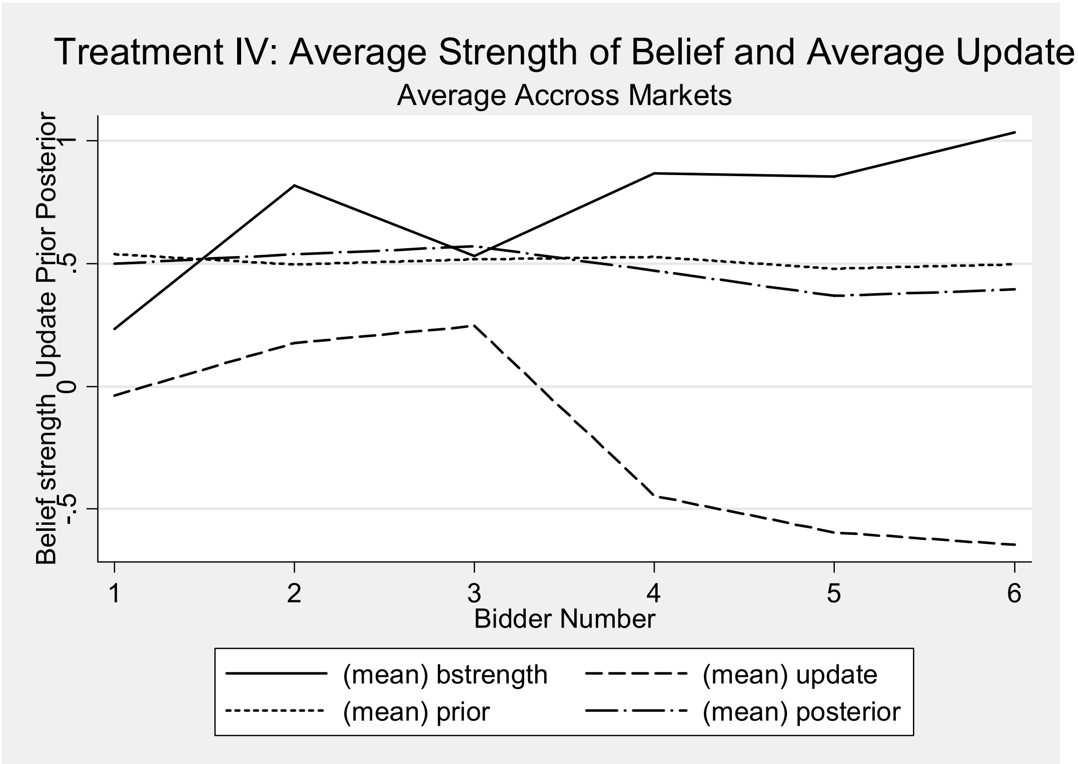

Figure 3.6 Treatment1: Bayesian and Estimated Belief Updates

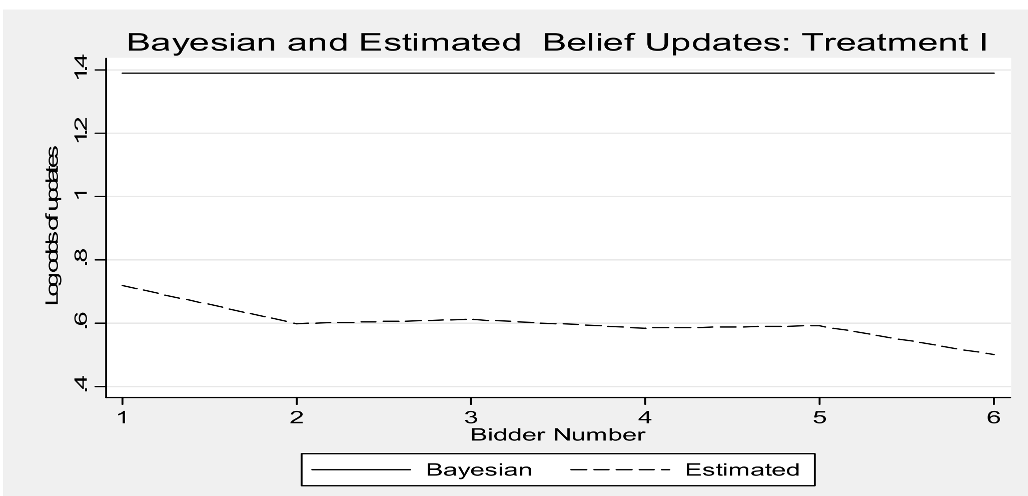

Figure 3.7Treatment 2: Bayesian and Estimated Belief Updates

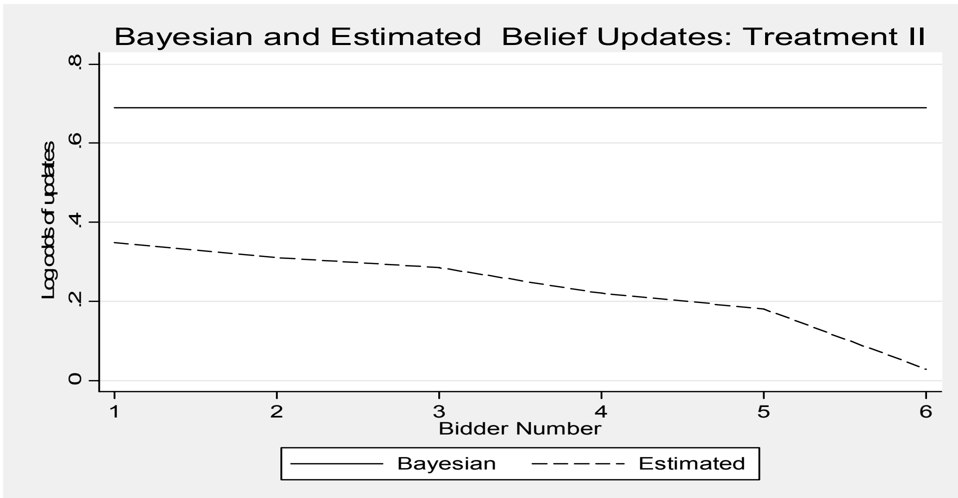

Figure 3.8Treatment 3: Bayesian and Estimated Belief Updates

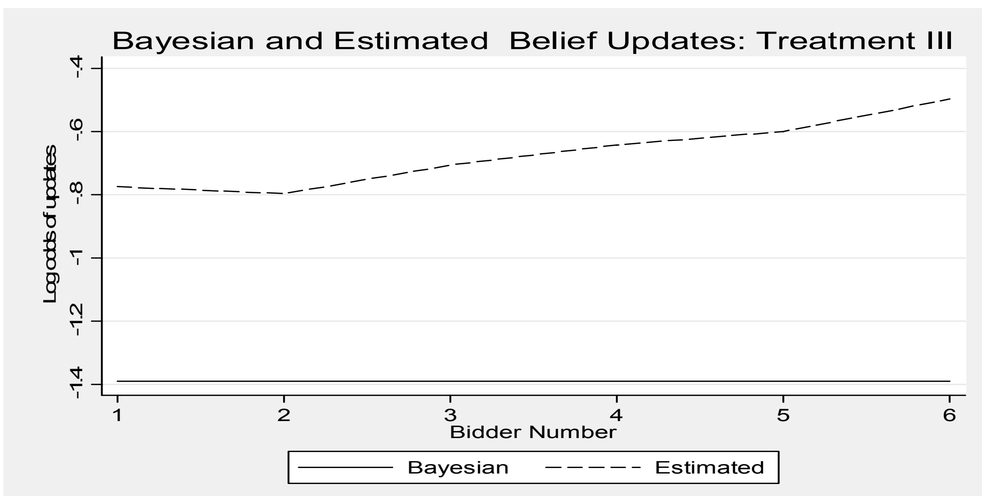

Figure 3.9Treatment 4: Bayesian and Estimated Belief Updates

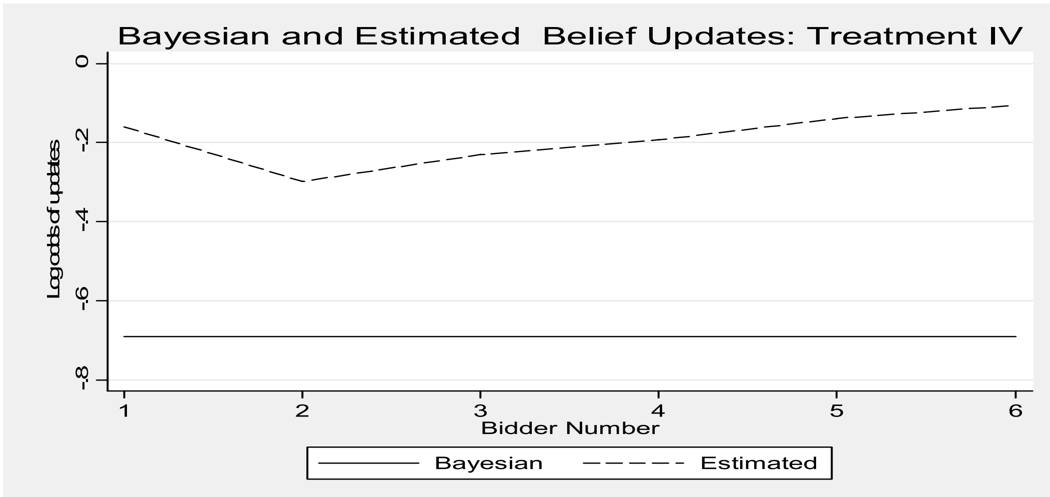

Table 3.2 Updating Beliefs: Treatment 1

	(1)		(2)	
	All	PBE	All	PBE
signal	1.67***	2.03***		
	[0.22]	[0.33]		
belief strength	-0.13	-0.13*		
	[0.08]	[0.08]		
confirming signal			0.02	0.06
			[0.24]	[0.23]
disconfirming signal			-0.31	0.01
			[0.33]	[0.33]
confirming belief strength			-0.28***	-0.26***
			[0.11]	[0.10]
disconfirming belief strength			-0.06	0.09
			[0.20]	[0.20]
Constant	-0.71***	-1.06***	0.85***	0.82***
	[0.19]	[0.32]	[0.16]	[0.15]
Observations	294	267	294	267
R-squared	0.17	0.13	0.04	0.04
Within R squared	0.17	0.13	0.04	0.04
Between R squared	0.73	0.81	0.66	0.2
Overall R squared	0.2	0.2	0.01	0.01
F1	28.79	18.83	2.7	2.72
F2	1.2	1.08	4.75	6.95
Log likelihood	-472.63	-414.22	-494.11	-426.82

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Note: F1 refers to the overall goodness of fit and F2 refers to the hypothesis that all fixed effects are zero.

Table 3.3 Updating Beliefs: Treatment 1I

	(1)		(2)	
	All	PBE	All	PBE
signal	1.62***	2.03***		
	[0.20]	[0.37]		
belief strength	-0.25**	-0.32**		
	[0.11]	[0.13]		
confirming signal			-0.04	-0.16
			[0.25]	[0.29]
disconfirming signal			-0.16	-0.08
			[0.28]	[0.35]
confirming belief strength			-0.37**	-0.48***
			[0.14]	[0.17]
disconfirming belief strength			0.12	0.23
			[0.21]	[0.25]
Constant	-0.70***	-1.03***	0.43***	0.83***
	[0.14]	[0.34]	[0.16]	[0.19]
Observations	246	167	246	167
R-squared	0.23	0.18	0.04	0.11
Within R squared	0.23	0.18	0.04	0.11
Between R squared	0.94	0.32	0.14	0.01
Overall R squared	0.32	0.19	0.02	0.08
F1	34.57	17.15	2.65	4.82
F2	0.73	0.96	7.86	2.69
Log likelihood	-369.04	-255.79	-395	-262.42

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Note: F1 refers to the overall goodness of fit and F2 refers to the hypothesis that all fixed effects are zero.

Table 3.4 Updating Beliefs: Treatment 1II

	(1)		(2)	
	All	PBE	All	PBE
signal	1.84***	1.53***		
	[0.32]	[0.40]		
belief strength	0.29	0.32		
	[0.24]	[0.22]		
confirming signal			0.09	0.08
			[0.29]	[0.77]
disconfirming signal			0.76**	0
			[0.31]	[0.51]
confirming belief strength			0.26*	0.09
			[0.14]	[0.65]
			-	
disconfirming belief strength			0.76***	-0.04
			[0.16]	[0.24]
			-	
Constant	-1.04***	-0.85***	0.82***	0.17
	[0.09]	[0.27]	[0.18]	[0.26]
Observations	299	84	299	84
R-squared	0.19	0.2	0.1	0
Within R squared	0.19	0.2	0.1	0
Between R squared	0.5	0.95	0.31	0.74
Overall R squared	0.2	0.34	0.07	0
F1	34.2	10.07	7.81	0.08
F2	1.6	0.29	3.71	6.89
				-
Log likelihood	-534.94	-136.96	-551.16	146.33

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Note: F1 refers to the overall goodness of fit and F2 refers to the hypothesis that all fixed effects are zero.

Table 3.5 Updating Beliefs: Treatment 1V

	(1)		(2)	
	All	PBE	All	PBE
signal	1.71***	2.26***		
	[0.20]	[0.30]		
belief strength	0.15	0.19		
	[0.16]	[0.13]		
confirming signal			0.08	-0.37
			[0.28]	[0.35]
disconfirming signal			-0.02	-0.97**
			[0.27]	[0.40]
confirming belief strength			0	-0.14
			[0.14]	[0.21]
disconfirming belief strength			-0.43**	0.70**
			[0.17]	[0.34]
Constant	-0.81***	-1.32***	-0.06	0.69***
	[0.09]	[0.25]	[0.16]	[0.17]
Observations	300	129	300	129
R-squared	0.25	0.33	0.05	0.06
Within R squared	0.25	0.33	0.05	0.06
Between R squared	0.87	0.42	0.28	0.83
Overall R squared	0.28	0.36	0.05	0.02
F1	48.63	30.12	3.77	2.03
F2	0.95	2.21	3.22	4.47
Log likelihood	-492.43	-182.03	-527.95	-203.7

Standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Note: F1 refers to the overall goodness of fit and F2 refers to the hypothesis that all fixed effects are zero.

Chapter 4 College-to-Work Migration of Technology Graduates and Holders of Doctorates within the United States

4.1 Introduction

Since the publication of the endogenous growth models of Lucas (1988) and Romer (1990), the idea that human capital is the primary driver of regional economic growth has achieved wide acceptance among both scholars and practitioners ((Mathur (1999), Florida (2002), Gottlieb and Fogarty (2003), Glaeser and Saiz (2003)). Impressed by the new thinking on human capital, policy makers in states and metropolitan regions have taken a variety of steps to stem the flow of college graduates outside their boundaries, or to recruit new graduates from elsewhere (Indiana Fiscal Policy Institute (2000), Schmidt (1998)). The problem these programs seek to solve is popularly known as “brain drain.” Especially in interior portions of the country with large state universities and older manufacturing or natural resource-based economies, politicians worry that talented graduates will leave town before they can jump-start local growth industries (McLaughlin (1999), Hansen, Ban, and Huggins (2003)).

Among the most popular programs at the state level are merit-based scholarships to local high school students. Pioneered by the State of Georgia and typically funded by lottery revenues, these scholarships can be used only at in-state institutions (Schmidt

(1998), Arnone (2003), Selingo (2001)). Although retention of top students in the state workforce was an important rationale for these programs, they have been evaluated largely on criteria of cost, equity, and impact on educational achievement (Selingo (2001), Selingo (2003b), Rubenstein and Scafidi (2002), Long (2004), Lee (2004)), and not on the geographic behavior of scholarship recipients.[33]

The present chapter will join a growing list of works that seek to inform brain drain policies by deepening our understanding of the revealed-preference geographic behavior of university graduates in the absence of government incentives (Tornatsky, Gray, Tarant, and Howe (1998), Tornatsky, Gray, Tarant, and Zimmer (2001), Kodrzycki (2001), Bound, Groen, Kedzi, and Turner (2004)). This chapter differs from previous works, however, in the detail with which it specifies personal characteristics (especially country of birth), the characteristics of origins and destinations below the level of the state, and interactions between personal and place characteristics. It is also the first major study of the college-to-work migration behavior of PhDs working outside of academia. The micro-dataset used for this study is the same as that employed in Tornatsky, Gray, Tarant, and Zimmer (2001). Provided in both public-access and licensed formats by the National Science Foundation, this dataset is weighted heavily with science and technology graduates, although it also contains a considerable number of people holding degrees in social science. People in professional fields like law and business administration are represented in much smaller numbers.

[33] A small subset of the new programs requires scholarships to be paid back if the student takes a job elsewhere (Indiana Fiscal Policy Institute (2000), Schmidt (1998)). This may be thought of as the individual worker equivalent of the "clawbacks" popular in economic development incentive programs aimed at firms. I are not aware of any detailed program evaluations of the impact of these scholarships on place of employment after the clawback expires.

4. 2 Research Questions

Of the handful of prior studies on college-to-work migration that use micro-data (Yousefi and Rives (1987), Tornatsky, Gray, Tarant, and Zimmer (2001), Kodrzycki (2001), Hansen, Ban, and Huggins (2003), only Tornatsky, et al. (2001) uses a technology-oriented sample. For this reason, it will also be useful to consult works on the migration behavior of technology workers long after graduation (Herzog Schlottmann, and Johnson (1986), Angel (1989) Malecki (1989), Barff and Ellis (1991) and Bagchi-Sen (2003)).

Herzog, Schlottmann, and Johnson (1986) present a thorough analysis of high-technology worker mobility into (out of) metropolitan areas using 1980 Public Use Micro-Sample data. Their study is well-grounded in both the survey research on high-technology firm location and the broader literature on economic migration. In addition to differences between technology and non-technology workers, these authors were interested in whether personal or place characteristics were a more important driver of migration for technology workers, reasoning that if the former, policy makers can do very little to influence the geographic behavior of this important target group.

Herzog, Schlottmann, and Johnson found few differences in the migration behavior of technology and non-technology workers. For both types of workers, they got highly significant migration results on four out of five personal factors, but far less significant results on six out of fifteen place factors, the remaining nine being statistically insignificant (with the notable exception of recreational amenities). The authors conclude that "states and metropolitan areas concerned with the retention of a high-technology workforce and/or the attraction of high-technology migrants…can exercise little control, if any, over these workers' mobility" (p. 457).

This conclusion may be premature, however, because of the way migration was defined in the study. Herzog, Schlottmann, and Johnson (1986) used a binary logit model to analyze the decision to leave or stay at the initial location. In such a model one can effectively measure the characteristics of only two places: the observed origin and the "rest of the world" (or equivalently, the observed origin compared to the average of all the other origins in the sample). Because such studies measure place attributes at only one end of the long-distance move, they ignore or average out a significant amount of behaviorally-relevant information on alternative places.

This binary logit approach is used in all prior studies of older technology workers employing micro-data (Herzog, Schlottmann, and Johnson (1986), Bagchi-Sen (2003) and in all studies of college-to-work migration employing micro-data, whether focused on technology workers or college graduates in general (Yousefi and Rives (1987), Hansen, Ban, and Huggins (2003), Kodrzycki (2001), Tornatsky, Gray, Tarant, and Zimmer (2001)).[34] This fact makes it difficult to review these chapters for comparable

[34] Kodrzycki (2001) recognizes the origin-destination problem, handling it with *ex post* descriptive data on "push" and "pull" factors for recent college graduates. This is the best one can do without estimating a multinomial discrete choice model. Yousefi and Rives (1987) and Hansen, Ban, and Huggins (2003) are survey studies that do not strictly qualify as revealed preference. They add valuable qualitative data, but both studies surveyed students at only one origin without specifying particular destinations, thus compounding the problem of missing place data.

findings on our population of interest, although I shall refer to their more salient and robust findings as I go along.

Fortunately, techniques exist that enable the researcher to analyze each migrant's ultimate choice from among a set of fully-specified geographic alternatives, incorporating personal and place characteristics together as interaction terms. Sjaastad (1962) is largely responsible for the theory of spatial optimization in migration, while McFadden (1973), McFadden (1976) pioneered the econometric models needed to analyze choices among multiple alternatives. McFadden-inspired models have been applied to migration behavior in McFadden (1978), Schultz (1982), Fields (1982), Linneman and Graves (1983), Gabriel, Justman, and Levy (1987), and Davies, Greenwood, and Li (2001), although not for technology workers, new graduates, or doctorates. The present chapter moves beyond the popular conditional logit technique to random parameters logit, the most general and flexible method of combining preferences with multiple choice characteristics (McFadden and Train (2000), Train (2003)).

Using this technique, the present article addresses the following questions about college-to-work migration:

First, are economic opportunities more important than amenities and lifestyle factors in the migration decisions of these important recruitment targets?[35] While young, "creative class" types are widely regarded as amenity-oriented in their location and lifestyle preferences (Florida (2002)), this hypothesis is rarely tested in formal migration

[35] A summary of the literature on this question for all workers may be found in Greenwood (1985)

studies. Empirical work on younger age cohorts and new college graduates using a variety of techniques has generally found that amenities are less important than economic factors for explaining their migration (Yousefi and Rives (1987), Hansen, Ban and Huggins (2003), Tornatsky, Gray, Tarant, and Zimmer (2001), Kodrzycki (2001), Gottlieb (2003)). Meanwhile, researchers appear divided on whether younger migrants are more amenity-oriented than older migrants (Gottlieb (2004), Clark and Hunter (1992)). An investigation of college to work migration among scientists and engineers using a full multinomial specification of alternative destinations seems an appropriate contribution to this literature.

Second, I would like to see how the location decisions of doctorate holders differ from those of other graduates. Doctorate holders have more human capital than other degree holders, and are presumably more likely to participate in labor markets that are technologically narrow and spatially extensive (Schwartz (1973)). Doctorate holders may be relatively insensitive to amenities; on the other hand, they may have sufficient bargaining power in employment negotiations to secure them. Because economic development impact is presumably related to the level of human capital held by knowledge workers, and not simply to the number of college graduates moving from place to place (see, e.g., Krieg, (1991)), a separate investigation of doctorate migration is warranted.

Third, the empirical literature inspired by the brain drain problem has looked at two factors associated with migration over which higher education officials actually have some control, through their admission policies. These are (a) whether a state's university graduates were born in the same state from which they are currently graduating, and (b) how many of a state's university graduates are international immigrants. These factors should logically be grouped together because they relate to a well-known predictor of migration — prior migration — as well as to intangibles like attachment to home or a desire to be with one's own group, whether that be in the place one grew up or at a location of second settlement (see, e.g., Greenwood (1969)). I have developed a particularly rich set of data on international students in order to explore this affinity-grouping behavior. Along the way I shall address Tornatsky, Gray, Tarant, and Zimmer (2001)'s somewhat surprising finding that foreign-born graduates are more likely than domestic-born graduates to stay and work in the place where they earned their most recent degree.

Findings like Tornatsky's are of particular interest to state-level policy makers. At least before 9/11, foreign students represented a growing share of the American college population, especially at the graduate levels, and in engineering and science. University officials argue that foreign-born students receive lower public subsidies than domestic students (or no subsidies at all), and that they are essential to any university's research mission and to its financial health (Wilson (2004)). On the other side of the debate, state legislators often complain that foreign-born students are not their constituents, and that they are less likely than homegrown students to contribute to the local economy upon graduation (Selingo (2003a)). Studies like ours and Tornatsky's effectively address this second concern.

Other variables common in migration studies, such as those related to the psychic costs of moving, distance, children, age, and gender, will be included in the various migration models as controls.

4.3 Theoretical Model

I examine the destination choice problem faced by each agent using the random utility maximization framework (Marschak (1960), Dagsvik (1994)). Each individual is assumed to have preferences over available destinations that can be described by a utility function. The utility function depends upon the attributes of the destinations and characteristics specific to the individual.

$$U_{ij} = \beta' x_{ij} + \varepsilon_{ij} : j \; \varepsilon \; J, i \; \varepsilon \; I \qquad (1)$$

where U_{ij} is the utility that individual i obtains by choosing destination j and x is a vector of attributes of destinations and individual characteristics. $\beta' x_{ij}$ represents the observed portion of utility and ε_{ij} represents the stochastic part which remains unobserved. The probability that individual i chooses destination j is the probability that the utility of destination j exceeds that of all the other destinations.

$$P_{ij} = \Pr(U_{ij} > U_{ik}) \quad \forall k \text{, where } k \varepsilon \; J \text{ and } k \neq j$$

$$= \Pr(\beta' x_{ij} + \varepsilon_{ij}) > \Pr ob(\beta' x_{ik} + \varepsilon_{ik}) \quad \forall k$$

The individual's objective is to choose the destination that maximizes her utility (Sjaastad (1962)). Because the unobserved portion of utility ε_{ij} is unknown to the researcher, all discrete choice models with a random utility formulation make assumptions about the distribution of this unobserved utility to estimate the probability that an individual will choose a particular destination. In the present chapter, I will look at the more traditional conditional logit model (CL) and a more recent and general approach, the random parameters logit model (RPL), to examine the destination choice problem faced by new graduates.[36]

4.3.1 Conditional Logit Model

It has been shown (McFadden (1973), McFadden (1978) that if the systematic portion of utility can be represented by an additively separable and linear in parameters functional form, and the residuals ε_{ij} are independently and identically distributed with a Type I Extreme value distribution, then the probability that an individual i will choose destination j is given by

$$\Pr(Y_i = j) = L_{ij}(\beta) = \frac{\exp(x_{ij}^{'}\beta)}{\sum_{j=1}^{J}\exp(x_{ij}^{'}\beta)} \qquad (2)$$

The restrictive assumption of independence placed on ε_{ij} requires that for any individual, the ratio of choice probabilities of any two alternatives is independent of the utility of any other alternative. This implies that the odds ratio between any two alternatives should not

[36] In the literature several names have been used to refer to random parameters logit models, like mixed logit, random coefficients logit, mixed multinomial logit, error components logit and probit with a logit kernel.

change by the inclusion or exclusion of any other alternative. This is the Independence of Irrelevant Alternatives (IIA) assumption.

The IIA property gives rise to unrealistic substitution patterns in individual choice. For example under IIA, if a graduate faced only three possible destinations — State College, Boston, and New York — the exclusion of any one of these options would be assumed to have an equal effect on the probability of choosing each of the other two. In reality, however, a large city like Boston is likely to be a better substitute for New York than the relatively remote college town of State College. So if New York were excluded from the list of possible destinations, Boston would be expected to draw a disproportionate share of the displaced decision makers, violating the IIA assumption. In fact, implementation of a test developed by Hausman and McFadden (1984) verifies that the IIA property does not hold in our sample. Therefore the conditional logit model shown in (2) is not appropriate for our data.

Another benefit of abandoning the conditional logit model, with its assumption that the stochastic component of individual utility is uncorrelated across choices, is that one may explore more realistic models of taste variation in the population. It seems likely that an unobserved component of utility that is specific to individuals will, in fact, lead to correlation of errors across destination choices — in violation of McFadden's strong independence assumption for conditional logit.[37] Three common approaches to bypass the IIA restriction are nested logit, multinomial probit, and random parameters logit

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[37] Random taste variation among individuals leading to correlation among the utility of destinations include among other things, preference for coastal areas or warm climate, etc.

(RPL), also known as mixed logit. The third of these approaches is regarded as the most general and flexible of the three (Hausman and Wise (1978); McFadden and Train (2000), Train (2003)).

4.4.2 Random Parameters Logit Model

The standard logit specification assumes that β is the same for all individuals in the population (see expressions (1) and (2) above). Under RPL, I allow β to vary within the population. This is done by specifying the unobserved portion of utility as a combination of independently and identically distributed extreme value error term and a separate random distribution that can take any form.[38] Very general patterns of correlation among destinations and substitution patterns can by obtained by appropriate specification of variables and parameters (McFadden and Train, 2000).

In this specification I allow some coefficients β to be fixed in the population and other coefficients η_i to vary across individuals in the population in order to capture individual heterogeneity and correlation across alternatives. The individual utility function in (1) can be rewritten as follows.

$$U_{ij} = \beta' x_{ij} + \eta_i' z_{ij} + \varepsilon_{ij} \qquad (3)$$

Here z is the vector of variables whose parameters are assumed to be random and z is a subset of x.[39] The researcher estimates β and does not observe η_i. Therefore η_i is

[38] In general normal, lognormal, triangular uniform and in one case Raleigh distribution has been used in the literature.

[39] If the elements of z are not contained in x I have a mixed logit model with error components specification. Because the parameters on variables common to the two vectors (*w)* are necessarily random and can be expressed as $(\beta' + \eta_i')w_{ij}$, making z a subset of x does not change the essential character of the model. Some parameters are simply fixed and others random.

specified to follow a given distribution $f(\eta_i|\theta)$, with θ being the parameters of the distribution. The unobserved portion of utility $\eta_i' z_{ij} + \varepsilon_{ij}$ will be correlated across destinations due to the common influence of η_i. In other words, tastes not observed by the researcher are used by the individual to evaluate destinations (random taste variation), and since the researcher does not observe these tastes completely, that portion of utility that is not observed by the researcher is correlated over destinations (unobserved attributes). Thus the mixed logit model handles the IIA problem automatically. By extension, if η_i is assumed to be zero, (3) reduces to the standard conditional logit model.

With this setup I can proceed to calculate the choice probabilities. Conditional on η_i, the probability that an individual i will choose destination j is as follows:

$$\Pr ob(Y_i = j) = L_{ij}(\beta, \eta_i) = \frac{\exp(x_{ij}'\beta + z_{ij}'\eta_i)}{\sum_{j=1}^{J} \exp(x_{ij}'\beta + z_{ij}'\eta_i)} \tag{4}$$

But since the researcher assumes η_i to vary in the population with the density $f(\eta_i|\theta)$, the unconditional probability of choosing destination j will be the integral of (4) over all possible values of η weighted by the density of η:

$$\begin{aligned} L_{ij}(\beta, \theta) &= \int L_{ij}(\beta, \eta) f(\eta|\theta) \partial\eta \\ &= \int \frac{\exp(x_{ij}'\beta + z_{ij}'\eta)}{\sum_{j=1}^{J} \exp(x_{ij}'\beta + z_{ij}'\eta)} f(\eta|\theta) \partial\eta \end{aligned} \tag{5}$$

This integral does not have a closed form solution and hence cannot be evaluated analytically. Simulation methods, which have been made possibly by increased computer speed, are used for this purpose (Brownstone and Train (1999)). In particular $L_{ij}(\beta,\eta)$ is calculated for values of η chosen randomly from the specified distribution $f(\eta|\theta)$. This process is repeated many times and the average of the resulting $L_{ij}(\beta,\eta)$ is taken as the choice probability. $L^{*}_{ij}(\beta,\theta) = \frac{1}{R}\sum_{1}^{R} L_{ij}(\beta,\eta) \mid \theta$ is the unconditional probability used to calculate the simulated likelihood function, where R is the number of draws of η. $L^{*}_{ij}(\beta,\theta)$ is an unbiased estimator of $L_{ij}(\beta,\theta)$ and as R increases the variance of the estimator decreases.[40]

The parameters to be estimated are β, the vector of fixed coefficients, and θ, the parameters that describe the distribution of η. The simulated mixed logit log likelihood functions for given values of β and θ is:

$$L(\beta,\theta) = \sum_{I}\sum_{J} y_{ij} \log L^{*}_{ij}(\beta,\theta) \tag{6}$$

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[40] $L^{*}_{ij}(\theta)$ is twice differentiable which helps the numerical search for maximum of the simulated log likelihood function. The number of draws of η is generally accepted as 250 and 500.

where $y_{ij} = 1$ if individual i chooses destination j and $y_{ij} = 0$ otherwise.[41] The choice probabilities are constructed and the parameters β and θ that maximize this log likelihood function are found by iteration (we assume that θ describes a normal distribution for each random parameter, which seems reasonable on behavioral grounds). The simulation technique for calculating (5) and improved computer speed allow us to estimate this more flexible and rich discrete choice model. In the following sections, I explain the data and then estimate a series of models that highlight the advantages of this technique over others.

4.4. Data

This study uses micro-data from the 1995 SESTAT files, obtained from the National Science Foundation under a restricted license.[42] The files contain demographic and career data on 104,616 individuals surveyed in April 1995. The respondents consist of U.S. residents who hold a doctorate, masters', or bachelors' degree in science or engineering, or who worked in science or engineering occupations during the survey week. The social sciences are included within the NSF's definition of science and engineering, but professional degrees/occupations like business, law, and clinical medicine are not.

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[41] If η is a N X 1 where N is the number of elements in Z, the estimation of the log likelihood function can be done by evaluating a N dimensional integral. This is done using simulation (Hajivasilliouand and Ruud (1994), Revelt and Train (1998). Simulation using Halton sequences is described in Bhat (2003) and Train (2000).

[42] See http://sestat.nsf.gov/ for comprehensive documentation on this database.

For purposes of the present study, respondents who earned their most recent degree before 1992 are excluded. For individuals employed outside of higher education, the National Science Foundation provided the zip code of the institution where the most recent degree was earned, as well as the zip code of the present employer. These zip codes were easily matched to federal codes for 1995 metropolitan areas (MSAs and CMSAs, in our case). The result is a list of individuals with at least some science and engineering background working in private industry, research labs, or government, along with information on metropolitan area of employment in April 1995 and metropolitan area where the last degree was earned any time between 1992 and 1994. A comparison of these two locations is used to signify school-to-work migration, even though some respondents could have moved more than once between time of graduation and the survey month of April 1995.

The 10,429 post-1991 graduates for whom I have complete geographic data earned their most recent degree in any one of 129 MSAs. Because multinomial logit techniques compare the place characteristics of all possible destinations to those of each origin, it is necessary to reduce the number of metropolitan areas examined in order to make migration analysis computationally feasible. To do this, the 129 MSAs were ranked by the number of 1992-1994 university graduates. A series of square matrices of i to j migration flows was prepared for identical lists of origins and destinations, by tens (120x120, 110x110, 100x100, etc.). These matrices were prepared by successively dropping the ten MSAs with the smallest graduate counts. This means, for example, that the 10x10 matrix contains the ten MSAs with the largest number of surveyed graduates.

In selecting a matrix dimension, the goal was to minimize a mathematical criterion consisting of the number of zero cells in the square matrix under consideration, plus the number of nonzero cells eliminated by moving from the full 129x129 matrix to each alternative matrix. It turns out that this criterion is minimized for a 40x40 square matrix, which is within the range of alternatives that can be handled by computer algorithms. An alternative selection criterion that sought to minimize the number of individuals removed from the sample with decreasing matrix size yielded optimal sizes of 40x40 or 70x70, depending on how the two sub-criteria were defined and aggregated into a single objective function.[43] It was felt that 70 origins and destinations would be beyond our computational capacity, and so the 40 largest degree-producing metros were selected in this first round.

To ensure that this would not simply be a study of migration among college towns (e.g., Boston to Champaign-Urbana), the ten MSAs with the largest populations not already included in the 40x40 matrix were added to the destination choice set, leading to a 40x50 asymmetric matrix summarizing the migration behavior of 5,530 individuals.[44] Because large metropolitan areas are common destinations, this expansion of the matrix

[43] Alternative objective functions include the sum of individuals removed and the number of zero cells; sum of the z-scores of these two criteria; sum of the z-scores of individuals removed and the percentage of zero cells; and the sum of these last two criteria standardized on the range 0 to 1 (which also leads to an optimum matrix size of 40x40). The five metropolitan areas with the largest counts of surveyed graduates ultimately omitted from the analysis were Iowa City, Oklahoma City, Syracuse, Bloomington, IN, and Columbia, MO. Of the ten large metropolitan areas added as destinations (see below), only Phoenix ranked among the top 60 origins. Given the relatively small number of its graduates sampled, however, it seemed best to keep the number of origins at 40.

[44] The original count was 6,202, but respondents who reported that they were working part-time because they were students were omitted from the sample. All new graduates analyzed here were therefore working full- or part-time at the time of the survey and did not describe themselves as students. This means that I are examining school-to-work migration, not school-to-school migration, to the greatest extent possible. See also note 13.

further reduced my selection criterion (i.e., it added more nonzero than zero cells to the 40x40 matrix). A list of the 50 metropolitan areas used in the study is shown in Table 4.1, with metropolitan areas that appear as potential destinations only shown in boldface.

The data characterizing the fifty MSAs were taken from a number of sources, and were measured either before or at each individual's year of graduation, to make them chronologically causal. The independent variables that characterize metropolitan areas are described in Table 4.2, along with constructed geographic data like the distance between each origin-destination pair. Table 4.3 describes migration-relevant data on individuals taken from the SESTAT micro-database. Note that in multinomial choice migration models, personal characteristics must be interacted with place characteristics (or places), so Table 4.3's variables will never appear alone in any of the regression models. There are strong parallels between the concepts measured in the list of personal variables and place variables — in the areas of technical specialty and country of origin, for example. These parallel variables permit us to construct interaction terms that describe the skill needs of certain industries, as well as spatial attraction to one's own kind in terms of ethnicity or age.

4.5 Results

CL and RPL regression results are shown in Tables 4.4 through 4.6. Table 4.4 shows results for all graduates in the 40x50 origin-destination matrix. Table 4.5 looks only at bachelors' and masters' degree holders, while Table 4.6 analyzes the migration behavior of doctorate holders. The groups in Tables 4.5 and Table 4.6 are mutually exclusive and completely exhaust the larger set of graduates analyzed in Table 4.

Under RPL, some parameters are randomized with a mean and standard deviation estimated, and others are not. The choice of which parameters to randomize is left up to the researcher. In our case, I randomized only parameters representing the attributes of places, reasoning that interaction terms already contain information on the unique characteristics (if not the utility functions) of individuals, while place variables do not. The same parameters were randomized for each subpopulation in order to make Tables 4.1 through 4.6 as comparable to each other as possible.

Having said that, it is not appropriate to compare the magnitude of estimated coefficients across different subpopulations. The reason is that estimated coefficients contain a scale factor that cannot be separately identified (Swait and Louviere (1993), Train (2003). Using the likelihood ratio test described in Swait and Louvierre (1993), I have verified that the population parameters almost certainly differ between doctorate and BS/MS graduates. This in itself justifies analyzing doctorates as a separate group. When comparing the results for each subpopulation side by side, however, one must rely on the signs and statistical significance of individual parameters, or else ratios of pairs of parameter estimates within a single model (Train (2003, pp.45)) because of the unknown scale factor that influences the relative magnitude of the parameter estimates. Marginal changes in selection probabilities with respect to place characteristics are also difficult to calculate and interpret when there are fifty alternatives, so this common method for reporting logit results is omitted.

If RPL makes certain types of direct comparisons a bit more difficult, it also provides one type of insight on behavioral parameters that CL is unable to provide. Because the mean and standard deviation of a given parameter are estimated, the researcher is able to make statements about the distribution of preference weights in the population, including the (often logical) observation that a certain portion of the population views a given place attribute as an attractor, while another portion of the population views that same place attribute as a repellant. (Standard logit models estimate a single "average" parameter that is either positive or negative.) For our dataset, Table 4.7 reports the percentage of each subpopulation that views each of our randomized parameters as an attractor, while 100% minus this figure gives an estimate of the percentage of each subpopulation that views the factor as a repellent. More important than the actual percentages is the fact that under RPL, the significance level of a random parameter's estimated standard deviation automatically provides a hypothesis test for variance in taste preferences within the population. Such hypothesis tests are of substantial behavioral interest in its own right.

4.5.1 Results for the Entire Sample

If I look at the results for all of the graduates together (Table 4.4), I can take comfort in the fact that a number of standard findings in the larger migration literature are confirmed. The two gravity variables are significant and have the expected signs (DISTANCE is negative; POP90, positive) (Zipf, (1946)). An interaction term between current salary and distance is positive, reflecting the greater distances migrated by those with more specialized human capital, who reap larger financial rewards in a labor market that is more spatially extensive (Sjaastad (1962); Schwartz (1973), Greenwood (1975)).

A special interaction term, TECH*POP90, was included to test the hypothesis that scientists and engineers are disproportionately attracted to large metropolitan areas when compared to graduates in other fields (Malecki (1989), Herzog, Schlottmann, and Johnson (1986); Bagchi-Sen (2003)). Not only is the coefficient on this interaction term negative, but the graduates in the present sample who hold science or technology degrees tend to live in smaller metropolitan areas than non-technology grads, even when industry structure at the destination is not controlled.

Before concluding that high-tech industries and their workers are disproportionately attracted to smaller cities, it is necessary to point out that the non-tech graduates in our sample are not perfectly representative of all non-technology occupations and industries in the economy; they entered the SESTAT sample frame because they have at least some professional connection to science or technology. Further confirmation of the city size preferences of tech versus non-tech workers (and industries) should therefore rely on a broader sample of surveyed individuals as well as metropolitan areas.[45]

[45] Partly for this reason, this is the only place in the study where the individual characteristic TECH is used. See Table 3 for its definition.

A dummy variable representing the location where the most recent degree was earned, indicating non-migration (SAME), is significant and positive in all models, reflecting the psychic costs of moving. People who were born in the state where they earned their most recent degree are less likely to migrate (BTHGRAD*SAME), which is consistent with past work on this dataset, and with other findings on technology workers and new graduates (Tornatsky, Gray, Tarant, and Zimmer (2001), Hansen, Ban, and Huggins (2003), Herzog and Schlottmann (1984), Herzog, Schlottman, and Johnson (1986)). Older graduates are more likely than younger graduates to stay in the metropolitan area where they earned their most recent degree (AGEGRAD*SAME), paralleling previous findings on life cycle migration (Greenwood (1975), Nakosteen and Zimmer (1980)). The reduced migration propensity caused by marriage, however (Mincer (1978); Graves and Linneman (1979), Jacobsen and Levin (1997), shows up only when the degree populations are disaggregated (Table 4.5, Table 4.6).

Moving on to other place attributes, high rates of poverty (POVPCT90) and high cost-of-living (PRCOL) at the destination deter in-migration; although there is evidence of taste variation related to poverty (see also Clark and Hunter (1992). The fact that the climate parameter (PRCLIM) exhibits significant taste variation appears reasonable on its face.

The coefficients on several other place attributes are of considerable interest. Metropolitan employment growth over the ten years prior to year of graduation is a significant factor in the choice of destination. Presumably, a high score on this variable increases the probability of landing a job in a particular destination, and serves as a signal of future opportunities to find or switch jobs within the metropolitan area. Also important are structural factors that are slower to change, like educational attainment at the destination (BACH90). Because everybody in this sample holds a bachelors' degree (less than 30% of the adult population does so nationwide) the positive coefficient on this variable may be interpreted as a desire to live near one's own kind. Less likely, new graduates may appreciate that they stand to earn greater lifetime earnings as a result of knowledge-related externalities in urbanized places with high proportions of educated workers (Rauch (1993). Under either interpretation, this finding does not bode well for less-educated cities, whose leaders worry about the self-reinforcing, "winner-take-all" economic outcomes implied by the endogenous growth models (Gottlieb and Fogarty (2003)). This worry seems valid to the extent that highly-educated graduates are attracted to highly-educated places, holding constant economic variables like industry structure.

As in a number of prior migration studies (see the discussion in Davies, Greenwood, and Li (2001), the unemployment rate at the destination (UNEMP) has an inexplicably positive effect on in-migration. In contrast to earlier studies, however, the RPL technique reveals that there is significant variance in this parameter, with a full 34% of the population estimated to respond to the unemployment rate in the manner normally predicted by labor economics. Different graduates appear to respond in different ways to this labor market indicator, an insight that would not have been available under CL.[46]

[46] I hypothesized that the positive estimated coefficient on unemployment rate might reflect a disproportionate preference for California cities, which were hit particularly hard in the early 1990s by a combination of recession and troubles in their defense industries. New engineering graduates, especially those in information and life sciences, did not necessarily compete for jobs with the older defense engineers

The independent variable on research and development spending (RD90) reflects federal funds going to universities. Divided by total employment, it is a good measure of the extent to which the metropolitan area is a "college town," dominated by its university as an employer and as an economic engine. The parameter on this variable has a negative sign in all models.

This is a potentially important finding when you consider that the presence or absence of technology industries, as well as the tendency for people to stay in the places where they earned their most recent degree, are already specified in the model. The interaction term relating younger graduates to destinations with lots of people in their 20s — an attribute that is understandably correlated with college town status — also carries a significant negative coefficient in all models but the doctorate. It appears that college towns are avoided by our target population as work destinations, holding equal a rather extensive list of other factors, including the tendency to stay in the place where one was educated. College towns may therefore be perceived to have lifestyle or economic disadvantages not captured by our measures of city size, amenities, or industry structure.[47] Note that that all of our respondents worked outside of postsecondary

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who swelled California's unemployment rolls in this period. When I added a Pacific coast dummy variable to the model, however, its coefficient was negative and the coefficient on unemployment rate remained positive. (This was true whether or not the four fixed effect dummies were included.) The unemployment rate coefficient was also positive in models that omitted the EGRO10 variable, which one might expect to be negatively correlated with UNEMP. An alternative explanation for this finding is that a large number of graduates move to desirable cities without a job in hand, swelling the unemployment roles (i.e., causation runs in the other direction). Such an argument, however, fails to explain exactly which desirable city characteristics are being proxied by the unemployment variable, since clearly such characteristics must have been omitted from any study that exhibits this phenomenon.

[47] College towns generally produce arts and cultural opportunities that are disproportionately high for the metropolitan area's size. If this is the omitted variable, however, then I would expect the coefficient on

teaching, and none reported that they were full-time students at the time they were surveyed.

As expected, the interaction terms relating a person's degree field to industry structure at destination (LIFE*PTHLTH92, IT*PCTAEA92, PHYS*MANPCT90) are significant and positive in all models (information technology doctorates being the lone exception). Most of the remaining interaction terms are designed to explore the attraction of foreign-born students to metropolitan areas that contain high concentrations of people with similar ethnic backgrounds.

All models show that foreign-born students are attracted to cities with high percentages of immigrants, holding constant such factors as skill match, city size, and growth (FORBTH*IMMPCT90). There is separate evidence of affinity grouping behavior among students born in China (CHIN*CHINPCT).[48] As far as I know, this is the first study to identify ethnic grouping behavior on the part of foreign-born college graduates, although the estimated coefficients are relatively small. I expect that larger sample sizes would identify such behavior among nationalities other than the Chinese.

Angel (1989) suggests that Silicon Valley dominates other metropolitan areas as a high-technology destination for reasons that may be difficult to capture using measurable

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RD90 to be positive rather than negative. The Places Rated Arts score cannot be used in this study because it is designed to be almost perfectly collinear with metropolitan area size, which I include as POP90. Measures of underground, "Bohemian" amenities or cultural attributes (Florida, 2002) are generally not available for a sample of metropolitan areas.

[48] Econometric theory suggests that the other significant ethnic affinity parameters in Table 4's CL model are spurious, capturing place-correlated components of individual utility not otherwise accounted for under CL's strong i.i.d. assumption for the errors.

place characteristics. To test this idea, four fixed-effect dummies (SAN FRANCISCO, NEW YORK, ATLANTA, and BOSTON) were included in the models, as in Davies, Greenwood, and Li (2001). [49] Angel's observation appears to be true for our dataset as well: San Francisco has a positive and rather large estimated coefficient in all three tables. The remaining city dummies are discussed in section 6 below, because they exhibit interesting differences among different types of degree holders.

4.6. The Three Research Questions Answered

We return now to the three research questions posed in section 2 above:

Question 1: In their choice of destinations, do new technology graduates respond primarily to quality of life or to economic considerations?

For graduates to respond to amenities across alternative destinations, it must first be established that they respond to measurable place factors at all — instead of selecting new locations on the basis of idiosyncratic family or job considerations that will show up in regression analysis only in the residual.

This first hurdle is met in the present study. It is clear from Table 4.4 that a great number of place factors are systematic migration drivers for this population, whether standing alone or interacted with personal characteristics. Contrast this with the findings of Herzog, Schlottmann, and Johnson (1986) and with many studies on college graduates'

[49] A number of econometric issues, including degrees of freedom, collinearity, and model convergence, prevent us from including many more than four city dummies as fixed effects. See, e.g., Davies, Greenwood, and Li (2001).

decisions to "stay or leave" (Hansen, Ban, and Huggins (2003), Tornatsky, Gray, Tarant, and Zimmer (2001), Yousefi and Rives (1987). These studies generally minimize the importance of place characteristics in explaining out-migration. It must be remembered, however, that they fail to measure place characteristics at the destination, considering only push factors at the origin. In this sense, *any* multinomial logit technique that incorporates place characteristics at all potential destinations will appear to "rescue" the importance of place characteristics as a migration driver.[50] This has now been done for new technology graduates, supplementing the findings on the general working population in such articles as Gabriel, Justman, and Levy (1987) and Davies, Greenwood, and Li (2001).

Outside of poverty and the cost of living, which deter in-migration, the impact of metropolitan-level amenities in this study is relatively weak. Recreational amenities are significant in none of the models. The coefficients on crime rate are sensible for the doctorates, but remind one of the unemployment paradox for the other graduates. The positive coefficient on climate tends to be small with weak statistical significance. In contrast to amenity factors, the logit coefficients for education of the incumbent population, city size, staying in the place where one graduated or was born, and selecting San Francisco, are quite large.

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[50] To be precise, any either-or distinction between personal and place factors in migration is a false dichotomy. Assuming rationality, all migration is by definition an adjustment in one's place on the expectation that the destination is preferable to the origin in some way. Personal factors always condition those expectations, and are, in many cases, observable. The dilemma identified by Herzog, Schlottmann, and Johnson is more properly framed in terms of the difference between the "signal" — statistically significant place characteristics I might change or take advantage of through public policy — and "noise," those personal evaluations of place I can never observe. With its assumption of different preference weights within a population, RPL presumably does a better job than CL of modeling personal evaluations. Of course it will never transform all noise into signal.

The one caution on this pessimistic conclusion regarding the role played by quality of life is the strong expected correlation between cosmopolitan amenities (restaurants, symphony, nightclubs, and major league sports) and city size (Gottlieb, 2003). All of our models contain information on each metropolitan area's status as a technology center. In contrast, the city size variable proxies the *scale* of skill-matched job opportunities (urbanization economies of value to job-seekers), as well as cosmopolitan amenities. This collinearity is fundamental: the attractive power of a very large professional job market and the "bright lights—big city" effect simply cannot be separated.

On balance, the findings on amenity orientation are similar to those of prior studies on both old and young workers. Quality of life appears to be of secondary importance even to younger workers (Gottlieb (2003)), but it becomes more important as workers age and accumulate additional human capital (see section following). Although the present study is restricted to technology workers, a comparison of its results with prior studies would not reveal fundamental differences in the spatial behavior of technology and non-technology workers possessing similar levels of human capital (Clark and Hunter, 1992; Herzog, Schlottmann, and Johnson (1986), Davies, Greenwood, and Lie (2001), Bagchi-Sen (2003)).

Question 2: Do doctorate holders working outside of academia differ from holders of other degrees in their migration behavior?

Prior studies have found that women are less likely to migrate than men (Nakosteen and Zimmer (1980)), but the current study identified this effect only for female doctorates. Another difference between doctorates and other degree holders is a more significant response among doctorates to cost-of-living conditioned by age and the presence of children.

Generally speaking, doctorates exhibit a stronger response than others to amenity factors like climate and crime, and a weaker response to economic factors like recent employment growth and the presence of IT jobs.

The first of these findings may be explained by the fact that doctorate degree holders have more bargaining power in employment negotiations, permitting them to demand and secure high amenities. Holding a terminal degree, they may also make location decisions with a longer time horizon in mind. The finding on amenities is also consistent with Clark and Hunter (1992)'s finding of a positive relationship between amenity-orientation and age.

The finding on doctorates' response to economic conditions also seems to relate to bargaining power. These workers have so much specialized human capital, they can probably afford to ignore many aggregate labor market conditions. Interestingly, unlike other graduates, doctorates in our sample do not migrate longer distances when they command higher salaries. One explanation is that all doctorates automatically participate in a national labor market and have salaries tightly clustered at the top end of our range. The other is that they exhibit a kind of academic indifference to the pecuniary considerations that underlie this phenomenon in other groups. (What remains to be explained, then, is why such specialized and task-focused individuals would respond more strongly than other graduates to amenities, and equally strongly to the unemployment rate.)

The doctorates display an interesting and understandable differential response to the four city dummy variables. Their unique positive response to Boston is equal to the entire sample's positive response to San Francisco, which likely plays host to a slightly higher ratio of commercial to purely academic knowledge. Similarly, doctorates are less likely than other graduates to avoid New York, and to a lesser extent Atlanta.

At least in the case of New York, this finding may simply be additional evidence that doctorates are indifferent to standard measures of economic performance. Manufacturing employment fell by 23% in the New York CMSA from 1988 to 1993 compared to 8% in all metropolitan areas, while the finance sector (a large employer of IT workers) lost 9% of its workers in New York compared to only 2% in all metropolitan areas.[51] These economic conditions, not captured elsewhere in our model, were apparently important to bachelors' graduates in the SESTAT sample but not to doctorates. More broadly, these significant fixed effects highlight the difficulty any

[51] Source of data: *REIS CD-ROM 1969-2001*, Regional Economic Information System, U.S. Department of Commerce, Economics and Statistics Administration, Bureau of Economic Analysis (May 2003).

researcher has in capturing all of the factors that will make a particular place attractive to new graduates at a particular time.

Question 3. Can state economic development officials take advantage of findings on the "staying" behavior of local high school graduates or foreign students?

Perhaps the first thing to note is that all of the models estimated here show a large and significant tendency among college graduates to stay rather than migrate, other things equal. This suggests that in the long run, training a relatively large number of university graduates in a metropolitan area could lead to a larger number of knowledge workers settling there (for a neo-classical explanation of this empirical observation, see Bound, Groen, Kedzi, and Turner (2004)). This does not mean that increasing local university enrollments is a perfect substitute for economic development: it clearly will be hard to retain top students if there are no jobs for them to take. It simply highlights "inertia" as a behavioral habit that economic development officials may be able to leverage, in addition to other factors.[52]

A relatively large number of college graduates will stay, but the effect is even more pronounced for college graduates who were born — or attended high school — in the state where they earned their most recent degree (Tables 4-6; Tornatsky, et al. (2001), Kodrzycki (2001)). Much has been made of this result in policy terms. Tornatsky, et al. (2001) write that "states can gain significant relative advantage by harvesting talented

[52] One of those other factors, of course, is the increased magnitude of basic research and technology transfer that might be expected if a metropolitan area succeeds in increasing the size (or quality) of its universities.

high school graduates from their state by aggressively encouraging and giving them incentives to stay home for college" (p. 28). Given that Tornatsky's research was commissioned by the Southern Technology Council for use by economic development officials in that region, it is likely to have influenced the nearly universal decision to restrict merit scholarships to constituents' children attending college in-state, in emulation of Georgia's HOPE program.

We believe that this policy conclusion is not yet supported by the evidence. First, having participated in numerous state-level policy discussions on brain drain, I believe there is a strong (and quite understandable) political bias in favor of retaining local high school graduates as permanent residents (see, e.g., Indiana Fiscal Policy Institute (2000), McLaughlin (1999)). One result of this bias is that the relative costs and benefits of recruiting out-of-state technology workers — at any stage of their educational or professional careers — are less frequently explored.

Second, statistical results on the college-to-work migration behavior of state natives, as measured in the present study and others, may reflect a selection effect rather than a treatment effect, and therefore not be amenable to policy intervention.

Recent studies by Groen and White (2004) and Groen (2004) make both of these points. These authors argue that the policy objectives of university officials and state legislators are at odds, with the former looking for the brightest students regardless of where they ultimately settle, and the latter willing to accept a lower level of graduate earnings provided that a larger share of those earnings are captured in-state. From the legislators' point of view, it is worth reducing tuition rates (or even admission standards) for in-state students — but only if the "treatment" of attending a state university has a larger impact on the ultimate settlement choice of natives than on those who enroll from out of state. Groen and White (2004) and Groen (2004) show that the difference in impact on settlement choice between the two groups is quite small when one adjusts for selection bias. These findings do not demolish the rationale for merit scholarships, but they do raise serious questions about any policy distinction between in-state and out-of-state students.[53]

University officials and state legislators also lock horns on the subject of international students (see section 2 above). With respect to the staying behavior of foreign students, Table 4.5 suggests that foreign-born BS/MS graduates are more likely than their domestic counterparts to stay in the metropolitan area where they earned their most recent degree (FORBTH*SAME). This finding confirms Tornatsky, et al. (2001)'s result on the same population. The finding does not, however, extend to doctorates (Table 4.6).

While these findings on foreign holders of the BS/MS degree would seem to contradict the concerns of state legislators about foreign students being more likely to leave, it is important to point out that it is a *ceteris paribus* finding that does not take

[53] The typical merit scholarship program targets in-state students with grade point averages of B or above. To the extent these scholarships affect the long-run location decision at all, the effect is stronger for high-ability students than for more marginal ones (Groen, 2004). It follows that scholarships good at state institutions (public or private) should be offered to high-ability students *regardless of birth state* (Groen and White (2004), Groen (2004).

account of the full range of variables that affect foreign students disproportionately. Overall in our sample, 75% of foreign-born students holding degrees other than doctorates stayed in the metropolitan areas where they earned their most recent degrees, as compared to 67% for domestic-born students.[54] The equivalent figures for holders of doctorates are 41% and 52%, respectively. Considering the many arguments made by university administrators in favor of international students, as well as new federal immigration controls that have made the issue moot, it is difficult to be alarmed by this new evidence on the leaving tendency of foreign doctorates.

4.7. Conclusion

This study has applied to the problem of college-to-work migration the multinomial choice model that most flexibly and realistically mixes together issues of taste and place. It operates at the metropolitan scale, providing a better description of skill-specific labor markets and amenities than the state-level data used in many prior studies. The fifty large metropolitan areas examined in this study represent a large share of the nation's production and consumption of knowledge workers, so the migration analysis should have external validity and be substantively important.

The study has demonstrated the RPL technique using a particularly rich micro-dataset. Virtually all findings from the prior migration literature are confirmed, including

[54] One reason for the finding on BS/MS graduates might be that foreign students disproportionately plan to earn an extra degree, typically a doctorate, at the same institution where they earned their bachelors' or masters' degree. Yet working full-time is a risky thing for a foreign student to do between degrees, since it could jeopardize visa status (note that nobody in our dataset was a student at the time they were surveyed). An alternative explanation is that these students have indeed completed their educations, but a relative lack of information on places within the U.S. and satisficing behavior leads them to work where they graduated, holding equal such factors as the concentration of technology jobs and the presence of other immigrants.

gravity effects, a general preference for “staying put,” and mobility that declines with age. The value of the RPL technique over CL is not so much that it reveals migration behaviors and motives that had previously been hidden. Instead, the more flexible technique helps avoid spurious results that are related to the improper IIA assumption. Furthermore, the very existence of preference weight variance within a population can be explored directly, opening up avenues for research using direct survey instruments.

Further research on the subjects covered in this article might focus on the collection of a wider, more detailed, and population-specific set of amenity data (a perpetual challenge); a deeper exploration of the causes and consequences of our findings on highly-educated places and college towns; a study that tests a limited-information theory of international student migration within the United States; and further work on the treatment versus selection effect of in-state college attendance on subsequent settlement choice. As in Groen (2004), the purpose of that work would be to test more rigorously the implicit assumptions underlying policies that states currently use to solve the problem of insufficient human capital.

Table 4.1 List of Metropolitan Origins and Destinations

Albany-Schenectady-Troy, NY MSA
Atlanta, GA MSA
Austin-San Marcos, TX MSA
Boston-Worchester-Lawrence-Lowell-Brockton, MA-NH CMSA
Buffalo-Niagara Falls, NY MSA
Champaign-Urbana, IL MSA
Charlottesville, VA MSA
Chicago-Gary-Kenosha, IL-IN-WI CMSA
Cincinnati-Hamilton, OH-KY-IN CMSA
Cleveland-Akron, OH CMSA
Columbus, OH MSA
Dallas-Fort Worth, TX CMSA
Denver-Boulder-Greeley, CO CMSA
Detroit-Ann Arbor-Flint, MI CMSA
Gainesville, FL MSA
Houston-Gavelston-Brazoria, TX CMSA
Indianapolis,IN MSA
KansasCity,MO-KS MSA
Knoxville, TN MSA
Lafayette, IN MSA
Lansing-East Lansing, MI MSA
Lawrence, KS MSA
Los Angeles-Riverside-Orange County, CA CMSA
Madison, WI MSA
Miami-Fort lauderdale, FL CMSA
Milwaukee-Racine,WI CMSA
Minneapolis-St. Paul, MN-WI MSA
New York-Northern New Jersey-Long Island, NY-NJ-CT-PA CMSA
NewOrleans,LA MSA
Norfolk-VirginiaBeach-NewportNews,VA-NC MSA
Orlando,FL MSA
Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD CMSA
Phoenix-Mesa,AZ MSA
Pittsburgh, PA MSA
Portland-Salem,OR-WA CMSA
Raleigh-Durham-Chapel Hill, NC MSA
Rochester, NY MSA
Sacramento-Yolo, CA CMSA
Salt Lake City-Ogden, UT MSA
San Diego, CA MSA
San Francisco-Oakland-San Jose, CA CMSA
SanAntonio,TX MSA
Santa Barbara-Santa Maria-Lompoc, CA MSA
Seattle-Tacoma-Bremerton, WA CMSA
St. Louis, MO-IL MSA
State College, PA MSA

Tallahassee, FL MSA
Tampa-St.Petersburg-Clearwater,FL MSA
Tucson, AZ MSA
Washington-Baltimore, DC-MD-VA-WV CMSA

Note: Metropolitan areas defined on the basis of 1995
1995 OMB county components.

Table 4.2 Place and Geographic Variables

Variable acronym	Number of levels	Description	Source
(1) MSA characteristics			
POP90	50	MSA population in 1990	U.S. Census, 1990
PCT20_29	50	Percent poplulation between 20 and 29 years of age in 1990	U.S. Census, 1990
IMMPCT90	50	Percent foreign born in 1990	U.S. Census, 1990
POVPCT90	50	Percent in poverty in 1990	U.S. Census, 1990
BACH90	50	Percent adults with BA degree or above in 1990	U.S. Census, 1990
MANPCT90	50	Percent employed in manufacturing industries in 1990	County Business Patterns
UNEMP	150	Unemployment rate in the year the individual graduated	Department of Labor, Bureau of Labor Statistics
EGRO10	150	Metropolitan area employment growth rate in the ten years immediately preceding year of graduation	Department of Commerce, Bureau of Economic Analysis, Regional Economic Information System
RD90	50	Federal R&D spending at universities per metropolitan employee, 1990	National Science Foundation CASPAR data; Bureau of Economic Analysis, Regional Economic Information System

PCTAEA92	50	Percent employees in AEA information technology industries in 1992	County Business Patterns; information technology industries identified by The American Electronics Association (AEA)
PTHLTH92	50	Percent employees in biomedical and health sectors in 1992	County Business Patterns; biomedical and health industries identified by Center for Regional Economic Issues (REI)
PTTECH92	50	PCTAEA92 + PTHLTH92	
ARPCT	50	Percent of residents born in Middle East or North Africa excluding Israel, 1990	U.S. Census, 1990
ASIAPCT	50	Percent of residents born in Asia, excluding China and Taiwan, 1990	U.S. Census, 1990
CARPCT	50	Percent of residents born in Carribean countries, 1990	U.S. Census, 1990
CHINPCT	50	Percent of residents born in China or Taiwan,1990	U.S. Census, 1990
INDPCT	50	Percent of residents born in India or Pakistan, 1990	U.S. Census, 1990
LATINPCT	50	Percent of residents born in Central America, South America, Spain, or Portugal, 1990	U.S. Census, 1990
OECDPCT	50	Percent of residents born in Canada, Europe, Australia, New Zealand, or Israel, 1990	U.S. Census, 1990
SSAPCT	50	Percent of residents born in sub-Saharan Africa, 1990	U.S. Census, 1990
PRCLIM	50	Places Rated Climate Score*	Boyer and Savageau (1993), software product

PRCOL	50	Places Rated Cost-of-Living Score*	Boyer and Savageau (1993), software product
PRCRIME	50	Places Rated Crime Score*	Boyer and Savageau (1993), software product
PRREC	50	Places Rated Recreation Score*	Boyer and Savageau (1993), software product
SAN FRANCISCO	2	= 1 if potential destination is San Francisco	
NEW YORK	2	= 1 if potential destination is New York	
ATLANTA	2	= 1 if potential destination is Atlanta	
BOSTON	2	= 1 if potential destination is Boston	
(2) Constructed geographic variables			
DISTANCE	1000	Distance between each pair of possible origins (40) and destinations (50)	Calculated using Albers coordinates provided by Benjamin Widner of Colorado State University
SAME	2	= 1 if individual stayed in MSA where graduated	SESTAT data, with geographic identifiers provided by NSF

* Aggregated from PMSA to CMSA level where necessary.

Table 4.3 Individual Characteristics

Variable acronym	Description
(1) Demographic variables	
AGEGRAD	Age of respondent when he/she graduated
AGE30	= 1 if AGEGRAD < 30
FEMALE	= 1 if female
MARRIED	= 1 if married in 1995
CHIL	= 1 if lived with children in 1995
SALARY	salary on present job
(2) Occupation-related variables	
LIFE	= 1 if most recent degree was in life sciences
IT	= 1 if most recent degree was in computer science or math
PHYS	= 1 if most recent degree was in physical sciences or engineering
TECH	= 1 if LIFE, IT, or PHYS. = 0 if degree was in social sciences or professional field outside of medicine
SALARY	salary on present job
(3) Origin and nationality	
AR	= 1 if born in Arab country or North Africa
ASIA	= 1 if born in Asian country excluding China
CAR	= 1 if born in Carribbean country
CHIN	= 1 if born in Chinese speaking country
IND	= 1 if born in India or Pakistan
LATIN	= 1 if Spanish or Portugese speaking and not CAR
OECD	= 1 if born in Canada, Europe, Australia, New Zealand, or Israel
SSA	= 1 if born in sub-saharan Africa
FORBTH	= 1 if born outside USA
USBTH	= 1 if born inside USA
BTHGRAD	= 1 if state of birth is the same as state of most recent degree

Source: Licensed SESTAT data for 1995. see http://www.sestat.nsf.gov

Table 4.4 Logit Models of Choice of Metropolitan Destination, All New Graduates

Conditional Logit Specification			Random Parameters Logit Specification			
Variable	Estimate	Standard Error	Variable		Estimate	Standard Error
Characteristics of destinations						
BACH90	0.548***	(0.048)	BACH90	Mean	0.631***	(0.061)
				Std. Dev.	0.466***	(0.082)
RD90	-0.453***	(0.044)	RD90	Mean	-0.773***	(0.105)
				Std. Dev.	0.817***	(0.195)
POVPCT90	-0.453***	(0.044)	POVPCT90	Mean	-0.397***	(0.063)
				Std. Dev.	0.447***	(0.117)
PRCRIME	0.045	(0.041)	PRCRIME	Mean	-0.020	(0.055)
				Std. Dev.	0.403***	(0.088)
PRCLIM	0.033	(0.035)	PRCLIM	Mean	0.086*	(0.046)
				Std. Dev.	0.508***	(0.133)
UNEMP	0.280***	(0.052)	UNEMP	Mean	0.205***	(0.064)
				Std. Dev.	0.489***	(0.194)
EGRO10	0.464*	(0.253)	EGRO10		0.779***	(0.299)
PRCOL	-0.502***	(0.077)	PRCOL		-0.510***	(0.092)
PRREC	0.044	(0.036)	PRREC		-0.008	(0.042)
Gravity effects						

POP90	0.736***	(0.045)	POP1990	0.801***	(0.05)
DISTANCE	-0.740***	(0.030)	DISTANCE	-0.827***	(0.031)
SALARY * DISTANCE	0.222***	(0.017)	SALARY * DISTANCE	0.240***	(0.015)
			Occupation-place match		
LIFE * PTHLTH92	0.321***	(0.070)	LIFE * PTHLTH92	0.331***	(0.078)
IT * PCTAEA92	0.148***	(0.057)	IT * PCTAEA92	0.145**	(0.061)
PHYS * MANPCT90	0.105***	(0.032)	PHYS * MANPCT90	0.148***	(0.035)
TECH * POP90	-0.114***	(0.024)	TECH * POP90	-0.118***	(0.025)
			Demographic factors		
SAME	3.097***	(0.073)	SAME	3.298***	(0.081)
BTHGRAD * SAME	0.875***	(0.076)	BTHGRAD * SAME	0.963***	(0.082)
FEMALE * SAME	-0.079	(0.069)	FEMALE * SAME	-0.055	(0.073)
MARRIED * SAME	0.052	(0.074)	MARRIED * SAME	0.020	(0.078)
AGEGRAD * SAME	0.409***	(0.041)	AGEGRAD * SAME	0.452***	(0.044)
FORBTH*SAME	-0.003	(0.089)	FORBTH*SAME	0.034	(0.094)
FORBTH*IMMPCT90	0.234***	(0.046)	FORBTH*IMMPCT90	0.248***	(0.053)
AGE30 * PCT20_29	-0.136**	(0.053)	AGE30 * PCT20_29	-0.123*	(0.067)
AGEGRAD * PRCOL	-0.041**	(0.019)	AGEGRAD * PRCOL	-0.043**	(0.021)
CHIL * PRCOL	-0.069*	(0.041)	CHIL * PRCOL	-0.077*	(0.043)
			Ethnic affinity factors		
CAR * CARPCT	0.229**	(0.098)	CAR * CARPCT	0.261	(0.206)
CHIN * CHINPCT	0.142***	(0.050)	CHIN * CHINPCT	0.140***	(0.051)

OECD * OECDPCT	-0.044	(0.081)	OECD * OECDPCT	-0.045	(0.084)
SSA * SSAPCT	0.251**	(0.114)	SSA * SSAPCT	0.242	(0.222)
IND * INDPCT	0.076	(0.071)	IND * INDPCT	0.065	(0.074)
ASIA * ASIAPCT	-0.035	(0.085)	ASIA * ASIAPCT	-0.020	(0.099)
LATIN * LATINPCT	0.094	(0.088)	LATIN * LATINPCT	0.101	(0.092)
AR * ARPCT	0.042	(0.101)	AR * ARPCT	0.024	(0.097)
Selected fixed effects					
SAN FRANCISCO	1.511***	(0.179)	SAN FRANCISCO	1.209***	(0.207)
NEW YORK	-0.661***	(0.159)	NEW YORK	-0.639***	(0.18)
ATLANTA	-0.278**	(0.131)	ATLANTA	-0.367**	(0.151)
BOSTON	0.633***	(0.167)	BOSTON	0.558***	(0.211)
Fit statistics					
Log likelihood	-9260.789		Log likelihood	-9198.911	
LR Chi^2	24745.400		LR Chi^2	24869.150	
Pseudo R^2	0.572		Pseudo R^2	0.575	
N	5530 x 50		N	5530 x 50	

*** 1% p-value
** 5% p-value
* 10% p-value

Table 4.5 Logit Models of Choice of Metropolitan Destination, BS/MS Graduates Only

Conditional Logit Specification			Random Parameters Logit Specification				
Variable	Estimate	Standard Error	Variable		Estimate		Standard Error
Characteristics of destinations							
BACH90	0.412***	(0.057)	BACH90	Mean	0.517	***	(0.068)
				Std. Dev.	0.465	***	(0.085)
RD90	-0.294***	(0.068)	RD90	Mean	-0.687	***	(0.107)
				Std. Dev.	0.851	***	(0.125)
POVPCT90	-0.446***	(0.051)	POVPCT90	Mean	-0.337	***	(0.058)
				Std. Dev.	0.379	***	(0.114)
PRCRIME	0.137***	(0.046)	PRCRIME	Mean	0.072	***	(0.059)
				Std. Dev.	0.414	***	(0.103)
PRCLIM	0.002	(0.041)	PRCLIM	Mean	0.066		(0.052)
				Std. Dev.	0.554	***	(0.078)
UNEMP	0.235***	(0.060)	UNEMP	Mean	0.144	**	(0.072)
				Std. Dev.	0.497	***	(0.097)
EGRO10	0.597**	(0.295)	EGRO10		0.765	**	(0.338)
PRCOL	-0.416***	(0.091)	PRCOL		-0.426	***	(0.106)
PRREC	0.042	(0.042)	PRREC		-0.009		(0.049)
Gravity effects							

POP90	0.721***	(0.051)	POP90	0.781	***	(0.056)
DISTANCE	-0.859***	(0.038)	DISTANCE	-0.982	***	(0.038)
SALARY * DISTANCE	0.204***	(0.025)	SALARY * DISTANCE	0.218	***	(0.023)
Occupation-place match						
LIFE * PTHLTH92	0.254***	(0.091)	LIFE * PTHLTH92	0.266	***	(0.102)
IT * PCTAEA92	0.146**	(0.067)	IT * PCTAEA92	0.139	**	(0.068)
PHYS * MANPCT90	0.109***	(0.036)	PHYS * MANPCT90	0.147	***	(0.040)
TECH * POP90	-0.139***	(0.027)	TECH * POP90	-0.147	***	(0.028)
Demographic factors						
SAME	3.194***	(0.084)	SAME	3.341	***	(0.091)
BTHGRAD * SAME	0.771***	(0.083)	BTHGRAD * SAME	0.857	***	(0.089)
FEMALE * SAME	-0.120	(0.078)	FEMALE * SAME	-0.095		(0.082)
MARRIED * SAME	0.185**	(0.087)	MARRIED * SAME	0.175	*	(0.091)
AGEGRAD * SAME	0.564***	(0.057)	AGEGRAD * SAME	0.608	***	(0.059)
FORBTH*SAME	0.340***	(0.115)	FORBTH*SAME	0.417	***	(0.120)
FORBTH*IMMPCT90	0.227***	(0.063)	FORBTH*IMMPCT90	0.250	***	(0.070)
AGE30 * PCT20_29	-0.129**	(0.064)	AGE30 * PCT20_29	-0.140	*	(0.076)
AGEGRAD * PRCOL	-0.066**	(0.030)	AGEGRAD * PRCOL	-0.067	**	(0.031)
CHIL * PRCOL	0.004	(0.059)	CHIL * PRCOL	0.003		(0.064)
Ethnic affinity factors						
CAR * CARPCT	0.206*	(0.123)	CAR * CARPCT	0.230		(0.253)
CHIN * CHINPCT	0.231***	(0.082)	CHIN * CHINPCT	0.255	***	(0.079)
OECD * OECDPCT	-0.022	(0.114)	OECD * OECDPCT	-0.031		(0.134)
SSA * SSAPCT	0.329**	(0.154)	SSA * SSAPCT	0.337		(0.288)

IND * INDPCT	0.022	(0.097)	IND * INDPCT	-0.015		(0.092)
ASIA * ASIAPCT	0.037	(0.115)	ASIA * ASIAPCT	0.079		(0.129)
LATIN * LATINPCT	-0.022	(0.129)	LATIN * LATINPCT	-0.022		(0.139)
AR * ARPCT	-0.178	(0.160)	AR * ARPCT	-0.174		(0.119)
			Selected fixed effects			
SAN FRANCISCO	1.348***	(0.211)	SAN FRANCISCO	1.001	***	(0.232)
NEW YORK	-0.919***	(0.187)	NEW YORK	-0.926	***	(0.205)
ATLANTA	-0.262*	(0.149)	ATLANTA	-0.401	**	(0.173)
BOSTON	0.355*	(0.196)	BOSTON	0.254		(0.240)
			Fit statistics			
Log likelihood	-6874.9432		Log likelihood	-6822.434		
LR Chi^2	21560.03		LR Chi^2	21665.050		
Pseudo R^2	0.6106		Pseudo R^2	0.614		
N	4513 x 50		N	4513 x 50		

Table 4.6 Logit Models of Choice of Metropolitan Destination, Doctorate Graduates Only

Conditional Logit Specification			Random Parameters Logit Specification			
Variable	Estimate	Standard Error	Variable		Estimate	Standard Error
			Characteristics of destinations			
BACH90	1.012***	(0.100)	BACH90	Mean	1.249***	(0.159)
				Std. Dev.	0.817***	(0.239)
RD90	-0.935***	(0.182)	RD90	Mean	-1.665***	(0.37)
				Std. Dev.	1.146***	(0.375)
POVPCT90	-0.474***	(0.107)	POVPCT90	Mean	-0.418**	(0.2)
				Std. Dev.	0.833***	(0.299)
PRCRIME	-0.363***	(0.106)	PRCRIME	Mean	-0.664***	(0.169)
				Std. Dev.	0.728***	(0.256)
PRCLIM	0.153**	(0.077)	PRCLIM	Mean	0.229*	(0.123)
				Std. Dev.	0.667**	(0.29)
UNEMP	0.462***	(0.116)	UNEMP	Mean	0.526***	(0.18)
				Std. Dev.	1.105***	(0.362)
EGRO10	0.434	(0.586)	EGRO10		1.050	(0.729)
PRCOL	-0.695***	(0.172)	PRCOL		-0.751***	(0.226)
PRREC	0.010	(0.078)	PRREC		-0.067	(0.098)
			Gravity effects			

POP90	0.900***	(0.110)	POP90	1.021***	(0.133)
DISTANCE	-0.345***	(0.057)	DISTANCE	-0.386***	(0.063)
SALARY * DISTANCE	0.026	(0.033)	SALARY * DISTANCE	0.039	(0.034)
Occupation-place match					
LIFE * PTHLTH92	0.432***	(0.111)	LIFE * PTHLTH92	0.420***	(0.152)
IT * PCTAEA92	0.213*	(0.122)	IT * PCTAEA92	0.240	(0.151)
PHYS * MANPCT90	0.154**	(0.071)	PHYS * MANPCT90	0.297***	(0.086)
TECH * POP90	-0.056	(0.056)	TECH * POP90	-0.041	(0.071)
Demographic factors					
SAME	1.627***	(0.213)	SAME	1.886***	(0.244)
BTHGRAD * SAME	1.026***	(0.230)	BTHGRAD * SAME	1.224***	(0.272)
FEMALE * SAME	0.348**	(0.168)	FEMALE * SAME	0.448**	(0.195)
MARRIED * SAME	0.468***	(0.179)	MARRIED * SAME	0.484**	(0.204)
AGEGRAD * SAME	0.875***	(0.093)	AGEGRAD * SAME	1.011***	(0.104)
FORBTH*SAME	-0.08	(0.178)	FORBTH*SAME	-0.075	(0.205)
FORBTH*IMMPCT90	0.296***	(0.081)	FORBTH*IMMPCT90	0.303***	(0.1)
AGE30 * PCT20_29	-0.197	(0.158)	AGE30 * PCT20_29	-0.181	(0.22)
AGEGRAD * PRCOL	-0.142***	(0.039)	AGEGRAD * PRCOL	-0.134***	(0.048)
CHIL * PRCOL	-0.207***	(0.060)	CHIL * PRCOL	-0.220***	(0.068)
Ethnic affinity factors					
CAR * CARPCT	0.314	(0.232)	CAR * CARPCT	0.286	(0.426)
CHIN * CHINPCT	-0.019	(0.066)	CHIN * CHINPCT	-0.019	(0.074)
OECD * OECDPCT	-0.1	(0.123)	OECD * OECDPCT	-0.079	(0.132)
SSA * SSAPCT	0.052	(0.236)	SSA * SSAPCT	0.029	(0.413)

IND * INDPCT	0.064	(0.123)	IND * INDPCT	0.081	(0.144)
ASIA * ASIAPCT	-0.239	(0.147)	ASIA * ASIAPCT	-0.266	(0.186)
LATIN * LATINPCT	0.209	(0.137)	LATIN * LATINPCT	0.245*	(0.139)
AR * ARPCT	0.082	(0.134)	AR * ARPCT	0.063	(0.172)
			Selected fixed effects		
SAN FRANCISCO	1.964***	(0.392)	SAN FRANCISCO	1.834***	(0.537)
NEW YORK	-0.11	(0.326)	NEW YORK	0.105	(0.446)
ATLANTA	-0.325	(0.303)	ATLANTA	-0.177	(0.361)
BOSTON	1.655***	(0.345)	BOSTON	1.833***	(0.538)
			Fit statistics		
Log likelihood	-2165.037		Log likelihood	-2133.207	
LR Chi^2	3626.980		LR Chi^2	3690.641	
Pseudo R^2	0.456		Pseudo R^2	0.464	
N	1017 x 50		N	1017 x 50	

Table 4.7 Proportion of respondents who Respond to the Factor Positively (100-X view the factor negatively)

Place Attribute	All Graduates	BS/MS Graduates	Doctoral Graduates
BACH90	91.2	86.9	93.7
RD90	17.3	20.9	7.3
POVPCT90	18.7	18.9	30.5
PRCRIME	48.1	56.7	18.1
PRCLIM	56.4	54.8	63.5
UNEMP	66.3	61.4	68.3

Chapter 5 Summary and Conclusion

This dissertation contains three essays on individual decision making. Chapter 2 and Chapter 3 report the results of a laboratory based experiment in which individuals make decisions in market like environments with common values. Chapter 2 looked into herd behavior and information cascades in markets with sequential bids. Also, in the chapter, I attempted to explore whether herd behavior and information cascades can explain the winners' curse. One of the main results of the Chapter is that the winner's curse is highly pervasive in sequential auction experimental settings. Information cascades on the equilibrium path are clearly visible in the early stages of bidding, but are short and fragile. However, a majority of observed events of herd behavior is not due to information cascades and hence rational herding is not a significant cause of the winners' curse. However, herd behavior due to disconfirmation bias and conservatism in beliefs are credited for the occurrence of the winner's curse. Cascades can explain the winner's curse only marginally. Bidders seem to act on the basis of their stated beliefs and update their beliefs, but mostly in a non-Bayesian fashion. A significant proportion of the bidding behavior can be explained by the use of other behavioral strategies which relaxes assumptions of rationality, common knowledge of rationality and Bayesian updating of beliefs. Results of the general Decision Weight Model indicate that private signals are the single most important determinant of bidding decisions.

In Chapter 3, I extended the analysis in Chapter 2 to examine how financially motivated individuals form their beliefs in markets with sequential bids. In particular, I attempted to understand whether heuristics and biases exhibited by bidders can explain deviations from Bayesian behavior. I found that bidders use conservatism heuristic and exhibit confirmation bias and disconfirmation bias in forming their subjective beliefs. However, the use of heuristics and the presence of biases in belief formation are sensitive to treatment conditions and cannot be generalized across treatments. But, across all treatments, bidders tend to update their beliefs in the direction of their private signal. Our analysis of the formation of beliefs in markets with common values also suggests an alternative explanation for overbidding in common value auction environments. Non optimal belief formation due to optimistic prior beliefs and conservatism in updating beliefs can explain overbidding in common value environments. It is important to point out that Perfect Bayesian Equilibrium actions are consistent with the presence of heuristics and biases in belief formation, suggesting that equilibrium actions need not be a result of equilibrium beliefs.

In Chapter 4, I looked into individual decision making from a more applied and policy context by examining the destination choice decisions of graduates and doctorate holders within the United States. The results of the random parameter logit analysis show that science and technology graduates migrate to better educated places, other things equal; that PhD graduates pay greater attention to amenity characteristics than other degree holders; and that foreign students from some immigrant groups migrate to places where those groups are concentrated. The present study will join a growing list of works that seek to inform brain drain policies in U.S. metropolitan areas by deepening our understanding of the revealed-preference geographic behavior of university graduates. In addition, the study demonstrates the richness of the random parameters technique for behavioral-geographic analysis.

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APPENDIX

Experiment: Instructions

Introduction

You are about to participate in an experiment in the economics of decision making. This research is funded by various research foundations. If you follow the instructions you may earn a considerable amount of money, which will be paid to you in cash at the end of the experiment.

In the experiment you will participate in a series of markets in which you will have the opportunity to bid to purchase an object. Other participants in the experiment will have the opportunity to bid to purchase the object as well. Your earnings will depend upon the bids that you make, and upon the bids that other participants in the market make. The details of how you can make bids and earn money will be explained below. You will also have the opportunity at various times to earn additional money by making predictions about the value of the object for which you are bidding. The details of how you make these predictions and how you earn money from your predictions will also be explained below.

The currency used in this experiment is *francs*. All monetary amounts are denominated in this currency. At the end of the experiment your earnings in francs will be converted into rupees at the rate of 1 rupee per 10 francs.

We are interested in how you make decisions under certain specific conditions. It is therefore important that you do not speak or communicate with other participants in the experiment at any time. If you have a question at any time, please raise your hand and one of the monitors will come and answer your question.

Specific Instructions

Please read these instructions carefully before you begin. You may return to the instructions at any time during the experiment by clicking with your mouse on the appropriate button on your screen.

You will participate in a series of markets. In each market, you will be one of 6 different potential bidders to purchase an object. This object has a *redemption value*. If you are able to purchase the object, then your profits are equal to the redemption value minus the price that you paid for the object. Only one bidder will purchase the object in each market.

You will begin the experiment with an *initial cash balance* of 1000 francs. You may use this cash balance to bid on the object that is for sale. <u>As you progress through the experiment, your cash balance will go up as you make profits (or go down if you make losses).</u>If you do not make a purchase in a market, then your cash balance remains unchanged.

The redemption value of the object that you are bidding on in any given market will be unknown to you. <u>The redemption value of the object is either HIGH (100 francs) or LOW (0 francs), and it is equally likely to be either high or low in each market.</u> The determination of the value of the object will be made at the start of each market, before the bidding begins. The true redemption value of the object will be revealed at the end of the market, when the final determination of who will purchase the object has been made.

Before you make a bid you will receive a *signal* that is suggestive of what the true redemption value of the object will be. All that you will know is that if the true redemption value of the object is HIGH, then the chances that you receive a signal indicating that the value is HIGH will be greater than the chances that you receive a signal indicating that the value is LOW. Similarly, if the true value is LOW, then the chances of receiving a signal indicating that the value is LOW will be greater than the chances that you receive a signal indicating that the value is HIGH. Thus, there is some chance that you receive a signal that is not accurate, but you are more likely to receive a signal that is accurate.

In order to help you to understand how informative the signal is, I provide the following information at the beginning of the market. That is $\Pr(s_H | V_H) = 0.8$. This also means that the probability of getting a LOW signal when the value is HIGH is 0.2.

Also the probability that you receive a LOW signal if the object is in fact of a LOW value is 0.8. That is $\Pr(s_L | V_L) = 0.8$. This also means that the probability of getting a HIGH signal when the value is LOW is 0.2. This information is announced at the beginning of each market and will be clearly exhibited on the black board.

Bidding

The bidding in each market will proceed as follows. In a random order, you will be called upon to place a bid for the object. That is, in each market the order in which the eight participants bid will be determined randomly, and then the bidding will begin. The first bidder will first receive a signal suggestive of the true value of the object. Then he or she will place a bid for the object in the form of an amount in francs that he or she would be willing to pay for the object. Then it will be the turn of the second bidder. The second bidder will be allowed to view the bid made by the first bidder, and then will receive an independent signal about the value of the object. The second bidder will then place a bid for the object. For subsequent bidders, the procedure is the same: first, the bidder will be allowed to view all of the bids that have been placed so far in the market. He or she will then receive an independent signal about the value of the object. Finally, the bidder is then given the opportunity to place a bid for the object.

When the Bidding Ends

You may or may not have additional opportunities to bid. There may be two or more full rounds of bidding, but there may be only one round of bidding. The bidding may even be ended in the middle of a round (though never in the first round).Thus, you cannot count on having more than one opportunity to place a bid in a particular market. When the bidding ends, the individual who has placed the highest bid will purchase the object and obtain profits or losses as described above. All other bidders will neither gain nor lose money. If more than one bidder has made the same highest bid for the object, one will be selected at random as the purchaser of the object.

Predicting the Value of the Object

In addition to the money that you can earn by bidding and purchasing the object, you will also be able to earn money by predicting what the true value of the object is. Specifically, you will have several opportunities to state what you believe the chances are that the value of the object is HIGH. Each time you bid, you will have two opportunities to make such a prediction. First, after you view the bids that have been made so far in the market, you will be asked to state your beliefs about this chance. That is, I will ask you to indicate, in light of the bids that previous bidders have made, by a number between 0 and 1 what you think the probability is that the object has the HIGH value. After you do this, you will then receive your private signal suggestive of what the value of the object is. I will then ask you, again, to state your belief about the chances that the value of the object is HIGH. Then you will be able to make your bid.

You will be paid an amount of money for each report of your beliefs that you make which depends upon whether the object is revealed to be HIGH or LOW value at the end of the bidding. In general, you will receive a higher payoff when you report a probability that is greater than .5 AND the object is HIGH value, or when you report a probability that is less than .5 AND the object is LOW value. However, you will always maximize your EXPECTED PAYOFF when you report your true belief about this probability.

More precisely, you will receive a payoff, in francs, of

25 - 25 x (1 - probability that you report) ^{2} if the value of the object is HIGH

And, 25 - 25 x (probability that you report) ^{2} if the value of the object is LOW.

This means, for example, that you will receive a payoff of 25 francs if you report a probability of 1 and the object is HIGH value, or if you report a probability of 0 and the object is LOW value. On the other hand, if you report of a probability of 1 and the object is LOW value, or if you report a probability of 0 and the object is HIGH value, then you will receive a payoff of 0.Thus, if you are not convinced that the value of the object is HIGH or LOW for certain, then you are better off, in terms of the payoff you can expect to receive, if you state your true best estimate of this probability.

Summary

You will participate in a series of markets in which you will have the opportunity to bid to purchase an object of uncertain value. You will be able to view the bids of those who have bid before you in the market, and you will also receive a private signal that is positively correlated with the true value of the object, before you bid on the object. You will also be able to earn additional money by reporting what you believe the chances are that the object is HIGH value. You will start out the experiment with an initial cash balance of 1000 francs ($10).Your profits or losses will be added to this balance as you progress through the markets. Your earnings from reporting your beliefs will also be added to this balance. At the end of the experiment, your total earnings in francs will be converted into dollars and you will be paid your earnings in cash.

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