ESSAYS IN MARKET DESIGN AND BEHAVIORAL ECONOMICS

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# Contents

Acknowledgements v

1 Introduction 1

2 Consumer and Producer Behavior in the Market for Penny Auctions: A Theoretical and Empirical Analysis 3

2.1 Introduction 3

2.2 Auction Description and Theoretical Analysis 9

2.2.1 Auction Description 9

2.2.2 Setup 10

2.2.3 Equilibrium Analysis 12

2.2.4 The Bidding Equilibrium - Equilibrium Predictions 15

2.3 Description of Data 17

2.3.1 Description of Swoopo 17

2.3.2 Description of Data 18

2.3.3 Value Estimation 19

2.3.4 Profit Analysis 20

2.4 Empirical Tests of Model 21

2.4.1 Research Question and Empirical Strategy 21

2.4.2 Consumer Goods 22

2.4.3 Cash and Bid Vouchers 25

2.5 Modeling Sunk Costs 27

2.6 Experience, Strategies, and Profits 30
List of Tables

2.1 Descriptive Statistics of the Auction-Level and Bid-Level Datasets . . 49
2.2 Descriptive Statistics of the Auction-Level and Bid-Level Datasets . . 50
2.3 Descriptive Statistics of Profit . . . . . . . . . . . . . . . . . . . . . . 51
2.4 Regressions of profit on experience . . . . . . . . . . . . . . . . . . . 51
2.5 Regressions of profit on experience, controlling for strategies . . . . 52
2.6 (Second stage) IV Regressions of desired supply on (predicted) demand 53
2.7 Regressions of instantaneous profit on number of users and auctions . 53
2.8 Descriptive Profit Statistics of competition (from October 2008) . . . 54

3.1 Regressions of Undervoting on Ballot Position . . . . . . . . . . . . 87
3.2 Regressions of "No" Votes on Ballot Position . . . . . . . . . . . . . . 88
3.3 Regressions of Candidate Vote Share on Appearing First * Ballot Position 89

4.1 Pre-Treatment Balance of Groups . . . . . . . . . . . . . . . . . . . . 101
4.2 Donation Rates and Amounts Across Treatment Groups . . . . . . . 102
4.3 Probit Regressions on Donation Rates . . . . . . . . . . . . . . . . . 103
4.4 Probit Regressions on Donation Rates . . . . . . . . . . . . . . . . . 104
List of Figures

2.1 Left Graph: Distribution of Auction Profits. Right Graph: Distribution of Auction Profits as Percentage of Good’s Value. . . . . . . . . 22
2.2 Empirical vs. Theoretical (Dashed) Survival Rates . . . . . . . . . 23
2.3 Empirical vs. Theoretical (Dashed) Hazard Rates . . . . . . . . . 24
2.4 Empirical vs. Theoretical (Dashed) Instantaneous Profit Rates . . . 24
2.5 Empirical vs. Theoretical (Dashed) Hazard and Inst. Profit. Left: Cash Auctions. Right: Bid Voucher Auctions . . . . . . . . 26
2.6 Predicted Hazard Rates of Sunk Cost Model: Effect of Sunk Costs (p) = .3. Graphs vary by "naivety" (n). . . . . . . . . . 31
2.7 Cumulative Number of Users and Generated Profit over Total Number of Bids Placed . . . . . . . . . . . . . . . . . . . . . . . . . . . . 33
2.8 Local Poly. Regression of Profit on Experience. Histogram of Experience at Each Bid Also Shown. . . . . . . . . . . . . . . . . 35
2.9 Number of Active Users over 48 Hours (Actual vs. Smoothed) . . 42
2.10 Iso-Auction Lines with Respect to Profit and Users . . . . . . . . 44
2.11 Estimated Actual vs. Optimal (Dashed) Supply Curves. Kernal Density of Number of Active Users Also Shown. . . . . . . . . . . . 46
3.1 Distribution of Number of Precincts with Proposition 35 at Different Ballot Positions . . . . . . . . . . . . . . . . . . . . . . . . . 58
3.2 Undervotes and "No" Votes Increase with the Ballot Position of Proposition 35 . . . . . . . . . . . . . . . . . . . . . . . . . . . . . 60
3.3 Kernal Density of variation from mean ballot position of a contest (separated by type of contests) . . . . . . . . . . . . . . . . . . . . 73
3.4 The histogram shows the distribution of the total expenditures (log) variable. The line is the estimated ballot order coefficient for different value of this variable.

3.5 Kernal Density of variation from mean contest-specific ordering of a candidate

4.1 The three solicitation postcards sent to (from left to right) the control, cooperative, and competitive groups.

4.2 Histogram of the Donation Amounts of the Control (top), Cooperative (middle), and Competitive (bottom) Groups.

4.3 The Difference between the Ally/Rival Treatments and the Control Contribution Distributions for all Contributions less than $100.

A.1 Change in non-bidding equilibria when the leader is allowed to bid.

A.2 Numerical Analysis of the hazard rate of auctions for different values (solid lines) when the multiple bids are accepted at each time period vs. the predicted hazard rate (dotted red line) when only one bid is accepted.
Chapter 1

Introduction

This dissertation is the combination of three distinct papers on Behavioral Economics and Market Design.

In the first paper, I theoretically and empirically analyze consumer and producer behavior in a relatively new auction format, in which each bid costs a small amount and must be a small increment above the current high bid. I describe the set of equilibrium hazard functions over winning bids and identify a unique function with desirable conditions. Then, I examine bidder behavior using two datasets of 166,000 auctions and 13 million individual bids, captured with a real-time collection algorithm from a company called Swoopo. I find that players overbid significantly in aggregate, yielding average revenues of 150% of the good’s value and generating profits of €18 million over four years. While the empirical hazard rate is close to the predicted hazard rate at the beginning of the auction, it deviates as the auction progresses, matching the predictions of my model when agents exhibit a sunk cost fallacy. I show that players’ expected losses are mitigated by experience. Finally, I estimate both the current and optimal supply rules for Swoopo using high frequency data, demonstrating that the company achieves 98.6% of potential profit. The analysis suggests that over-supplying auctions in order to attract a larger userbase is costly in the short run, creating a large structural barrier to entrants. I support this conclusion using auction-level data from five competitors, which establishes that entrants collect relatively small or negative daily profits.
CHAPTER 1. INTRODUCTION

The second paper (joint with Scott Nicholson) addresses the impact of making multiple previous choices on decision making, which we call "choice fatigue." We exploit a natural experiment in which different voters in San Diego County are presented with the same contest decision at different points on the ballot, providing variation in the number of previous decisions made by the voters. We find that increasing the position of a contest on the ballot increases the tendency to abstain and to rely on decision shortcuts, such as voting for the status-quo or the first candidate listed in a contest. Our estimates suggest that if an average contest was placed at the top of the ballot (when voters are "fresh"), abstentions would decrease by 10%, the percentage of "no" votes on propositions (a vote for the status-quo) would fall by 2.9 percentage points, and the percentage of votes for the first candidate would fall by .5 percentage points. Interestingly, if this occurred, our results suggest that 22 (6.25%) of the 352 propositions in our dataset would have passed rather than failed. Implications of the results range from the dissemination of information by firms and policy makers to the design of electoral institutions and the strategic use of ballot propositions.

The third paper (joint with Jesse Cuhna) paper presents evidence from a field experiment on the impact of inter-group competition on intra-group contributions to a public good. We sent political solicitations to potential congressional campaign donors that contained either reference information about the past donations of those in the same party (cooperative treatment), those in the competing party (competition treatment), or no information (the control group). The donation rate in the competitive and cooperative treatment groups was 85% and 42% above that in the control, respectively. Both treatments contained a monetary reference point, which influenced the distribution of donations. While the cooperative treatment induced more contributions concentrated near the mentioned reference point, the competitive treatment induced more contributions at nearly twice the level of the given reference point, leading to a higher total contributed amount. This suggests that both cooperative and "pro-social" motives can drive higher contribution rates and total contributions, but the elicitation of competitive behavior can be more profitable in certain fundraising situations.
Chapter 2

Consumer and Producer Behavior in the Market for Penny Auctions: A Theoretical and Empirical Analysis

2.1 Introduction

This paper theoretically and empirically explores consumer and producer behavior in the relatively new market for penny auctions, using two datasets collected from the largest auctioneer, Swoopo.\(^1\) This auction provides an ideal field laboratory to study individual behavior as it is a reasonably transparent game (the rules are discussed below) played by many people (there are over 20,000 unique participants per week in my dataset) for relatively high stakes (the value of auctioned goods averages over €200) over a long period of time (the auctions have been run since 2005). Additionally, as the auctioneer must make important supply choices and many companies have recently begun to run the auctions, the analysis yields insights into producer optimization and market dynamics in a nascent auction market.

\(^1\)As of June 2009, Swoopo appeared to be the largest company running penny auctions by all important measures, such as revenue, number of daily auctions, and number of daily users.
CHAPTER 2. BEHAVIOR IN PENNY AUCTIONS

My analysis leads to three main contributions to the auction, market design, and behavioral economics literature. My first main result is that the auctioneer collects average revenues that exceed 150% of the value of the auctioned good, providing an unequivocal example of consistent overbidding in auctions. In order to better understand this behavior, I model the penny auction in a game-theoretic framework and solve for the equilibrium hazard rates of winning bids. My second main result is that, relative to equilibrium predictions, bidders overbid more and more as the auction continues. I establish that this behavior is consistent with the predictions of my model when agents exhibit a naive sunk cost fallacy. I show that higher levels of experience in the auction mitigate these losses. For my third main result, I use high-frequency data to separately estimate both the actual and optimal supply rules for Swoopo, demonstrating that the company captures nearly 99% of potential short term profits. The analysis suggests that over-supplying auctions for a given number of users leads the auctions to end prematurely, which can produce negative profits for the auctioneer. This effect implies a structural barrier to entrants, who must over-supply auctions in order to attract a larger userbase. This conclusion is consistent with findings from data on five major competitors, which establishes that entrants are not making significant daily profits in the medium term.

Before detailing my main results, it is useful to briefly describe the rules of the penny auction. First, players are restricted to bid a fixed bid increment above the current bid for the object, which is zero at the beginning of the auction. For example, if the current bid is €10.00 and the bid increment is €.01, then the next bidder must bid €10.01, the next €10.02, and so on. The auction is commonly referred to as a "penny auction" as a result of the common use of a one penny bid increment. Second, players must pay a non-refundable fixed bid cost (€.50 in my dataset) to place a bid. The majority of the auctioneer’s final revenue is derived from the bid costs collected throughout the auction. Finally, the end of the auction is determined by a countdown timer, which increases with every bid (by approximately ten seconds in my dataset). Therefore, a player wins the object when her bid is not followed by another bid in a short period of time. Of traditionally studied auctions, the penny auction is most
closely related to the War-of-Attrition (WOA).\(^2\)

Using a theoretical analysis, I find that this auction format induces a mixed-strategy equilibrium in which the winning bid amount is stochastic. Moreover, by characterizing all equilibrium hazard rates, I show that any equilibrium in which play continues past the second period must be characterized by a unique global hazard function from that point onward. I demonstrate that this prediction is robust to a variety of changes and extensions to the game. I then test these predictions using auction-level data on 166,000 unique auctions and bid-level data on 13 million bids. The bid-level data was captured from Swoopo’s website using a multi-server real-time collection algorithm that recorded nearly every bid from every person on every auction over a hundred day period.

My first main empirical result is that the average revenue from these auctions significantly exceeds the easily-obtainable value of the goods. Although Swoopo makes negative profit on more than half of the auctions in the dataset, the average profit margin is 52\%, which has generated €18M in profits over a four year period. In an illustrative example, my dataset contains over 2,000 auctions for direct cash payments, in which the average profit margin is 104\% of the face value of the prize. This finding contributes an unambiguous field example of overbidding in auctions to a large literature on the subject, which includes experimental work\(^3\) and a number of recent field studies.\(^4\) Perhaps the most convincing of the field studies is Lee and Malmendier (2008), who show that bidders pay 2\% above an easily accessible "buy it

\(^2\)In both the WOA and penny auctions, players must pay a cost for the game to continue and a player wins when other players decide not to pay this cost. However, there are two main differences. First, in the penny auction, only one player potentially pays the bid cost in each period, unlike in a WOA, in which all players who continue to play must pay a cost in each period. Second, unlike in a WOA, the winning player must pay an additional cost of the winning bid, leading to a drop in the net value of the object as the game progresses.

\(^3\)Overbidding has been documented in first-price common value auctions (see Kagel and Levin (2002)), second-price auctions (Kagel and Levin (1993), Heyman et al (2004), Cooper and Fang (2006)), and all-pay-like auctions (Müller and Pratt (1989), Murnighan (2002), Gneezy and Smorodinsky (2007)).

\(^4\)These studies have suggested overbidding in a variety of contexts, ranging from real estate auctions (Ashenfelter and Genesove, 1992) to the British spectrum auctions (Klemperer, 2002). This literature often struggles with difficulties of proving the true value of the auctioned items, leading more recent studies to focus on online auction markets (see, for example, Ariely and Simonson (2003)).
now" in a second-price eBay auction on average, a much smaller effect than exhibited in this paper.

I then investigate players’ strategies more closely by comparing the empirical and theoretically predicted survival and hazard functions. My second main finding is that the empirical hazard rate of these auctions starts at the rate predicted by equilibrium analysis, but deviates further and further below this rate as the auction continues. This decline implies that the expected return from bidding (and paying €.50) drops as the auction continues, from nearly €.50 in the beginning of the auction to only €.12-€.16 at later stages in the auction. Using a modified version of my theoretical model, I show that this behavior is consistent with that of agents who exhibit a naive sunk cost fallacy: as agents continue to play the game, they spend more money on bids, leading them to experience a higher psychological cost from leaving the auction (the modification follows Eyster (2002)). This finding provides suggestive empirical evidence of the existence and effects of sunk costs, which has been demonstrated in experiments (Arkes and Blumer (1985), Dick and Lord (1998)), but has been more difficult to observe empirically.\footnote{As noted in Eyster (2002), "Empirically testing for the sunk-cost fallacy is complicated by the fact that information-based explanations for behavior are often difficult to rule out." Eyster suggests that the most valid empirical paper on sunk costs Camerer and Weber (1999), which shows that NBA players are given more playing time than predicted if their team used a higher draft pick to acquire them. I partially surmount these difficulties by focusing on global, rather than individual, hazard rates.}

The individual bid-level data, which contains approximately 96% of all bids made on the site for a three month period (13 million bids for over 129,000 users) allows me to describe the behavior of the market well. Participation in the auction is highly skewed: although half of the users stop playing after fewer than 20 bids, the top 10% of bidders in my dataset place an average of nearly 800 bids. Profits are gained largely from the most active users: the top 25% of users generate 75% of the profit. Interestingly, experience is associated with a significantly higher expected return from bidding. Users with little or no experience receive an expected return of only €.18 on each €.50 bid, while those with a large amount of experience (over 5000 bids) receive slightly over €.50. By controlling for user fixed effects and allowing learning rates to vary across users, I show that this effect is partially due to learning,
as opposed to selection bias. Finally, I determine the specific bidding strategies that drive the relationship between experience and profit by controlling for each strategy in the regression. This analysis suggests that two-thirds of the gain in expected profits associated with additional experience is due to the increased use of "aggressive bidding" strategies, in which the player bids immediately and continuously following other players’ bids.

For my third main finding, I examine the supply side of the market. Using user and auction data at each point in time, I separately estimate Swoopo’s actual and optimal supply rule: the number of auctions supplied for a given number of users on the site. For coordination purposes, Swoopo releases auction with very high initial timers, which gives them little ability to adjust to real-time changes in the number of users or auctions on the site. This process allows me to match the number of expected auctions at a point in the future with the number of expected users on the site at that time, which is Swoopo’s actual supply curve. Then, I use natural deviations in the number of actual active users and active auctions from this expectation to estimate the optimal supply rule. These curves are extremely similar; Swoopo’s supply curve obtains 98.6% of estimated potential profits given the empirical distribution of the number of users on the site. Both curves show that there are significant diminishing returns to the supply of auctions for a given number of users, because auctions are more likely to end prematurely when there are fewer users bidding on each auction. This finding suggests that there are high short-term costs for an entrant attempting to over-supply auctions in order to develop a userbase, creating a barrier to entry even though the initial startup cost of an Internet auction site is very cheap. Auction-level data that I collected from the top five competitors supports this conclusion: only one of Swoopo’s five main competitors is making large daily profits, which still amount to only 6.6% of Swoopo’s daily profits.

There are only a small number of empirical\textsuperscript{6} and experimental\textsuperscript{7} papers on the

\textsuperscript{6}Examples include Card and Olsen (1995) and Kennan and Wilson (1989), which only test basic stylized facts or comparative statics of the game. Hendricks and Porter (1996)’s paper on the delay of exploratory drilling in a public-goods environment (exploration provides important information to other players) is an exception, comparing the empirical shape of the hazard rate function of exploration to the predictions of a WOA-like model.

\textsuperscript{7}See Horisch and Kirchkamp (2008), who find systematic underbidding in controlled experimental
WOA, as it is difficult to observe a real-life game in which the setup is the same as a WOA and there is a known bid cost and good value. Therefore, even though the games are different, this insights from penny auctions are potentially useful in understanding the way that people act in a WOA (and the closely related All-Pay Auction), which has been used to model a variety of important economic interactions. The results also contribute to the broader understanding of behavioral industrial organization, which studies behavior biases in the marketplace (see Dellavigna (2008) for a survey). Additionally, the paper relates to a set of recent papers that study other "innovative" auction formats, such as the lowest and highest unique price auction (Eichberger and Vinogradov (2008), Houba et al (2008), Östling et al. (2007), Rapoport et al. (2007)). Finally, the paper complements two other recent working papers on penny auctions. Using a subset of the Swoopo’s American auction-level data, Platt et al. (2009) demonstrate that allowing flexibility in both risk-loving parameters and the perceived value of each good can explain the majority of bidding behavior. Hinnosaar (2009) studies the theoretical effect of imposing complementary assumptions to those in this paper, producing bounds on equilibrium behavior.

The paper is organized as follows: The second section presents the theoretic model of the auction and solves for the equilibrium hazard rates. The third section discusses the data and provides summary statistics. The fourth section compares the empirical survival and hazard rates with the equilibrium rates found in the second section. The fifth section outlines a theoretical model of sunk costs in this auction. The sixth section analyzes the effect of experience on performance of the bidders and discusses potentially profitable strategies. The seventh section focuses on the market for these auctions by providing an analysis of Swoopo’s supply curve and its five top competitors. Finally, the eighth section concludes.

Wars of attrition.

8For example: competition between animals (Bishop, Canning, and Smith, 1978), competition between firms (Fudenberg and Tirole, 1986), public good games (Bliss and Nalebuff, 1984), and political stabilizations (Alesina and Drazen, 1991). Papers with important theoretical variations of the WOA include Riley (1980), Bulow and Klemperer (1999), and Krishna and Morgan (1997).

9The paper also contributes to a growing literature that uses games and auctions to study behavior. There have been a large number of papers to study online auctions, which are surveyed by Bajari and Hortacsu (2004). More recently, Hartley, Lanot, and Walker (2005) and Post et al (2006) study such popular TV shows as "Who Wants to be a Millionaire?" and "Deal or No Deal?"
2.2 Auction Description and Theoretical Analysis

2.2.1 Auction Description

In this section, I briefly discuss the rules of the auction. There are many companies that run these auctions in the real-world and, while there are some small differences in the format, the rules are relatively consistent.

In a penny auction, there are multiple players bidding for one item. The bidding for the item starts at zero and rises with each bid. If a player chooses to bid, the bid must be equal to the current high bid plus the bidding increment, a small fixed monetary amount known to all players. For example, if the bidding increment is €0.01 and the high bid is currently €1.50, the next bid in the auction must be €1.51. Players must pay a small non-refundable bid cost every time that they make a bid. The auction ends when a commonly-observable timer runs out of time. However, each bid automatically increases the timer by a small amount, allowing the auction to continue as long as players continue to place bids. When the auction ends, the player who placed the highest bid (which is also the final bid) receives the object and pays the final bid amount for the item to the auctioneer.

The most similar commonly-studied auction format to the penny auction is the discrete-time war-of-attrition (WOA). In both auctions, players must pay a cost for the game to continue and a player wins the auction when other players decide not to pay this cost. However, there are two main differences. First, in a WOA, each player must pay the bid cost at each bidding stage in order to continue in the game. In the penny auction, only one player pays the bid cost in each bidding stage, allowing players to use more complex strategies because they can continue in the game without bidding. This difference also causes the game to continue longer on average in equilibrium, as agents spend collectively less in each period. Second, if the bidding increment is strictly positive, the net value of the good falls as bidding continues (and players’ bids rise) in the penny auction, whereas the value of the good in the WOA increases.

\[ \text{(10)} \]

In a WOA, each active player chooses to bid or not bid at each point in time. All player that bid must pay a bid cost. All players that do not bid must exit the game. The last player in the game wins the auction.
stays constant.\textsuperscript{11} This addition destroys the stationarity of the WOA model, as the agent’s benefit from winning the auction changes throughout the auction.

The following section presents a theoretical model of the penny auction and provides an equilibrium analysis. In order to make the model concise and analytically tractable, I will make simplifying assumptions, which I will note as I proceed.

\textbf{2.2.2 Setup}

There are $n + 1$ players, indexed by $i \in \{0, 1, ..., n\}$: a non-participating auctioneer (player 0) and $n$ bidders. There is a single item for auction. Bidders have a common value $v$ for the item.\textsuperscript{12} There is a set of potentially unbounded periods, indexed by $t \in \{0, 1, 2, 3, ...\}$.\textsuperscript{13} The current high bid for the good starts at 0 and weakly rises by the \textit{bidding increment} $k \in \mathbb{R}^+$ in each period, so that the high bid for the good at time $t$ is $tk$ (note that the high bid and time are deterministically linked).\textsuperscript{14} Each period is characterized by a publicly-observable current leader $l_t \in \{0, 1, 2, 3, ..., n\}$, with $l_0 = 0$. To simplify the discussion, I often refer to the \textit{net value} of the good in period $t$ as $v - tk$.

In each period $t$, bidders simultaneously choose to bid or not bid. If any of the bidders bid, one of these bids is randomly \textit{accepted}. In this case, the corresponding bidder becomes the leader for the next period and pays a non-refundable cost $c$. If none of the players bids, the game ends and the current leader receives the object and pays the final bid ($tk$). At the end of the game, the auctioneer’s payoff consists of the final bid ($tk$) along with the total collected bid costs ($tc$).

I assume that players are risk neutral and do not discount future consumption. I

\textsuperscript{11}If the bidding increment is \(€0.00\) (as it is in 10\% of the consumer auctions in my dataset), the price of the object stays at \(€0.00\) throughout the bidding.

\textsuperscript{12}I assume that the item is worth $v < v$ to the auctioneer. The case in which bidders have independent private values $v_i \sim G$ for the item is discussed in the appendix. As might be expected, as the distribution of private values approaches the degenerate case of one common value, the empirical predictions converge to that of the common values case.

\textsuperscript{13}It is important to note that $t$ does not represent a countdown timer or clock time. Rather, it represents a "bidding stage," which advances when any player makes a bid.

\textsuperscript{14}The model takes place in discrete time so that each price point is discrete, allowing players to bid or not bid at each individual price. This matches the setup of the real-life implementation of the game.
2.2. AUCTION DESCRIPTION AND THEORETICAL ANALYSIS

assume that \( c < v - k \), so that there is the potential for bidding in equilibrium. I assume that \( \text{mod}(v - c, k) = 0 \), for reasons that will become apparent (the alternative is discussed in the appendix). To match the empirical game, I assume that the current leader of the auction cannot place a bid.\(^{15}\) I refer to auctions with \( k > 0 \) as a \((k)\) declining-value auctions and auctions with \( k = 0 \) as constant-value auctions.

The majority of the analysis focuses on the discrete hazard rate at each period, \( \tilde{h}(t) \), which is the expected probability that the game ends at period \( t \) given that the game reaches period \( t \). I use subgame perfection as my solution concept unless otherwise noted. For exposition purposes, I sometimes discuss a players' symmetric Markov strategy to avoid players conditioning their strategies on the past actions of other players in situations of indifference, although all of the results hold for non-symmetric and non-Markov strategies. Player \( i \)'s Markov strategy set consists of a bidding probability for every period given that they are a non-leader \( \{x_0^i, x_1^i, x_2^i, ..., x_t^i, ...\} \) with \( x_t^i \in [0,1] \). Note that, in the case of Markov strategies, \( \tilde{h}(t) = \prod_{i=1}^n (1 - x_t^i) \).

It is important to briefly discuss two subtle simplifications of the model. First, unlike in the real-life implementations of this auction, there is no "timer" that counts down to the end of each bidding round in this model. The addition of timer complicates the model without producing any substantial insights; any equilibrium in a model with a timer can be converted into an equilibrium without a timer that has the same expected outcomes and payoffs for each player. Second, when two agents make simultaneous bids, only one of the bids is counted. In current real-life implementations of this auction, both bids would be counted in (essentially) random order. Modeling this extension is difficult, especially with a large number of players, as it allows the time period to potentially "jump" from each period to many different future periods.\(^{16}\) However, the predictions of the models are qualitatively similar (numerical analysis suggests that the hazard rate of the equilibrium of the extended game is

\(^{15}\) This assumption has no effect on the preferred bidding equilibrium below, as the leader will not bid in equilibrium even when given the option. However, the assumption does dramatically simplify the exact form of other potential equilibria, as I discuss in the appendix.

\(^{16}\) Hinmosaar (2009) models this extension, although with slightly different assumptions on the game and the possible parameters. He is able to provide bounds on some types of equilibrium behavior, which are consistent with the exact numerical results in the Appendix.
much more locally unstable, but globally extremely similar). These considerations are discussed in depth in the Appendix.

2.2.3 Equilibrium Analysis

In this section, I describe the equilibrium hazard rates for the penny auction, including a set of bidding hazard rates, which I use to make empirical predictions. The proofs for each proposition are in the Appendix.

I begin with the relatively obvious fact that no player will bid in equilibrium once the cost of a bid is greater than the net value of the good in the following period, leading the game to end with certainty if this condition is satisfied.

**Proposition 1** Define \( F = \frac{v - c}{k} - 1 \) if \( k > 0 \).

If \( k > 0 \), then in any equilibrium \( \bar{h}(t) = 1 \) for all \( t > F \)

I refer to the set of periods that satisfy this condition as the final stage of the game. Note that there is no final stage of a constant-value auction, as the net value of the object does not fall and therefore this condition is never satisfied. However, as there is a final stage for all declining-value auctions, strategies in these periods are set, allowing us to use backward induction to determine potential equilibria. To begin, I identify the bidding hazard rates of the game:

**Proposition 2** There is an equilibrium in which \( \tilde{h}(t) = \begin{cases} 0 & t = 0 \\ \frac{c}{v - tk} & 0 < t \leq F \\ 1 & t > F \end{cases} \).

In this equilibrium, some players use strictly mixed strategies for all periods after time 0 and up to (and including) period \( F \). In these periods, players are indifferent between bidding and not bidding as their chance of winning the item in the following period (given that they bid) is \( \frac{c}{v - (t+1)k} \), which is the cost of the bid divided by the benefit from winning the auction (the net value in the following period). Crucially, in a declining-value auction players in period \( F \) are indifferent given that players in period \( F + 1 \) bid with zero probability, which they must do by Proposition 1. This
indifference allows players in period $F$ to bid such that the hazard rate is $\frac{c}{v-Fk}$.\(^{17}\)

Note that in a declining-value auction the hazard rate rises over time, with no bids placed after time period $F$. To understand this result intuitively, note that in order to keep players indifferent between bidding and not bidding, the probability of winning (which is equal to the hazard rate) must rise as the net value of the good is declining. In a constant-value auction, the net value and hazard rate stay constant throughout time as in the standard equilibrium of a WOA model.

Not surprisingly, there are continuum of other equilibria in this model that lead to hazard rates that are described completely in the following proposition:

**Proposition 3** Consider any $p^* \in [0,1]$ and $t^* \in \mathbb{N}$ with $t^* \leq F$. Let $\psi = \begin{cases} 0 & \text{if } p^* \leq \frac{c}{v-tk} \\ 1 & \text{if } p^* > \frac{c}{v-tk} \end{cases}$.

Then, there is an equilibrium in which

$$\tilde{h}(t) = \begin{cases} 0 & \text{for } t < t^* \text{ and } \mod(t + \psi + \mod(t^*, 2), 2) = 0 \\ 1 & \text{for } t < t^* \text{ and } \mod(t + \psi + \mod(t^*, 2), 2) = 1 \\ p^* & \text{for } t = t^* \\ \frac{c}{v-tk} & \text{for } t^* < t \leq F \\ 1 & \text{for } t > F \end{cases}$$

Furthermore, $\tilde{h}(t)$ in all equilibrium can be characterized by this form.

This proposition demonstrates that all equilibrium hazard rates can be described by two parameters, $p^* \in [0,1]$ and $t^* \in \mathbb{N}$. To understand the intuition behind this result, recall that in any equilibrium that leads to the hazard rates in Proposition 2, players are indifferent at every period $t < F$ because of the strategies of players in the following period. Consider a situation in which players follow strategies that lead to the hazard rates in Proposition 2 for periods after $t^*$. If this is the case, players in period $t^*$ are indifferent to bidding. Imagine that these players bid such that the

\(^{17}\)For declining-value auctions, this requires the use of the assumption that $\mod(v - c, y) = 0$. If this is not true, the players in the period directly before the final stage are not indifferent and must bid with certainty. As a result, the players in previous period must bid with zero probability (they have no chance of winning the object with a bid), causing players in the period previous to that to bid with certainty, and so on. This leads to a unique equilibrium in which the game never continues past period 1. However, as is discussed in the Appendix, there is an $\varepsilon$-equilibrium for an extremely small $\varepsilon$ in which the hazard rates match those in Proposition 2.
hazard rate at \( t^* \) is some \( p^* > \frac{c}{v - t^*k} \) (the rate for period \( t \) in Proposition 2). Given this strategy, players in period \( t^* - 1 \) will strictly prefer to bid in that period (as they now have a higher chance of winning in the following period), leading to a hazard rate of 0. As a result, players in period \( t^* - 2 \) will strictly prefer to not bid (as they have no chance of winning in the following period), leading to a hazard rate of 1. Consequently, players in period \( t^* - 3 \) will strictly prefer to bid, and so on, leading to alternating periods of bidding and not bidding (the argument is similar if players bid such that \( p^* < \frac{c}{v - t^*k} \)). All potential hazard rates are formed in this manner.

Note that these backward alternating periods of bidding and not bidding must occur in any equilibrium in which the hazard rate at some period \( t \) deviates from \( \frac{c}{v - t^*k} \), which must lead to either \( \tilde{h}(0) = 1 \) or \( \tilde{h}(1) = 1 \), causing the game to end in either period 0 or period 1. Corollary 4, which is one of my main theoretical results, formalizes this intuition and notes that if we ever observe bidding after period 1 in equilibrium, we must observe the hazard rates in Proposition 2 for all periods following period 1. Corollary 5 notes that Proposition 2 lists the unique set of equilibrium hazard rates for which the auctioneer’s expected revenue is \( v \), which might be considered a natural outcome of a common value auction with many players.

**Corollary 4** In any equilibrium in which the game continues past period 1, \( \tilde{h}(t) \) must match those in Proposition 1 for \( t > 1 \).

**Corollary 5** For any \( \alpha \in \left[ \frac{v}{c}, 1 \right] \), there exists a symmetric equilibrium in which the auctioneer’s expected payoff is \( \alpha v \). The equilibrium in Proposition 2 is the unique equilibrium of the game in which the auctioneer’s expected revenue is equal to \( v \).

In the following empirical sections of this paper, I restrict attention to the bidding equilibrium hazard rates in Proposition 2 for the reasons outlined in Corollaries 4 and 5. In addition to satisfying desirable theoretical characteristics, these hazard rates form the basis for clear and testable empirical predictions, which are unaffected by parameters such as the number of players in the game.
2.2. AUCTION DESCRIPTION AND THEORETICAL ANALYSIS

2.2.4 The Bidding Equilibrium - Equilibrium Predictions

As previously noted, I model the game in discrete time in order to capture important qualitative characteristics that cannot be modeled in continuous time (such as the ability to bid and not bid in each period). However, in order to make smooth empirical predictions about the hazard rates, I will now focus on the limiting equilibrium strategies when the size of the time periods shrinks to zero. While this does not significantly change any of the qualitative features of the discrete hazard rates, it creates smoother predictions, which allows the survival and hazard rates to be compared across auctions with different parameters.

Specifically, let $\Delta t$ denote a small length of a time and modify the model by characterizing time as $t \in \{0, \Delta t, 2\Delta t, 3\Delta t, \ldots\}$ and changing the cost of placing a bid to $c\Delta t$. With this change in mind, define the non-negative random variable $T$ as the time that an auction ends. I define the survival function $S(t; y, v, c)$, hazard function $h(t; y, v, c)$, and cumulative hazard function $H(t; y, v, c)$ for auctions with parameters $y, v, c$ in the normal fashion (as $\Delta t \to 0$ and suppressing dependence on $y, v, c$):

$$S(t) = \lim_{\Delta t \to 0} \Pr(T > t)$$

$$h(t) = \lim_{\Delta t \to 0} \frac{S(t) - S(t + \Delta t)}{\Delta t \cdot S(t)}$$

$$H(t) = \int_0^t h(\tilde{t})d\tilde{t}$$

Solving for these functions leads to the following proposition:

**Proposition 6** In the preferred equilibrium, $h(t) = \frac{c}{v - tk}$ for $t < \frac{v}{k}$.

When $k = 0$, $H(t) = \frac{c}{v}t$ and $S(t) = e^{-\left(\frac{c}{v}\right)t}$.

When $k > 0$, $H(t) = \frac{c(\ln(v) - \ln(v - tk))}{k}$ and $S(t) = (1 - \frac{tk}{v})^\frac{c}{v}$ for $t < \frac{v}{k}$.

For the situation in which $k > 0$, note that each function approaches the corresponding function when $k = 0$ as $k \to 0$, which is reassuring:

$$\lim_{k \to 0} \frac{c(\ln(v) - \ln(v - tk))}{k} \frac{t}{\frac{c}{v}} = \frac{ct}{v}$$

(2.4)
\lim_{k \to 0} \left(1 - \frac{tk}{v}\right)^{\hat{t}} = e^{-(\hat{t})t} \quad (2.5)

While Proposition 6 is useful to determine the hazard and survival rates for a specific auction, it is more useful to compare hazard and survival rates across auctions for goods with different values. To that end, define \( \hat{t} = \frac{t}{v} \) as the normalized time period, define random variable \( \hat{T} \) as the (normalized) time that an auction ends, define the normalized Survival and Hazard rates in a similar way to above:

\[
\hat{S}(\hat{t}) = \lim_{\Delta \hat{t} \to 0} \Pr(\hat{T} > \hat{t}) \quad (2.6)
\]

\[
\hat{h}(\hat{t}) = \lim_{\Delta \hat{t} \to 0} \frac{\hat{S}(\hat{t}) - \hat{S}(\hat{t} + \Delta \hat{t})}{\Delta \hat{t} \cdot \hat{S}(\hat{t})} \quad (2.7)
\]

With this setup, it is easy to show that:

**Proposition 7** In the bidding equilibrium,

\( \hat{h}(\hat{t}) = \frac{e}{1 - \hat{t}k} \) for \( \hat{t} < \frac{1}{k} \)

When \( k = 0 \), \( S(t) = e^{-c\hat{t}} \)

When \( k > 0 \), \( \hat{S}(\hat{t}) = (1 - \hat{t}k)^{\hat{t}} \)

Proposition 7 forms the basis for my empirical analysis, as it establishes a way for to directly compare the survival and hazard rates of auctions for goods with different values. For example, the proposition indicates that an auction for a good with a value 50 will have the same probability of surviving to period 50 as an auction for a good with a value 100 surviving to period 100. Note that the proposition does not provide a way to compare the rates of auctions with different bidding increments.
2.3 Description of Data

2.3.1 Description of Swoopo

Swoopo is the largest and longest-running company that runs penny auctions (five of Swoopo’s competitors are discussed later in the paper). Swoopo was founded in Germany in 2005, and currently provides local versions of their website for other countries, such as the United Kingdom (started in December 2007), Spain (started in May 2008), the United States (started in August 2008). Nearly every auction is displayed simultaneously across all of these websites, with the current highest bid converted into local currency. Swoopo auctions consumer goods, such as televisions or appliances, as well as packages of bids for future auctions and cash payments. As of May 2009, Swoopo was running approximately 1,500 auctions with nearly 20,000 unique bidders each week.

The general format of auctions at Swoopo follows the description in Section 2.2.1: (1) players must bid the current high bid of the object plus a set bidding increment, (2) each bid costs a non-refundable fixed bid cost, and (3) each bid increases the duration of the auction by a small amount. While most companies that run penny auctions solely use a bidding increment of €.01, Swoopo runs auctions with bidding increments of €.10 (76% of the auctions), €.01 (6%), and €.00 (18%). The cost of a bid in Europe has stayed constant at €.50 (the cost of a bid for most of my dataset was usually £.50 and $.75 in the United Kingdom and the United States, respectively).

In most auctions, Swoopo allows the use of the BidButler, an automated bidding system available to all users. Users can program the BidButler to bid within a specific range of values and the BidButler will automatically place bids for the user when the timer nears zero. Certain auctions, called Nailbiter Auctions (9.5% of

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18 For this paper, I will always refer to costs and prices in Euro.
19 In July 2009, Swoopo changed the possible bidding increments to €.01, €.02, €.05, and €.20. My dataset ends before this change.
20 The cost of a bid in the United States was $1.00 from September 2008 to December 2008. Note that incorporation of this change would only increase Swoopo’s estimated profit.
21 If two players program a BidButler to run at the same time for the same auction, all the consecutive BidButler bids are placed immediately.
auctions), do not allow the use of the BidButler. As of November 2008, Swoopo also runs Beginner Auctions (10.8% of recent auctions), which are restricted to players that have never won an auction.

2.3.2 Description of Data

My data on Swoopo consists of two distinct datasets, both of which were captured using a multi-server website collection algorithm.

(1) Auction-Level Data

The auction-level data contains approximately 166,000 auctions for approximately 9,000 unique goods spanning from September 2005 to June 2009. The data was retrieved separately from Swoopo’s American, German, Spanish, and English websites. For each auction, the dataset contains the item for auction, the item’s value (see Section 2.3.3), the type of auction, the bidding increment, the final (highest) bid, the winning bidder, and the end time. From October 2007 on, the data also contains the final (highest) ten bidders for each auction. The summary statistics for this dataset are listed in Table 2.1.

(2) Individual Bid-Level Data

The bid-level data contains approximately 13.3 million bids placed by 129,000 unique users on 18,000 auctions, and was captured in real-time from Swoopo’s American website from late February 2009 to early June 2009.\(^{22}\) The algorithm has the ability to record new information every 2-3 seconds, depending on the Internet connection and the website’s response time. As the Swoopo website posts a live feed of the last ten bids in each auction, the algorithm can capture the vast majority of bids even when bids are made very rapidly. The one exception is the situation in which multiple people use a BidButler at the same time in one auction. In this case, each players’ automated bids are made instantaneously, causing the current high bid to jump immediately to the lowest of the high bounds of the two BidButlers. Fortunately, it is relatively simple to spot this issue in the data and infer the bids that

\(^{22}\)Due to various issues (including a change in the way that the website releases information), the capturing algorithm did not work from March 6th-March 8th and April 8th-April 11th. Furthermore, the efficiency of the algorithm improved with a change on March 18th.
are not listed. Using Nailbiter Auctions (in which BidButler use is forbidden), I estimate that the algorithm captures 96% of the bids in the periods when it is running. Each observation in this dataset contains the (unique) username of the bidder, the bid amount, the time of the bid, the timer level, and if the bid was placed by the BidButler.\textsuperscript{23} Note that the auctions in this dataset are a subset of the auctions in the auction-level dataset. The summary statistics for this dataset are listed in Table 2.2.

In addition to data about Swoopo, I captured similar auction-level datasets for five of Swoopo’s competitors: BidStick, RockyBid, GoBid, Zoozle, and BidRay. I will refer to this data briefly when I analyze the market for these auctions.

### 2.3.3 Value Estimation

Analyzing the auctions requires an accurate estimate of the value of the good. For each good, Swoopo publishes a visible "worth up to" price, which is essentially the manufacturer’s recommended price for the item. This price is one potential measure of value, but it appears to be only useful as an upper bound. For example, Swoopo has held nearly 4,000 auctions involving 154 types of watches with "worth up to" prices of more than £500. However, the vast majority of these watches sell on Internet sites at heavy discounts from the "worth up to" price (20-40%). It is difficult, therefore, to justify the use of this amount as a measure of value if the auctioneer or participant can simply order the item from a reputable company at a far cheaper cost. That said, it is also unreasonable to search all producers for the lowest possible cost and use the result as a measure of value, as these producers could be disreputable or costly for either party to locate.

In order to strike a balance between these extremes, I estimate the value of items by using the price found at Amazon.com and Amazon.de for the exact same item and using the "worth up to" price if Amazon does not sell the item. I refer to this new value estimate as the \textit{adjusted value} of the good.\textsuperscript{24} As prices might have changed

\textsuperscript{23}The algorithm captures the time and timer level when the website was \textit{accessed}, not at the time of the bid. The time and timer level can be imperfectly inferred from this information.

\textsuperscript{24}This is a somewhat similar idea to that in Ariely and Simonson (2003), who document that 98.8
significantly over time, I only use Amazon prices for auctions later than December
2007 and scale the value in proportion to any observable changes in the "worth up

to" price over time. Amazon sells only 20% of the unique consumer goods sold on
Swoopo, but this accounts for 49% of all auctions involving consumer goods (goods
that are sold in Amazon are likely to occur more in repeated auctions). For the
goods that are sold at Amazon, the adjusted value is 74% of the "worth up to" price
without shipping costs and 71% when shipping costs are added to each price (Amazon
often has free shipping, while Swoopo charges for shipping). As the adjusted value
is equal to the "worth up to" price for the 51% of the auctions for consumer goods
that are not sold on Amazon, it still presumably overestimates the true value.25

To test the validity of the measure of value, note that the equilibrium analysis
(and general intuition) suggest that the winning bid of an auction should be positively
correlated with the value of the object for auction. Therefore, a more accurate
measure of value should show a higher correlation with the distribution of winning
bids for the good. The correlation between the winning bids and the "worth up to"
price is $0.521$ (with a 95% confidence interval of (0.515,0.526)) for auctions with a
$e^{0.10}$ increment for the items I found on Amazon.26 The correlation between the
winning bids and the adjusted value is $0.708$ (with a 95% confidence interval of
(0.704,0.712)) for these auctions. A Fisher test of correlation equality confirms that
the adjusted value is (dramatically) significantly more correlated with the winning
bid, suggesting that it is a more accurate measure of value.

2.3.4 Profit Analysis

According to the equilibrium analysis above, one would not expect the auction format
used by Swoopo to consistently produce more revenue than the market value of the

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25 The main results of the paper are unchanged when run only on the subset of goods sold at
Amazon.

26 Note that I cannot compare aggregate data across auctions with different bid increments for
these coorelations, as the distribution of final bids of auctions for the same item will be different.
The results are robust to using the (less common) bid increments of $e^{0.00}$ and $e^{0.01}$. 
One of the main empirical findings of this paper is that this auction format consistently produces this level of revenue. Averaging across goods, bidders collectively pay 52% over the adjusted value of the good, producing an average profit of €112. For the 166,000 auctions over four years in the data set, the auctioneer’s profit for running the auction is €18M. The distribution of monetary profit and percentage profit across all auctions is shown in Figure 2.1 (with the top and bottom 1% of auctions trimmed). Perhaps surprisingly, the auctioneer’s profit is below the value of the good for a slight majority (51%) of the items. Table 2.3 breaks down the profits and profit percentage by the type of good and the increment level of the auction. Notice that auctions involving cash and bid packages (items with the clearest value) produce profit margins of over 104% and 214%, respectively. Consumer goods, which are potentially overvalued by the adjusted value measure, still lead to an estimated average profit margin of 33%.

2.4 Empirical Tests of Model

2.4.1 Research Question and Empirical Strategy

The theoretical analysis above yields multiple empirical predictions about the survival and hazard functions of penny auctions. I am able to identify the empirical survival and hazard rates of the auctions as the final auction outcomes (the final and highest bid in auction) are stochastic. Recall from Section 2.2.4 that normalizing the time measure of the auctions by the value of the goods allows the comparison of these rates across auctions for goods with different values (given that they have equal bid increments).

\[^{27}\text{This profit measure does not include the tendency for people to buy multi-bid packages but not use all of the bids ("breakage"). The bid-level data suggests that this is a significant source of revenue for Swoopo.}\]
2.4.2 Consumer Goods

Figure 2.2 displays the Kaplan-Meier Survival Estimates (and confidence intervals, which are extremely tight) of the normalized time measure of consumer goods auctions for the three increment levels, along with the survival rates predicted by the equilibrium hazard rates derived in Section 2.3. The survival functions are consistently higher than the equilibrium survival functions for each normalized time measure, which is expected given the profit statistics above and the fact that the auctioneer receives more profit from auctions that last longer. For auctions with bidding increments of €.10 and €.00 (which represent 94% of the auctions in the dataset), it appears that the survival rates follow the equilibrium survival rates closely for early normalized time measures before rising consistently above the predicted survival rates.

Survival rates are difficult to interpret because they represent the cumulative effect of auction terminations up to each normalized time period. The empirical hazard functions are more illustrative of players’ behavior at each point. Figure 2.3 displays the smoothed hazard rates with confidence intervals along with the hazard functions.
2.4. **EMPIRICAL TESTS OF MODEL**

![Graph showing empirical vs. theoretical survival rates for different bid increment levels.](image)

**Figure 2.2: Empirical vs. Theoretical (Dashed) Survival Rates**

predicted by equilibrium strategies for each increment level. Notice that the equilibrium hazard functions for the different increments are the same at the beginning of the auction (as the bids always start at zero), stay constant if the increment is €.00 (as the current bid amount is always constant), and rise more steeply through time with higher increments (as the current bid rises faster with a higher increment). Most interesting, for auctions with bid increments of €.00 or €.10, the hazard function is very close to that predicted by equilibrium analysis in beginning periods of the auction. However, for all auctions, the deviation of the empirical hazard function below the equilibrium hazard function increases significantly over time.

While the hazard functions are suggestive of the global strategies of the players, it is difficult to interpret the economic magnitude of the deviations from the predicted actions. In order to determine this magnitude, note that the bidder at period $t - 1$ is paying the auctioneer a bid cost $c$ in trade for a probability of $h(t)$ of winning the net value of the good $(v - tk)$ at time $t$. In other words (assuming risk-neutrality of both parties), the auctioneer is selling the bidder a stochastic good with an expected value of $h(t)(v - tk)$ for a price $c$ at time $t$. Therefore, I define *percent instantaneous markup* as the percentage of the cost of this good above its value at the point it is

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28 For this estimation, I used an Epanechnikov kernel and a 10 unit bandwidth, using the method described by Breslow and Day (1986) and Klein and Moeschberger (2003). The graphs are robust to different kernel choices and change as expected with different bandwidths.
Figure 2.3: Empirical vs. Theoretical (Dashed) Hazard Rates

Figure 2.4: Empirical vs. Theoretical (Dashed) Instantaneous Profit Rates

Definition 1  Percent Instantaneous Markup (at time t) = \( \frac{c}{h(t)(v-tk)} - 1 \) * 100

Figure 2.4 displays the percent instantaneous markup and confidence intervals along with the predicted percent markup for each increment level at each (normalized) time period. Note that the predicted markup is always zero because the expected equilibrium payoff from a bid is equal to the cost of the bid at each period. For auctions with bidding increments of €.10 and €.00, the empirical instantaneous markup starts near this level, but rises over the course of the auction to 200-300%. This
estimate suggests that, if an auction survives sufficiently long, players are willing to pay €.50 (the bid cost) for a good with an expected value of €.12-€.16. Therefore, rather than making uniform profit throughout the auction, the auctioneer is making a large amount of instantaneous profit at the end of the auction.

2.4.3 Cash and Bid Vouchers

One concern about the results for the consumer good auctions is that the measure of the true value of the good is noisy and values presumably differ across users. Furthermore, for the auctions with positive bid increments, the net value of the good changes over time (as the current high bid rises through the game). To address these issues, this section focuses on the 18,790 auctions for cash payments and vouchers for bids. In these auctions, the value of the item is arguably common across participants (bid vouchers are immediately available on Swoopo for a common fixed price) and, focusing on auction with a bid increment of €.00 (73% of the auctions), the net value is constant throughout the auction.

As suggested earlier in Table 2.3, the profits for these auctions are significantly higher than those for consumer goods. The reasons for this result are unclear, although it might be that the measure of value is more accurate in these auctions, more people are attracted to these auctions, or a specific subset of players bid on these auctions. The hazard rates and percent instantaneous profits for these auctions are shown in Figure 2.5. As would be expected from the profit estimations for these auctions, the empirical hazard functions are dramatically lower than the equilibrium hazard functions, even at the beginning of the auction. However, consistent with the important qualitative features of the consumer good auctions results, there is still a upward trend in the empirical instantaneous profits for both types of auctions. In the cash auctions, the instantaneous profit is 50-100% during the first stages of the auction, but rises to around 150-300% in the later stages. In the bid voucher auctions, the instantaneous profit is between 100-150% during the first stages of the auction (minus a very short initial period) but steadily rises to over 300% in the later stages.
Figure 2.5: Empirical vs. Theoretical (Dashed) Hazard and Inst. Profit. Left: Cash Auctions. Right: Bid Voucher Auctions

Notes: Markup graphs truncated at 300% for readability
2.5 Modeling Sunk Costs

The previous section demonstrated that the deviation of the empirical hazard rates from the predicted hazard rates changes dramatically over the course of an auction. Therefore, any explanation for this behavior must include a factor that changes as an auction progresses. For example, a simple misunderstanding of the rules of the game or an consistent underprediction of the number of participants cannot explain these results alone as they would predict constant deviations from the predicted hazard rate. Furthermore, any potential explanation must account for behavior in auctions with different bidding increments. For example, if players do not account for the current bid over time, they will overbid in decreasing-value auctions, but this reasoning cannot account for the empirical decreasing hazard observed in constant-value auctions. Even with these constraints, there are still a variety of explanations that cannot be separately identified with my data. For example, the behavior could be explained by a tendency for players to make worse predictions about others' behavior as the auction continues, possibly because there are fewer learning opportunities at later stages in the auction (these stages are less likely to occur). In this section, rather than discussing all of the possibilities, I focus on the naive sunk cost fallacy as a potential explanation and demonstrate that modifying the model to include this effect leads to qualitatively similar hazard rates to those observed in the data.

Following Ashraf et al (2008), I use the framework proposed by Eyster (2002) to model sunk costs.29 The reader is referred to that paper for technical details of the utility function. Applying Eyster’s model and terminology, agents in the modified model desire "consistency" in their decisions and pay a psychological cost, which I call "regret", if they spend money on bids and do not win the auction, weighted by the parameter $\rho \in [0, \infty)$ in the utility function. As a result, agents receive less utility from exiting the auction as they pay for more bids, even though these costs are sunk. Note that this modification alone will cause agents to underbid as they will require a premium (in the form of a higher probability of winning) to continue at any stage to offset their (correctly predicted) future psychological losses from the

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29 In fact, Eyster considers a standard discrete war of attrition model as an example in his paper, producing similar results.
sunk costs. Therefore, I follow Eyster in assuming that agents consider the effect of their current decisions on their future utility, but they naively believe that their weight on future regret will be $\rho(1 - \eta)$ with $\eta \in [0, 1].^{30}$

In the interest of simplicity, I deviate from the Eyster’s multiple period model in one substantial way. Rather than assuming that an agent feels regret for all decisions in the game, I assume that an agent simply feels regret from his initial decision (to play or not play in the game). To elucidate this difference, consider an agent who leaves the game after bidding 10 times, with bids costing 1 unit. In Eyster’s model, the agent experiences regret from each past decision to stay in the auction for a total of $55\rho$ units (he would have saved 10 units had he exited instead of placing the first bid, 9 units if he had exited instead of placing the second bid, 8 units...). In my model, the agent simply experiences $10\rho$ units of regret as he would have saved 10 units from not playing the game. As one could just rescale $\rho$ to account for this difference, the substantial difference between the models lies in the growth of regret as the game continues. In Eyster’s model, regret grows "triangularly" over time, from 1 to 3 to 6 to 10, etc. In my model, regret grows linearly over time, from 1 to 2 to 3 to 4, etc. I do not believe that there is a good reason to choose either model over the other in this application, so I proceed with the linear model in the interest of simplicity.

Specifically, consider an agent who has placed $b$ bids up until time period $t$. The total utility of the agent from never bidding again becomes:

$$-bc - \rho bc$$

That is, the agent experiences the monetary loss ($-bc$) of the bids as well as regret ($-\rho bc$) from deciding to play the game in the first place.

Similarly, if an agent bids in period $t$, does not win in the next period, and never bids again, he will receive utility of:

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$^{30}$A note on terminology: I choose to use $\eta$ instead of $v$ (Eyster’s parameter of naivety) to avoid confusion with the value of the object $v$. 
2.5. MODELING SUNK COSTS

\[-(b + 1)c - \rho(b + 1)c\]  \hspace{1cm} (2.9)

However, due to naivety, he (mistakenly) perceives that his feeling of regret will be lower than it really is:

\[-(b + 1)c - (1 - \eta)\rho(b + 1)c\]  \hspace{1cm} (2.10)

The case in which an agent bids and wins the auction in the next period is slightly more complicated. The level of regret depends on the situation. If the net value of the item is weakly higher than the total cost the agent, the agent does not regret his decision to enter the auction. In this case, he simply receives the utility of:

\[v - ty - (b + 1)c\]  \hspace{1cm} (2.11)

Notice that \(bc\) (the monetary bid cost up to period \(t\)) occurs in equations 2.8, 2.10, and 2.11, which is consistent with \(bc\) as a sunk cost. However, the regret term only occurs if the person exits the auction, which is consistent with the notion of the sunk cost fallacy. If the person is naive, he believes that the weight on the regret will be lower in the future than today.

Alternatively, if the net value of the auction is higher than the value of the object, the agent does regret his decision to enter the auction. In this case, he receives utility:

\[v - ty - (b + 1)c - \rho(b + 1)c\]

Note that, in this situation, the regret term appears in the utility term in all situations, so the agent fully recognizes the sunk cost (as before, if the agent is naive, he perceives this term to be \(v - ty - (b + 1)c - (1 - \eta)\rho(b + 1)c\)).

In order for this modification to affect equilibrium behavior, agents must be able to condition their strategies on the number of bids each player has made (because this now affects agents’ payoffs). Following the general path of Eyster’s solution (in which naive players correctly perceive other’s true strategies, although they misperceive their
own) yields the following outcome of the preferred equilibrium and the hazard rate, which is summarized in Proposition 8

**Proposition 8** There is an equilibrium of the modified game in which:

\[
h(t) = \begin{cases} 
\max\{0, \frac{c+cp-c\eta t}{v-ty+(1-\eta)cp(t+1)}\} & \text{for } t \leq \frac{2(v-c)}{c+2p} \\
\max\{0, \frac{c+cp-c\eta t}{v-ty}\} & \text{for } t > \frac{2(v-c)}{c+2p}
\end{cases}
\]

The effect of the regret over spending fixed costs is slightly complicated. At the beginning of the auction, agents with regret are less likely to bid than agents without regret because they have no current mistakes to regret and they realize (to the extent that they are sophisticated) that they will have to pay regret costs in the future if they bet and lose. As the auction proceeds, this difference diminishes as agents amass larger sunk costs through bidding. At some point, if agents are naive, the game continues with higher probability than with normal agents because agents (incorrectly) believe that their amassed fixed costs will be lessened if they bid and then drop out in the following period. If agents are particularly naive, they can reach a point in which no one drops out, with bidders staying in the game only because they (incorrectly) believe that bidding and dropping out tomorrow will reduce the regret from their large fixed costs.

Figure 2.6 displays the equilibrium hazard rates for \( \rho = .3, c = \€.50 \), for an increment of \( \€.00 \) as \( \eta \) rises. Note that the curves with higher levels of naivety display the same qualitative features as those in the empirical data.

### 2.6 Experience, Strategies, and Profits

#### 2.6.1 Effect of Experience on Profits

**Research Question and Empirical Strategy**

The empirical results above demonstrate that, regardless of the reason(s), players in aggregate are bidding in a way that consistently leads them to make (reasonably large) negative expected payoffs. This section addresses the effect of experience on the expected payoffs of the players.
2.6. EXPERIENCE, STRATEGIES, AND PROFITS

Figure 2.6: Predicted Hazard Rates of Sunk Cost Model: Effect of Sunk Costs \((p) = .3\). Graphs vary by "naivety" \((n)\).

Broadly, there are two strategic ways in which a player could improve their profits. The first is simply to stop bidding. If the empirical hazard rates seen in previous sections were consistent across all auctions, the best response of a monetary-maximizing player would be to never bid, as bidding leads to a negative expected value throughout the auction. However, to the extent that there is heterogeneity in auction hazard rates (in different items or at different times of day) and one's strategy can affect other player's actions (such as increasing the future hazard rate by playing very aggressively), there might exist bidding strategies that increase profits. I discuss the effect of experience on these two broad strategies.

There are multiple potential measures of "experience." For my analysis, I define the experience of a player at a point in time as the number of bids made by that player in all auctions before that point in time\(^{31}\). On potential concern with this measure is that, as the coverage of the bid-level data starts long after Swoopo began running auctions, some players enter this dataset with previous experience from past

\(^{31}\)The qualitative results below are robust to using different experience measures, such as the number of auctions previously played or the total time previously spent on the site.
auctions. Fortunately, the auction-level data contains a list of the final ten bidders for the auctions before the start of the bid-level data, which I use to estimate the number of bids placed by each player before entering the bid-level dataset. To accomplish this, I first perform an OLS regression to estimate the relationship between the number of appearances in the top ten lists and the number of bids made by a player using the bid-level data. Second, given the number appearances in the top ten before the individual dataset, I use this estimate to predict the number of bids each player made in this time period. While this measure is imperfect (it does not capture players that bid before the bid-level dataset without finishing in the top ten and assumes that the relationship between bids and appearances in the top ten is consistent across time), it does provide a rough measure of the number of previous bids for players that enter with large amounts of experience.

Using this measure, the bid level data provides the necessary variation to identify the relationship between profits and experience. Specifically, the data contains natural variation in the profit from each bid (winning is dependant on other players’ choices in the following period, which is not deterministic) as well as experience across users (some users enter with more experience and some users stay longer than others) and within users (the heaviest 10% of users place an average of nearly 800 bids in my dataset).

(Indirect) Evidence that Bidders Learn to Stop Bidding

Figure 2.7 displays the cumulative density of users against the users’ experience at the end of the dataset (in log scale). The figure demonstrates that many players stop bidding after placing relative few bids. For example, 75% of users stop bidding before placing 50 bids and 86% stop bidding before placing 100 bids. While there are many reasons that users might leave the site, this statistic is indirect evidence that players learn that, on average, bidding is not a profitable strategy.

For reference, Figure 2.7 also displays the a "cumulative profit curve," which plots the percentage of the auctioneer’s total profit produced by players at or below each

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32 According to the regression estimates, an appearance in a top ten list is associated with 59.6 bids.
level of experience. For example, while 75% of users make less than 50 bids, the cumulative profit curve shows that these users only generate 25% of the total profit. Conversely, the top 11% of bidders in terms of experience create more than 50% of the total profit.

**Experienced Players Learn Strategies to Increase Profits**

In the previous section, I demonstrated that players that make many bids account for a large percentage of Swoopo’s profit. In this section, I examine the relationship between experience and expected bid profits for these players. First, I use a non-parametric regression to show a clear positive relationship between experience and the expected profit from each bid. Then, I parametrize the regression to demonstrate that this relationship is highly statistically significant. Finally, in order to control for potential selection effects, I add user fixed effects and allow learning rates to vary across users, demonstrating that learning partially drives the relationship between experience and profits.

As discussed in Section 2.4.2, each bid can be interpreted as an independent "bet"
in which the bidder pays the bid cost in exchange for a chance to win the net value of the good in the following round. Note that the expected profit from this bet lies between losing the bid cost ($-€.50$) and the net value of the object $(v - (t + 1)k)$. There are two potential reasons that higher levels of experience might be associated with an increase in the expected profit of this bet. First, users might learn better bidding strategies (such as bidding on certain items or bidding "aggressively") through playing the game. Second, users that naturally use better strategies might be more likely to continue playing the game, thus leading to a correlation between experience and high expected value through selection.

Rearranging the dataset into an (incomplete) panel dataset in which users are indexed by $i$ and the order of the bids that an individual places is indexed by $t$, let $y_{it}$ be the payoff of user $i$’s $t$th bid. Then, a general model of the effect of experience on profit is

$$y_{it} = L_i(t) + \varepsilon_{it}$$

where $L_i(t)$ is individual $i$’s learning function and $\varepsilon_{it}$ is the error that arises from the stochastic nature of the auction. As a first step towards understanding the learning functions, Figure 2.8 displays a non-parametric regression constraining $L_i(t) = L(t)$ as well as a histogram of the number of bids made at each experience level. Clearly, there appears to be a positive relationship between the profit of a bid and the level of experience of the bidder. A player with no experience can expect to lose €.40 per each €.50 bid, while those with very high experience levels have slightly positive expected payoffs per each bid. However, note that this positive effect requires a relatively large amount of experience: raising the expected value of a bid to near zero requires an experience level of nearly 10,000 bids.

Following the quadratic shape of the non-parametric regression and still constraining $L_i(t) = L(t)$, I first parameterize the model as:

---

33Note that, confusingly, this is a different $t$ than in the theoretical section. In that section, $t$ represented a change in the bid level, while $t$ here represents a level of experience for a user.
2.6. EXPERIENCE, STRATEGIES, AND PROFITS

Figure 2.8: Local Poly. Regression of Profit on Experience. Histogram of Experience at Each Bid Also Shown.

\[ y_{it}^U = \beta_0 + \beta_1 t + \beta_2 t^2 + \varepsilon_{it} \]  

(2.13)

with the results shown in the first column of Table 2.4 (with standard errors clustered on users). These estimates show that, on average, there is an economically and statistically significant concave relationship between experience and profits, which demonstrates that there are strategies which consistently yield higher profits. Specifically, for each 1000 bids, players initially increase the expected return from each €.50 bid by €.03 from a baseline of €.17.

However, as discussed above, it is not clear that this result is due to individual learning. It is possible that individuals with larger coefficients continue in the game for longer, leading \( t \) to be positively correlated with the error term. To help mitigate this selection problem, I estimate the model with fixed effects for users:

\[ y_{it}^U = \beta_1 t + \beta_2 t^2 + \phi_i + \varepsilon_{it} \]  

(2.14)

with the results shown in the second column of Table 2.4. This specification suggests
that, to the extent that the heterogeneity in learning functions is captured by an added constant, there is a selection effect, but learning alone does play a role in the positive association between experience and profits. However, this specification does not account for the possibility that learning rates differ across individuals. If these learning rates are correlated with high levels of experience, there will still be selection bias. To capture this effect, I define $T_i$ as the highest level of experience achieved by a player and allow the learning rate to vary linearly with $T_i$:

$$y_{it}^U = (\alpha_0 + \alpha_1 T_i) t + \beta_2 t^2 + \phi_i + \epsilon_{it}$$

with the results shown in the third column of Table 2.4. Interestingly, the coefficient estimate $\hat{\alpha}_1$ is negative, suggesting that there is a negative selection effect with respect to learning rates.\footnote{The coefficient estimate $\hat{\alpha}_2$ on a quadratic interaction effect $T_i^2 t$ is insignificant and does not change the results.} For example, the estimated linear effect on profits of each additional 1000 bids for a player that leaves the game with very little experience is nearly €0.035, while that for a player that leaves after making 10,000 bids is only €0.009. This relationship is consistent with the previous findings that more experienced players have high natural expected profits (on average) and that there are decreasing returns to experience as expected profits rise. Crucially, both specifications 2.15 and 2.14 maintain an economically and statistically significant positive estimate on the experience coefficient even when controlling for selection effects, suggesting that players do learn strategies that increase their expected profit (especially at low levels of experience).

### 2.6.2 Strategies Used by Experienced Players to Increase Profits

This section determines the specific strategies that allow players with higher levels of experience to produce higher expected profits. My basic empirical strategy (discussed in detail below) is to estimate the effect of experience on profit (as in specification 2.13), while controlling for the effect of using specific strategies.
that the relationship between higher experience levels and profit is driven by the use of each strategy, the coefficient on experience will be reduced accordingly. I find experienced players are not making higher expected profits as a result of time-based strategies (bidding at certain times of the day or days of the week) or item-based strategies (bidding on certain items), but that "aggressive bidding" strategies (bidding immediately whenever possible) account for the majority of the profit associated with higher levels of experience.

Formally, note that any change the expected profits from a bid must be driven by the use of different bidding strategies. Specifically, letting variables $s_1, s_2, \ldots$ denote the level of use of each strategy (and allowing strategies to represent any level of interaction of multiple strategies), it must be that

$$y^U = S_1(s_1) + S_2(s_2) + \ldots + \varepsilon$$

(2.16)

for some functions $S_1(\cdot), S_2(\cdot), \ldots$, with $\varepsilon$ again representing the natural stochastic nature of winning the auction. Therefore, any estimate of experience on expected profits (like those in Section 2.6.1) must be indirectly capturing the effect of experience on the use of these different strategies, so that

$$y^U_{it} = L_1(t) + \varepsilon_{it} = S_1(L_1^1(t)) + S_2(L_1^2(t)) + \ldots + \varepsilon_{it}$$

(2.17)

for some learning functions $L_1^1(\cdot), L_1^2(\cdot), \ldots$ To parameterize this model, I follow the first (quadratic, user-consistent) parametrization of the effect of experience above for each learning function, so that

$$s_l = L^l_1(t) = \delta^l_0 + \delta^l_1 t + \delta^l_2 t^2$$

(2.18)

for each strategy $l = 1, 2, 3, \ldots$ Finally, I linearly parametrize the $S_l(\cdot)$ functions, so that:

$$y^U_{it} = \gamma_0 + \gamma_1(\delta^1_0 + \delta^1_1 t + \delta^1_2 t^2) + \gamma_2(\delta^2_0 + \delta^2_1 t + \delta^2_2 t^2) + \ldots + \varepsilon_{it}$$

(2.19)

Using this interpretation, the estimated coefficient $\hat{\beta}_1$ in specification 2.13 is a
consistent estimate of $\gamma_1 \delta_1^1 + \gamma_2 \delta_2^1 + \ldots$, the total effect of $t$ on the use of each strategy ($\delta_1^1$) multiplied by the effect of that strategy on profits ($\gamma_t$). Crucially, note that if $s_{1it}$ (the use of strategy 1 by person $i$ at time $t$) is observable and included in the regression, the estimated coefficient on $t$ becomes a consistent estimate of $\gamma_2 \delta_2^2 + \gamma_3 \delta_3^2 + \ldots$, the total effect on profit of the use of all strategies except strategy 1. Note that it is possible to produce a consistent estimate of $\gamma_1 \delta_1^1$ (the effect of profits of the linear change in the use of strategy 1 through experience) by differencing these estimates.

In order to focus on strategies in the simplest version of the game, I report results for Nailbiter Auctions, in which the BidButler is not allowed. The first column of Table 2.5 presents the results of a regression of experience on profits for Nailbiter Auctions. Following the logic above, the rest of the table presents the same regression, controlling for a variety of strategies. For example, the second column displays the regression while controlling for item fixed effects. While there are significant and positive coefficients on certain items (suggesting that bidding on these items leads to significantly higher profits), the coefficients on experience remain virtually unchanged, suggesting that the strategy of bidding on certain items is not driving the relationship between experience and profits. Similarly, the third column, which displays the regression controlling for time-of-day and day-of-week fixed effects, suggests that time-based strategies are also not driving this relationship.

There are strategies that have significant effects on the estimates of the experience coefficient. Broadly, the most important appears to be "bidding aggressively," in which a player bids extremely quickly following another player’s bids (rather than wait until the timer runs to a few seconds) and bids repeatedly for a large number of bids. Column four of Table 2.5 presents the results of the regression controlling for these strategies, with the "seconds" categorical variables representing the number of seconds from the previous bid (zero seconds representing the most aggressive bid) and the "streak" categorical variables representing the number of bids made in the auction previous to this bid (with higher numbers representing more aggressive bids). First, note that "aggressive bidding" strategies have a very significant effect on profitability of each bid. Bidding extremely quickly after the previous bid (within one second) raises the expected profit by €.58 over waiting over 20 seconds to bid. Having
2.7. SUPPLIER BEHAVIOR

previously bid more than 20 times raises the expected profit by €.25 over bidding for the first time in the auction. Second, note that the coefficient on experience has been reduced dramatically, suggesting that increased use of aggressive bidding by experienced players drives the majority of the increase in profits from experience. In fact, €.02 of the €.03 gain in expected profits associated with an additional 1000 bids arises from the increased use of aggressive bid strategies.

2.7 Supplier Behavior

In the previous sections, I examine the behavior of participants in penny auctions. In this section, I analyze the behavior of suppliers. First, I calculate the optimality of Swoopo’s behavior by separately estimating Swoopo’s actual and optimal supply rule (the number of auctions to provide for a given number of participants). This analysis suggests that high supplier profits require a consistent and large group of users participating in the auction and that over-supplying auctions can be costly to the firm. Interestingly, this finding suggests a potential barrier to new entrants to the market. While there is very little cost to creating a similar auction site, entrants must over-supply auctions in order to attract a larger userbase, but the attraction process takes time and consequently this leads to significant short-term losses. I then show that evidence from five of Swoopo’s top competitors is consistent with this conclusion, as none of the firms are making relatively large profits and three are making negative profits.

35 Some observers have commented on the potential for Swoopo to make shill (fake) bids in order to keep the auction running. Based on my analysis of patterns in the bid-level data, I do not find any evidence of the most obvious shill bidding techniques (creating fake bidders and using them nearly exclusively for shill bids). I cannot rule out the possibility that Swoopo is using more sophisticated techniques that are more difficult to identify.

36 Note that the theoretical analysis does not make this prediction. In a theoretical model, players adjust correctly to the number of players (or expected players) and the hazard rates remain consistent with the theoretical predictions given changes in the number of users.
2.7.1 Supply Rules: Empirical Strategy

In the following sections, I study the optimal provision of auctions for a given number of users at Swoopo. First, I identify Swoopo’s actual supply rule, which is the number of auctions it attempts to supply for a given number of users on the site. Swoopo releases auctions with very high initial timers, so it must predict the number of users on the site in the future when the auction’s timer will become very low and players will start to bid (note that, as Swoopo is an automated website and faces no time-based constraints, the changes in the number of expected users across the day are independent of supply capacity). Therefore, it is possible to determine Swoopo’s supply rule by matching the expected number of auctions (given the release times) with the expected number of users on the site (given past user data). However, as Swoopo does not adjust the number of auctions in real-time, there is significant natural variation in the number of auctions and users once a point in time is actually reached, due to the natural stochastic nature of the ending times of auctions and the natural randomness in the number of users on the site. I use this variation to determine the profit curves from supplying a given number of auctions for a given number of users, which can be used to determine the optimal short-term supply curve.

Note that, unlike Swoopo, I cannot determine the precise number of users looking at the auctions at any instant in time. As a proxy for this measure, I calculate the number of bidders that placed a bid within 15 minutes of that time, which I call active users.\footnote{The qualitative results are robust to changes in the intervals of time.} I define an active auction as one in which the timer of the auction shows less than one minute. To create the dataset for determining Swoopo’s optimal supply curve, I determine the average number of active users and auctions in each ten-second interval in my dataset.\footnote{The qualitative results are robust to time windows from ten seconds to one hour (at which point there is not enough data to accurately estimate the coefficient).} As I mention in Section 2.3.2, the data capturing algorithm was improved on March 18th. In order to keep the measure of number of users consistent over different days, I only use data after that point.
2.7. SUPPLIER BEHAVIOR

2.7.2 Swoopo’s Actual Supply Rule

The goal of this section is to determine Swoopo’s chosen number of auctions for a given number of active users (the supply curve) at each point in time (each observation represents a ten second interval, as discussed above). Importantly, note that Swoopo releases auctions with many hours on the timer (12-24 hours) and that Swoopo is an automated website and therefore faces no time-constraints on supply.

In order to determine Swoopo’s expected number of auctions for a given point in time, one can use the initial timer, the value of the object, and the empirical survival rates in Section 2.4 to estimate a expected survival function \( S(t; v) \) for each auction. \( S(t; v) \) maps each time period \( t \) into the probability that the auction of an item with value \( v \) is active at that point.\(^{39}\) Using this survival function, I estimate Swoopo’s desired supply at time \( t \), \( \tilde{Q}_{St} \), as

\[
\tilde{Q}_{St} = \sum_{Auctions} S(v, t) \quad (2.20)
\]

When Swoopo releases this auctions, it must estimate the number of users that will be on the site when the auction becomes active (the timer shows less than one minute). Luckily, the number of users \( Q_{Dt} \) varies predictably depending on the time of the day and the day of the week, as demonstrated by the fact that the regression of users on time:

\[
Q_{Dt} = \beta_0 + \beta_1 TimeDummies + \varepsilon_t \quad (2.21)
\]

yields an \( R^2 \) of .716.\(^{40}\) The predicted values \( \tilde{Q}_{Dt} \) from this regression are shown with the bold line in Figure 2.9.

The relationship between the expected supply and the expected demand is Swoopo’s actual supply rule (note that there is no concern of endogeneity in this regression

\(^{39}\)Note that this is not the same as the survival function in the theoretical section. In that section, \( t \) represented a change in the bid level, while \( t \) here represents ten second intervals of clock time. As each rise in the bid level is associated with an average 9 second rise in the timer, these measures are related, but not the same.

\(^{40}\)My chosen specification uses dummies for time of day (broken into 10 minute sections) and individual day. A variety of specifications with different time-dummies yield nearly identical results.
CHAPTER 2. BEHAVIOR IN PENNY AUCTIONS

Figure 2.9: Number of Active Users over 48 Hours (Actual vs. Smoothed)

as there is no way for the expected supply to impact the expected demand when an auction is released):

\[ \bar{Q}_{sl} = \beta_0 + \beta_1 \bar{Q}_{Dt} + \varepsilon_t \]  

(2.22)

with the results shown in the first column of Table 2.6. The results are highly significant and suggest that Swoopo attempts to supply a new auction for every 42 new active users. Given the nature of the data, there is a concern that the error term is serially correlated. Rather than attempt to correct for this correlation, which is potentially complicated in nature, I run the same regression using only every 360th observation (each hour), with the results shown in the second column of table 2.6. The results remain largely unchanged. In order to check the potential for a non-linear supply, I run a regression with a quadratic term, with the results shown

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41 Given the shape of the survival function, it is not possible to perfectly match the expected supply at each point in time with an arbitrary desired supply, which leads to error, captured with \( \varepsilon_t \). Modelling the effect of this constraint on \( \varepsilon_t \) is difficult.

42 The results are consistent regardless of the chosen interval. I report results for one hour as this is the largest interval with enough observations to produce reasonably significant results.
in the third column of Table 2.6. As I show in Section 2.7.4, the estimated supply curve is largely unchanged for the normal range of active users.

### 2.7.3 Swoopo’s Optimal (Short Term) Supply Rule

Even though Swoopo attempts to match the number of active auctions with the number of active users, there is significant variation in the actual number of active auctions for a given number of active users (and vice versa). Specifically, for a given number of users, the number of active auctions is nearly normally distributed around the desired number of auctions with a standard deviation of 2.83. This variation arises from the natural stochastic nature of the ending times of auctions and the number of users on the site. I use this variation to compare the (instantaneous) profit from supplying different number of auctions given a number of users to determine the optimal short-term supply curve. Note that as I have no exogenous variation in the long-term supply, I cannot identify the effect of changes in supply on long-term profit (presumably, a higher supply will attract more users to the site in the long-term, affecting profits). Therefore, my estimation of the optimal supply curve does not take into account any potential effects of supply on demand in the long-term.

Formally, let \( y_{jt}^A \) be the auctioneer’s payoff at time \( t \) from auction \( j \), which must lie between the bid cost (€.50) and the net value of the object. Then, a general model of the effect of the number of users \( Q_{Dt} \), the number of auctions \( Q_{St} \), and a vector of auction characteristics \( \bar{x}_j \) on profit is

\[
y_{jt}^A = P(Q_{Dt}, Q_{St}, \bar{x}_j) + \varepsilon_{jt} \tag{2.23}
\]

As a first step towards understanding the profit function \( P(\cdot) \), Figure 2.10 displays non-parametric regressions of the number of active users on instantaneous profit for multiple equal sized groupings of the number of active auctions. First, note that an increase in the number of active users consistently increases the predicted instantaneous profit for each number of active auctions. Second, note that an increase in the number of active auctions consistently reduces the predicted instantaneous profit for each number of active users. Finally, note that these effects appear to be largely...
linear and independent of each other.

With these results in mind, I parametrize the model as

$$y^A_{jt} = \beta_0 + \beta_1 Q_{Dt} + \beta_2 Q_{St} + \varepsilon_{jt}$$

(2.24)

with the results shown in the first column of Table 2.7. This regression estimates that instantaneous profit rises by €0.088 for each additional hundred active users on the site, but falls by €0.034 for each additional auction. The results of a quadratic regression are shown in the second column of Table 2.7. The results of a regression with item fixed effects (to control for the heterogeneous effects of the item for auction) are shown in the third column of Table 2.7. As I show in Section 2.7.4, the estimated effects are largely unchanged across these regressions for the normal range of active users.

From these results, it is straightforward to determine the optimal number of active auctions for a given number of active users. For example, using the first specification, the predicted instantaneous profit $\hat{\pi}^A$ to the auctioneer from running $Q_S$ auctions...
2.7. SUPPLIER BEHAVIOR

given $Q_D$ users is

$$\hat{\pi}^A(Q_S, Q_D) = Q_S(\hat{\beta}_0 + \hat{\beta}_1 Q_D + \hat{\beta}_2 Q_S)$$  \hspace{1cm} (2.25)

Consider a situation in which there are 200 active users. Using the estimates from the first specification, the predicted profit from running one auction is €.368, from running two auctions is $2 \times (€.368 - €.034) = €.669$, from running three auctions is $3 \times (€.368 - €.068) = €.903$, and so on. It is easy to show that, given the estimates from the first specification, $\hat{\pi}^A(Q_S, Q_D)$ is a strictly concave in $Q_S$ with a unique maximum $Q^*_S(Q_D) = \frac{\hat{\beta}_0 + \hat{\beta}_1 Q_D}{-2 \times \hat{\beta}_2} = \frac{225 + 0.000883 Q_D}{2 \times 0.0335}$. Solving this equation when $Q_D = 200$ leads to an estimated optimal supply of $Q^*_S(Q_D) \approx 6$ auctions.

Using the same logic for the other specifications, it is easy to calculate the optimal (short-term) supply curve for each specification. These curves are compared with the actual supply functions in the following section.

2.7.4 Comparison between Actual and Optimal Supply Rules

In the previous two sections, I estimated the actual and optimal short-term supply curve of auctions. Figure 2.11 displays these curves for each specification along with a kernel density estimation of the number of active users on the site. Clearly, the different specifications for both curves produce extremely similar qualitative results.

It is possible to compare the supply curves quantitatively by comparing the estimated profits from each curve. Specifically, given the estimated empirical distribution of users $f(Q_D)$ and the estimated profit function $\hat{\pi}^A(Q_S, Q_D)$, the estimated profit from following supply curve $Q_S(Q_D)$ is

$$\hat{\Pi} = \int f(Q_D) \hat{\pi}^A(Q_S(Q_D), Q_D) dQ_D$$

Using estimates from the first specifications of both models, the optimal supply curve yields expected instantaneous profits of €1.48, while the estimated supply curve yields €1.46, suggesting that Swoopo captures 98.6% of potential profits in its supply curve.
This section has produced a variety of results, with three important points. First, it appears that Swoopo is efficient at profit-maximization with respect to its supply curve. Second, all else equal, the auctioneer’s profit is increased by additional users and reduced by additional auctions. Therefore, for a given number of users, supplying the optimal number of auctions is important. Third, the auctions require a reasonable number of consistent active users (over 40, based on my measure) to run successfully.

2.7.5 Competitor Profits

As Swoopo makes a large amount of profit for running penny auctions, why would other companies not begin to offer these auctions? Swoopo holds no intellectual property and the cost of creating a nearly identical product is extremely cheap.\textsuperscript{43} Furthermore, as bidders would presumably prefer to compete with fewer other bidders

\textsuperscript{43}In fact, companies that sell pre-designed website templates for these auctions allow a potential competitor to start a similar site in a few hours.
(there is a negative network externality), entrants could be potentially favored over an established firm. Consistent with this logic, there has been a large influx of competitor firms in this market.\textsuperscript{44}

However, the above results concerning the supply rules suggest a potentially important structural barrier to entrants in this market. As there are significant diminishing returns to the supply of auctions, over-supply of auctions for a given number of users can be costly. However, entrants must over-supply auctions in order to attract a larger userbase, leading to large costs until the userbase grows to match the supply.\textsuperscript{45} This conclusion is bolstered by auction-level data compiled from competitor sites. Table 2.8 displays the (recent) use and profit statistics of Swoopo and five other major entrants to this market.\textsuperscript{46} Only one of the five major competitors is making large daily profits, which are still an extremely small percentage (6.6\%) of Swoopo’s daily profits. The other four competitors are making small or negative daily profits. This analysis suggests that entrants will not immediately reduce the rents in this market, at least in the medium term.

\section*{2.8 Discussion and Conclusion}

This paper presents a variety of theoretical and empirical results concerning the market for penny auctions, a relatively new auction format. My first result is that, in aggregate, players significantly overbid in these auctions, leading to large expected profits for the auctioneer. Comparing the empirical hazard function with theoretically predicted function yields my second result: players overbid more and more as the auction continues. I show that this behavior matches the predictions of a model with agents that exhibit a naive sunk cost fallacy. Interestingly, players with higher levels of experience have higher empirical returns from bidding, most notably through

\textsuperscript{44}Simply searching google for "penny auction" or "swoopo" will reveal a variety of paid advertisements for other companies running penny auctions.

\textsuperscript{45}Another potential reason is switching costs. Although it would appear that switching costs are low, users appear to switch between companies very rarely. Only 24 (of over 129,000) Swoopo usernames in the bid-level dataset appear in the top ten lists of the five largest competitors.

\textsuperscript{46}Based on cursory research, these five companies were the top five competitors to Swoopo as of June 2009.
the increased use of a set of "aggressive bidding" strategies. For my third main result, I demonstrate that Swoopo nearly optimally matches the expected number of active auctions to the expected number of users on the site at each point in time. The supply rules suggest that an entrant that attempts to over-supply auctions in order to attract a large userbase will incur large short term losses, creating a structural barrier to entry. I show that this conclusion is consistent with findings from data from five competitors, which shows that competitors lag significantly behind the sole market leader in terms of daily profit.

From a policy perspective, the conclusions of the paper raise the question of regulation for this type of auction. On one hand, the auction appears to resemble a lottery, with large numbers of participants losing relatively little, one participant winning a significant prize, and the auctioneer making large profits. This suggests that, to the extent that governments choose to regulate lotteries (which they often do, for moral, paternalistic, or revenue-generating reasons (Clotfelter and Cook(1990)), there is a role for regulation of these auctions. However, there are also some key differences which make the role of government regulation less clear: this auction possesses no exogenous source of randomness (all randomness arises from the strategies of other players); skill does play a role in the expected outcome; and there is no obvious deception or manipulation of the players of the game.

There are multiple avenues for further research in the market for penny auctions. For example, while my results are suggestive that players exhibit a sunk cost fallacy, the format of Swoopo’s auction makes it difficult to fully differentiate between this and a small set of other potential explanations. Laboratory study would allow for the controlled variation needed to more precisely identify the appropriate model of players’ behavior. Alternatively, it might be possible to achieve this goal empirically by using variation in the rules of the auctions run by new and future entrants. Finally, as the market for penny auctions is still relatively young, time will allow a more comprehensive study of the evolution of individual producer behavior and market dynamics as the market matures.
Table 2.1: Descriptive Statistics of the Auction-Level and Bid-Level Datasets

<table>
<thead>
<tr>
<th>Auction-Characteristics</th>
<th>Number of Observations</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Fifth Percentile</th>
<th>Ninety-Fifth Percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Worth Up To Value</td>
<td>166,379</td>
<td>287.62</td>
<td>380.90</td>
<td>25.00</td>
<td>1099.00</td>
</tr>
<tr>
<td>Adjusted Value (Sec. 2.3.3)</td>
<td>166,379</td>
<td>252.29</td>
<td>353.58</td>
<td>18.95</td>
<td>999.00</td>
</tr>
<tr>
<td>Nailbiter Auction</td>
<td>166,379</td>
<td>.039</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Beginner Auction</td>
<td>166,379</td>
<td>.095</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

| Bidding Increment               |                        |         |                    |                  |                         |
| €.00                            | 166,379                | .176    | -                  | -                | -                       |
| €.01                            | 166,379                | .064    | -                  | -                | -                       |
| €.10                            | 166,379                | .759    | -                  | -                | -                       |

| Types of Good                   |                        |         |                    |                  |                         |
| Consumer Goods                  | 166,379                | .883    | -                  | -                | -                       |
| Bid Vouchers                    | 166,379                | .100    | -                  | -                | -                       |
| Cash                            | 166,379                | .013    | -                  | -                | -                       |

Note: Categories represented by dummy variables.
For example, mean(nailbiter auction)=.039 implies 3.9% of all auctions are nailbiter auctions
### Table 2.2: Descriptive Statistics of the Auction-Level and Bid-Level Datasets

<table>
<thead>
<tr>
<th>Bid-Level Data</th>
<th>Number of Mean Standard Fifth Ninety-Fifth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>129,329</td>
</tr>
<tr>
<td>Number of Wins</td>
<td>0</td>
</tr>
<tr>
<td>Number of Auctions</td>
<td>129,329</td>
</tr>
<tr>
<td>Number of Wins</td>
<td>0</td>
</tr>
<tr>
<td>Number of Auctions</td>
<td>129,329</td>
</tr>
</tbody>
</table>

#### Auction Characteristics

| Number Unique Bidders | 53.81 |
| Number Unique Bidders | 90.01 |
| Number Unique Bidders | 5  |

#### Bid Characteristics

| Number of Wins | 0 | 0.17 |
| Number of Auctions | 129,329 | 16.37 |
| Number of Wins | 0 | 0.01 |
| Number of Auctions | 129,329 | 0.00 |

#### User Characteristics

| Number of Bids | 102.96 |
| Number of Auctions | 7.47 |
| Number of Bids | 1.05 |

#### Note:

- Categories represented by dummy variables.
- For example, mean(nailbiter auction) = 0.97 implies 3.9% of all auctions are nailbiter auctions.
Table 2.3: Descriptive Statistics of Profit

<table>
<thead>
<tr>
<th></th>
<th>Number of Observations</th>
<th>Average Profit</th>
<th>Average Profit Margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>166,379</td>
<td>€112.68</td>
<td>52.20%</td>
</tr>
<tr>
<td>Website</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-Web</td>
<td>119,617</td>
<td>€129.56</td>
<td>66.20%</td>
</tr>
<tr>
<td>Pre-Web (Phone)</td>
<td>46,762</td>
<td>€69.50</td>
<td>16.40%</td>
</tr>
<tr>
<td>Bidding Increment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>€.10</td>
<td>123,693</td>
<td>€38.64</td>
<td>28.41%</td>
</tr>
<tr>
<td>€.01</td>
<td>7,861</td>
<td>€729.38</td>
<td>102.92%</td>
</tr>
<tr>
<td>€.00</td>
<td>15,528</td>
<td>€224.38</td>
<td>35.65%</td>
</tr>
<tr>
<td>Types of Prizes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consumer</td>
<td>147,589</td>
<td>€95.18</td>
<td>33.21%</td>
</tr>
<tr>
<td>Bid Vouchers</td>
<td>16,603</td>
<td>€250.18</td>
<td>214.16%</td>
</tr>
<tr>
<td>Cash Voucher</td>
<td>2,187</td>
<td>€431.90</td>
<td>104.06%</td>
</tr>
</tbody>
</table>

Table 2.4: Regressions of profit on experience

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) FE</th>
<th>(3) FE + slope FE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Instant. Profit</td>
<td>Instant. Profit</td>
<td>Instant. Profit</td>
</tr>
<tr>
<td>Experience (1000)</td>
<td>0.0300*** (14.07)</td>
<td>0.0107*** (3.27)</td>
<td>0.0355*** (8.52)</td>
</tr>
<tr>
<td>Experience (sq)</td>
<td>−0.000474*** (7.51)</td>
<td>−0.0000421 (.55)</td>
<td>0.00146*** (8.78)</td>
</tr>
<tr>
<td>User FE</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Max Exp * Exp</td>
<td></td>
<td></td>
<td>−0.00264*** (9.59)</td>
</tr>
<tr>
<td>Constant</td>
<td>−.328*** (75.37)</td>
<td>−.291*** (27.88)</td>
<td>2.215*** (119.02)</td>
</tr>
<tr>
<td>Observations</td>
<td>13,315,570</td>
<td>13,315,570</td>
<td>13,315,570</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001. Errors clustered on users when no user FEs.
### Table 2.5: Regressions of profit on experience, controlling for strategies

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Experience</strong></td>
<td>1.097</td>
<td>0.250</td>
<td>0.250</td>
<td>0.250</td>
<td>0.991</td>
</tr>
<tr>
<td><strong>Experience (sq)</strong></td>
<td>0.153</td>
<td>0.085</td>
<td>0.085</td>
<td>0.085</td>
<td>0.153</td>
</tr>
<tr>
<td><strong>Item FE</strong></td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td><strong>Time FE</strong></td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td></td>
</tr>
<tr>
<td><strong>Streak (1-5)</strong></td>
<td>0.981</td>
<td>0.981</td>
<td>0.981</td>
<td>0.981</td>
<td></td>
</tr>
<tr>
<td><strong>Streak (&gt;20)</strong></td>
<td>0.201</td>
<td>0.201</td>
<td>0.201</td>
<td>0.201</td>
<td></td>
</tr>
<tr>
<td><strong>Seconds (0-1)</strong></td>
<td>0.801</td>
<td>0.801</td>
<td>0.801</td>
<td>0.801</td>
<td></td>
</tr>
<tr>
<td><strong>Seconds (1-5)</strong></td>
<td>0.201</td>
<td>0.201</td>
<td>0.201</td>
<td>0.201</td>
<td></td>
</tr>
<tr>
<td><strong>Seconds (5-20)</strong></td>
<td>0.097</td>
<td>0.097</td>
<td>0.097</td>
<td>0.097</td>
<td></td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses

- \( p < 0.05 \)
- \( p < 0.01 \)
- \( p < 0.001 \)

Table 2.5: Regressions of profit on experience, controlling for strategies.
Table 2.6: (Second stage) IV Regressions of desired supply on (predicted) demand

<table>
<thead>
<tr>
<th></th>
<th>(1) [10 seconds]</th>
<th>(2) [one hour]</th>
<th>(3) [quadratic]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Auctions</td>
<td>Auctions</td>
<td>Auctions</td>
</tr>
<tr>
<td>Predicted Num Users</td>
<td>0.0238***</td>
<td>0.0246***</td>
<td>0.00982***</td>
</tr>
<tr>
<td></td>
<td>(776.68)</td>
<td>(40.03)</td>
<td>(62.90)</td>
</tr>
<tr>
<td>Predicted Num Users (sq)</td>
<td>0.000029***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(91.06)</td>
</tr>
<tr>
<td>Constant</td>
<td>.638***</td>
<td>.659***</td>
<td>2.215***</td>
</tr>
<tr>
<td></td>
<td>(90.14)</td>
<td>(4.63)</td>
<td>(119.02)</td>
</tr>
<tr>
<td>Observations</td>
<td>595718</td>
<td>1655</td>
<td>595718</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses *p < 0.05, **p < 0.01, ***p < 0.001
Statistics calculated using robust standard errors

Table 2.7: Regressions of instantaneous profit on number of users and auctions

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS Instprofit</th>
<th>(2) Quadratic Instprofit</th>
<th>(3) OLS with FE Instprofit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auctions</td>
<td>-0.0335***</td>
<td>-0.0335***</td>
<td>-0.0359***</td>
</tr>
<tr>
<td></td>
<td>(-20.13)</td>
<td>(-20.08)</td>
<td>(-20.72)</td>
</tr>
<tr>
<td>Users</td>
<td>0.000883***</td>
<td>0.000782***</td>
<td>0.00101***</td>
</tr>
<tr>
<td></td>
<td>(15.68)</td>
<td>(3.07)</td>
<td>(16.74)</td>
</tr>
<tr>
<td>Users (sq)</td>
<td></td>
<td>1.74·10⁻⁷</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.41)</td>
<td></td>
</tr>
<tr>
<td>Item Fixed Effects</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Constant</td>
<td>0.225***</td>
<td>0.238***</td>
<td>0.206***</td>
</tr>
<tr>
<td></td>
<td>(17.42)</td>
<td>(6.77)</td>
<td>(15.03)</td>
</tr>
<tr>
<td>Observations</td>
<td>10,157,214</td>
<td>10,157,214</td>
<td>10,157,214</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses *p < 0.05, **p < 0.01, ***p < 0.001
Statistics calculated using robust standard errors
Table 2.8: Descriptive Profit Statistics of competition (from October 2008)

<table>
<thead>
<tr>
<th>Company</th>
<th>Active Since</th>
<th>Auctions Per Day</th>
<th>Profit Per Day</th>
<th>Average Profit Margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Swoopo</td>
<td>10/2005</td>
<td>271.77</td>
<td>€42,215.98</td>
<td>62.74%</td>
</tr>
<tr>
<td>BidStick</td>
<td>10/2008</td>
<td>38.22</td>
<td>€2,812.60</td>
<td>51.76%</td>
</tr>
<tr>
<td>RockyBid</td>
<td>03/2009</td>
<td>9.98</td>
<td>€-483.63</td>
<td>-11.9%</td>
</tr>
<tr>
<td>GoBid</td>
<td>02/2009</td>
<td>9.53</td>
<td>€-146.79</td>
<td>-0.13%</td>
</tr>
<tr>
<td>Zoozle</td>
<td>02/2009</td>
<td>6.64</td>
<td>€126.36</td>
<td>3.31%</td>
</tr>
<tr>
<td>BidRay</td>
<td>04/2009</td>
<td>1.75</td>
<td>€55.82</td>
<td>62.31%</td>
</tr>
</tbody>
</table>

Note: Statistics from Oct 2008-June 2009
Chapter 3

Choice Fatigue: The Effect of Making Previous Choices on Decision Making (w/ Scott Nicholson)

3.1 Introduction

Do people really find the pure act of decision-making to be exhausting or effort-consuming? If so, how do a person’s decisions change after they have just made other decisions? In this paper, we answer this question by exploiting a natural experiment that generates conditionally random variation in the number of decisions a voter must make before reaching her decision on a certain contest on the ballot. We provide evidence that making more decisions prior to a particular decision increases the likelihood of abstention from the decision as well as the reliance on heuristics (such as choosing the status-quo) in decision-making. We label this effect "choice fatigue," which we define broadly to describe the effects of cognitive exertion from making multiple decisions, such as annoyance or physical fatigue.

Choice fatigue is economically important because decisions in many economic domains are made in sequential order. The effect of cognitive load on different decisions
CHAPTER 3. CHOICE FATIGUE

has been discussed in other recent work in behavioral economics and consumer psychology. For example, Levav et.al. (2007) find in a field experiment that German car buyers customizing their Audi are more likely to rely on defaults – and thus spend more money on the car – if decisions with larger numbers of alternatives are placed at the beginning of the sequence of customization decisions. Also, Iyengar & Kamenica (2007) find that employees at firms with more funds to choose from in their 401(k) plan ultimately allocate more money to bond funds and less to equity funds. Although these papers provide motivation for our hypothesis, they cannot directly address the pure role of fatigue due to a lack of exogenous variation in the position of certain decisions.

For example, in previous research on voting, the phenomenon of "roll-off" describes voters as less likely to cast a vote as they move down the ballot (Burnham 1965). While there is no debating this stylized fact, the explanation for it is unclear. Voters may indeed become fatigued as they make more and more decisions, but contest saliency also generally decreases between top-of-the-ballot contests such as President and Governor and lesser-known statewide and local offices and propositions (Bowler, Donovan & Happ 1992, Bullock & Dunn 1996). Thus, if voters become less motivated to participate in contests further down the ballot due to a decrease in the saliency of the contest, then the effects of fatigue cannot be separated from those of saliency. Therefore, one of the main contributions of this paper is the analysis of choice fatigue by using variation in decision order that is uncorrelated with other potential explanatory variables.

The ability to disentangle the role of fatigue from other informational hypotheses is important. For instance, if people hesitate to make decisions because they find it costly to gather information, a benevolent policy maker might shower them with free information. On the other hand, if people hesitate to make decisions because they find the act of making decisions inherently fatiguing, the policy maker might restrict their decision set or even deprive them of information. It is possible that people are better off making all of their decisions in a slightly uninformed way rather than making only some of their decisions in a fully informed way.1 Or, from a different

---

1This behavior is completely consistent with the characterization of survey-takers as moving from
perspective, a firm with a less benevolent interest in consumer welfare may find it profitable to exploit fatigue in consumer decision-making, as demonstrated by the Audi example.

In addition to providing the necessary variation to identify choice fatigue, the voting application provides an ideal environment to study these issues for several reasons. First, a person who is in a voting booth has already voluntarily invested her time in registering to vote, going to the polls and standing in line, so it is clear that the voter is motivated to make some decisions. Second, the voter knows that there is no opportunity to delay decision-making since the contests are only open for voting on Election Day. Finally, it is relatively easy for the voter to not make a decision by *undervoting* (choosing to not vote) on a particular contest or make a decision using a variety of choice heuristics.

With these motivations in mind, the main result of this paper is that the number of prior decisions made affects both the level of abstention and the chosen decision. In particular, we find that lowering a given contest by one position on the ballot increases precinct-level undervotes by .13 percentage points. Given the average ballot position (15.7) and level of undervotes of contests in our data (21.6%), this suggests that choice fatigue is responsible for 9.3% of undervotes in these contests. We also find that voters are more likely to use decision shortcuts as they become fatigued. For example, in statewide and local propositions ("yes-no" decisions), lowering a given proposition by one position increases votes for the status-quo ("no" votes) by .11 percentage points. In statewide and local office races (multi-candidate decisions), lowering a given contest by one position increases the tendency to vote for the first candidate listed for that contest by .05 percentage points. To understand the economic impact of these results, consider that the average propositions is presented 26.8 positions from the top of the ballot. This estimate suggests that "no" votes would decrease by an average of 2.9 percentage points if these contests appeared at

\[\text{an optimizing behavior to a satisficing behavior as they move through a survey (Krosnick 1999).}\]

\[\text{2I also contrast the results for polling precinct voters with absentee voters. A significant selection problem exists in the assignment of voters to the two groups and this likely passes through to the effects of ballot position on participation and choice.}\]

\[\text{3Although some states have propositions in which a "yes" vote is the status quo, a "no" vote always maintains the status-quo for California propositions.}\]
the top of the ballot. Therefore, given the ballot position of each proposition, we calculate that 22 of the 352 propositions (6.25%) in our dataset would have passed rather than failed if the proposition was presented to voters as the first contest on the ballot.

Figure 3.1: Distribution of Number of Precincts with Proposition 35 at Different Ballot Positions

To further motivate the central idea and natural experiment, consider Proposition 35, a California statewide ballot measure in the 2000 general election regarding the removal of certain restrictions on the use of private contractors in public works projects. This proposition appeared on every ballot in the state, but because of the constitutionally-mandated ordering of contests and the differences in local ballot

---

4The title of the proposition that appeared on the ballot is “Public works projects. Use of private contractors for engineering and architectural services.”
composition across the state, voters were presented with different numbers of previous decisions before seeing Proposition 35. For example, voters in San Diego County saw Proposition 35 listed anywhere between 9th and 19th on the ballot. Figure 3.1 illustrates the within-election variation in the ballot position of Proposition 35 across precincts. From the perspective of the standard economic model of decision-making, we would not expect a contextual variable, such as ballot position, to affect outcomes. However, as Proposition 35 moved down the ballot, the choice behavior of voters changed. Figure 3.2 shows a positive and significant association between the ballot position of Proposition 35 and the percentage of "no" votes and undervotes (i.e., abstentions) in the respective precincts. The figure also shows that no such positive relationship exists across the same precincts in the average fraction of undervotes for the U.S. Senator race, which was the last contest appearing at a common ballot position across the precincts. While this example only illustrates a simple relationship for one contest, it highlights the central contribution of this paper: providing econometric evidence of the pure role of choice fatigue and how it exacerbates the reliance on shortcuts in decision-making.

To better understand the relevance of this paper’s research contribution, the next section discusses the relevant previous literature on decision-making and rolloff. Section 3.3 then briefly provides a theory of choice fatigue. The empirical results are broadly broken into two categories. In section 3.5, we investigate the effect of choice fatigue on undervotes, which represented the "decision to decide." In section 3.6, we discuss the effects of choice fatigue on the actual decision, given that a decision was made. The implications of the results for political economics and theories of decision-making, as well as practical concerns for the design of electoral institutions are discussed in section 3.7.

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5 Aside from variation generated by the set of overlaying local political jurisdictions, the staggering of even and odd State Senate contests across presidential and gubernatorial elections also provides down-ballot variation in ballot position. This is discussed further in section ??.
3.2 Previous Literature

The central hypothesis of this paper is that a contextual variable, the number of previous decisions made in the choice environment, can affect decision outcomes. As we are concerned with the effect of this variable on both abstentions and the decision itself, we will review the relevant literature in both of these areas. In both cases, given that the application in this paper is voter decision-making, we first briefly discuss relevant research in this area and later return to more broadly motivating work in consumer psychology and economic choice.
The Effect of Fatigue on "Deciding to Decide"

Three explanations are offered in the existing literature on the effects of ballot composition on participation in individual contests: information, confusion and fatigue. Within this body of work the fatigue effects cannot be disentangled from other participation hypotheses due to methodological limitations that disallow any sort of causal inference. We discuss two representative papers here. First, Darcy and Schneider (1989) study the 1986 Oklahoma gubernatorial general election in which the usage of fill-in-the-bubble optical voting technology by some counties placed the high-salience U.S. Senator contest in obscure or unusual places on the ballot. While their data analysis is simple (e.g., no standard errors are given or hypothesis tests performed) and no causality can be established, the data on a superficial level suggest that counties using optical voting technology are associated with 3 to 7 percentage points more undervotes compared to other counties using lever machines. Clearly no inferential conclusions can be made to explain the difference, but the authors do present an example of how the relative position of a contest on the ballot may be important for voter choice.

Second, Bowler, Donovan & Happ (1992) discuss how voter fatigue may influence abstentions. They refer to Downs (1957) in arguing that motivations for voting are driven by a cost-benefit analysis. These benefits and costs are directly affected by informational and political economic channels such as contest controversy, expected winning margin and campaign expenditures (Downs 1957, Magleby 1989, 1984). If informational costs exceed the benefits of voting, then voters may resort to cheap decisions such as abstaining. Bowler, Donovan & Happ’s empirical approach to identifying fatigue uses a state-level dataset of votes on California ballot propositions for 1974-1988 to analyze how voters behave as they move down the ballot. In their analysis, differences in the ballot positions of different propositions provides the variation in the number of previous decisions made by a voter. Clearly, if information demands

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6Beyond the statistical limitations, characteristics of the three 'treated' counties are confounded with the effect of the change in voting technology.
increase as voters move down the ballot, then any evidence of voter fatigue is confounded with explanations regarding information and saliency.\textsuperscript{7} Consequently, they cannot separate proposition-specific factors from the effects of ballot position. Given these limitations, a main contribution of this paper is to disentangle fatigue from other contest-level participation covariates such as the level of available information or contest saliency.

Apart from fatigue, several authors look directly at the role of information in abstention. For example, Coupé and Noury (2004) use data from a survey experiment to find the "pure" effect of information on the decision to abstain. While not an application based on empirically observed voter choice behavior, their conclusions are intuitive and suggest that those with less information about a particular survey question are more likely to abstain. Another example is Wattenberg, McAllister \& Salvanto (2000). They characterize voters as "treat[ing] voting as if it were a test, picking out the questions that they can answer." While they argue that voters with less information are more likely to abstain, their empirical approach uses survey data which likely overreports participation and provides noisy measures of a voter’s level of information. These issues are avoided with our approach since our data are observed voter choices and contest saliency is controlled for by analyzing within-contest variation in ballot position.\textsuperscript{8}

As there are many economic environments in which sequential decisions are made in a choice environment, there is previous work in behavioral economics and consumer psychology regarding the role of similar contexts in decision-making. For example,

\textsuperscript{7}In fact, propositions appear on the ballot according to the following categories: general obligation bond measures (e.g., education, transportation, earthquake retrofitting, etc.), legislative bond measures, legislative constitutional amendments, referenda, and citizen’s initiatives. Within these categories, propositions appear on the ballot in the order in which they qualified. Both of these factors make the ordering of propositions endogenous.

\textsuperscript{8}A table in Wattenberg, McAllister \& Salvanto further highlights one major shortcoming in this literature and the corresponding innovation in our work. Table 1 (p. 237) lists contests on the California statewide ballot in the 1994 general election, with the ballot position of the last statewide elective office (Superintendent of Public Schools) at 15th and the first statewide proposition (Prop. 181) at 16th. However, a potentially long list of local candidate contests are sandwiched between these contests on the ballot. If this variation is not taken into account, the ordering of contests does not accurately measure the number of decisions previously made (even if one controls for contest-specific saliency effects).
Boatwright and Nunes (2001) provide additional evidence that decisions made sequentially can be affected by the attributes of individual choices. They find in a natural experiment at an online grocer that reductions in assortment within 42 product categories increase sales by an average of 11%. Additionally, 75% of the grocer’s customers increased their overall expenditures. Although the evidence points to a general story that simpler decision contexts may be associated with less choice fatigue, it is not clear whether the observed increase in purchases (decisions) is due to within-category or across-store variety reductions. The alternate explanation that within-product (and not necessarily across-product) decreases in variety increase sales is in line with the choice overload literature, spearheaded by Iyengar & Lepper (2000).\textsuperscript{9} They find in experiments on the variety of jams (and separately, chocolates) in a tasting booth and the number of ideas for extra-credit essays that decisions with more alternatives are associated with more choice overload, i.e., less actions taken. Dhar (1997a, 1997b) finds that preference for a "no-choice" option (i.e., choice deferral) increases when there is no single alternative in the choice set that has a clear advantage.

**Effect of Fatigue on Decisions**

For motivation on understanding how voters’ decisions are affected by choice fatigue, it is first useful to discuss the literature on voter choice in low information environments. Having no information about candidates or a proposition does not imply that voters will choose a candidate randomly. Instead, there are myriad contest characteristics available to them that they can use to make a low-information decision about how to vote. Contexts which can serve as a cue or heuristic to the voter in individual decisions are candidate ordering (Meredith & Salant 2007, Koppell & Steen 2005), ballot configurations/design (Walker 1966), and candidate cues such as gender (McDermott 1997), ballot designation/incumbency (McDermott 2005), race/ethnicity (Washington 2006, Engstrom & Caridas 1991, Vanderleeuw & Utter 1993) and partisanship (Sniderman, Brody & Tetlock 1991). Additionally, these effects may be

\textsuperscript{9}Other references in this literature include Bertrand et. al. (2005), and Gourville and Soman (2001). Furthermore, theoretical arguments (Kamenica 2008) and experimental evidence (Salgado 2005) exist for why consumers may prefer smaller choice sets over larger ones.
exacerbated in the absence of other cues (Miller & Krosnick 1998). Our goal is not to examine the effect on these cues on decisions, but how these types of characteristics might interact with fatigue to affect voter decision-making. Specifically, we will focus on the effect of fatigue level on choosing the status-quo or the first candidate, as these are arguably the cues that require the least effort to determine.\(^\text{10}\)

More broadly, previous research has examined the effect of cognitive exertion on the ability to make decisions and the potential resulting bias in observed choice in a variety of domains. For example, Levav et al. (2007) find in a field experiment with buyers of Audi cars in Germany that the sequencing of car customization decisions affects final outcomes. Customers in their experiment are randomly assigned to treatments in which the first 8 of 67 decisions over car attributes are ordered either in increasing or decreasing order of the number of attributes available for each decision. Levav et al. find that customers in the "Hi-Lo" treatment (decisions with more alternatives first) are more likely to take the default choices than those in the "Lo-Hi" (decisions with less alternatives first) treatment. In addition, the reliance on default options cause the "Hi-Lo" customers to spend more money on the car. Note that although this experiment has random variation in the number of car characteristics presented before arriving at a particular decision, there are only two orderings and these are constructed purely with the attributes of individual decisions in mind.

Complementing the evidence in political science, economics and marketing, survey researchers have examined similar issues with regard to how survey respondents behave as they navigate through a survey. Krosnick (1999) describes another perspective in his survey of recent convergences and discoveries in the survey literature. Dating back to Simon (1953), Krosnick describes survey subjects as falling into two categories: optimizers and satisficers. While optimizers are thorough in their decision-making, other types of people are less thoughtful as they provide responses to questions. Krosnick describes these people as "agree[ing] merely to provide answers, with

\(^{10}\)Candidates are listed in a particular order, and this order is observed with virtually no effort. Similarly, the status quo option on propositions is always "no," and requires no effort to determine. On the other hand, to make a decision based on the candidates' gender, the voter must read each candidates name, determine the likelihood that the candidate is male, and compare these likelihoods across candidates.
no intrinsic motivation toward high quality." These "respondents may satisfy their desires to provide high-quality data after answering a few questions, and become increasingly fatigued and distracted as a questionnaire progresses." As a result, these respondents rely more on shortcuts as such as choosing the status quo or "no opinion" for questions appearing later on in a questionnaire (Ying 1989).

### 3.3 A Simple Theory of Choice Fatigue

The theory of choice fatigue in voter decision-making presented in this chapter is provided to serve as a guide to motivate the estimated reduced-form regressions in the subsequent chapters. To reiterate the research’s primary motivation, we hypothesize that the process of making decisions induces a "fatigue" on an individual, decreasing the likelihood that she will take action and increasing the likelihood she will rely on choice heuristics in a subsequent decision. Note that in the model, and in the regression specifications, we assume that voters make their ballot decisions in the order in which the contests appear on the ballot.\(^\text{11}\)

The model focuses on a rational voter that receives utility from voting according to her preferences. However, her preferences are costly to determine, and become more costly as she makes more decisions. As a result, she optimally decides to abstain from a decision or rely on less-accurate information when making a decision. Obviously, it would be possible to design a similar model in which the voter makes a "mistake," in the sense that they make sub-optimal decisions as a result of naiveness about the effect of fatigue on their decisions. However, as we can not distinguish between these models in our data, we will remain agnostic about the level of "mistakes" and focus on the simpler, rational-choice, model.

In the model, there is a representative voter who is presented a ballot with \(n\) contests, indexed by \(i \in \{1, 2, ..., n\}\), each with alternatives 0 and 1. The voter’s

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\(^{11}\)Unfortunately in my dataset there is no way to know how many voters fill out their ballots by jumping around rather than moving sequentially from the first contest to the last contest. One type of data that could help determine this could be electronic voting records. If an electronic voting machine were designed to keep track of all of the voter’s click behavior, and the time spent on each contest, this would surely be a very valuable data source.
decision for contest $i$ is denoted as $d_i \in \{0,1\}$. Before voting begins, nature chooses a state of the world $s_i \in \{0,1\}$ for all of the contests. The voter does not know these states of the world, but for each contest she has the same prior $\Pr(s_i = 0) = p > 0.5$. The objective of the voter is to match her decision for each contest with the state of world. That is, her utility for each decision after the state of the world is revealed is

$$u(d_i) = \begin{cases} 1 & \text{if } d_i = s_i \\ 0 & \text{otherwise} \end{cases}$$

and total utility is then $\sum_{i=1}^{n} u(d_i)$.

Prior to making a decision, the voter may obtain exactly one costly signal of $s_i$ with which she updates her prior. Choosing to make a "thoughtful" decision results in signal $t_i$, whereas making a "quick" decision results in signal $q_i$. Although both signals on average return the true state of the world, thoughtful decision-making provides a more accurate signal than quick decision-making. Specifically, $T_i \sim N(s_i, \sigma_T^2)$ and $Q_i \sim N(s_i, \sigma_Q^2)$, with $\sigma_Q^2 > \sigma_T^2$ and $t_i$ and $q_i$ being realizations of the two distributions, respectively. The cost of receiving the signal $q_i$ is 0 and the cost of signal $t_i$ is $c(F_i) > 0$, where $c(\cdot)$ is differentiable and $F_i$ is the stock of "fatigue" or "mental depletion" at decision $i$. To capture the idea that choice fatigue increases with the number of decisions made, it is true that $c'(\cdot) > 0$, i.e., the cost of obtaining a thoughtful signal increases with the stock of fatigue.

$F_i$ evolves according to the following rules:

- $F_1 = 0$
- $F_i = F_{i-1} + 1$ if the signal at decision $i - 1$ was a thoughtful one ($t_{i-1}$)
- $F_i = F_{i-1} + a$ if the signal at decision $i - 1$ was a quick one ($q_{i-1}$), with $0 < a < 1$

Since $c$ is a function of $F_i$ and $F_i$ is strictly increasing in the number of decisions made, the evolution of $F_i$ tells us that the cost of obtaining a thoughtful signal increases in not only the stock of fatigue, but also in the number of decisions made.

Once a signal is observed, the voter chooses to take an action $d_i \in \{0,1\}$ or to allow a random process to make the decision for her. In particular, the random process
decides according to \( \Pr(d_i = s_i) = r > 0.5 \). This random process serves as the ability for the voter to abstain and allow other voters to decide for her. We assume that \( r > 0.5 \) so that the random process is more likely to provide the "correct" decision than chance.

After observing the signal, the voter updates her prior. If the signal \( x \) is a realization from the distribution \( X \sim N(s_i, \sigma^2) \) with corresponding pdf \( \phi(x) \), the voter uses Bayes' rule to determine the posterior distribution:

\[
\Pr(s_i = 0 \mid X = x) = \frac{p \phi(x)}{p \phi(x) + (1-p) \phi(\frac{x-1}{\sigma})} \equiv p^*(x) \tag{3.2}
\]

Given the utility mapping and this updated belief about whether the state of the world is 0, then the optimal decision rule is decided by choosing the action with the highest expected value:

- \( E(d_i = 0 \mid X = x) = p^*(x)(1) + (1 - p^*(x))(0) = p^*(x) \)
- \( E(d_i = 1 \mid X = x) = p^*(x)(0) + (1 - p^*(x))(1) = 1 - p^*(x) \)
- \( E(\text{random}) = r(1) + (1 - r)(0) = r \)

The cost of the signal can be ignored while evaluating the expected value to each action since it is the same across actions. These expected benefits lead to the decision rule:

- choose \( d_i = 1 \) if

\[
E(d_i = 1 \mid X = x) > E(\text{random}) > 0.5 > E(d_i = 0 \mid X = x)
\]

\[
\iff 1 - p^*(x) > r > 0.5 > p^*(x)
\]

\[
\iff p^*(x) < 1 - r
\]
• choose \( d_i = 0 \) if

\[
E(d_i = 0 \mid X = x) > E(\text{random}) > 0.5 > E(d_i = 1 \mid X = x)
\]

\[\iff\]

\[p^*(x) > r > 0.5 > 1 - p^*(x)\]

\[\iff\]

\[p^*(x) > r\]

• otherwise, choose to let the random process decide, i.e., \( r < p^*(x) < 1 - r \)

Given this decision rule, our goal is to determine how the probability of each action changes (since it is a function of the signal \( x \)) as the voter makes more and more decisions. Since thoughtful decisions provide more accurate signals of the state of the world and only become more costly, they will be frontloaded and at some point only quick decisions will subsequently be made. Thus, to see how the probability of each action being taken changes as the voter makes more and more decisions, it is really only necessary to see how these probabilities change as the variance of the signal increases, i.e., moving from thoughtful to quick decision-making. Intuitively, a thoughtful signal provides more accuracy around the true state of the world \( s_i \), which in turn makes the voter less likely to undervote and also less likely to vote her prior. Thus, the opposite is then true: if the signal is more noisy, then the voter is more likely to undervote and also more likely to rely on her prior (vote zero/no).

**Proposition 9** As the voter moves through the sequence of decisions, the probabilities of choosing \( d_i = 0 \) and letting the random process decide both increase.

This theory of voter decision-making describes voters as less likely to make careful decisions as they become more fatigued, and thus also more likely to rely on abstaining and following their prior. If we think of reliance on the status quo as a prior, and that voting "no" is a vote against change (i.e., for the status quo), then the voter will become more likely to vote "no" as she becomes more fatigued. Similarly, abstention can be though of as another heuristic which the voter uses to aid decision-making. With this theory in mind, we now move on to a discussion of the institutional and empirical details necessary to clearly understand the validity of the natural experiment used in the identification strategy.
With this theory of contest-specific voter participation in mind, we now move on to a discussion of the empirical strategy used to test the assertions of the theory.

### 3.4 Data

The analysis uses a precinct-level panel dataset of participation and number of votes cast for every federal, statewide and local contest on the primary and general election ballot in San Diego County, California between 1992 and 2006. This dataset is unique and novel. Importantly, it depicts the number of votes across the entire menu of contests on the ballot, which is the main reason why the ballot position effects can be identified.

Constructing the dataset was a major endeavour: data for each election are reported in varying formats and identifiers for candidate vote totals (and thus contests and jurisdictions) were created manually. In total, there are 3.1 million precinct-contest-option observations. As undervotes are determined at the contest-level, the analysis in section 3.5 uses a collapsed dataset of 1.1 million precinct-contest observations, which includes participation and number of votes cast for every contest. The ballot position for every precinct-contest observation is inferred from the rules in §13109 of the Elections Code of the California State Constitution (the exact rules are discussed in detail in section 3.5.1).

The source of the data is the Statement of the Vote/Official Canvas published by the San Diego County Registrar of Voters on their website.\textsuperscript{12} San Diego County was chosen due to data availability and the large variation across precincts and elections in the number of overlaying local political jurisdictions. Official canvas data are also available for other counties, but obtaining electronic or paper files has proven difficult, mainly for lack of preservation of records and limitations on public access. Electronic precinct-level data are available for San Francisco, for example, but due the lack of special districts within the City and County, it is not feasible to exploit the necessary variation to identify ballot position effects.

Unfortunately, the turnout data by party in the 2004 primary, 2004 general and

\textsuperscript{12}http://www.sdcountry.ca.gov/voters/Eng/Eindex.html
2006 primary elections are unreliable due to an aggregation of absentee and polling voters. We drop these elections due to difficulty in separating the polling precinct voters from the absentee voters. Thus, the analyses focus on 1992-2002, except for the California judicial retention questions, for which we use data from the 2006 general election.\textsuperscript{13}

Another concern with the data is that precinct borders may change over time and thus the longitudinal dimension of the data may not be tracking a consistent unit of observation. For instance, the precinct "ALPINE 553110" in the 1992 primary may have different geographical boundaries than the precinct with the same label in the 1998 general election. This may be especially true in the 2002 and 2006 elections, which took place after the usual post-2000 Census redistricting. Conversations with the San Diego Registrar of Voters have suggested that this is not a significant problem since precinct boundaries change primarily to keep the number of registered voters within a precinct roughly equal and any changes will stay geographically and demographically close to the old boundaries.\textsuperscript{14}

A similar concern is the identification of consistent precincts for absentee voters, which is important as we use precinct-level fixed effects. While it is possible to track the same polling precinct across elections, this is not possible for absentee voters because absentee precincts are defined by ballot types (all voters with the exact same ballot) rather than all voters in the same area. Given that multiple precincts use the same ballot type and this group of precincts (somewhat) change over time, there is no way to assign a consistent precinct to each absentee precinct. As an imperfect substitute, we find 646 groups of the 3825 polling precincts that often use similar ballot types over time to create a set of "grouped" precincts, which have a composition that is relatively consistent across time.

Finally, there are some changes in the set of overlaying political districts across time due to the 2000 Census redistricting and the creation and merging of local districts. This is a small issue since it does not affect our primary source of variation.

\textsuperscript{14}A related issue is the attrition and creation of precincts over the dataset due to population growth.
within an election.

3.5 Choice Fatigue and the "Decision to Decide"

In this section, we focus on how the number of previous decisions in the electoral choice environment affects a voter’s decision to participate in voting on a particular contest, ignoring the actual decision made. As discussed in detail in the following section, this is accomplished by analyzing a natural experiment in which different voters see the same contest in different ballot positions as a result of differences in the number of contests in the overlaying local political jurisdictions in which a voter resides.

3.5.1 Empirical Strategy

The estimates of the effect of ballot position on the decision to cast a vote in a particular contest are identified by exploiting exogenous variation in ballot position across precincts. The natural experiment providing the exogenous variation in ballot position is characterized by the structure of all voting ballots in California. Namely, §13109 of the Elections Code of the California State Constitution dictates that contests appear in the same ordering across ballots.\textsuperscript{15} Federal, statewide and local offices always appear above the statewide propositions, which in turn appear above the local propositions. Additionally, statewide propositions are ordered by type\textsuperscript{16} and listed in the order in which they were qualified for the ballot\textsuperscript{17}, e.g., Proposition 53,

\textsuperscript{15} Charter cities and counties are allowed flexibility in their elections code. Of the 4 charter cities in my dataset, the only deviation from the state elections code that is relevant to my dataset is discussed in section 3.6.1: the City of San Diego rotates city contest candidates in a different way than the state elections code.

\textsuperscript{16} §13115 of the California Elections Code states that proposition types appear on the ballot in the following order: bond measures, constitutional amendments, legislative measures, initiative measures and referendum measures.

\textsuperscript{17} A proposition qualifies for the ballot when the Secretary of State approves the submission of the required number of signatures petitioning to put the proposition on the ballot. The number of signatures required is 5% and 8% of the number of votes in the previous gubernatorial general election for initiatives and constitutional amendments, respectively.
CHAPTER 3. CHOICE FATIGUE

Proposition 54, Proposition 55, etc. This order is the same for all voters across the state.

As different precincts contain (potentially) different contests in various sections of the ballot, voters in these precincts will see the same contest in later sections in different ballot positions.\(^\text{18}\) This variation is primarily due to the local contests, but the State Senate districts also provide some variation. Beyond the local political jurisdictions and State Senate districts, a third source of within-contest differences in ballot position across voters is partisan ballots. In primary elections, it may be that the Democratic Party is running candidates in fewer statewide contests than the Republican party (this effect is more pronounced with "third" parties who run candidates in generally only a few statewide contests). In this case, Republican voters will have made more decisions by the time they decide on the first statewide proposition. Unfortunately there is no by-party breakdown of votes cast for propositions and nonpartisan offices. However, we can use the variation by constructing ballot position for partisan voters in the same precinct as a registration-weighted average of the within-precinct ballot position for a given contest, across parties.

These factors generate significant variation in the ballot position of the same contest across different voters. Note that some contests (such as Governor, President, Secretary of State, etc.) will appear at the same position (the top of the ballot) for all voters. These contests are dropped. To illustrate the variation that remains, Figure 3.3 describes the distribution of deviations from the mean ballot position in each contest for the four types of contests (this implicitly assumes the use of contest fixed-effects, which are discussed below). Note that statewide propositions contain the most variation, followed by local propositions, elected offices, and statewide judicial offices. Furthermore, note that statewide propositions and judicial offices contain the most precinct-level observations per contest, as every voter observes these contests on their ballot.

\(^{18}\)Variation in the ballot across precincts arises from differences in contests in the following sections: State Senator, County Board of Education Members, Community College Board Members, Unified School Board Members, High School Board Members, Elementary School Board Members, Board of Supervisors, Mayor, City Council, Other City Offices, Other District Offices
3.5. **CHOICE FATIGUE AND THE "DECISION TO DECIDE"**

There are many contest-level factors that both affect voter behavior and are potentially correlated with the ordering of the contest, such as saliency, expected contest closeness, and the size of polity. If each of these factors are not controlled for, any estimate of the effect of ordering on voter outcomes will be potentially biased. However, controlling for these factors is extremely difficult using observable contest characteristics. Fortunately, the natural experiment in this paper avoids this problem by permitting the identification and inclusion of contest-specific fixed effects, which fully control for all observable and unobservable contest-specific factors that might affect voting behavior. The inclusion is a key contribution of this paper as it allows us to untangle the effect of choice fatigue from the multiple explanations for voter behavior in a particular contest on the ballot.

**Figure 3.3: Kernal Density of variation from mean ballot position of a contest (separated by type of contests)**

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One story which potentially voids this part of the identification strategy is that there may be a selection bias generated by our primary source of exogenous variation. Consider a contest which appears 10th on the ballot for some voters and 15th for others. The contest appears 15th as a result of more local offices appearing higher up on the ballot. If that characteristic of the ballot – more local offices – causes the less informed voters to turnout, then the down-ballot fatigue effects we purport to exist may actually be driven by the selection bias of voters who are more likely to undervote to the polls. Unfortunately, there is no way to directly control for this effect. However, we do not believe this is a threat to the identification strategy for two reasons. First, we don’t find it likely that this type of selection would be so consistently applied so as to bias the results exactly in the same way as our priors for the fatigue coefficients. Second, in the results to follow we still find fatigue effects for the contests highest up on the ballot (statewide judicial retention questions). These contests have variation of only one or two positions, and this variation is not caused by local political jurisdictions.

A similar concern is that there are precinct-level factors that both affect voter behavior and are potentially correlated with the ordering of the contest. For example, it may be that certain precincts tend to both participate less and also to have more local offices on the ballot. In this case, statewide propositions will appear relatively further down the ballot and observed increases in abstention will be caused by precinct differences rather than position effects. Fortunately, the longitudinal nature of the data permits the addition of precinct fixed effects, which capture all observable and unobservable precinct-level factors that might affect voter behavior.

Note that this approach assumes that the precinct-level effects are constant over time. For example, consider a group of precincts that become wealthier and more educated over time (perhaps by gentrification). If this causes a change in the number of local elected contests on the ballot in these precincts as well as changes in voter behavior, then the effects of ballot position on voter behavior could be mistaken for the effects of changing demographics. In a similar manner to the potential concerns with contest fixed-effects, we cannot control for this effect. However, we find it unlikely to be particularly important as the direction of this effect is not obvious and
the ballot position effects are mainly identified by the within-election variation in ballot position

With these points in mind, we claim that the ballot position of a given contest in a particular precinct is an exogenous determinant of the likelihood that a voter will abstain. The main results in this section come from the estimation of the parameter \( \beta_{UV} \) in the following equation:

\[
UV_{ci} = \alpha_{UV} + \beta_{UV} \cdot POSITION_{ci} + \rho_{c}^{UV} + f_{i}^{UV} + v_{ci} \tag{3.3}
\]

where \( UV_{ci} \) denotes the percentage of undervotes in contest \( c \) and precinct \( i \) as a percentage of turnout in precinct \( i \). Note that election dates are implicitly indexed by \( c \) because we define a contest as a contest in a particular election, which appears on the ballot only once. \( POSITION_{ci} \) refers to the ballot position of contest \( c \) in precinct \( i \). For all regression results we include proposition and precinct fixed effects \( \rho_{c} \) and \( f_{i} \), respectively. \( v_{ci} \) contains is the unobservable predictors of \( UV_{ci} \) and is uncorrelated with any of the included regressors.

### 3.5.2 Results

Column 1 in Table 3.1 provide the estimate of equation 3.3. This benchmark specification estimates that moving a particular contest down one position (thus increasing the number of decisions a voter makes prior to observing this contest by one) increases the number of undervotes by .129 percentage points. Given that an average contest in the dataset appears at ballot position 15.7, this estimate suggests that undervotes would decrease by an average of 2 percentage points if these contests appeared at the top of the ballot. As the average level of undervotes is 21.6%, this suggests that choice fatigue is responsible for 9.3% of undervotes in these contests.

Column 2 cuts the results by contest type (with separate precinct level fixed effects for each type, which we do throughout the paper for all regressions with different types of contests, elections, or voters). The results for statewide propositions, local propositions, and offices have very similar point estimates of .07-.08 percentage points. However, the estimate for judicial races (.411) is clearly significantly larger than those.
for the other contest types. This is not surprising as judicial races induce more than twice the percentage of undervotes than other races (39% vs. 19%), presumably because statewide judicial retention contests are some of the lowest-salience contests on the ballot. Similar logic to above (with type-specific statistics) suggests that undervotes for local propositions, statewide propositions, statewide judicial races, and offices would be reduced by 14.8%, 19.7%, 5.4%, and 8.9% if the contests appeared at the top of the ballot, respectively.

The regressions in Column 3 estimate primary and general election-specific coefficients. The primary coefficient is not significantly different from zero, suggesting that the majority of the effects of choice fatigue occur in general elections (where the coefficient is .18). This is not surprising if, as described in Brockington (2003), primary voters are more motivated than general election voters and high motivation mediates the effects of choice fatigue.

Finally, Column 4 separates the sample by the absentee status of voters. Somewhat surprisingly, the coefficient for the absentee voters is nearly three times that of voters that vote in polling places. One might predict a smaller or negligible choice fatigue effect for absentee voters, as they have more time to vote, potentially more information at their disposal, and have been characterized as of a higher socioeconomic status and more politically active (Karp and Banducci 2001). As we will see in the following section, absentee voters are also more likely to choose the status quo when making a decision. Our dataset does not allow us to determine the precise reason for this effect, although selection effects might play a role (absentee status is usually self-chosen by the voter).

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19 This is due to a couple of main factors. First, the institution of electing judges is one of retention rather than competition. As a result, in the words of the California Courts’ homepage, "Appellate court justices generally do not actively campaign for retention." Thus, voters likely have very low levels of information regarding these contests. Second, information provided on the ballot in these statewide judicial contests provides voters with no cues regarding ballot designation, partisan identification, endorsements or incumbency. Instead, voters are simply asked questions such as, "Shall Presiding Justice Judith McConnell be elected to the office for the term provided by law?"

20 Local propositions, statewide propositions, statewide judicial races, and offices appear on average at ballot positions 33.1, 24.8, 18.6, and 8.4, respectively, and have average undervote rates of 16.9%, 10.1%, 24.1%, and 39%, respectively.
3.6 Choice Fatigue and Choice Across Alternatives

The previous section analyzed the effect of the number of previous decisions on the "decision to decide." While this result provides evidence of choice fatigue, the economic impact is unclear. If voters that choose to abstain vote similarly to those that choose to vote, the abstentions will not affect the final result of the election. Consequently, in this section, we look at the changes in the actual decisions made by voters (conditional on making a decision) as they become fatigued by previous choices. Specifically, we examine the impact of fatigue on the likelihood of making decisions that maintain the status-quo (voting "no" on propositions) or are extremely easy to process (voting for the candidate that is listed first). The empirical strategy, which is discussed separately for these two outcomes, is similar to that in the previous section.

3.6.1 The Effect of Fatigue on Maintaining the Status Quo in Propositions

In California, a "No" vote on statewide and local propositions always represents maintaining the status quo. Voters may have no information about changes implied by a particular proposition, or any desire to expend cognitive effort to uncover this information. However, they are likely more familiar with the status quo given that they have lived in the status quo environment for at least some time. In this section, we analyze the impact of fatigue on the tendency to vote "no" on propositions.

Empirical Strategy

As discussed in section 3.5.1, the structure of the California ballot provides exogenous variation in ballot position of particular propositions, which we assume impacts the number of previous decisions made by a voter before confronting that proposition. In order to determine the effect of ballot position on voting "no", we use the following
CHAPTER 3. CHOICE FATIGUE

general specification:

\[ NO_{ci} = \alpha_{NO} + \beta_{NO} \cdot POSITION_{ci} + \rho_{c}^{NO} + f_{i}^{NO} + \eta_{ci} \]  \hspace{1cm} (3.4)

where \( NO_{ci} \) is defined to be the number of "no" votes in a contest as a fraction of the total votes cast in the contest (yes + no votes). In order to identify the parameter of interest \( \beta_{NO} \), the identification strategy employed for this model is exactly the same as in equation 3.3. Note that as the dependent variable is a fraction of the total yes and no votes cast in the contest, this equation is determined conditional on voting in the contest since.

In addition, we will use a specification similar to 3.4 with an interaction of the ballot position variable with (log) total campaign expenditures. This captures the effect of contest-specific campaign expenditures on the ballot-position effect. The expenditures data were taken from California Secretary of State's Cal-Access database as well as past issues of the now-defunct "Campaign Finance Reports" series.

Results

Column 1 in Table 3.1 provide the estimate of equation 3.4. This benchmark specifications estimate that moving a particular contest down one position increases the number of "no" votes by .11 percentage points. Given that an average proposition race in our dataset appears at ballot position 26.8, this estimate suggests that "no" votes would decrease by an average of 2.9 percentage points if these contests appeared at the top of the ballot. Interestingly, given the average ballot position of each proposition, we calculate that 22 of the 352 propositions in our dataset would have passed rather than failed if the proposition was presented to voters as the first contest on the ballot.

Column 2 compares the coefficients for local and state propositions. The coefficients are very economically similar, estimated at .125 and .102 respectively. Similarly, Column 3 displays primary and general election-specific coefficients. As with the estimated coefficients on the effect of choice fatigue on undervotes in Section 3.5,
3.6. CHOICE FATIGUE AND CHOICE ACROSS ALTERNATIVES

the coefficient for the general elections is significantly higher than that for all elections, and the coefficient for primary elections is lower (and, in this case, significantly lower than zero). Again, this suggests that the high motivation associated with primary voters reduces the effects of choice fatigue. The impact of absentee status is shown in Column 4. The estimate for absentee voters is higher than for those that vote in polling places, which is surprising, although consistent with the estimated coefficients on undervotes for absentee voters in Section 3.5.

Finally, Column 5 provides the estimation of equation 3.4 with an added term that interacts ballot position with the log of campaign expenditures for state propositions. Presumably, this variable provides a reasonable proxy for contest saliency, as we would expect that higher campaign spending would cause a contest to be better known and better known races would receive more contributions (leading to higher spending). Our results suggest that higher expenditures lead to a mitigation of choice fatigue effects, represented by the negative coefficient on the "BP * Expend" term. To understand the economic impact of this coefficient, first note that the log of expenditures are somewhat binary: zero expenditures occur in 25% of races, while log expenditures range from 10 and 17 (representing expenditures of $22,000 and $24 Million, respectively) for the other 75% of the races (the full histogram is show in Figure 3.4). Figure 3.4 shows the estimated ballot position coefficient for these expenditure levels. The coefficient for races with zero expenditures is relatively large at .324, while the coefficient is relatively close to zero for the majority of races with positive expenditures. One obvious explanation of this finding is that voters have not yet made decisions on election day on low-saliency elections, leaving them more susceptible to choice fatigue. This suggests that the estimates in previous sections are conservative, as they include situations in which voters have previously made a decision and therefore are not subject to choice fatigue.

21 We focus on state propositions due to data availability.
3.6.2 The Effect of Fatigue on Voting for the First Candidate in Elections

As opposed to the "yes/no" questions of propositions, voters participating in elected office contests vote for one or more candidates. In this section, we will analyze the effect of choice fatigue on the tendency to choose the first candidate in the ordering, which is presumably the lowest-effort decision shortcut possible.\textsuperscript{22}

\textsuperscript{22}This follows strong evidence seen in previous literature on ballot order effects (Meredith and Salant 2007, Miller and Krosnick 1998, Koppel and Steen 2004, etc.)
3.6. CHOICE FATIGUE AND CHOICE ACROSS ALTERNATIVES

Empirical Strategy

As in section 3.5.1, in order to separately identify ballot position coefficients, fixed effects for each contest and precinct are included in each specification. In addition, another natural experiment permits the addition of candidate-specific fixed effects in this section. For almost all elected offices on the ballot, the ordering of candidates is determined by the drawing of a random alphabet by the Secretary of State. For some of these offices, candidates are rotated across certain subsets of precincts within the office’s political jurisdiction. This rotation places the same candidate at different within-contest positions in different precincts, allowing the estimation of candidate-specific fixed effects in order to control for all candidate-specific observables and unobservables. Figure 3.5 describes the distribution of deviations from the mean within-contest position in each candidate, demonstrating that this variation is sufficient to identify the candidate fixed effects.

This three-way fixed effects model is quite a large computational task, with 950,482 polling precinct observations, 408,990 absentee precinct observations, 3473 precinct effects, 509 candidate effects and 195 contest effects in the dataset. With these three sets of fixed effects included in the regression, the primary goal is to estimate the coefficient on the interaction term between ballot position and a dummy variation FIRST that represents that a candidate is that the top of the within-contest ordering:

\[ \text{voteshare}_{ci} = \alpha + \beta \cdot \text{POSITION}_{ci} \cdot \text{FIRST}_{coi} + \gamma \cdot \text{FIRST}_{coi} + \psi_c + \rho_o + f_i + \eta_{coi} \quad (3.5) \]

The only exception in our dataset is the City of San Diego, whose city charter dictates that city office candidates are to be forward-rotated across city council districts.

For statewide contests (e.g., Insurance Commissioner), county-wide contests (e.g., Sheriff), congressional or State Board of Equalization districts, the candidates are backward-rotated (first moves to last, second moves to first, third moves to second, etc.) across State Assembly districts. The statewide contests are rotated throughout all of the state’s assembly districts, whereas the other rotation contests are rotated only through those assembly districts which appear within the county. There is no rotation otherwise, except for two special cases. The first is charter cities and counties with elections codes that are potentially different from the state’s. In San Diego County, the only relevant deviation from the state’s elections code is the City of San Diego, which forward-rotates city office candidates across city council districts. The other exception is when a State Assembly or State Senate district appears in more than one county. In this case, a random alphabet is drawn in each county to determine the candidate ordering. All other contests are not rotated and follow the random alphabet drawn by the Secretary of State.
where $voteshare_{c oi}$ is the percentage of the total votes cast in contest $o$ that candidate $c$ receives in precinct $i$, and $\rho_c$, $f_i$, $\psi_c$ represent proposition, precinct, and candidate fixed effects, respectively. We interpret the coefficient $\gamma$ as the effect to a candidate’s vote share of appearing first in the contest ordering, while the coefficient $\beta$ is interpreted as the additional effect on candidate’s voteshare of appearing first for each single change in ballot position of the contest. Note that $POSITION$ does not enter the equation by itself. Given that this analysis is conditional upon a vote being cast in the contest, $POSITION$ does not belong in the regression model as a predictor of candidate vote share in a particular contest because it is constant within a contest. As a result, it only acts as a conduit to examine the interactions of fatigue with the tendency to vote for the first candidate listed.
3.7 DISCUSSION AND CONCLUSION

Results

Column 1 in Table 3.3 provides the estimate of equation 3.5. This benchmark specification demonstrates both that appearing first in the intra-contest ordering has a significant positive impact on the candidate’s voteshare of .50 percentage points, and that choice fatigue has a significant impact on the tendency to use this shortcut. Specifically, moving the contest down one position increases the expected voteshare of the first candidate by .057 percentage points. As the average office race in our dataset appears at ballot position 8.9, this estimate suggests that the first candidate receives, on average, an additional .51 percentage points as a result of choice fatigue.

Column 2 estimates a separate coefficient for state and local offices, suggesting similar effects across contest types. Column 3 displays the effect by election type, suggesting (as in the previous regressions above) that the effect is larger for voters in general elections than primary elections. Finally, Column 4 separates the effect for polling and absentee voters. Unlike in the previous regressions above, we find no significant difference in the effect across different types of voters.

3.7 Discussion and Conclusion

3.7.1 Discussion

Even though the empirical application in this paper focuses on voter behavior, the strength of the identification strategy and established evidence suggest that it is reasonable to extrapolate the results to a broader set of consumer and economic choice problems in which a person makes a bundle of decisions. If firms or policy makers know about this characteristic of decision behavior, then this may influence their strategy in how they order decisions or disseminate information.

For example, it is not unusual for consumers shopping online for electronics to be offered the possibility to compare the attributes of a handful of similar items. If consumers experience fatigue while comparing a long list of attributes, then a retailer may strategically place attributes at particular positions in the comparison sequence so as to mitigate or exacerbate fatigue. Evidence of the importance of this type of
strategic behavior is highlighted in Levav et al. (2007), which focuses on the full customization of a single product rather than the comparison of products. Presumably, a firm’s optimal strategy is dependant on level of naiveness of the consumer about this behavioral tendency, which we are unable to estimate with our dataset.

Portfolio choice and diversification is another commonly-studied task that involves bundled decisions. If decision-making among investors in 401(k) funds is susceptible to fatigue, a benevolent planner will take care in the dissemination of information regarding the investment options and the ordering of decisions. In particular, if certain decisions carry more weight in terms of utility (i.e., equity fund investments), then these decisions should be placed towards the beginning of the decision sequence so as to minimize the likelihood that the investor is fatigued and making less-than-careful decisions. Similarly, the results also potentially have implications for other applications in decision-making such as health plan selection (see, e.g., McFadden 2005), car insurance interviews and the physical arrangement of items in a store.

As our result directly concerns voting behavior, we will discuss several theoretical and practical implications relevant this context.

First, special interest groups may want to exploit the control that they have over the position in which their proposition appears on the ballot. For example, citizens’ initiatives appear in the order in which they qualify and thus it may be optimal for the group to qualify their proposition as early as possible if they wish to minimize the "no" effect from voter fatigue. Alternatively, it also makes sense for these actors to consider proposition placement across elections, given that the top of the ballot is significantly longer in gubernatorial elections.

Second, and in a similar vein to the first point, the evidence provided may contribute to the literature on the endogenous timing of school bond elections (Romer & Rosenthal 1978, Meredith 2006). This research suggests that an agenda setter may find it optimal to put a school bond proposition on the ballot in off-year special elections when the electorate who chooses to turn out will be relatively motivated in

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25 Initiatives qualify for the ballot in two steps. First, the initiative is approved and phrased by the Attorney General. Second, the proponents of the initiative must collect signatures from registered voters. For initiative statutes, the number of necessary signatures is equal to 5% of the number of votes in the last gubernatorial contest. Initiative constitutional amendments require 8%. 
favor of passage of the bond. The evidence in this paper suggests another reason to take this strategy: propositions listed towards the end of the ballot are more likely to experience "yes" votes when placed on a relatively short special election ballot.

Third, a theoretical result by Besley and Coate (2000) finds that there are welfare gains to the unbundling of policies from candidates, i.e., the addition of initiatives to the ballot as a separate contest to the candidate election. Our result suggests a potential problem with this method, as an increase in the number of decisions will increase choice fatigue.

Fourth, if the documented fatigue effect is undesirable, then elections officials could consider randomizing the order in which the contests appear on the ballot in order to remove the position effects. While this may be impractical for the entire ballot, even a within-block randomization would partially mitigate the effects. A large body of previous work on the effects of candidate position within a contest (Krosnick & Miller 1998, Koppell and Steen 2004) is in line with our work and confirms that order matters. A number of states have begun to randomize candidate orderings across precincts in an election, suggesting that elections officials may be open to the idea.

Fifth, if voters experience choice fatigue and this affects their ability to participate in the democratic process, then elections officials may want to think about either limiting the length of ballots or holding more frequent elections. As an example, Canada holds national and local elections on separate dates.

Finally, if having the ballot at home for a length of time mitigates the position effects, elections officials may want to increase efforts to convert citizens from polling station voters to absentee voters. However, while this solutions seems intuitive, our results suggest that absentee voters are actually more likely to be affected by choice fatigue. This might be a result of selection (most absentee voters choose this status), which we cannot distinguish in our data.

### 3.7.2 Conclusion

This paper isolates the effect of choice fatigue on individual decision-making through a natural experiment in which the same ballot contest appears at different positions
across voters. Through this exogenous variation in the number of previous decisions that voters makes before deciding on a particular contest, we are able to separate the effects of choice fatigue from other competing explanations of choice behavior. We find that voters are more likely to abstain and more likely to rely on decision shortcuts, such as voting for the status quo or the first candidate listed in a race, as the ballot position of a contest falls. In terms of economic impact, we estimate that if an average contest was placed at the top of the ballot, undervotes would decrease by 10%, the percentage of no votes on propositions would fall by 2.9 percentage points, and the percentage of votes for the first candidate would fall by .5 percentage points.

As discussed in section 3.7.1, the results have broad implications for economic choice and for the design of electoral institutions, which offer opportunities for future work. For example, this paper does not distinguish between decisions with different levels of complexity, which presumably affects the level of choice fatigue induced by making the decision. This suggests a possible interaction between for the fatigue effects documented here and the "choice overload" phenomenon discussed in Iyengar and Lepper (2000).

The fact that decision outcomes are dependant on the number of previous decisions made is presumably useful to creators of decision-making environments, such as a company or policy maker. For example, as we estimate that 6% of propositions would have different outcomes if placed at the top of the ballot, governments might consider enacting policies to limit the number of decisions on an individual ballot or take action to encourage spreading these decisions over a larger period of time.
Table 3.1: Regressions of Undervoting on Ballot Position

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS Undervotes</th>
<th>(2) Contest Type† Undervotes</th>
<th>(3) Election Type† Undervotes</th>
<th>(4) Voter Type† Undervotes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ballot Pos. (BP)</td>
<td>0.129***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.56)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - State Prop</td>
<td>0.0757***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.24)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - Local Prop</td>
<td>0.0804***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13.13)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - Offices</td>
<td>0.0711</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.91)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - State Judge</td>
<td>0.411***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(5.15)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - General</td>
<td></td>
<td>0.188***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(21.70)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - Primary</td>
<td></td>
<td>0.0000433</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP - Polling</td>
<td></td>
<td></td>
<td>0.126***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(8.62)</td>
<td></td>
</tr>
<tr>
<td>BP - Absentee</td>
<td></td>
<td></td>
<td>0.363***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(13.29)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>910,498</td>
<td>910,498</td>
<td>910,498</td>
<td>910,498</td>
</tr>
</tbody>
</table>

*Note: t statistics in parentheses  *p < 0.05, **p < 0.01, ***p < 0.001
All specifications include contest and precinct fixed effects
†Precinct fixed effects calculated separately for groupings
Table 3.2: Regressions of “No” Votes on Ballot Position

<table>
<thead>
<tr>
<th>Ballot Pos. (BP)</th>
<th>0.324***</th>
<th>0.320***</th>
<th>0.258***</th>
<th>0.230***</th>
<th>-0.0211***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.247</td>
<td>0.121</td>
<td>0.135</td>
<td>0.857</td>
<td>-0.0857</td>
</tr>
<tr>
<td></td>
<td>12.70</td>
<td>6.92</td>
<td>9.27</td>
<td>13.91</td>
<td>6.29</td>
</tr>
<tr>
<td></td>
<td>50.76</td>
<td>22.68</td>
<td>19.97</td>
<td>19.97</td>
<td>6.03</td>
</tr>
<tr>
<td></td>
<td>610,146</td>
<td>610,146</td>
<td>610,146</td>
<td>610,146</td>
<td>610,146</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses

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

All specifications include contest and precinct fixed effects.
Precinct fixed effects calculated separately for groupings.
### Table 3.3: Regressions of Candidate Vote Share on Appearing First * Ballot Position

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) Contest Type†</th>
<th>(3) Election Type†</th>
<th>(4) Voter Type†</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Vote Share</td>
<td>Vote Share</td>
<td>Vote Share</td>
<td>Vote Share</td>
</tr>
<tr>
<td>Appears First</td>
<td>0.503 ***</td>
<td>0.341 ***</td>
<td>0.433 ***</td>
<td>0.378 ***</td>
</tr>
<tr>
<td></td>
<td>(14.42)</td>
<td>(9.46)</td>
<td>(10.44)</td>
<td>(13.44)</td>
</tr>
<tr>
<td>Ballot Pos.<em>First (BP</em>F)</td>
<td>0.057 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(17.16)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP*F - State Offices</td>
<td>0.0723 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(12.02)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP*F - Local Offices</td>
<td>0.0647 ***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.98)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP*F - General</td>
<td></td>
<td>0.0747 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(19.09)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP*F - Primary</td>
<td></td>
<td>0.0450 ***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(8.90)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BP*F - Polling</td>
<td></td>
<td></td>
<td>0.058 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(17.46)</td>
<td></td>
</tr>
<tr>
<td>BP*F - Absentee</td>
<td></td>
<td></td>
<td>0.050 ***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.78)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,101,159</td>
<td>1,101,159</td>
<td>1,101,159</td>
<td>1,101,159</td>
</tr>
</tbody>
</table>

*Note: t statistics in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001*

All specifications include contest and precinct fixed effects.
†Precinct fixed effects calculated separately for groupings.
Chapter 4

Using Competition to Elicit Cooperation in a Political Public Goods Game: A Field Experiment (w/ Jesse Cuhna)

4.1 Introduction

Previous research has demonstrated that positive information about the contributions of other players can increase contributions to a public good, both in the laboratory (Fischbacher et al. (2001)) and in the field (Frey and Meier (2004), Shang et al. (2005, 2006, 2008)). These papers concern donations to a single public good (such as a public radio station), in which all players work towards a commonly-desired goal and suggest that cooperation can a powerful contribution motivator. But, is the impact of competition in these environments stronger than that of cooperation? Multiple laboratory experiments (Bornstein and Ben-Yossef (1993), Bornstein et al. (2002)) and at one field experiment (Erev et al. (1999)) suggest that competition across groups can be a strong driver of cooperative behavior within groups.

In this paper, we test this hypothesis in a competitive public goods game by presenting information to people about the contributions of members of their own group
or those of the competing group. In the field experiment, which was run during the 2008 campaign for the US House of Representatives, 10,000 potential donors to a Democratic candidate were separated into three equal-sized demographically-balanced groups and sent a solicitation postcard. Depending on the group, the postcard contained a non-informative statement ("control" group), or a reference statement about the past donation behavior of either Democrats ("cooperative" group) or Republicans ("competitive" group), such as "small Republican contributions have been averaging $28." Both reference statements mentioned the same monetary reference point, allowing us to identify the differential effect of the reference point in the treatment groups.

Our results suggest that both cooperative and competitive motives can drive higher contribution rates and total contributions, but the elicitation of competitive behavior is more profitable to the fundraiser. Specifically, we find that the competitive and cooperative treatment groups contributed at a rate of 85% and 42% more than that of the control, respectively. Furthermore, while the cooperative treatment induced more contributions concentrated near the given reference point ($28), the competitive treatment induced more contributions at nearly twice the level of the given reference point (around $50). As a result, the competitive and cooperative treatment groups yielded 82% and 16% higher total monetary contributions than the control, respectively.

Several papers have studied the effect of "social information" on solicitation behavior.¹ For example, Frey and Meier (2004) conducted a field experiment in which students that are asked contribute to a University fundraising campaign are informed that certain percentages of students have contributed to the campaign in the past. The authors find evidence of conditional cooperation - after controlling for past contribution history, there is a significant (although relatively small) 4.6 percentage points

¹There are also many papers in which reference points are used to change contribution behavior in cooperative situations (without explicit social information), such as DeJong & Oopik (1992), Desmet and Feinberg (2003), Fraser, Hite and Sauer (1988), Schibrowsky & Peltier (1995), Smith and Berger (1996), Weyant (1996). Broadly, these papers show that reference points do affect contribution behavior, with high reference points often increasing the amount of contributions but decreasing the contribution rate.
increase in the contribution rate between students informed of high (64%) past contribution rates versus low (46%) past contribution rates. Shang et al (2005,2006,2008) use multiple field experiments with a public radio solicitation drive to study the effect of social information on contribution amounts. Broadly, these papers use a variety of social comparisons ("A member like you just contributed...", "She just contributed...") and an array of reference points to show that social comparisons can affect contribution rates and amounts, particularly for new contributors and when there is a high similarity between the donor and the reference individual.

There are also multiple papers about the effect of intergroup competition on intragroup cooperation. In the laboratory, Bornstein and Ben-Yossef (1993) show that participants are almost twice as likely to cooperate in a prisoner’s dilemma game when it is embedded in a game with intergroup competition. Similarly, Bornstein et al. (2002) use a laboratory experiment to demonstrate that intergroup competition increases group efficiency in a coordination game. Finally, in a laboratory-like field experiment on an orange grove with free-riding inducing group payment schemes, Erev et al. (1999) show that subjects’ productivity increases when there is competition across groups.

More generally, there are related papers on the effect of different incentives in charitable giving, such as matching schemes (Huck and Rasul (2008)), seed money (List and Lucking-Reily (2002)), rebates (Eckel and Grossman (2005)), and gift exchange (Falk (2007)). There are also many papers pointing to the effect of cooperative motives, both laboratory ((Fischbacher, Gächter and Fehr (2001)) and theory (Rabin (1993)) based.

In the next section, we describe the Congressional campaign environment and the field experiment. Section 3 describes differential contribution rates and amounts across treatment groups. Section 4 concludes with a discussion.

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2 The authors are able to present these different contribution rates without being deceptive by use of vague language in describing the statistics. We employ a similar technique to ensure that the reference contribution amounts are the same across our two treatment groups.

3 In this paper, we show that people contribute more when given information about individuals that are different than them because the different implies that the person is a competitor.
4.2 The Field Experiment

4.2.1 The Congressional Election and the Intervention

The experiment took place during a 2008 campaign for the US House of Representatives in Florida. We worked with the Democratic challenger, who had never run for public office in Florida. The district had a high percentage of registered Republicans (62%) and had consistently voted for Republican candidates in previous national races. The Republican candidate was the incumbent and had held the office since 1988.

Working with the candidate, we identified 10,000 potential donors to receive a solicitation postcard in the final weeks of the campaign. These recipients were chosen from a list of past donors to Democratic campaigns and a set of voters identified as strong Democrats from their participation in past primary elections (as determined by public voting records). The majority (over 70%) of the recipients lived in the congressional district contested by our candidate.

The recipients were randomly assigned to one of three treatment groups. Each of these groups received a large postcard with a picture of the candidate and a short message urging them to contribute to the campaign: see Figure 4.1. The text of the postcard was written to convey the message that the race was close and that marginal contributions could be pivotal. The only difference between the groups was a single emphasized sentence in the center of the message:

- **Control Group:** "Your contribution can make a big difference."
- **Cooperative Treatment:** "Small Democratic contributions have been averaging $28"
- **Competitive Treatment:** "Small Republican contributions have been averaging $28"

We performed the experiment with two broad hypotheses:

**Hypothesis 1:** Social Information, whether cooperative or competitive, will induce

---

4Note that these are true statements given that "small" contributions are defined as those less than $75.
CHAPTER 4. USING COMPETITION TO ELICIT COOPERATION

Figure 4.1: The three solicitation postcards sent to (from left to right) the control, cooperative, and competitive groups.

higher rates of donation.

**Hypothesis 2:** The distribution of donations will be affected by the reference point, as well as the social group mentioned in the treatment

### 4.2.2 Data and Identification

After the mailing were send out, the candidate began to receive contributions in the mail and online, which were recorded by campaign staff. Before we discuss the data and demonstrate that the sample is balanced across treatment groups, it is necessary to address two issues concerning the data.

First, during the time of the mailings, the candidate was involved in other campaign activities (such as a fund-raising concert) which might have also prompted donations from recipients of the postcard. In most cases, these donations were marked by the campaign and are excluded from our sample. Still, there are a handful of questionable cases. Luckily, the number of these cases is relatively small as the mailing was sent out 10 days before election day. In the analysis, we only use donations by mailing recipients that occurred one week after the receipt of the mailing and are not clearly due to any other campaign event. The results are robust to changes in the window of acceptance.

Second, although we attempted to remove duplicates from our mailing list (people who had given to multiple Democratic campaigns might appear on our master list more than once), we discovered that three recipients were placed in multiple treatment
4.3. RESULTS

groups after the mailings were sent out. We removed these recipients from the list, leaving a total of 9,992 recipients.

Once we determined our final list, we obtained several demographic characteristics of the recipients by matching their names and addresses with Florida voter files. This publicly available information contains the name, address, sex, age, race, and registered party affiliation for all registered voters in the state. We were able to match 8,750 of the 9,992 recipients, including all of the actual donors.\(^5\) In order to include non-matched recipients in the regression analysis below, we assume that they have the average characteristics of the matched recipients. The first column of Table 4.1 characterizes the recipients as a whole. The recipients are mostly older and white, reflecting the demographic make-up of the district. As expected, most of the sample consists of Democrats, although 6% are Republicans who contributed to Democratic races in the past.

Columns 2-4 of Table 4.1 contain mean demographic characteristics of each group, while columns 5-7 contain p-values of F-tests of the equality of the means. Note that the only significant difference at the 5% level is between the Cooperative and Control groups with respect to age: a 0.7 year difference. Given that the sample is presumably also balanced in other outcome-relevant characteristics that are unobservable and that we control for all observable demographic variables in the analysis, our randomization allows for the identification of the differential effects of the treatments.

4.3 Results

4.3.1 Donation Rates

Our first main result concerns the donation rate. Table 4.2 details donation rates for the sample as a whole and across groups, as well as the p-value of tests of equality across groups. Overall, the donation rate was 1.1%, which was slightly above the

\(^5\)The unmatched recipients likely had significant misspellings in their names and addresses or had moved.
expectation of the campaign. This table suggests our first main finding in this paper:

**Finding 1:** The use of social information and a reference point increased the donation rate. The donation rate in the competitive treatment was 85% higher than that of the control treatment, and significant (p-value=0.02). The cooperative treatment was 42% higher than the control, although not significant (p-value=0.23).

As would be expected in a balanced random experiment, a Probit regression which controls for demographic variables does not change the point estimates or significance in a dramatic way, as shown in Table 4.3. While our results suggest that the competitive treatment led to a higher donation rate than the control, the effect of the cooperative treatment is less clear. This is due to the small number of donations and the location of the point estimate (nearly exactly between the estimate of other groups).

### 4.3.2 Donation Distribution

Our second main result concerns the donation distribution of the different treatment groups. The bottom panel of Table 4.2 shows the descriptive statistics for the sample as a whole and for each group, as well as the p-value of a test of the mean equality to the control group. While there is a difference in the unconditional donation amount, the difference is driven by the donation rates observed above. In fact, there is no significant difference in the means of donations conditional on donating (the intensive margin of donating). The mean donation conditional on donating across all groups is $62.75.

However, while there is no difference in the conditional mean contribution amount, visual inspection of the frequency distributions (shown in Figure 4.2) suggests that the treatments did have an effect on the distribution of amounts. Furthermore, the common reference point of $28 in the Cooperation and Competition treatments appears to have induced a differential effect on the distribution. The cooperative treatment appears to have a larger concentration in the $20-$30 range, while the
competitive treatment appears to have a much larger spike at the $50 level. Note that the reference point had an absolute effect as well, in that there are multiple donations of $28 for the Competitive and Cooperative treatment groups and none for the Control group.

Figure 4.2: Histogram of the Donation Amounts of the Control (top), Cooperative (middle), and Competitive (bottom) Groups.

To demonstrate these differences more clearly, the plot in Figure 4.3 displays the differences between the frequency distribution of the two treatments and the control for donations at or less than $100, which represents the vast majority (94%) of donations. This figure could be interpreted as the additional effect of the cooperative and competitive treatments above the control, given that all groups would have contributed with the exact same distribution if they received the control mailing. Clearly, the majority of "additional" contributions in the cooperative treatment appear to be centered in the $20-$30 range, whereas there are multiple "additional"
contributions in the competitive treatment at $28, $50, and $100, with the majority located at $50.

Figure 4.3: The Difference between the Ally/Rival Treatments and the Control Contribution Distributions for all Contributions less than $100.

To test this effect statistically, we run a probit regressions on the probability of contributing between $20-$30, $50, and $100, with the results reported in Table 4.4. This leads to our second set of results:

**Finding 2:** The members of the cooperative treatment were more likely to contribute $20-$30 than those in the control, but not more likely to contribute $50 and $100.

**Finding 3:** The members of the competitive treatment were more likely to contribute $50 than those in both other groups, but not more likely to contribute $20-$30
and $100.

Note that the members of the competitive treatment were more likely to contribute $50 than those in the cooperative group, but the members of the cooperative group were not more likely to contribute $20-$30 than those in the competitive group. Finally, note that there is no other $10 interval (such as $10-$20) that does not include $25 or $50 in which either group contributes at a significantly higher rate than the control. Thus, it appears that the "additional" donations are concentrated at these points. While the interpretation of this result is open, it appears that the cooperative treatment induces people to donate around (or slightly lower) than the reference point, whereas the competitive treatment induces people to donate nearly twice as much the reference point.

4.4 Discussion and Conclusion

This paper presents the results of a field experiment in which a political solicitation was sent to a large group of potential donors that contained information about previous donations of those on the same political side ("cooperative"), those on the other side ("competitive"), or no information about past donations ("control"). We find that both treatments induced changes in the donation rate and distribution amounts in comparison to the control group, but the competitive treatment was more effective overall. Interestingly, while members of the cooperative group were more likely to contribute around the stated reference point of their peers, the members of the competitive group were more likely to contribute nearly an amount of nearly twice the stated reference point.

The behavior elicited in our experiment is consistent with a variety of explanations, which we cannot distinguish with our experimental design. In their experiment, Frey and Meier (2007) mention three potential explanations for people to contribute more to a public good as a result of social information about their peers: People may desire to conform to social norms; people may exhibit some level of fairness-based preferences; and contributions by others may signal the quality of the public good (the candidate). In a competitive public goods framework, players also have reasons
to change their behavior when given information about contributions of players on
the opposing group. For example, as demonstrated in past research, people appear
to receive utility from winning, particularly in competitive settings, perhaps leading
them to contribute a higher amount. However, even a purely outcome-focused person
might be induced to contribute more as a result of social information if it changes
her perception about the distribution of potential total contributions of the opposing
group in a certain way (of course, another change might could also induce her to
contribute less). We believe that understanding the precise way that these motiva-
tions interact could clarify our result and its potential impact on profit-maximizing
solicitation behavior.
Table 4.1: Pre-Treatment Balance of Groups

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Treatment Group</th>
<th>P-value on Tests of Equality of Means</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Male</td>
<td>0.47</td>
<td>0.47</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Age</td>
<td>61.4</td>
<td>61.2</td>
<td>61.1</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.26)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>Democratic</td>
<td>0.91</td>
<td>0.90</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Republican</td>
<td>0.060</td>
<td>0.062</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>White</td>
<td>0.84</td>
<td>0.85</td>
<td>0.84</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Black</td>
<td>0.11</td>
<td>0.10</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
</tbody>
</table>

Note: Level of significance: *** p<.001, ** .01<p<.05, * .05<p<.10
### Table 4.2: Donation Rates and Amounts Across Treatment Groups

<table>
<thead>
<tr>
<th></th>
<th>Comp</th>
<th>Coop</th>
<th>Cont</th>
<th>Com=Coo</th>
<th>Com=Con</th>
<th>Coo=Con</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Num. Recipients</strong></td>
<td>9,881</td>
<td>3,280</td>
<td>3,297</td>
<td>3,304</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>Num. Contributors</strong></td>
<td>111</td>
<td>48</td>
<td>37</td>
<td>26</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td><strong>Cont. Rate</strong></td>
<td>1.12%</td>
<td>1.46%</td>
<td>1.12%</td>
<td>0.79%</td>
<td>0.26</td>
<td>0.02**</td>
<td>0.23</td>
</tr>
<tr>
<td><strong>Avg Cont. ($)</strong></td>
<td>0.70</td>
<td>0.96</td>
<td>0.61</td>
<td>0.53</td>
<td>0.13</td>
<td>0.07*</td>
<td>0.69</td>
</tr>
<tr>
<td>(s.e.)</td>
<td>–</td>
<td>(0.18)</td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>–</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Avg Cond. Cont. ($)</strong></td>
<td>62.76</td>
<td>66.41</td>
<td>54.81</td>
<td>67.30</td>
<td>0.36</td>
<td>0.96</td>
<td>0.47</td>
</tr>
<tr>
<td>(s.e.)</td>
<td>–</td>
<td>(8.31)</td>
<td>(9.37)</td>
<td>(14.66)</td>
<td>–</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Level of significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The asterisk (*) indicates statistical significance.
### Table 4.3: Probit Regressions on Donation Rates

<table>
<thead>
<tr>
<th>Dich. Depend. Var: Any Contribution</th>
<th>No Controls</th>
<th>Demographic Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient (z-value)</td>
<td>Marginal</td>
</tr>
<tr>
<td>Cooperative Treatment</td>
<td>0.131 (1.39)</td>
<td>0.39%</td>
</tr>
<tr>
<td>Competitive Treatment</td>
<td>0.232*** (2.56)</td>
<td>0.73%</td>
</tr>
<tr>
<td>Age</td>
<td>.008*** (2.69)</td>
<td>.02%</td>
</tr>
<tr>
<td>White</td>
<td>.408*** (2.63)</td>
<td>1%</td>
</tr>
<tr>
<td>Male</td>
<td>-.034 (.44)</td>
<td>.09%</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.418*** (34.01)</td>
<td>-.326*** (13.92)</td>
</tr>
<tr>
<td>N</td>
<td>9,993</td>
<td>9,993</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>-606.53</td>
<td>-596.89</td>
</tr>
</tbody>
</table>

Note: Level of significance: *** p<.001, ** .01<p<.05, * .05<p<.10
### Table 4.4: Probit Regressions on Donation Rates

<table>
<thead>
<tr>
<th>Contribution Amount</th>
<th>Dichotomous Treatment</th>
<th>Competitive Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$20-$30</td>
<td>0.285**</td>
<td>0.192</td>
</tr>
<tr>
<td>($34)</td>
<td>0.39</td>
<td>0.34%</td>
</tr>
<tr>
<td>$50</td>
<td>0.068</td>
<td>0.361***</td>
</tr>
<tr>
<td>($0.05)</td>
<td>0.05%</td>
<td>0.06%</td>
</tr>
<tr>
<td>$100</td>
<td>0.011</td>
<td>0.197</td>
</tr>
<tr>
<td>($0.01)</td>
<td>0.00%</td>
<td>0.06%</td>
</tr>
</tbody>
</table>
| **Note:** Level of significance: *** p < 0.001, ** p < 0.01, * p < 0.05, .10 **p < 0.10

| Log Likelihood      | -258.40                | -198.13               |

**Dependent Variable:** Donation Rates
Appendix A

Robustness of the Model in Chapter 2

A.1 \( \text{mod}(y-k,c) \neq 0 \)

The results in the analytic section relied heavily on the assumption that \( \text{mod}(v-k,c) = 0 \). If this assumption does not hold, there is no equilibrium in which the game continues past period 1. However, as the following proposition shows, strategies that lead to the hazard rates in Proposition 2 form an \( \epsilon \) equilibrium with \( \epsilon \) very small and limiting to 0 as the size of time periods shrinks to 0:

**Proposition 10** If \( \text{mod}(v-c,k) \neq 0 \), there is no equilibrium in which the game continues past period 1. Define \( F^* = \max(t|t < \frac{v-c}{k} - 1) \). There is an \( \epsilon \)-perfect equilibrium which yields the same (discrete) hazard rates as those in Proposition 2 with \( \epsilon = \frac{1}{n}(1 - \frac{c}{v-F^*k})(v-(F^*+1)k-c)[\prod_{t=1}^{F^*-1} (1 - \frac{c}{v-tk})] \). There is a contemporaneous \( \epsilon^c \)-perfect equilibrium (Mailath (2003)) which yields the same (discrete) hazard rates as those in Proposition 2 with \( \epsilon^c = \frac{1}{n-1}(1 - \frac{c}{v-F^*k})(v-(F^*+1)k-c) \). There is a contemporaneous \( \epsilon^c \)-perfect equilibrium which yields the same hazard and survival rates as those in Proposition 6 with \( \epsilon^c \to 0 \) as \( \Delta t \to 0 \).

To give an idea of the magnitude of the mistake of playing this equilibrium in auctions in my dataset, consider an stylized auction constructed to make \( \epsilon \) as
high as possible, with \( v = €9.95, c = €.50, k = €.10, \) and \( n = 20. \) In this case, \( \epsilon = €.0000000000224 \) and \( \epsilon^c = €.00060. \) That is, even in the most extreme case and using the stronger concept of contemporaneous \( \epsilon^c \)-perfect equilibrium, players lose extremely little by following the proposed strategies. This is because their only point of profitable deviation is at the end of the game, where their equilibrium strategy is to bet with low probability, there is a small chance that their bet be accepted, and the cost of the bet being accepted is small (and, ex ante, there is an extremely small chance of ever reaching this point of the game).

### A.2 Independent Values

In the model in the main paper, I assume that players have a common value for the item. The equilibrium is complicated if players have values \( v_i \) is drawn independently from some distribution \( G \) of finite support before the game begins or \( v_i(t) \) is drawn independently from \( G \) at each time \( t \). In these equilibria, players’ behavior is dependant largely on the exact form of \( G \); with very few clear results about bidding in each individual period (which is confirmed by numerical simulation). However, if players have independent values which tend to a common value, the distribution of hazard rates approaches the bidding hazard rates in the following way:

**Proposition 11** Consider if (1) \( v_i \) is drawn independently from \( G \) before the game begins or (2) \( v_i(t) \) is drawn independently from \( G \) at each time \( t \). For any distribution \( G \), there is a unique set of hazard rates \( \{\tilde{h}^G(1), \tilde{h}^G(2), \ldots \tilde{h}^G(t)\} \) that occur in equilibrium. Let the the support of \( G_i \) be \([v - \delta_i, v + \delta_i]\). For any sequence of distributions \( \{G_1, G_2, \ldots\} \) in which \( \delta_i \to 0 \) and the game continues past period 1 in equilibrium, \( \tilde{h}^G(t) \to \tilde{h}(t) \) from Proposition 2 for \( t > 0 \). For any sequence of distributions \( G \) with \( \delta \to v \) and \( \Delta t \to 0 \), there exist a sequence of corresponding contemporaneous \( \epsilon^c \)-perfect equilibria with hazard and survival rates equal to those in Proposition 6 in which \( \epsilon^c \to 0 \).
A.3 Leader can bid

Throughout the paper, I assume that the leader cannot bid in an auction. This assumption has no effect on the preferred equilibrium below, as the leader not bid in equilibrium even when given the option. However, the assumption does dramatically simplify the exact form of other potential equilibria, as shown below.

Consider a modified game in which the leader can bid. Now, a (Markov) strategy for player $i$ at period $t$ is the probability of betting both if a non-leader ($x_i^{NL,t}$) and, for $t > 0$, when a leader ($x_i^{L,t}$) (there is no leader in period 0).

**Proposition 12** In the modified game, Proposition 2 still holds.

The equilibria in the situation in which non-leaders bid becomes significantly more complicated and finding a closed form solution becomes extremely difficult. For example, consider the equilibrium in which no player bids at period $F$ (this is the equilibrium characterized by $t = F$ and $p = 0$ in Proposition 3). The (numerically) solved equilibrium hazard rates are shown for $v = 10$, $c = .5$, $k = .1$ and $n = 3$ in Figure A.1 Notice the obvious irregularities in the equilibrium hazard rates in the modified game. This occurs because the ability of a leader to bid in period $t$ distorts the incentives of non-leaders in previous periods. To see this, consider the situation in which $\hat{h}(t+1) = 1$ and $\hat{h}(t) = 0$. When leaders cannot bid, there is no benefit from a non-leader bidding in period $t - 1$ as he will not win the object in period $t$ (because the game will continue with certainty) or period $t + 1$ (because he cannot bid in period $t$ and therefore will never be a leader at $t + 1$), at which point the game will end. However, when leaders can bid, non-leaders in period $t - 1$ can potentially benefit from bidding. Although there is still no chance that the non-leader in period $t - 1$ will win the object in period $t$ by bidding, she will be able to bid (as a leader) in period $t$, leading to the possibility that she will win the object in period $t + 1$. Therefore, non-leaders will potentially bid in this situation in equilibrium not to win the object in the following period, but simply to keep the game going for a (potential) win in the future.
APPENDIX A. ROBUSTNESS OF THE MODEL IN CHAPTER 2

Figure A.1: Change in non-bidding equilibria when the leader is allowed to bid.

A.4 Allowing Multiple Bids to Be Accepted

Allowing multiple bids to be accepted significantly complicates the model, especially in a declining-value auction. Consider a player facing other players that are using strictly mixed strategies. If the player bids in period $t$, there is a probability that anywhere from 0 to $n - 2$ other non-leading players will place bids, leading the game to immediately move to anywhere from period $t + 1$ to period $t + n$. In each of these periods, the net value of the object is different, as is the probability that no player will bid in that period and the auction will be won (which is dependant on the equilibrium strategies in each of the periods).

It is possible to solve the model numerically, leading to a few qualitative statements about the hazard rates. Figure A.2 shows the equilibrium hazard rates (with $k = .1, c = .5, n = 10$) given small changes in the value of the good ($v = 10, 10.25, 10.5, 10.75$), as well as the analytical hazard rates from Proposition 2. These graphs demonstrate three main qualitative statements about the relationship between the equilibria in the modified model and the original model:

1. The hazard rates of the modified model are more unstable locally (from period-to-period) than those from Proposition 2, especially in later periods. As $n$ increases, this instability decreases (I do not present graphs for lack of space).

2. The hazard rates of the modified model closely match those from Proposition 2 when smoothed locally.
Figure A.2: Numerical Analysis of the hazard rate of auctions for different values (solid lines) when the multiple bids are accepted at each time period vs. the predicted hazard rate (dotted red line) when only one bid is accepted.
3. The hazard rates of the modified model are more stable globally to small changes in parameters in the model. Recall that the hazard rates in Proposition 2 were taken from an equilibrium when \( \text{mod}(y - c, k) = 0 \). When \( \text{mod}(y - c, k) \neq 0 \), the hazard rates oscillated radically (although they were smooth in an \( \varepsilon \)-equilibrium with very small \( \varepsilon \)). The modified model is much more globally robust to these changes.

A.5 Timer

In the model in the paper, unlike that in the real world implementation of the model, there is no timer within each period. Consider a game in which, in each discrete period \( t \), players can choose to place a bid at one sub-time \( \tau \in [0, T] \) or not bid for that period. As in the original game, if no players bid, the game ends. If any players bid, one bid is randomly chosen from the set of bids placed at the smallest \( \tau \) of all bids (the first bids in a period). Now, a player’s (Markov) strategy set is a function for each period \( \chi^i_t(\tau) : [0, T] \to [0, 1] \), with \( \int_0^T \chi^i_t(\tau)d\tau \) equaling the probability of bidding at some point in that period.

**Proposition 13** For any equilibrium of the modified game, there exists an equilibrium of the original game in which the distribution of the payoffs of each of the players is the same.

This proposition demonstrates that, while the timer adds complexity to the player’s strategy sets, it does not change any of the payoff-relevant outcomes.
Appendix B

Proofs for Chapter 2

Proposition 1

Proof: Assume that an equilibrium exists in which \( e(t^*) < 1 \) for some \( t^* > \frac{v-c}{k} - 1 \). There must be some player \( i \) with \( x_{it} > 0 \). Consider any proper subgame starting at period \( t^* \). For each period in this game, there is some probability \( a_i^t \in [0,1] \) that player \( i \) has a bid accepted in that period and some probability \( q_t \) that the game ends at that period. As \( x_{it} > 0 \), \( a_i^t > 0 \) and \( q_t < 1 \). Player \( i \)'s continuation payoff starting at time \( t^* \) is

\[
\sum_{t=t^*}^{\infty} a_i^t(-c+q_{t+1}(v-(t+1)k)) < \sum_{t=t^*}^{\infty} a_i^t(-c+q_{t+1}(v-(\frac{v-c}{k}+1)k)) < \sum_{t=t^*}^{\infty} a_i^t(-c+q_{t+1}(c-k)) < 0.
\]

But, player \( i \) could deviate to never bidding and receive a payoff of 0. Therefore, this can not be an equilibrium.

Proposition 2

Proof: Consider the following symmetric strategies: \( x_{it} = \begin{cases} 1 & \text{for } t = 0 \\ 1 - \frac{n^{-1}}{v-tk} & \text{for } 0 < t \leq F \\ 0 & \text{for } t > F \end{cases} \).

Note that: for \( t = 0 \), \( \tilde{h}(t) = 0 \); for \( 0 < t \leq F \), \( \tilde{h}(t) = (1-(1-\frac{n^{-1}}{v-tk})^{n-1}) = \frac{c}{v-tk} \); for \( t > F \), \( \tilde{h}(t) = 1 \).

Claim: this is a subgame perfect equilibrium.

First, consider if \( k > 0 \). I will show that, for each period \( t \), the following statement (referred to as statement 1) is true: there is no strictly profit deviation in period \( t \) and the continuation payoff from entering period \( t \) as a non-leader is 0. For the subgames starting in periods \( t > F \), refer to the proof of Proposition 1 for a proof of
the statement. For the subgames starting in period \( t \leq F \), the proof continues using (backward) induction with the statement already proved for all periods \( t > F \). In period \( t \), player \( i \) will receive a continuation payoff of 0 from not betting at time \( t \) (she will receive 0 in period \( t \) and will enter period \( t+1 \) as a non-leader, which has a continuation payoff of 0 by induction). By betting, there is positive probability her bid is accepted. If this is the case, she receives \(-c\) in period \( t \) and receives \( v - (t+1)k \) in \( t + 1 \) with probability \( \frac{c}{v-(t+1)k} \) and 0 as a continuation payoff in period \( t + 2 \) with probability \( 1 - \frac{c}{v-tk} \). If she does not win the object, the continuation payoff from entering period \( t + 2 \) must be 0 by induction. This leads to a total continuation payoff from her bid being accepted of \(-c + \frac{c}{v-(t+1)k}(v - (t + 1)k) = 0 \). If the bid is not accepted, she enters period \( t + 1 \) as a non-leader and must receive a continuation payoff of 0 by induction. Therefore, the continuation payoff from betting must be 0. Therefore, the statement 1 is true for all periods and this is a subgame perfect equilibrium.

**Proposition 3**

**Proof:** The proof is two steps.

(1) Each of the proposed set of hazard rates can occur in equilibrium. This closely follows the proof of Proposition 2.

Consider the following symmetric strategies:

\[
x_{t}^{i*} = \begin{cases} 
1 & \text{for } t < t^* \text{ with } \text{mod}(t + GT + \text{mod}(t^*, 2), 2) = 0 \\
0 & \text{for } t < t^* \text{ with } \text{mod}(t + GT + \text{mod}(t^*, 2), 2) = 1 \\
1 - \frac{n}{\sqrt{p}} & \text{for } t = t^* \\
1 - \frac{n}{\sqrt{\frac{v-tk}{v-tk}}} & \text{for } t^* < t \leq F \\
0 & \text{for } t > F 
\end{cases}
\]

Note that, as in the proof of Proposition 2. these strategies yield the hazard rates listed in the proposition.

Claim: This is a subgame perfect equilibrium.

First, consider if \( k > 0 \). The proof of Proposition 2 demonstrates that there is no strictly positive deviation from the strategies for any subgame starting in any period \( t > t^* \). Consider period \( t^* \). From the proof of Proposition 2, the continuation payoff from betting and not betting at \( t^* \) are the same (0) for all subgames and therefore
there is no strictly profitable deviation from playing \( 1 - \alpha - \sqrt[\alpha]{p} \) in period \( t^* \) in any subgame. Now, consider period \( t^* - 1 \). Following the same logic as Proposition 2, the continuation payoff from betting and having a bid accepted is \( \pi_A = -c + p(v - (t^*)k) \), and the continuation payoff from betting and not having the bid accepted is \( \pi_{NA} = 0 \). The continuation payoff from betting is \( \pi = \alpha \pi_A + (1 - \alpha) \pi_{NA} \), with the probability of having a bid accepted \( \alpha \in (0, 1] \). Simple algebra shows that \( p \leq \frac{c}{v - tk} \Leftrightarrow \pi \leq 0 \).

If \( \pi > 0 (\pi < 0) \), then players must strictly prefer to bid (not bid) in period \( t^* - 1 \), leaving no profitable deviation (note that if \( \pi = 0 \), players also do not strictly prefer to deviate). Similar logic shows that players must strictly prefer to not bid (bid) in period \( t^* - 2 \), bid (not bid) in period \( t^* - 3 \), and so on. This leaves no profitable deviation in any period and therefore the above strategies are a subgame perfect equilibrium.

(2) No other set of hazard rates can occur in an equilibrium.

Suppose there exists a different set of hazard rates \( \hat{h}(t) \) that occur in some equilibrium which can not be characterized this set of hazard rates for some \( p \) and \( t^* \). Proposition 1 shows that the hazard rates in this supposed equilibrium must be follow this characterization in periods \( t > F \). Note that the hazard rates in Proposition 2 with any hazard rate \( p \) in period 0 can be characterized by \( p \) and \( t^* = 0 \). Therefore, there must be some \( 0 < t \leq F \) such that \( \hat{h}(t) \neq \frac{c}{v - tk} \). Define \( t^* = \max(t | \hat{h}(t) \neq \frac{c}{v - tk}, t \leq F) \) and \( p = \hat{h}(t^*) \). There must be some \( t < t^* \), in which \( \hat{h}(t) \) differs from the listed set of hazard rates. However, by the proof above, players in periods \( t < t^* \) strictly prefer to play the strategies defined above, leading to the a member of the listed set hazard rates, which is a contradiction.

**Corollary 4**

**Proof:** By Proposition 3, the hazard rates in this equilibrium must be a member of the listed set of hazard rates and characterized by some \( p \) and \( t^* \). If \( t^* > 1 \), then the hazard rate in this equilibrium must be 1 in either period 1 or 0. Therefore, if an equilibrium continues past period 1, it must be that \( t^* \in \{0, 1\} \). For all of these equilibria, the hazard rates match those in Proposition 2 for all \( t > 1 \).

**Corollary 5**

**Proof:**
(1) Claim: the auctioneer’s expected revenue is equal to \( v \) in the equilibrium in Proposition 2: Note the item must be sold to some bidder as \( \tilde{h}(0) = 0 \). Therefore, the combined expected profit of the bidders must be \( v \). Next, note that by the proof of Proposition 2, each player must have a continuation payoff of 0 at the start of the auction. Therefore, the auctioneer must have an expected continuation payoff of \( v \).

(2) Claim: For any \( \alpha \in \left[ \frac{1}{2}, 1 \right] \), there exists an equilibrium in which the auctioneer’s expected payoff is \( \alpha v \). Consider the equilibrium hazard rates characterized by \( t^* = 1 \) and \( p \in \left[ \frac{e}{v-k}, 1 \right] \). Given these hazard rates, \( \tilde{h}(0) = 0 \).

**Proposition 6**

**Proof:** Let \( S(t) = p \). As \( \tilde{h}(t) = \frac{ct}{v-(t+k)p} \) for \( t \leq F \), \( S(t + \Delta t) = \left(1 - \frac{c(1-F)}{v-(t+k)p}\right)p \).

Therefore, \( S(t) = \lim_{\Delta t \to 0} \frac{S(t) - S(t + \Delta t)}{\Delta t} = \lim_{\Delta t \to 0} \frac{p \left(\frac{ct}{v-(t+k)p}\right)}{\Delta t} = \frac{c}{v-(t+k)p} \). As \( H(t) = \int_0^t \frac{c}{v-(t+k)d\tilde{t}} \), \( H(t) = \frac{c}{v-(t+k)} \) for \( k > 0 \) and \( t \leq F \), while \( H(t) = \frac{\xi}{v} \) if \( k = 0 \). Note that \( H(t) = \frac{c}{v} \left[\frac{S(0)}{S(t)} - \frac{S(0)}{S(t + \Delta t)}\right] - \int_0^t \frac{1}{S(t)} \frac{d}{dt} \left(S(t)\right) d\tilde{t} = - \ln S(t) \).

Therefore \( S(t) = \frac{e^{-H(t)}}{S(t)} \) and \( S(t) = \left(1 - \frac{t}{p}\right)^{\frac{\xi}{v}} \) if \( k > 0 \) and \( t \leq F \), while \( S(t) = \frac{e^{-\frac{\xi}{v} t}}{S(t)} \) if \( k = 0 \).

Note that, as \( \tilde{h}(F + \Delta t) = 1 \), \( \lim_{\Delta t \to 0} \Pr(T > F) = 0 \) and therefore \( S(F) = 0 \).

**Proposition 7**

**Proof:** \( S(tv_1; v_1) = (1 - \frac{tv_1 v}{v_1})^{\frac{\xi}{v}} = (1 - tv_2 v_2) = S(tv_2; v_2) \) if \( k > 0 \) and \( t \leq F \). \( S(tv_1; v_1) = 0 = S(tv_2; v_2) \) if \( k > 0 \) and \( t > F \). \( S(tv_1; v_1) = e^{-\frac{\xi}{v}tv_1} = e^{-ct} = e^{-\frac{\xi}{v}tv_2} = S(tv_2; v_2) \) if \( k = 0 \). \( S(t_{c_1}; v_1, c_1) = e^{-\frac{\xi}{v}t_{c_1}} = e^{-ct} = e^{-\frac{\xi}{v}tv_2} = S(t_{c_2}; v_2, c_2) \) if \( k = 0 \).

**Proposition 10**

**Proof:** Consider the strategies noted in the proof of Proposition 2 with \( F = F^* \).

For the standard \( \epsilon \)-perfect equilibrium, we consider the ex ante benefit of deviating to the most profitable strategy, given that the other players continue to follow this strategy. Following the proof of Proposition 2, it is easy to show that there is no profitable deviation in periods \( t > F^* \) and \( t < F^* \). Therefore, the only profitable deviation is to not bet in \( t = F^* \). This will yield a continuation payoff of 0 from period \( F^* \). The ex ante continuation payoff from betting is \( \epsilon = \frac{1}{n} \left(1 - \frac{\epsilon}{v-(F^*+1)k-c}\right) \prod_{t=1}^{F^*-1} (1 - \frac{\epsilon}{v-(t+k)}) \). (To see this, note that there is a \( \prod_{t=1}^{F^*-1} (1 - \frac{\epsilon}{v-(t+k)}) \) change that the game
reaches period $F^*$. In period $F^*$, there is a $(1 - \frac{c}{v-F^*k})$ probability that at least one player bets. As strategies are symmetric, this means that, ex ante, a player has a $\frac{1}{n}(1 - \frac{c}{v-F^*k})$ probability of her bet being accepted in this period, given that the game reaches this period. If the bet is accepted, the player will receive $(v - (F^* + 1)k - c)$. Therefore, the ex ante benefit from deviating to the most profitable strategy is $\epsilon$. For the contemporaneous $\epsilon$-perfect equilibrium, we consider the benefit of deviating to the most profitable strategy once period $F^*$ is reached, given that the other players continue to follow this strategy. This is $\epsilon^c = \frac{1}{n-1}(1 - \frac{c}{v-F^*k})(v - (F^* + 1)k - c)$ (To see this, note that in period $F^*$, there is a $(1 - \frac{c}{v-F^*k})$ probability that at least one player bets. As strategies are symmetric, this means that, ex ante, a non-leader has a $\frac{1}{n-1}(1 - \frac{c}{v-F^*k})$ probability of her bet being accepted in this period (as there are only $n-1$ non-leaders). If the bet is accepted, the player will receive $(v - (F^* + 1)k - c)$.

**Proposition 11**

**Proof:** In case 1, I will refer to $v_i(t) = v$. The proof is simple (backward) induction on the statement that there is a unique hazard rate that can occur in each period in equilibrium. By the same logic in the proof to Proposition 1, $\tilde{h}(t) = 1$ for all $t > \frac{v + \delta - c}{k} - 1$. Consider periods $t \leq F^* = \max\{t | t \leq \frac{v + \delta - c}{k} - 1\}$ where $\tilde{h}(t + 1)$ is unique in equilibrium by induction. If $\tilde{h}(t + 1) = 0$, then $\tilde{h}(t) = 1$ as any player with finite $v_i(t)$ strictly prefers to not bid. If $\tilde{h}(t + 1) > 0$, a player with cutoff type $v^*(t) = \frac{c}{h(t+1)} + (t+1)k$ is indifferent to betting at time $t$ given $\tilde{h}(t + 1)$.

Therefore, $\tilde{h}(t) = G(\max(\min(v^*, v + \delta), v - \delta))$ and the statement is true.

Suppose $G_i$ is such that the game continues past period 1.

Claim 1: If $\delta < k$, then (1) $\tilde{h}(t) = 0$ for $t \leq F \Rightarrow \tilde{h}(t - 1) = 1$ and (2) $\tilde{h}(t) = 1$ for $t \leq F \Rightarrow \tilde{h}(t - 1) = 0$.

> (1) This is true as a bidding leads to $-c$, a lower payoff than not bidding.

> (2) If $\tilde{h}(t) = 1$, then the payoff of bidding for a player with value $\tilde{v}$ at period $t - 1$ is $\Pr[\text{Bid Accepted}](\tilde{v} - tk - c)$. Note that $\Pr[\text{Bid Accepted}] > 0$ if a player bids. Note that $t \leq F \Rightarrow t \leq \frac{v - \delta - c}{k} - 1 \Rightarrow 0 \leq v - c - (t + 1)k \Rightarrow 0 < v - \delta - c - tk$ as $\delta < v$. Therefore, $0 < \Pr[\text{Bid Accepted}](\tilde{v} - (t + 1)k - c)$ for every $\tilde{v} \in [v - \delta, v + \delta]$ and therefore $\tilde{h}(t) = 0$ and the claim is proved.

Claim 2: If $\delta < k$, $\tilde{h}(t) \in (0, 1)$ for every $0 < t \leq F$. Suppose that $\tilde{h}(t) = \{0, 1\}$ for
some $0 < t \leq F$. If $\tilde{h}(1) = 1$, then game ends at period 1, leading to a contradiction. If $\tilde{h}(1) = 0$, then $\tilde{h}(0) = 1$, and game ends at period 0, leading to a contradiction. If $\tilde{h}(t) = 1$ (alt: 0) for $0 < t \leq F$, then $\tilde{h}(t-1) = 0$ (alt: 1), $\tilde{h}(t-2) = 1$ (alt: 0) by claim 1. But, then $\tilde{h}(1) = \{0, 1\}$, which is leads to a contradiction as above.

Claim 3: By the same logic in the proof to Proposition 1, $\tilde{h}(t) = 1$ for all $t > \frac{v+\delta_t - c}{k} - 1$. Therefore, $\tilde{h}^G(t) = 1$ for $t > \frac{v-c}{k} - 1 = F$ as $\delta_t \to 0$. For $0 < t \leq F$, note that for some $i^*, \delta_i < k$ for all $i > i^*$ and therefore claim 1 holds for all $i > i^*$. If claim 1 holds, $\tilde{h}(t-1) \in (0, 1)$ implies a cutoff value $v^*(t) = (v - \delta, v + \delta)$ from above, which by the definition of $v^*(t)$ implies that $\tilde{h}(t) \in (\frac{c}{(v-\delta - (t+1)k), \frac{c}{(v+\delta - (t+1)k)})$, and therefore $\tilde{h}^G(t) \to \frac{c}{v-tk}$ for periods $0 < t \leq F$ as $\delta_t \to 0$. Therefore, $\tilde{h}^G(t) \to \tilde{h}(t)$ from Proposition 2 for $t > 0$.

**Proposition 12**

**Proof:** Set $x_t^{i,NL*} = x_t^{i*}$ from the proof of Proposition 2 and set $x_t^{i,L*} = 0$ for all $i$ and all $t$. Note that, as in the proof of Proposition 2, these strategies yield the hazard rates listed in the Proposition 2. The same proof for Proposition 2 shows that, if strategies are followed, the continuation payoff from entering period $t$ as a non-leader is 0 and there is no profitable deviation for a non-leader. Now, consider if there is a profitable deviation for a leader. For the subgames starting in periods $t > F$, refer to the proof of Proposition 1 for a proof that there is no profitable deviation for a leader in these periods. For the subgames starting in period $0 < t \leq F$, the proof continues using (backward) induction with the lack of profitable deviation already proved for all periods $t > F$. In period $t$, by not bidding, the leading player will receive $v$ with probability $\frac{c}{v-tk}$ (with the game ending) and 0 as a continuation probability as a non-leader in period $t + 1$ with probability $1 - \frac{c}{v-tk}$, yielding an expected payoff of $v (\frac{c}{v-tk}) > 0$. By bidding, the game will continue to period $t + 1$ with certainty, with some positive probability that her bid is accepted. If her bid is accepted, she receives $-c$ in period $t$ and receives $v - (t + 1)k$ in $t + 1$ with probability $\frac{c}{v-(t+1)k}$ and 0 as a continuation probability as a non-leader in period $t + 2$ with probability $1 - \frac{c}{v-tk}$, leading to a continuation payoff of $-c + (v - (t + 1)k)(\frac{c}{v-tk}) = 0$. If her bid is not accepted, she will receive a continuation probability of 0 as a non-leader in period $t + 1$. Therefore, the payoff from not bidding in period $t$ is strictly higher than the
payoff from bidding.

**Proposition 13**

**Proof:** Consider a vector of bidding probabilities \( x = [x^1, x^2, \ldots, x^n] \in [0, 1]^n = X \) in some period. Let \( \Psi : X \rightarrow \Delta^n \) be a function that maps \( x_i \) into a vector of probabilities of each player’s bid being accepted, which I will denote \( a = [a^1, a^2, \ldots, a^n] \).

Claim: For any \( a^* \in \Delta^n, \exists x \in X \) such that \( \Psi(x) = a^* \).

Consider the following sequence of betting probabilities, indexed by \( j = \{1, 2, 3, \ldots\} \). Let \( x^i(1) = 0 \). Define \( a(j) = \Psi(x(j)) = \Psi([x^1(j), x^2(j), \ldots, x^n(j)]) \). Define \( \tilde{a}_i(j) = \Psi([x^1(j-1), x^2(j-1), \ldots, x^i(j), \ldots, x^n(j-1)]) \) and let \( x^i(j) \) be chosen such that \( \tilde{a}_i(j) = a^i \). Claim: \( x(j) \) exists, is unique, \( x(j-1) \leq x(j) \) and \( a_i(j) \leq a^* \) for all \( j \). This is a proof by induction, starting with \( t = 2 \). As \( x(1) = 0, x(2) = a^* \) by the definition of \( \tilde{a}_i(j) \). Therefore, \( x(2) \) exists, is unique, \( x(1) \leq x(2) \) and \( a_i(2) \leq a^* \) as \( \frac{\partial \Psi}{\partial x_i} < 0 \) for \( k \neq i \). Now, consider \( x^i(j) \). Note (1) \( x^i(j) = 0 \) \( \Rightarrow \tilde{a}_i(j) = 0 \), (2) \( x^i(j) = 1 \) \( \Rightarrow \tilde{a}_i(j) \geq 1 - \sum_{k \neq i} a^k(j-1) \geq 1 - \sum_{k \neq i} a^k(j-1) \geq 1 - \sum_{k \neq i} a^k \) follows by \( a_i(j-1) \leq a^* \), which follows by induction (3) \( \tilde{a}_i(j) \) is continuous in \( x^i(j) \) and \( \frac{\partial \Psi}{\partial x_i} > 0 \). Therefore, there is a unique solution \( x^i(j) \) such that \( \tilde{a}_i(j) = a^i \). As \( a_i(j-1) \leq a^* \) by induction, it must be that \( x_i(j) \geq x_i(j-1) \) as \( \frac{\partial \Psi}{\partial x_i} > 0 \). Finally, note that if \( \tilde{a}_i(j) = a^i \), then as \( a_i(j) \leq a^i \) as \( \frac{\partial \Psi}{\partial x_i} < 0 \) for \( k \neq i \) and \( x_k(j) \geq x_k(j-1) \) for \( k \neq i \).

Set \( x^* = \lim_{j \to \infty} x(j) \). Claim: \( x^* \) exists and \( \Psi(x^*) = a^* \). First, \( \lim_{j \to \infty} x(j) \) must exist as \( x^i(j) \) is bounded above by 1 and weakly increasing. Next, note that \( \sum_i x_i^* \) must also exist with \( \sum_i x_i^* \leq n \). Now, suppose that \( \Psi(x^*) \neq a^* \). Then, as \( \Psi(x(j)) = a(j) \leq a^* \) for all \( j \), \( \Psi(x^*) \leq a^* \) and there must be some \( i \) such that \( \Psi_i(x^*) - a^i = z > 0 \). Choose \( L \) such that \( |\sum_i x_i^* - \sum_i x_i(j)| < \frac{z}{2} \) for all \( j > L \). By the definition of \( x^i(j+1) \), it must be that \( x_i(j+1) \geq x_i(j) + z \). But, as \( x(j+1) \geq x(j) \), then \( \sum_i x_i(j+1) \geq \sum_i x_i(j) + z \geq \sum_i x_i^* + \frac{z}{2} \), which is a contradiction of \( L \). Therefore, the claim is proved.
Bibliography


Chapter 3:


**Chapter 4:**


