DEMAND ESTIMATION AND POLICY IMPLICATIONS IN MARKETS FOR CASINO GAMING AND ELECTRICITY

by

MARIA LAUVE

A Dissertation submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Economics

written under the direction of

Martin K. Perry

and approved by

____

____

____

____

New Brunswick, New Jersey

October, 2007

ABSTRACT OF THE DISSERTATION

Demand Estimation and Policy Implications in Markets for

Casino Gaming and Electricity

By MARIA LAUVE

Dissertation Director:
Martin K. Perry

Two studies explore the potential for demand models to inform policy decisions when only aggregated price and quantity data are available. The first is a study of the Atlantic City casino industry. Legislation recently adopted by Pennsylvania and New York is generating new growth in the casino industry in the northeastern United States. Studies have shown that product differentiation is the best way for existing casinos to remain competitive under these conditions. The state of New Jersey and the Atlantic City casinos have undertaken several improvements in and around the casinos to improve the overall gaming experience. While these improvements will go a long way toward ensuring that the casinos maintain market share of gaming revenues and that the state continues to reap the economic benefits of the industry, unexploited potential may remain. This study estimates a discrete-choice model to determine which product characteristics will have the greatest impact on demand. Results suggest the overall number of recipients of complementary goods is more important than the total value of these goods. Additionally, consumers appear to prefer newer casinos and newer gaming technology indicating that regular upgrades in casino facilities may be justified.

The second is a study of California's energy markets. Evidence of energy conservation in California during the deregulation crisis of 2000-2001 raises questions about the role of altruism, or social responsibility, in household and firm behavior. The crisis provides a unique opportunity to reexamine the theories and empirical findings previously developed in the context of over-compliance (cases in which firms reduce pollution emissions below the levels required by regulations). This study capitalizes on the fact that retail energy prices are constant over a significant portion of the observation period, thereby eliminating rising prices as a cause for reduced energy consumption. The study attempts to shed new light on the subject of social responsibility by examining the behavior of economic agents across sectors. Monthly panel data, aggregated by sector, for the period beginning February 1997 and ending December 2001 are used in the analysis. Results suggest that households may be more sensitive to public media announcements than firms.

Acknowledgments

Special thanks go to my advisor, Martin K. Perry, for his role as my academic and professional mentor. From the moment he proposed a topic for research, Marty gave generously of his time and energy and has been instrumental in helping me finish my dissertation as well as furthering my professional development. Over these last few years, Marty has introduced me to several people in the casino industry who have assisted me in my research; he has included me in related consulting projects and field work; and he has dedicated countless hours to discussions about my research as well as reading drafts of my dissertation, which have improved the clarity of my work enormously.

I would also like to acknowledge Professors John Landon-Lane, Colin Campbell and Roger Klein for making many helpful suggestions regarding analytical techniques to consider and ways to improve the presentation of results; Professor Michael Rothkopf for suggesting the idea for the energy study; and Professor Loren Lutzenhiser, of Portland State University, for useful discussions regarding his own research on energy conservation. Thanks also go to graduate students Ying Zhang and Volkan Cetinkaya for helping me enter and check the monthly casino data; and to Dorothy Rinaldi for overseeing the peace of mind of every graduate student in the Rutgers Department of Economics.

Many thanks to my contacts in Atlantic City for all that they have taught me about the city's casino industry. Daniel Heneghan, Director of Communications at the New Jersey Casino Control Commission, provided me with access to the monthly and quarterly casino reports and gave me a place to enter the data. He was an excellent source of information about this data as well as other aspects of casino regulation. I also benefited from discussions with Steve Dzubaty, James Fogerty and Bob Latimer of the New Jersey Division of Gaming Enforcement.

Finally, I gratefully acknowledge financial support from the Peter Asch Memorial Scholarship and from the Graduate School Fellowship Fund at Rutgers, The State University of New Jersey.

Table of Contents

List of Tables

List of Figures

Part I

Estimating the Demand for Gaming in Atlantic City

Chapter 1: Introduction

Previous studies have helped characterize the relationship between new and existing casino establishments and the extent to which they compete with one another. This study expands on these findings by investigating the means by which Atlantic City casinos will most effectively differentiate themselves from the next wave of gaming entrants: Pennsylvania race-track casinos (racinos) and Indian casinos in New York. Using price and quantity data aggregated at the firm level, I employ a discrete-choice model to estimate the demand for gaming within Atlantic City. The results are then interpreted to reveal the strength of preferences among visitors who gamble in Atlantic City with respect to a set of key characteristics that define the gaming product.

1.1 A Review of the Casino Literature

Over the last thirty years changes in the state and federal laws that regulate gaming have led to a dramatic increase in the number of casinos operating in the United States.[1] These events have afforded some interesting opportunities to investigate the nature of competition between new casino entrants and previously established casinos. In this section I review three articles which attempt to measure the impact of various types of entrants on the demand for gaming at incumbent casinos. These papers examine how entrants have affected the demand for the incumbent's product, either negatively or

[1] Factors contributing to these changes include federal recognition of certain rights of Native American tribes; states' interest in realizing a significant and previously untapped source of revenue; and changing attitudes towards gaming.

positively. The implications of these papers will inform an interpretation of the results of my own empirical analysis of competition in Atlantic City.

Since the arrival of legalized gambling in Las Vegas, the first major legislative change to the casino industry came in 1976 when New Jersey residents voted to approve a law that would allow casino gaming in Atlantic City. Within two years the first casino opened and eleven more were operating by the end of 1985. During this period, the number of Las Vegas visitors originating in the East fell by 43.8 percent.[2] Shonkwiler (1993) investigated this trend by constructing a model to measure the magnitude of the impact that casino openings in Atlantic City had on the demand for gaming in Las Vegas. He found that Las Vegas casinos experienced diminished growth in casino wagers throughout much of the mid-eighties because of the new entrants in Atlantic City. The resulting losses in quarterly gaming revenues stabilized at around 12 percent by the end of 1991.

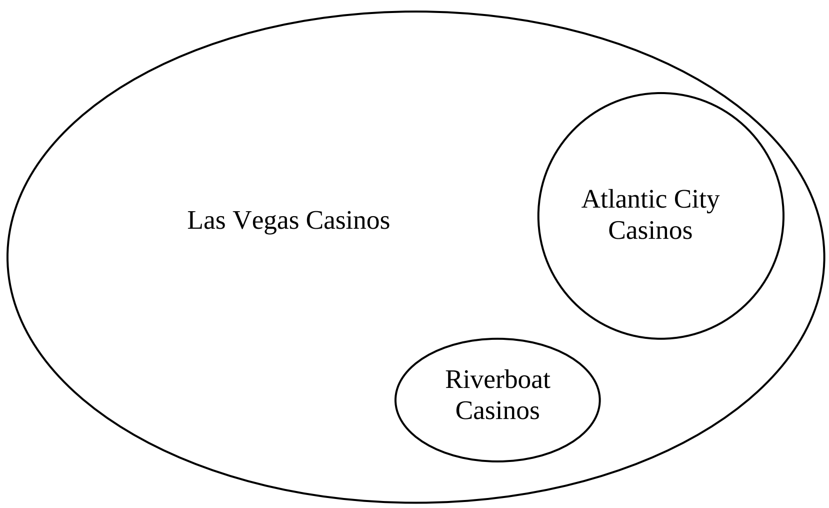
Although it was not the focus of his paper, Shonkwiler's findings provide more general evidence regarding the nature of competition in the casino industry. Diminished revenues in Las Vegas, when considered jointly with a reduction in the number of visitors from the East, suggest that the early success enjoyed by the casinos in Atlantic City may have been attributable to the creation of new demand in addition to a reallocation of existing demand. This conclusion is further supported by the fact that most of the visitors

[2] Comparable reductions were not observed for the South, Midwest and West regions of the United States. See Table I from Shonkwiler (1993) for a comparison of Las Vegas visitor data by region for the periods 1978-1980 and 1985-1987.

arriving in Atlantic City come from within a 150-mile radius (Hunsaker, 2001) and travel almost exclusively by car or bus.[3]

Shonkwiler's findings suggest that the geographic relationship between the gaming markets of Atlantic City and Las Vegas can be illustrated as in Figure 1 below. In Figure 1, the smaller represents the Atlantic City market, which broadly covers the Eastern region of the United States. The larger area, which encompasses the smaller one, represents the Las Vegas market. The boundaries of this area extend to broadly cover the entire United States.

Figure 1. The Geographic Market of Riverboat Casinos Relative to Las Vegas and Atlantic City Casinos.



The relative size and position of these two market areas are most likely explained by differences in the gaming experience offered by each location. Compared to Atlantic City, Las Vegas has a greater number of casinos, a larger variety of non-gaming

[3] Information regarding visitor modes of transportation is reported annually by the South Jersey Transportation Authority in the SJTA Annual Visitor Statistics.

activities, and a well-established brand identity. Consequently, Las Vegas competes in a broader leisure and entertainment market that includes multi-day vacations with and without gaming. Consumers in this market are willing to commit to extended stays and incur substantial travel expenses. By contrast, Atlantic City has competed primarily for daily and weekend visitors who, on average, incur low to moderate travel expenses.

In a related study, Hunsaker (2001) examined the impact of new riverboat casinos in the Midwest and South on the demand for gaming in both Las Vegas and Atlantic City. She found that under certain conditions new entrants may increase, rather than decrease, the demand at incumbent casinos. Estimates for her empirical model indicate that when a new riverboat casino opens, the demand for gaming in Las Vegas increases in the following quarter. In other words, Las Vegas and riverboat casinos have a complementary relationship. A complementary relationship between casinos (or clusters of casinos) may arise when the geographic market of a new entrant lies within a broader regional or national market but does not contain any competing casinos. In this case, the new casino provides gaming access to a population of potential consumers who have never tried gaming before. Some of these potential consumers have never experienced gaming because of the monetary and time costs associated with a visit to Las Vegas. Given the proximity of the new casino, these first-time consumers will try gaming and may even discover they enjoy it. Ultimately, some will decide to take their next vacation at a casino resort in Las Vegas. Throughout this process, the new casino is recruiting new consumers, thereby increasing the demand for gaming at incumbent casinos.

Hunsaker’s results do not find a similar relationship between riverboat casinos and the casinos in Atlantic City. This suggests that the geographic markets for these two gaming locations do not overlap and, consequently, that changes in one market do not impact the demand in the other market. In summary, Hunsaker's findings suggest that a new entrant will not diminish the demand for the incumbent if a) the geographic market of the entrant does not overlap that of the incumbent, or b) the geographic markets overlap, but any reallocation of prior demand is offset by the number of new consumers recruited for the incumbent.

Proximity plays an important role in a new casino's ability to generate new demand and reallocate prior demand. A new casino can generate new demand by either attracting new consumers or increasing the frequency of visits among existing consumers. If the new casino is able to reduce consumers' travel costs by providing a more accessible gaming venue (i.e. by means of proximity), then an increase in both the number of consumers and the frequency with which they visit is expected to follow. Similarly, proximity can lead to a reallocation of demand if existing consumers forego visits to an established casino in favor of a newer casino that is more conveniently located. This can happen even in cases where the incumbent casino is superior in terms of all other measures of quality. In short, casinos with a geographic advantage need not compete as vigorously on other aspects of quality.

Given that the arrival of casinos in Atlantic City had a negative impact on gaming demand in Las Vegas while the new riverboat casinos on the Mississippi River did not (Shonkwiler (1993) and Hunsaker (2001)) one can make two inferences. First, the number of consumers that the riverboat casinos gained through a reallocation of demand was small relative to the number of consumers that they attracted who were new to gaming, whereas the reverse was probably true for the Atlantic City casinos. Second, the riverboat casinos had fewer characteristics in common with the casinos in Las Vegas than did the casinos in Atlantic City. Otherwise consumers who had had their first gaming experience at a riverboat casino would have continued playing at riverboat casinos, rather than subsequently deciding to vacation in Las Vegas. Recall that an entrant and incumbent casino establish a complementary relationship through an indirect, implicit recruitment process. The initial phase of the process requires that the entrant attract new consumers into their casino. The incumbent can then attract these new consumers to its own casino for subsequent gaming vacations. The more similar the entrant casino is to the incumbent casino, the less likely the indirect, implicit transfer of new consumers will take place. In this case the entrant would be more of a substitute than a complement for the incumbent casino.

Of the three groups of casinos described thus far, riverboat casinos and Las Vegas casinos have the fewest traits in common. This is also the pair that demonstrates the strongest complementary relationship. Recall that riverboat casinos are often stand-alone facilities with few, or no, neighboring gaming establishments, whereas the Las Vegas casinos represent the highest concentration of casinos and related attractions in the United States. On the contrary, the two groups having the most traits in common would be the Las Vegas and Atlantic City casinos. It is their similarities which make each such a good substitute for the other and, consequently, lead to the observed post-entry reallocation of demand for gaming.

In another related study, Przybylski and Littlepage (1997) investigate the impact on existing casinos resulting from new casinos that open in a neighboring city. They summarize their findings as follows: “In estimating the model, it was found that casino gaming falls between the two extreme cases of having a fixed demand and completely creating its own demand. Each new casino will both increase the total demand for casino gaming in the region and reallocate consumers between the existing and new casinos." These observations are consistent with the conclusions of Shonkwiler (1993) and Hunsaker (2001).

In this study the proximity of the entrants and incumbents creates significant overlap in their respective geographic markets. This means that the potential for recruiting new consumers is low because the new casino has not significantly lowered the transportation costs of consumers in that geographic market. In the absence of new consumers, an increase in overall demand results almost entirely from an increase in the frequency with which consumers visit a casino. According to the authors, "simulations in this study found the ratio [of trips to population] to drop rapidly with distance." For example, a consumer who previously visited an incumbent casino once per month may decide to visit the entrant four times per month, no longer making the usual trip to the incumbent casino. Because entrants and incumbents in this study are so similar in terms of most characteristics, proximity is the trait by which entering casino distinguishes itself. As a result, this casino will benefit from a combination of new demand resulting from an increase in the frequency with which existing consumers visit that casino as well as a portion of the existing demand previously belonging to the incumbent.

Together these studies suggest a means by which the casinos in Atlantic City might maintain, even increase, their consumer base in the face of several new casinos arriving in the Northeast. Their success will depend on their ability to attract repeat visits from consumers who may choose to make regular visits to one or more of the new casinos because of their more convenient location. By providing consumers with everything these new casinos have to offer and more, casinos in Atlantic City will benefit from a complementary relationship with these new casinos and be able to attract new and old consumers alike for weekend, vacation and holiday visits.

1.2 Relating the Literature to the Atlantic City Casino Industry

Since 1990, several states adjoining New Jersey have legalized gaming. Two large casinos opened in Connecticut, three racinos opened in Delaware, video lottery terminals (VLTs) became available in New York, and over 60,000 slot machines have been approved for racetracks and other locations in Pennsylvania.[4] A list of entrants and the corresponding number of slot machines is provided in Table 1. Previous market studies have provided insights into the type of competition that casinos in Atlantic City can expect to face from these entrants. In short, the portion of Atlantic City's geographic market that does not overlap with any other casino is becoming smaller, even as the number of consumers in its wider geographic market grows.

The casinos in Atlantic City have several advantages that will allow them to remain competitive with new casinos in the Northeast: an ocean-side location, a large inventory of hotel rooms, a greater variety of gaming options including table games, and an increasing number of non-gaming alternatives such as entertainment, shopping and restaurants. These will be essential to their long-term success. By contrast, the new

[4] New York approved VLTs at racetracks on October 24, 2001 although the first machines didn't begin operating there until January 2004. The licenses for state-wide casinos (other than racetracks) in Pennsylvania were awarded in December, 2006.

competitors will not be allowed to offer table games and they will not enjoy the advantages of scale that casinos in Atlantic City have.

Table 1. Gaming Entrants in Delaware, Connecticut and New York: 1990-2004

Casino/Racino	State	Type	Number of Slot Machines[a]	Entry Date
Foxwoods	CT	Casino	7,451	January 1993
Delaware Park	DE	Racino	2,500	December 1995
Dover Downs	DE	Racino	2,500	December 1995
Harrington Raceway's Midway Slots	DE	Racino	1,435	August 1996
Mohegan Sun	CT	Casino	6,254	October 1996
Saratoga Raceway	NY	Racino	1,324	January 2004
Finger Lakes	NY	Racino	1,010	February 2004
Fairgrounds (Buffalo)	NY	Racino	990	March 2004
Monticello	NY	Racino	1,744	June 2004

[a] As of December 2004 for Delaware and Connecticut; August 2004 for New York.

Certain consumers won't be sensitive to the qualities that distinguish Atlantic City casinos from their competition. This group includes consumers who make frequent or midweek visits and consumers who prefer slots to table games. These consumers are likely to make shorter visits and engage in fewer non-gaming diversions. As a result, they are likely to be more sensitive to the monetary and time expense associated with travel and more sensitive to slot win percentages as well as cash and food awards. On the other hand, they are likely to be less sensitive to free rooms and the availability of non-gaming entertainment alternatives. The degree to which the casinos in Atlantic City depend on these daily visitors for their gaming revenues will determine how vulnerable they will be to entering competition.

By contrast, the weekend visitor compares the cost of travel to a casino in Atlantic City to the cost of travel to alternative weekend destinations. These visitors have a different perspective on the time and expense required to travel to their preferred vacation destination. The casinos in Atlantic City are responding to this reality by undertaking a number of costly upgrades that will provide visitors with a wider range of entertainment and amenities suited for weekend and multi-day vacations. The casinos in Atlantic City will be able to successfully differentiate themselves from the competition as long as their consumer base is attracted by these alternatives to slot machine gaming.

In the following sections I introduce a discrete-choice model of gaming demand, which I use to measure the impact of various product characteristics on consumer choice. In Chapter 2 I begin by describing, without estimating, a multiple-unit discrete-choice model that would be the natural approach if consumer-level data were available. In Chapter 3, I describe the methodology behind the single-unit discrete-choice model that can be estimated using the available product-level price and quantity data. This chapter includes a discussion of the relevant discrete-choice literature and a detailed description of the model. Chapter 4 contains a review of the data used in the estimation and Chapter 5 provides a summary of estimation results and main conclusions regarding the best practices for casinos competing for market share in the gaming market of the Northeast. Finally, Chapter 6 suggests possible alternatives for estimating the model and for extensions to the model.

Chapter 2: A Preliminary Multiple-Unit Discrete-Choice Model

A pull on the handle of a slot machine is a type of lottery. But the total gaming experience, even for consumers who prefer slots over all other games, cannot be described as simply a series of little lotteries. The casino choice problem faced by a typical consumer at a casino destination such as Atlantic City depends on a larger set of factors. In this chapter I begin by introducing the basic concepts behind the slot lottery. I then incorporate elements of the lottery into a multiple-unit discrete-choice model based on Allenby et al (2004) in which the consumer solves a two-step utility maximization problem subject to a budget constraint. If consumer-level data were available, this model would be estimated using maximum likelihood techniques. In the following chapter I present an alternative discrete-choice model which I estimate using the product-level price and quantity data that are publicly available.

2.1 The Lottery

The utility that a consumer derives from purchasing a lottery has been extensively debated in the economics literature. These debates center around three main issues: 1) the proper expression of expected utility, 2) the proper expression of the utility of money, and 3) the entertainment value of participating in a lottery. With respect to the first, I assume von Neumann-Morganstern expected utility, which has the following representation: [5]

[5] There are many alternatives to expected utility theory including prospect theory, rank-dependent expected utility theory and weighted utility theory. I omit a discussion of these here because it would not advance the

$$E[U(x)] = \sum_{i=1}^{n} p_i U(x_i) .$$

where x_i is the payout received with probability p_i for $i = 1,\ldots,n$.

Within this framework of expected utility, Friedman and Savage (1948) pioneered early efforts to find a representation of the utility of money that was consistent with the observation that some consumers both purchase insurance and gamble. At the time, it was standard to assume that utility functions were concave in income, implying that consumers were everywhere risk averse. This was consistent with the prevailing belief in the diminishing marginal utility of money. By contrast, the utility function introduced by Friedman and Savage included an inflection point which made it concave at low levels of income and convex at higher levels of income. The result was a representation of utility in which low-income consumers, with an initial income near the inflection point, were viewed as simultaneously risk averse and risk loving. In a modified version of this function, Friedman and Savage added a second inflection point and a concave segment to the right of the convex portion of the function in order to account for risk-averse behavior observed among the very rich.

Critics of this approach pointed out that changes in initial wealth could correspond to radical changes in behavior (Machina, 2001). Markowitz (1952) showed how this phenomenon could be avoided by assuming that initial wealth is customary wealth, or status quo, regardless of level and by ignoring windfall gains. He implemented this change by shifting the entire utility function down and to the left so that the first inflection point lies at the origin, and he proposed that units measured on the x-axis be

purpose of this section, which is to identify those aspects of the slot lottery that influence the consumer's perception of quality.

considered changes in income rather than income levels. As a result, the y-axis becomes a measure of changes in utility corresponding to changes in an individual's customary level of wealth. Utilities to the left of the origin correspond to monetary losses, and utilities to the right of the origin correspond to monetary gains. I denote Markowitz utility, which is normalized for each consumer and each income, as $\hat{U}$ such that $\hat{U}(0)=0$.

Markowitz (1952) also assumes that people generally avoid symmetric bets, i.e.

$$\left|\hat{U}(-x)\right| > \hat{U}(x), \quad x > 0,$$

where x is now the observed change in income. This representation of utility is consistent with purchases of fair or slightly unfair insurance and fair or slightly unfair lotteries. Moreover, it applies to both rich and poor consumers, except that the definitions of large and small losses and payouts change accordingly.

It would now be a straightforward exercise to write an expression for the expected utility associated with participating in a basic two-outcome lottery. Before generalizing this to slot gaming, however, it is important to address a few of the differences that distinguish the type of lottery that a consumer encounters at a slot machine from the type they encounter when buying a ticket from a traditional state lottery. First, the top payout at a slot machine tends to be considerably smaller than payouts awarded by large state lotteries.[6] Second, consumers tend to purchase many more slot pulls than lottery tickets.

---

[6] An exception to this would be payouts from progressive slot machines. These payouts tend to be relatively large because jackpots are formed by pooling a portion of the total dollars wagered across multiple machines and, sometimes, across multiple casinos.

And third, a slot lottery can typically result in several different outcomes whereas a traditional lottery typically results in just two.

In practice, consumers never actually compute the true expected utility. Instead, they are likely to attempt an estimate based on the information that is available. Although the possibility of multiple outcomes complicates this task, I will show that by employing a few basic rules and simplifying assumptions, the expected utility problem faced by a consumer playing slots can be transformed into a problem similar to the one faced by a consumer purchasing a standard, two-outcome lottery ticket.

To start, suppose that the typical consumer always reinvests small payouts and retains large ones. Small payouts, once reinvested, are then re-classified by the consumer as non-payouts, even though each one reduces the overall effective price of a slot pull. By classifying payouts into two groups (large and small), the consumer can begin to view the slot lottery as a basic, two-outcome lottery. Assuming small payouts are relatively frequent, a consumer playing 1-dollar slots with an initial gaming budget of \$20 will likely have the opportunity to purchase more than the 20 pulls that their initial budget would have allowed, extending both playing time and the number of opportunities to win a large payout. Note that the true lottery is a *simple lottery*.

Definition. A *simple lottery* is a vector $L = \left(r_0, ..., r_N\right)$ with $r_n \geq 0$ for all n and $\sum_{n=0}^{N} r_n = 1$, where r_n is interpreted as the probability of outcome n occurring.

Suppose further that we can distinguish between the small, frequent payouts corresponding to outcomes $0, ..., m$ (including a zero payout) and the top payouts corresponding to outcomes $m+1,...,N$. We can then construct a *compound lottery* having just two compound outcomes rather than several simple outcomes.

Definition. Given K simple lotteries $L_k = (r_0^k,...,r_N^k)$, $k=1,...,K$, and probabilities $\lambda_k \geq 0$ with $\sum_{k=1}^{K} \lambda_k = 1$, the *compound lottery* $(L_1,...,L_K;\lambda_1,...,\lambda_K)$ is the risky alternative that yields the simple lottery L_k with probability λ_k for $k=1,...,K$. The probability of outcome n in the reduced lottery is $r_n = \lambda_1 r_n^1 + ... + \lambda_K r_n^K$.

The compound lottery faced by the consumer with each pull of the slot handle comprises two simple lotteries:

$$1-\lambda \qquad L_1 = \left(r_0^1, r_1^1, ..., r_m^1, 0, ..., 0\right)$$

$$\lambda \qquad L_2 = \left(0, ..., 0, r_{m+1}^2, r_{m+2}^2, ..., r_N^2\right)$$

where L_2 is a lottery over large payouts that occurs with probability $\lambda = r_{m+1} + ... + r_N$; and L_1 is a lottery over small payouts that occurs with probability $1-\lambda = r_1 + ... + r_m$. Note that the lotteries L_1 and L_2 are each well-defined lotteries such that $\sum_{i=0}^{m} r_i^1 = 1$ and $\sum_{i=m+1}^{N} r_i^2 = 1$, i.e.

$$r_i^1 = r_i \big/ \left(r_0 + r_1 + ... + r_m\right) \qquad \text{for } i \leq m$$

and

$$r_i^2 = r_i \big/ \left(r_{m+1} + r_{m+2} + ... + r_N\right) \qquad \text{for } i > m.$$

It follows that the expected value associated with a slot pull can be expressed as

$$D\left[-1+(1-\lambda)\left(r_0^1 z_0 + r_1^1 z_1 + \ldots + r_m^1 z_m\right) + \lambda\left(r_{m+1}^2 z_{m+1} + r_{m+2}^2 z_{m+2} + \ldots + r_N^2 z_N\right)\right]$$

where the denomination D is the face value of the slot coin; -1 represents the coin wagered; and $z_0,\ldots z_N$ are the possible payouts expressed in number of coins. Distributing -1 across both small and large outcomes we can rewrite this expression as

$$(1-\lambda)\cdot D\cdot\left[\left(r_0^1 z_0 + r_1^1 z_1 + \ldots + r_m^1 z_m\right)-1\right] + \lambda\cdot D\cdot\left[\left(r_{m+1}^2 z_{m+1} + r_{m+2}^2 z_{m+2} + \ldots + r_N^2 z_N\right)-1\right]$$

$$= (1-\lambda)\left(-p^e\right) + \lambda\cdot D\cdot\left(z^* - 1\right). \qquad (1)$$

From Equation 1, $p^e = -D\cdot\left[\left(r_0^1 z_0 + r_1^1 z_1 + \ldots + r_m^1 z_m\right)-1\right]$ is the effective price for a single pull on a slot machine or, equivalently, the face value of the slot coin adjusted for the expected value of small payouts. The term $z^* = r_{m+1}^2 z_{m+1} + r_{m+2}^2 z_{m+2} + \ldots + r_N^2 z_N$ is the expected value of the large payouts, given that a large payout occurs. In general, there is an inverse relationship between the size of the payout and its probability of occurring such that if the relationship between the probabilities is $r_0 > r_1 > \ldots > r_N$ then the relationship between payouts is typically $z_0 < z_1 < \ldots < z_N$.

In practice, a good approximation of the effective price is the consumer's initial gaming budget divided by the total number of slot pulls made: $y/pulls$. The effective price is an important concept in slot gaming because it represents the true price of participating in the same lottery repeatedly, as is the case with slot machine gaming. The effective price captures how consumers adjust their gaming budgets by reinvesting small payouts in order to extend their playing time and increase their opportunities for winning a big payout. It differs from more familiar indicators of price, such as casino win (CW), in that it ignores large payouts which most consumers either do not win or do not factor into their gaming budgets. Depending on which payouts the consumer chooses to reinvest, the effective price can reach a maximum value of D, which is the value of the coin itself, and a theoretical minimum of $CW \cdot D$, which is -1 times the expected value of the lottery. Note that casino win is the portion of each dollar wagered that is not redistributed to consumers in the form of payouts. In other words, it is the percentage of all wagers that the casino keeps.

In cases where the consumer chooses not to reinvest any payouts, the effective price will achieve its maximum, D:

$$p^e = -D \cdot \left(r_0^1 z_0 - 1\right) = -D(0-1) = D\ .$$

Alternatively, in cases where the consumer chooses to reinvest *all* payouts, the effective price will approach its theoretical minimum, $CW \cdot D$:

$$p^e = -D \cdot \left[\left(r_0^1 z_0 + r_1^1 z_1 + ... + r_N^1 z_N\right) - 1\right] = -D \cdot \left[\left(1 - CW\right) - 1\right] = CW \cdot D\ .$$

Recognizing that the expected value of a slot pull, as shown in Equation (1), is equal to minus casino win times the face value of the slot coin, a general expression for p^e can be written as

$$p^e = \frac{D}{1-\lambda}\left[CW + \lambda\left(z^* - 1\right)\right].$$

This expression provides insight into the consumer's decision-making process by revealing two facts: first, that p^e is increasing λ; and second, that λ (and consequently p^e) depends on the consumer's preferences with respect to which payouts are reinvested and which payouts are retained. A consumer who reinvests all payouts except the top prize will have a λ very close to 0 and an effective price that, in theory, is only slightly larger than $CW \cdot D$. Alternatively, a consumer who prefers to retain slot payouts more frequently will raise the effective price per pull while simultaneously decreasing the total expected playing time.[7] The benefit of this second strategy is that it also increases the probability of leaving the casino with some prize money.

Ultimately, the effective price cannot be observed, even with micro data, because the cutoff point m that defines which payouts are reinvested and which are retained is not observed. If, however, the value of λ, which reflects this cut-off, is similar across consumers, it may not be necessary to address this cutoff specifically within a demand model. Instead we can focus on other elements of the slot lottery that would influence the demand for slot gaming, and which would be included in the model as product characteristics explaining product quality. From Equation (1), we find that this set of factors includes the casino win CW, the denomination D, and the expected value of the large payout z^*. Components of z^* include the unobserved payout cutoff point m as well as the payouts z_n and their probabilities r_n^2. Note that payouts and probabilities are determinants of price that are easy to observe because payout tables listing their values are available at every slot machine. Because they can be easily compared from one machine to the next, these values are more likely to be stable across casinos and denominations than are other determinants of price. As a result, they are likely to lack sufficient variation to contribute meaningfully to the model. That leaves only D and CW. The denomination D could easily be incorporated into a demand model as either a

[7] Note that effective price computations are only estimates. Casino win percentages vary even between slot machines at the same casino and between slot machines with the same denomination. Kilby and Fox (1998), p. 117, point out that after 1,000 pulls, a slot machine with a theoretical return of 85.495% could reasonably be expected to have returned between 54.11% and 116.88%.

fixed-effect term for denomination or as a single independent variable indicating the dollar value of the denomination. After adjusting for unit size, the casino win CW could enter a demand model as the price.

2.2 The Entertainment Value of Playing Slot Machines

In any model of slot demand it is important to acknowledge that the utility consumers derive from playing slots cannot be explained by the expected value of the lottery alone. Using von Neumann-Morganstern expected utility and the representation of the utility of money proposed by Markowitz, an expression for the expected marginal utility that a consumer would derive from participating in a slot lottery can be written as

$$\hat{U}\left[(1-\lambda)\left(-p^{e}\right)+\lambda\cdot\left(Dz^{*}-D\right)\right] \;=\; (1-\lambda)\hat{U}\left(-p^{e}\right)+\lambda\cdot\hat{U}\left(Dz^{*}-D\right).$$

According to this formula, a consumer would prefer wagering \$1 at a dollar-slot machine, for a total of 1 pull, to wagering \$1 at a nickel-slot machine, for a total of 20 pulls. This can be attributed to the fact that, all else equal, a higher casino win for nickel slots makes the effective price per dollar wagered less favorable for nickel slots than for dollar slots. Based on the current popularity of low denomination slot machines in Atlantic City, this conclusion seems at odds with reality. The missing factor is what Walker (1998) and Conlisk (1993) refer to as “the thrill of the gamble”, or the entertainment value of playing slot machines.

Suppose a consumer experiences a fixed amount of entertainment value T with each pull of the slot machine. Then a consumer who wagers \$1 at a nickel-slot machine will derive $20T$ units of entertainment value, whereas a consumer who wagers \$1 on a dollar-slot machine will derive just T units of entertainment value. Given a sufficiently large T, it is easy to see that the marginal utility derived from 20 pulls, or $1 wagered, on a nickel-slot machine could surpass 1 pull, or $1 wagered, on a dollar-slot machine. To estimate the impact that this entertainment value per pull has on demand, it is sufficient to include a variable in the demand model equal to $1/D$ (i.e. the number of pulls a consumer makes per dollar wagered), where the denomination D is the face value of the slot coin.

2.3 The Choice Problem

Slot machines in Atlantic City can be identified according to the casino in which the machine is located as well as the denomination. The slot denomination specifies the face value of the coin that must be deposited into the machine in order to make a bet. Traditionally, a pull of the slot handle is the action that initiates the spinning of the slot reels, whose final position determines the player's payoff. However, changes in technology have enabled consumers to perform this action, which I refer to as a pull, with the press of a button or touch of the display screen.

When consumers consider their choices with respect to slot gaming, they do so with respect to both the casino and the denomination. However, rather than treat the entire set of unique casino-denomination pairs (c,d) as distinct choice alternatives, I construct a casino-choice model of slot demand in which denominations are treated as different package sizes, each associated with a different price per unit. This approach parallels that of Allenby et al (2004) who estimated the demand for light beer controlling for package size as well as prices that vary according to the quantities purchased.

The demand for slot machines fits nicely into this framework because the concept of slot denominations can easily be extended to that of package sizes. Notice, for example, how the product available at nickel slot machines comes in very small packages of 5 cents per pull (or "pack") while the product available at 50-cent slot machines comes in somewhat larger packages of 50 cents per pull. In order to purchase one unit of slot gaming, which I define as $1 wagered, a consumer must buy 20 pulls at the nickel-slot machine, but only two pulls at the 50-cent slot machine.

In general, the payout rate for small denominations is lower than for large denominations, which means the effective price per dollar wagered at a nickel slot mechanism tends to be higher than the effective price per dollar wagered at a 1-dollar slot machine. In other words, casinos offer quantity discounts by setting lower prices for slot wagers that come in larger pack sizes. Note that because prices are non-linear with respect to quantity, solutions cannot be based on first-order conditions. In particular, non-linear pricing introduces non-linear budget constraints which can fail to produce a solution under first-order conditions if, for example, the utility maximizing value does not occur at a point of tangency, or if the result is a utility minimizing, rather than maximizing, solution. To avoid this problem, the proposed random utility choice model could be solved using maximum likelihood methods.

Towards defining the consumer's choice problem, let y be the budget allotment each consumer will have to spend in Atlantic City. A portion of this budget will be spent on τ^s slot machine units (where 1 unit = 1 dollar wagered) while the remainder will be spent on τ^a units of the numeraire, or outside good, which can be applied toward a variety of non-slot casino activities such as dining, shopping or playing table games.[8] The

[8] The most popular games in Atlantic City are slots. In 2004, slot gaming accounted for approximately 85% of gross gaming revenues in Atlantic City. Gross gaming revenues are computed as total table game and

following Cobb-Douglas utility function describes the trade-off in expenditure between the set of slot products and the outside (or alternative) good:

$$\ln u(\tau^s, \tau^a) = \alpha_0 + \alpha_s \ln u(\tau^s) + \alpha_a \ln(\tau^a) .$$

Here $\tau^s = \left(\tau_1^s, ..., \tau_C^s\right)$ is the vector of total dollars wagered on slots at each casino, τ^a is the corresponding amount of the outside good purchased, and $u(\tau^s)$ is a subutility function that describes the tradeoff between slots at one casino versus another.

Allenby et al (2004) proposed a nonhomothetic subutility function which can be expressed as

$$u(\tau^s) = \sum_{c=1}^{C} \psi_c\left(\bar{u}\right)\tau_c^s$$

$$\ln \psi_c\left(\bar{u}\right) = \phi_c - Q_c \bar{u}\left(\tau^s, \tau^a\right) + \varepsilon_c$$

where $\bar{u}$ is the deterministic and implicitly defined part of marginal utility, Q_c and ϕ_c are vectors of product characteristics, and ε_c is a casino-level stochastic element. This particular subutility function has two advantages. First, it results in linear indifference curves, which implies that the utility maximizing solution will have non-zero consumption for just one brand, casino in this case. Second, for strictly positive Q_c, the resulting linear indifference curves will fan out, but not overlap. In other words, as the attainable level of utility increases the marginal utility of some brands will increase while the marginal utility of others decreases. Therefore, as the budget constraint shifts outward consumers will switch from lower quality brands to higher quality brands (Allenby,

---

simulcast drop, excluding poker, plus slot handle. Harrah's 2004 Report states that three quarters of casino gamblers play slots, "America's favorite casino game."

1991). By contrast a simple linear utility would imply that the optimal quantity for each brand depends only on price, and not on quality.

2.4 Nonhomothetic Subutility

A nonhomothetic subutility function is ideally suited for slot demand because there are many casino characteristics that can only be appreciated at higher levels of total utility. Suppose, for example, that a consumer has a modest budget of $25 dollars to spend on slot machines and other casino activities. With only $25, this consumer is limited in the number of options available since dinner at a restaurant, a shopping excursion, or even drinks at a bar can easily exceed a budget of $25. An afternoon playing nickel slots, however, would be entirely feasible. Consequently, that consumer is likely to disregard many of a casino's non-slot qualities, such as entertainment acts and restaurants, when choosing where to play nickel slot machines. By contrast, that same consumer might make an entirely different decision regarding where to play slot machines if their budget allowed for playing slot machines and having dinner at an expensive restaurant.

The terms ϕ_c and Q_c, from the subutility function, jointly define the quality of slots at casino c. The term, ϕ_c, is a linear combination of product characteristics, each of which impacts the likelihood of choosing casino c over all other casinos. Product characteristics that could reasonably enter the model through ϕ_c include variables that contribute to the overall gaming atmosphere, such as the number of slot machines and total casino floor space. The term, Q_c, is a function of a linear combination of product characteristics, each of which influences the quantity of dollars wagered on slots at casino

c. Recall that Q_c must be strictly positive in order to obtain indifference curves with the desired properties. Once satisfied, $Q_i < Q_j$ implies that brand *i* is relatively superior to brand *j*. Allenby et al (2001) restrict Q_c to be positive by estimating $Q_c^* = \ln Q_c$ with Q_c^* unrestricted and setting Q^* of the reference casino equal to 0. Therefore, Q_c can be expressed as

$$Q_c \;=\; \exp\left(Q_{0c} + \beta_A\left(charA\right) + \beta_B\left(charB\right) + \ldots\right)$$

where $Q_c^* = Q_{0c} + \beta_A\left(charA\right) + \beta_B\left(charB\right) + \ldots$; Q_{0c} is a constant measuring the quality of casino c relative to the reference casino; and $charA$, $charB$ are other determinants of quality that are believed to influence the optimal quantity of dollars wagered at casino c.

There are three slot characteristics that are particularly well suited for the Q_c term. The first is denomination, which could be captured by a denomination dummy or a pulls-per-dollar variable. Total dollars wagered may be sensitive to slot denomination simply because people who spend more money playing slot machines do not necessarily want to spend more time playing slot machines. Consequently, larger expenditures on slot machines may be associated with larger denominations, which require fewer pulls-per-dollar wagered and, therefore, take less time. The other two characteristics that are well suited for the Q_c term are the dollar value and frequency of casino complimentaries. Complimentaries are defined as free goods that the casino awards to consumers based on their gaming history at that casino. The optimal expenditures on slot machines may be influenced by a casino's policies regarding how players are rewarded based on total amount wagered.

Note that some casino-level characteristics may simultaneously describe a casino's slot product as well as the outside good, which could influence the proper interpretation of the corresponding coefficient estimates. To see, consider a consumer who finishes playing quarter slots at the Borgata then continues to spend the remainder of their budget on dining, shopping and playing table games at the Borgata. While certain product characteristics specific to the Borgata may have initially attracted this consumer into the casino to play slots, these same characteristics could have ultimately diverted the consumer's attention toward other activities, which limited the total number of slot units that the consumer purchased.

Examples of this type of characteristics might include the number of shows featuring popular entertainment acts or the number of restaurants featuring star chefs. These characteristics could feasibly impact both the number of units purchased and the choice of casino. However, estimated coefficients for these characteristics are more likely to agree with prior expectations if they are allowed to enter the model through ϕ_c rather than through Q_c. Otherwise, if the relationship between the inside and outside good is strong and the characteristics enter through Q_c, then it is possible that negative coefficients will appear on parameters which, a priori, were expected to have a positive impact on demand. To determine the optimal role for these characteristics, it is recommended that multiple specifications be tested and that care is taken when interpreting the results.

2.5 Two-Step Utility Maximization

Consumers will maximize their utility such that the combined expenditures on all slot products plus other casino activities exactly equals their budget allotment, i.e.

$$\sum_{c=1}^{C} p_c\left(\tau_c^s\right)+\tau^a = y\,,$$

where

$$p_c\left(\tau_c^s\right)=\sum_{d=1}^{D} CW_{cd}\cdot\tau_{cd}^s\,.$$

Recall that casino win CW_{cd} is the portion of total dollars wagered on denomination d that are retained by casino c, for $d=1,\ldots,D$. It follows that $p_c\left(\tau_c^s\right)$ is the total price for wagering τ_c^s dollars on slot machines at casino c. Allenby et al (2004) proved that the consumer's utility maximization problem as described here has a corner solution. Therefore, consumers would ultimately choose only one variant of the good, which they would consume in variable amounts. When only one element of τ^s is nonzero, the consumer solves the choice problem by maximizing utility over all possible combinations of slot denominations $\bar{d}$:

$$\underset{\bar{d}}{Max}\left\{\alpha_0+\alpha_s\ln\left(\psi_c\left(\bar{u}\right)\tau_{c\bar{d}}^s\right)+\alpha_a\ln\left(y-p_c\left(\tau_{c\bar{d}}^s\right)\right)\right\}$$

$$=\underset{\bar{d}}{Max}\left\{\alpha_s\ln\psi_c\left(\bar{u}\right)+\alpha_s\ln\tau_{c\bar{d}}^s+\alpha_a\ln\left(y-p_c\left(\tau_{c\bar{d}}^s\right)\right)\right\}.$$

The solution to this problem is a two-step procedure. The first step is to identify the optimal quantity $\hat{\tau}_c^s$ for each casino separately. Maximization is done over all possible combinations of slot denominations $\bar{d}$. The second step is to determine the probability that casino c is chosen. This process can be expressed as

$$\underset{c,\bar{d}}{Max}\left\{\ln u\left(\tau^{s}_{c\bar{d}}, y - p_c\left(\tau^{s}_{c\bar{d}}\right)\right)\right\}$$

$$= \underset{c}{Max}\left[\underset{\bar{d}|c}{Max}\left\{\ln u\left(\tau^{s}_{c\bar{d}}, y - p_c\left(\tau^{s}_{c\bar{d}}\right)\right)\right\}\right]$$

$$= \underset{c}{Max}\left[\alpha_0 + \alpha_s \ln u\left(\hat{\tau}^{s}_{c}\right) + \alpha_a \ln\left(y - p_c\left(\hat{\tau}^{s}_{c}\right)\right)\right]$$

$$= \underset{c}{Max}\left[\alpha_0 + \alpha_s\left(\phi_c - Q_c\bar{u}^{c} + \varepsilon_c\right) + \alpha_s \ln\left(\hat{\tau}^{s}_{c}\right) + \alpha_a \ln\left(y - p_c\left(\hat{\tau}^{s}_{c}\right)\right)\right]$$

where $\hat{\tau}^{s}_{c}$ is the optimal quantity for product c from step 1, and $\varepsilon_c \sim EV(0,1)$. The casino-level error term ε_c gives rise to the following expression for the choice probabilities:

$$\Pr(\tau^{s}_{i}) = \frac{\exp\left[\phi_i - Q_i\bar{u}^{i} + \ln\left(\tau^{s}_{i}\right) + \left(\alpha_a/\alpha_s\right)\ln\left(y - p_i\left(\tau^{s}_{i}\right)\right)\right]}{\sum_{c=1}^{C}\exp\left[\phi_c - Q_c\bar{u}^{c} + \ln\left(\tau^{s}_{c}\right) + \left(\alpha_a/\alpha_s\right)\ln\left(y - p_c\left(\tau^{s}_{c}\right)\right)\right]}$$

where $\bar{u}^{i}$ solves the equation: $\ln\bar{u}^{i} = \phi_i - Q_i\bar{u}^{i} + \ln\left(\hat{\tau}^{s}_{i}\right) + \left(\alpha_a/\alpha_s\right)\ln\left(y - p_i\left(\hat{\tau}^{s}_{i}\right)\right)$.

Parameter estimates for this model, including the value of $\bar{u}^{i}$, can be obtained by using maximum likelihood techniques. Allenby et al (2004) use a Markov chain monte carlo procedure, which generates draws of parameter values from a multivariate normal distribution.

2.6 Conclusion

If micro data were available, this model would have several advantages over the discrete-choice model that is described and estimated in the next chapter. First, this model naturally imposes a logical nested structure on an otherwise large set of choice alternatives. Second, the estimates from this model would provide more information with less potential for bias because it is a multiple-unit discrete-choice model as opposed to a single-unit discrete-choice model. As such, market shares would be expressed both in terms of the number of consumers who choose casino c and in terms of the total dollars wagered on slot machines at casino c. And finally, by estimating the impact of certain product characteristics on quantities demanded, this model would implicitly estimate the impact that these characteristics have on the amount of time consumers spend inside the casino. This follows from the fact that dollars wagered can easily be converted into time using denomination to find the number of pulls per dollar wagered and assuming an average number of pulls per hour.[9]

[9] Gaming columnist John Grochowski uses an estimate of 500 pulls per hour in an article taken from the website: http://info.detnews.com/casino/newdetails.cfm?column=grochowski&myrec=294 dated September 15, 2005, and accessed June 16, 2007.

Chapter 3: Methodology for the Estimated Discrete-Choice Model

The Atlantic City hotel and casino industry is a differentiated products oligopoly consisting of six firms operating a total of twelve casino hotels. The structure of the industry is determined, in part, by the enabling legislation and regulatory policies of the New Jersey Casino Control Commission. For example, legislation restricts casino gaming to particular areas within Atlantic City, places a maximum on casino win percentage from slot machines, and regulates the maximum allowable floor space per casino.[10] That aside, it is the nature of competition and demand that has been the primary determinant of the evolution of the gaming market since the introduction of casinos into Atlantic City in 1978.

To estimate demand, I employ a logit-based discrete-choice model for differentiated product markets as described in Berry (1994), Berry, Levinson, and Pakes (BLP) (1995) and Nevo (2000 and 2001). This model has three main benefits. First, it allows for the use of instrumental variables, which are needed to address the fact that prices may be endogenously determined by price-setting firms. Second, it requires only firm-level price and quantity data for estimating the consumer's indirect utility equation. And third, the model is flexible enough to allow the coefficients to vary according to consumer characteristics. These characteristics can enter the model either parametrically by making assumptions about the distribution of the characteristics, or non-parametrically if population data are available.

[10] Slot payout: NJSA 5:12-83(c), NJAC 19:43-6.4(a); Floor space: NJSA 5:12-83(c), NJAC 19:43-6.4(a).

3.1 Discrete Choice and Casino Gaming

At a given casino, every possible type of wagering activity is classified according to one of eleven types of games: slots by denomination (5-cent, 25-cent, 50-cent, 1-dollar, 5-dollar, 25-dollar, 100-dollar, multi-denominational and other); table games (excluding poker); and simulcast. Denomination is defined as the face value of the coin, or minimum wager, required to spin the reel of a slot machine. For the purpose of the econometric analysis described here, the gaming product is defined as a unique casino-game pair. Assuming a maximum of 12 casinos, that means up to 131 products may be available in any given month. In other words, the set of choice alternatives includes playing nickel slots at the Showboat, dollar slots at the Atlantic City Hilton, table games at the Borgata, and so on. This particular system for defining products is convenient because price and quantity data are reported at the casino-game level. Note that in the case of slot machines there may be many different models of the same game, or denomination, that a consumer can choose from. Likewise, table games include baccarat, black jack, craps, among others.

A discrete-choice model is particularly well-suited for estimating gaming demand because it can accommodate data that are aggregated at the product level. However, it means that we must assume that consumers purchase a single unit of just one casino-game combination even though consumers are commonly observed purchasing multiple units (e.g., slot pulls) of a particular game, and they frequently purchase multiple units of multiple games. For this reason, I refer the reader to the multiple-unit choice model presented in Chapter 2 while discussing here how the single-unit constraint on the consumer's optimization problem can be applied to casino gaming in the context of a single-unit discrete-choice model.

Intuitively the notion that consumers will play just one game at just one casino over the course of their visit is restrictive, but defensible. After all, many consumers subscribe to a player rewards program, which gives them an incentive to play primarily at their preferred casino so as to maximize the rewards they earn. Moreover, consumers can play their preferred game at their preferred casino without sacrificing variety because each game may have several models, or themes, to choose from. This gives consumers a sense of variety even if they choose to play a single game.

3.2 Defining the Product Unit and Price

A unit of casino gaming could be defined in a variety of ways: as a complete visit, a wager or slot pull, or a dollar wagered. Because we are using a discrete-choice model and the working assumption is that each consumer purchases just one unit of the preferred product, I define product units on a per-visit basis, i.e. one unit is equal to the average total dollars wagered per visitor. This is equivalent to defining a unit as one dollar wagered, except that quantities have been rescaled so that a single unit represents the average total dollars wagered per visitor. Moreover, relative to a wager or slot pull, total dollars wagered is an economically more meaningful measure of quantity. As I will show later, this definition of the product unit also simplifies the relationship between the choice alternatives and the outside good, which is based on the state population of New Jersey.

Unlike a traditional discrete-choice model, if the unit is defined as a wager or dollar wagered, then the distribution of individual consumers over the product set will not necessarily correspond to the distribution of wagers, or dollars wagered, over the same product set. This is because not every consumer will make the same number of wagers or wager the same number of dollars during the course of a visit. Between the two alternatives, however, defining quantity in terms of dollars wagered, rather than total number of transactions (or wagers), will give market shares a more meaningful and intuitive interpretation with respect to the demand for gaming for both economists and casino management.

The unit price, or price per visit, is computed by multiplying the casino win percentage by the average total dollars wagered per visitor. Casino win is reported monthly at the casino-game level as a percentage equal to the total dollars retained by the casino divided by the total dollars wagered. Both price and quantity have a natural interpretation in terms of the casino terminology found in the regulatory reports of casino operations. Dollars wagered is referred to as handle for slot machines and drop for table games. The fraction of wagers retained by the casino is referred to as casino win. The difference between slot handle and casino win amounts to the total dollars returned to consumers in the form of payouts.

3.3 A Review of the Discrete-Choice Literature

The market for gaming in Atlantic City comprises a large number of distinct products. In certain periods, as many as 120 distinct products can be identified in the data. The estimation of a simple market-level demand model in which the quantities of all products are expressed as a linear combination of own and competitor prices (Stone, 1954) would require computing a prohibitively large number of parameters, even with restrictions on the cross-product relationships. The reason is that the system of equations used to estimate the model would comprise 120 equations, each with as many regressors, for a total of 14,400 parameters to estimate. Fortunately, recent developments have made it possible to estimate demand models for differentiated products by letting the aggregate discrete-choice decisions made by individual consumers depend on a set of observed and unobserved product characteristics as well as a set of consumer characteristics. These models are more parsimonious because they require only aggregate (product-level) price and quantity data.

McFadden (1974) pioneered an early version of this model when he introduced the conditional logit model to capture the discrete choice of consumers. Several improvements have followed since then. In particular, these models can now address the endogeneity of prices and relax the assumptions on the distribution of consumer attributes which determine cross-price elasticities. Berry (1994) describes the procedure for estimating discrete-choice models of differentiated products using the logit, nested logit, vertical differentiation and random coefficients models. He also uses a Monte Carlo experiment to illustrate the importance of using instruments for price. BLP (1995) employ similar techniques for their study on automobile prices, and Berry, Carnall and Spiller (1996) provide an application to airline hubs in which they assume a bi-modal distribution for consumer types.

Nevo (2000) provides a description of the mechanics of the random-coefficients discrete-choice (RCDC) model, elaborating on many of the techniques previously introduced in the related literature. He applies the model to the ready-to-eat cereal industry and illustrates the advantages of using non-parametric distributions to model consumer types. Nevo (2001) demonstrates a full application of the RCDC model to the ready-to-eat cereal industry. Finally, Davis (2001) provides an application of the model to the demand for movie theatres, focusing on geographic product differentiation and its effect on competition.

3.4 The Model

Monthly prices and quantities are observed for each game $d = 1,...,D$ at each Atlantic City casino $c = 1,...,C$ operating in month $t = 1,...,T$. Individual markets are defined across time so that each month represents a different market for gaming in Atlantic City and the product is defined as a unique casino and game combination. Observations occur at the month-casino-game level. The product $j \in (1,...,J)$ is defined as a fixed dollar-amount of wagers on a particular game at a particular casino. This dollar amount is computed monthly according to the total average dollars wagered per visitor. For convenience of notation, individual products will be referred to as j.

The consumer's utility depends on product characteristics and individual taste parameters. I assume that the conditional indirect utility that consumer i obtained from product j at time t is

$$u_{ijt} = \alpha_i (y_i - p_{jt}) + x_{jt}\tilde{\beta}_i + \tau_d + \gamma_c + \xi_{jt} + \varepsilon_{ijt},$$

where y_i is the income of consumer i, p_{jt} is the price of product j at time t, and α_i is the marginal utility of income. Observed product characteristics affecting demand are denoted by the vector x_{jt}, and the individual-specific taste coefficients are denoted by $\tilde{\beta}_i$. The specification also includes fixed effects τ_d and γ_c for the game and casino. These have the form $\tau_d = x_d \chi_d + \xi_d$ and $\gamma_c = x_c \chi_c + \xi_c$. The fixed effects capture the value of denomination-specific and casino-specific observable product characteristics, x_d and x_c, that do not vary across markets (i.e. months) as well as the mean value of the product characteristics that are unobservable to the econometrician.[11] Finally, I introduce two error terms. The first error term ξ_{jt} represents the market-specific deviation from the value $\xi_d + \xi_c$ associated with a product's time-invariant unobservable characteristics. The second error term ε_{ijt} captures the variation of consumer preferences about ξ_{jt}. I assume that market participants observe all characteristics and market decisions.

For each product characteristic h, $h = 1,...,H$, the coefficients $\tilde{\beta}_i$ can be expressed as the sum of two components:

$$\tilde{\beta}_{ih} = \beta_h + \sigma_h \zeta_{ih}$$

where β_h is the mean value of the taste parameter, and σ_h is the coefficient that allows the parameter value to vary according to the distribution of consumer characteristics ζ_{ih}. Rearranging terms of the indirect utility

$$u_{ijt} = \alpha_i y_i + x_{jt}\beta - \alpha_i p_{jt} + \tau_d + \gamma_c + \xi_{jt} + v_{ijt}$$

allows us to separate the mean valuation of the good

$$\delta_{jt} \equiv x_{jt}\beta - \alpha p_{jt} + \tau_d + \gamma_c + \xi_{jt}$$

[11] The combined number of fixed effects is fewer than if I had included a dummy for each product. This is possible because of the way in which products are defined. An example of a time-invariant characteristic would be the value of the lottery (by game) and geographic location (by casino).

from the random component

$$v_{ijt} = \left(\sum_{h=1}^{H} x_{jth} \sigma_h \zeta_{ih} \right) + \varepsilon_{ijt} .$$

This model implies that all consumers face the same observable and unobservable product characteristics. The quasi-linear utility specification is free of wealth effects. Alternatively, if one had information regarding the distribution of consumers' incomes, then one could employ a Cobb-Douglas function as BLP (1995) do to describe the utility a consumer derives from purchasing an automobile.

3.5 The Estimation Procedure

The set of individuals who choose product j in period t can be described by

$$A_{jt}\left(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \Sigma\right) = \left\{\zeta_i, \varepsilon_{i0t}, ..., \varepsilon_{iJt} \mid u_{ijt} > u_{ikt} \forall k \neq j\right\}$$

where $x_{\cdot t} = \left(x_{1t}, ..., x_{Jt}\right)$, $p_{\cdot t} = \left(p_{1t}, ..., p_{Jt}\right)$, and $\delta_{\cdot t} = \left(\delta_{1t}, ..., \delta_{Jt}\right)$ are the characteristics, prices and mean valuations for all gaming products and Σ denotes all of the non-linear parameters of the model σ_h, $h = 1, ..., H$. The vector $\left(\zeta_i, \varepsilon_{i0t}, ..., \varepsilon_{iJt}\right)$ represents individual i having characteristics ζ_i subject to product-specific shocks $\varepsilon_{i0t}, ..., \varepsilon_{iJt}$. The aggregate market share can, therefore, be expressed as the integral over the set of consumers A_{jt}:

$$s_{jt}\left(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \Sigma\right) = \int_{A_{jt}} dP^*\left(\zeta, \varepsilon\right)$$

where $P^*(.)$ is the population distribution function.

3.6 The Traditional Logit Model

Assume for simplicity that there are no interaction effects between consumer and product characteristics, i.e. $v_{ijt} = \varepsilon_{ijt}$. Then, rather than explicitly capturing consumer characteristics through population data and interacting these variables with product characteristics, we can instead model the variation across consumer preferences that is captured by ε_{ijt} as independent and identically distributed (i.i.d.) according to an extreme value distribution:

$$\Pr\left(\varepsilon_{ijt} \le \varepsilon\right) = e^{-e^{-\varepsilon}} .$$

This is the conditional logit model (McFadden, 1974) under which the share of product j at time t can be expressed as:

$$s_{jt} = \frac{e^{\delta_{jt}}}{\sum_{m=0}^{J} e^{\delta_{mt}}}$$

where the outside good $j = 0$ is the reference good. For a proof of this see Domencich and McFadden (1975). In this form, the coefficients can be estimated using a maximum likelihood procedure. However, because prices and product characteristics enter non-linearly, any endogeneity of prices cannot be addressed using standard instrumental variable techniques. By rearranging the market share equation, we can obtain a new share equation that expresses a simple function of observed market shares S_{jt} and S_{0t} as a linear combination of product characteristics:

$$\ln\left(S_{jt}\right) = \ln\left(e^{\delta_{jt}}\right) - \ln\left(\sum_{m=0}^{J} e^{\delta_{mt}}\right)$$

$$\ln\left(S_{jt}\right) - \ln\left(S_{0t}\right) = \ln\left(e^{\delta_{jt}}\right) - \ln\left(\sum_{m=0}^{J} e^{\delta_{mt}}\right) - \ln\left(\frac{1}{1+\sum_{m=1}^{J} e^{\delta_{mt}}}\right) = \delta_{jt}$$

$$\ln\left(S_{jt}\right)-\ln\left(S_{0t}\right)=\delta_{jt}=x_{jt}\beta-\alpha p_{jt}+\xi_{jt}.$$

The new linear expression can be estimated using a least squares instrumental variable method. Suppressing the time subscript t, elasticities η_{kj} can be expressed as $-\alpha_j p_j(1-s_j)$ if $j=k$ and as $\alpha_k p_k(1-s_k)$, otherwise. These formulas are derived in Appendix A.

3.7 Problems with the Traditional Logit Model

Note that according to the elasticity formulas above, the cross-price elasticity of all products $1,...,J$, where $j \neq k$, depends entirely on the price and share of product k, where the market share of k has only a small influence because the share of any one product is small relative to the outside good. Any two products will have the same cross-price elasticity with a third product whether or not the two pairs are similar in terms of their individual product characteristics and prices. In the market for casino gaming, this means that estimated elasticities will indicate that the market shares of both 25-dollar slots at the Taj Mahal and quarter slots at the Tropicana will be equally sensitive to changes in the price of nickel slots at the Tropicana. In reality, consumers are much more likely to substitute among slot games that are located within the same casino or games that accept a comparable minimum wager, i.e. games of the same denomination.

3.8 The Generalized Extreme Value (Nested Logit) Model

For differentiated product markets in which goods can be easily grouped according to a predominant characteristic, the elasticity constraint can be relaxed by allowing the consumer’s tastes to be correlated within groups of products. Recall that under the traditional logit model the consumer's indirect utility function is simply the mean valuation δ_{jt} plus an i.i.d. error term ε_{ijt} having an extreme value distribution. The nested logit model is a variation on this model that involves introducing a new term into the consumer's utility function and redefining the error term as follows:

$$u_{ijt} = \delta_{jt} + \zeta_{ig} + (1-\sigma)\varepsilon_{ijt}.$$

The new term, ζ_{ig}, is common to all products within a group g of products, and its distribution depends on σ, where $0 \le \sigma \le 1$. The value of σ, which can be estimated, determines the distribution of the group-specific component ζ_{ig} and indicates the strength of within-group correlation among products. The closer σ is to 1, the stronger the correlation among products within the same product group. Values of σ close to 0 suggests that the groups are not well defined.

The nested logit model is one of the simplest ways to introduce random coefficients into a discrete-choice model, and the technique is not computationally demanding. It has been shown that if ε_{ijt} is an extreme value random variable, then $\zeta_{ig} + (1-\sigma)\varepsilon_{ijt}$ is also an extreme value random variable (Berry, 1994). That means the market share equation can be inverted analytically, as for the traditional logit model. This exercise is presented in Appendix B.

One of the potential drawbacks of this model is that product groups must be assigned prior to estimation. This can be a problem if product groups are not well defined, or if multiple classifications are possible and there is no obvious hierarchy of assignment that would guide a consumer's decision-making process. In the Atlantic City casino industry, the set of games available is nearly identical from one casino to the next.

Therefore, the products can be grouped easily, either by casino or by game. Both classifications are equally unambiguous. Because product groups are so well-defined, the nested logit model is ideally suited for analyzing demand in the gaming industry.

Of course, the econometrician is not restricted to these two nesting alternatives. One could, for example, choose to group products based on geographic location. Games at casinos in the marina district of Atlantic City could form one product group, while games at casinos at the north end of the boardwalk could form another, and so on. These alternatives have not yet been explored.

For the purpose of this analysis I assume the hierarchy of decision making is such that the consumer's choice of game takes precedence over their choice of casino. In other words, each consumer is assumed to have a general preference for playing a certain type of game, be it nickel slots or table games. The choice of casino is considered secondary. As such, the correlation among consumer types is expected to be higher between products of the same game type than the correlation among consumer types between different types of games, even within the same casino. Own-price elasticities for the nested logit model can be computed according to

$$\varepsilon_{jj} = \alpha_j p_j \left(s_j - \frac{1}{1-\sigma} + \frac{\sigma}{1-\sigma} s_{j/g} \right),$$

whereas the cross-price elasticities are computed according to

$$\varepsilon_{jk} = \begin{cases} \alpha_k p_k s_k, & (k \neq j, k \notin g) \\ \alpha_k p_j \left(s_k + \dfrac{\sigma}{1-\sigma} s_{k/g} \right), & (k \neq j, k \in g) \end{cases}.$$

These formulas are derived in Appendix C.

3.9 Instruments for Price

In demand models for differentiated products, unobserved product characteristics may be correlated with price. Assuming the error term ξ_{jt} captures these unobserved product characteristics, instrumental variables are required in order to obtain unbiased estimates of the coefficients. Exogenous product characteristics are commonly used as a source of instruments in demand models for differentiated products because they are likely to be correlated with price but independent of the error term ξ_{jt} (BLP (1995), Bresnahan (1997) and Nevo (2000)). Likewise, suitable instruments can be constructed from the characteristics of other products. These characteristics are assumed to be correlated with price because the markup over marginal cost depends on the distance, in product space, between the product and its nearest neighbor (Nevo, 2001).

The set of instruments that I considered here includes the observed product characteristics of good j, X_h; the means and sums of X_h for rival products of the same denomination or game; and, for characteristics that vary at the game level, the means and sums of X_h for rival products within the same casino. To illustrate, total floor space at the Tropicana enters the model as a characteristic for dollar slots at the Tropicana. Instruments constructed using total floor space include the variable itself as well as the sum and mean of total floor space observed for dollar slots at all other casinos. Note that because this characteristic is observed at the casino level, the set of instruments does not include the sum and mean of total casino floor space over all other games at the Tropicana.

With two exceptions, this technique is similar to the one Bresnahan (1997) uses to estimate the Principles of Differentiation (PD) Generalized Extreme Value (GEV) model.

First, Bresnahan restricts his set to counts and means of X_h for other products rather than sums and means, where count is computed as the number of other products in the market sharing a particular trait. Second, he expands on this set of instruments by computing the counts and means of X_h for products that share both the same principle of differentiation (i.e. products with the same defining product characteristic) and the same ownership (i.e. products produced by the same firm). By definition, there are no two gaming products that correspond in this way. BLP (1995) use a similar approach to construct a set of three instruments from each exogenous product characteristic including the value of the characteristic for that product, the sum of the values of that characteristic over the other products produced by the same firm, and the sum of the values of that characteristic over the other products produced by rival firms.

Methods for employing instruments vary by author. Davis (2001) uses an exactly identified model (i.e. one instrumental variable per endogenous variable) whereas previous authors (e.g. BLP (1995)) preferred using an over-identified model (i.e. multiple instruments per endogenous variable).

3.10 Market Size and the Outside Good

As is customary in this generation of discrete-choice models, I specify an outside good and define it as the option to not buy. For consumers who decide against a visit to Atlantic City the entertainment alternatives could include anything from a day at the beach in Cape May to shopping in New York City to dinner and a movie near their home. The outside good enables the model to predict changes in market shares more realistically by allowing for the possibility that the combined shares of all inside goods decline in the event that the prices of all inside goods increase. Once the outside good has been determined, the size of the potential market can be established. This should equal the number of consumers who either purchase one unit of the inside good or choose instead the option to not buy. Only then can the observed market share of product j at time t be computed according to the formula:

$$S_{jt} = q_{jt} / M_t \, .$$

where q_{jt} are the unit sales of product j at time t and M_t is the size of the potential market. Recall that the product is defined as a unique casino-game pair for which the unit is the average total dollars wagered per visit over all visitors to Atlantic City during time t.

Various strategies have been used to define the size of the potential market. For example, Berry, Carnall and Spiller (1996) let the potential market for travel between two cities equal μM where M is the geometric mean of the populations of the origin and destination cities. M is assumed to be proportional to the actual potential market by a factor of μ, which is estimated in the model. Alternatively, Bresnahan (1997) took the entire population of office-based workers (39 million) as the potential market for computers so that market shares would equal unit sales divided by 39 million. In some cases, even the unit size must be decided before shares can be computed. Nevo (2000) let the potential market equal the size of the population and then computed shares of ready-to-eat breakfast cereal as the number of servings sold per capita per day. I use a similar strategy to compute shares of the gaming product. Specifically, I define units on a per-trip basis as the average total dollars wagered per visitor.[12] It follows that unit sales, q_j, are equal to the total dollars wagered on a particular casino-game j, divided by the average total dollars wagered per visitor. This is the estimated number of people who bought product j at time t.

Ideally, the size of the potential market for gaming in Atlantic City would reflect the number of people who live within the geographic market of the casinos in Atlantic City and are of legal age to gamble. A reasonable substitute for this figure is the total population for the state of New Jersey. Therefore, using publicly available data, I set the size of the potential market M equal the population of New Jersey. The observed market share S_{jt} for product j in time t is computed as q_{jt} (the estimated number of visitors who purchased j in time t) divided by M_t (the total number of people at time t who had the option to purchase one unit of the inside good or to not purchase at all). Alternative definitions of the potential market for casino gaming in Atlantic City might include the combined populations of people of legal gaming age in New Jersey, New York and Pennsylvania. However, increasing the size of the potential market is not expected to significantly impact the results as long as these alternative definitions of the potential market grow at approximately the same rate.

[12] Annual visitor data are provided by the South Jersey Transportation Authority. Monthly visitor counts are interpolated from annual data by weighting according to the total dollars wagered at the casinos in Atlantic City in each of the 12 months.

Chapter 4: The Data

Monthly data, including prices, quantities and product characteristics, were collected at the casino-game level for the 26-year period beginning 1978 and ending December 2004. A subset of this data covering the period from July 1992 to December 2004 is used in the regression analysis due to changes in reporting practices that occurred as of the start date. The data are obtained from a variety of sources including monthly and quarterly financial reports for each casino provided by the New Jersey Casino Control Commission (CCC), visitor data from the South Jersey Transportation Authority (SJTA), and population data from the United States Bureau of Economic Analysis.

4.1 Price and Quantity

Data collected from the CCC monthly financial reports include total slot handle, table game drop and casino win by casino and game.[13] Drop and handle are measures of total dollars wagered and are used to derive both market shares and prices.[14] Casino win, also known as hold, is the portion of the total dollars wagered that is not returned to consumers in the form of winnings. Unit prices (price_vst) are computed for each product by multiplying the product-level casino win percentage (win divided by drop or handle) by the average total dollars wagered per visitor. The dependent variable (depvar_pop),

---

[13] The CCC reports monthly win and drop for the following games: (tables) blackjack, craps, roulette, Big 6, baccarat, mini-baccarat, poker and other table games; (slots) 5-cent, 25-cent, 50-cent, 1-dollar, 5-dollar, 25-dollar, 100-dollar, multi-denomination, and other slots; simulcast.

[14] It is worth noting that drop is an imperfect measure of the amount customers are willing to risk (i.e. wager) since some customers may exchange currency for chips at one table and play the chips at another table (or even casino) (Skolnick, 1978).

which is a function of the observed market shares, is computed as the log ratio of the share of good j to the share of the outside good: $\ln(S_j) - \ln(S_0)$.

4.2 Product Characteristics

In addition to prices and quantities, the monthly CCC reports are the source of a number of product characteristics as well. Casino floor space (*sqft_casino*) is a measure of the physical size of the casino excluding simulcast space; slot and table game units (*units*) indicate the number of slot machines, or tables, on the casino floor; and simulcast space (*sqft_simul*) indicates both the physical size and availability of a casino's simulcast racing facility, an area within the casino that allows consumers to bet on the outcome of horse races that are broadcast live by video.[15] I derive several more variables through various transformations on these data. For example, casino floor space, simulcast space and gaming units are used to compute the game ratio (*gameratio*). The game ratio is the percentage of casino floor space, including simulcast space, dedicated to each game.[16] This variable is expected to have a positive coefficient because games with higher game ratios are easier to locate on the casino floor. Additionally, I use data on table game units to derive an index of variation among table games (*tbl_hhi*) by applying the Herfindahl-Hirschman Index (HHI) formula to shares of table game units. Table game HHI is a measure of how concentrated the mix of table games is at a particular casino. It is computed by summing the squared unit shares over the eight standard table games: blackjack, craps, roulette, Big 6, baccarat, minibaccarat, other table games and poker. A

[15] Atlantic City's first simulcast racing facility opened in June of 1993.

[16] Slot units are converted to square feet by multiplying by 18, which is the estimated footprint in square feet per slot machine. The floor space dedicated to table games is equal to the total casino floor space, including simulcast space, less the floor space dedicated to slot machines.

casino with a high table game HHI will have a high concentration of certain table games, such as poker or blackjack; whereas casinos with a low table game HHI will have a more balanced assortment of table games. A casino with a high HHI may be trying to position itself to attract consumers with an interest in a particular game such as poker or blackjack.

Other variables derived from the monthly CCC reports include the age of the casino in months (*age_mos*), the number of casinos in the market (*firm_count*) and *crowding*. The coefficient on casino age is expected to be negative, indicating a preference for novelty over the characteristics of more established casinos which could suffer from outdated facilities. Crowding, on the other hand, is expected to have a negative coefficient. Crowding is a measure of the average level of activity associated with a given game. For slot games, this is computed as the number of pulls per unit, where pulls is estimated by taking total dollars wagered divided by the slot denomination and units are the number of slot machines of a given denomination available on the casino floor. For table games and simulcast, I assume a fixed wager amount of $1 and compute crowding as the total dollars wagered divided the number of table units or, in the case of simulcast, by the total square feet of simulcast space.

Finally, I define two variables that measure the impact that new rooms and added floor space have on demand (*chng_sqft* and *chng_rooms*). To construct these variables, I compute the change from one period to the next in the monthly room-nights and casino floor-space data. This gives the total rooms and square feet added in a given period. To capture the lingering effect that these changes might have on consumer preferences I experiment with various lag lengths of both variables in the model, but ultimately use just the current value of the change in the model.

In addition to the physical characteristics of a casino, one aspect of gaming that plays an important role in demand is casino complimentaries, or comps. Comps are goods and services that casinos award to consumers free of charge. They have two essential functions. The first is to bring consumers into the casino. The second is to encourage consumers to play longer. Throughout the 1980s, as the casinos in Atlantic City were trying to establish themselves, they focused heavily on attracting the large number of visitors who were arriving by bus.[17] Comps were regularly distributed to these consumers immediately upon arrival as they entered the casino. These were often redeemable for food or cash and coupons, which could be exchanged for slot machine tokens. Throughout this period, encouraging consumers to play longer was somewhat more complicated than it is now. The reason is that a lack of information regarding the gaming activity of most consumers made it difficult to comp them in a consistent manner. At the time, a consumer's gaming activity had to be monitored by casino personnel and this level of attention was costly. For that reason, comps of this second type would have been reserved for a relatively small number of high-dollar players.

Improvements in technology have drastically changed the way casinos reward comps. The biggest contribution in this respect is the ability to electronically track consumers' gaming histories. This is accomplished by allowing consumers to join a players club program, entitling them to certain membership benefits. Benefits are accrued according to each consumer's gaming activity and they typically take into account both a

[17] In 1988, 45.0% of all Atlantic City visitors arrived by bus. By 2004, just 22.6% of all visitors arrived by bus (SJTA Annual Visitor Stats – 2004).

player’s wins and losses. Gaming activity is tracked electronically each time a consumer inserts a membership card into a slot machine or presents it at a table game.

Using this information, casinos are able to distribute comps in a manner that reflects each consumer’s value to the casino. Moreover, casinos fulfill both of the essential functions of comps by structuring the timing of the distribution of these rewards. That is, the casinos give consumers the incentive they need to play longer based on the rewards they earn and, at the same time, motivate them to return for another visit by making at least some of these rewards redeemable upon their next visit. Consumers must return to claim meals, entertainment and rooms earned during a previous visit. In this way, marketing efforts are directed toward those who are most likely to visit.

The complimentaries data, taken from the CCC quarterly financial reports, reflect the general changes in comping strategies across the Atlantic City casino industry. Figure 2, which is located at the end of this chapter, shows that the number of recipients for cash and coupon comps has remained fairly stable relative to increases in the total value of cash and coupons awarded to consumers. This means that as casinos were devoting an increasing amount of resources to cash and coupon comps, they were doing so by increasing the amount awarded to individual consumers rather than increasing the total number of consumers comped. The sharp increase in the value of cash and coupon comps in the mid-1990s coincides with the introduction of players club card programs around the same time. The data suggest that advances in technology and the ability to track consumers’ gaming activities have made it possible for casinos to allocate more resources toward a known set of valuable repeat consumers.

Each quarter, casinos report the dollar value and number of recipients for each type of complimentary good awarded. Because the system used to classify comps by type has changed over time, I have identified eight general categories into which all types fall: food, beverage, cash and coupon, entertainment, rooms, travel, other, and total comps. A subset of these—food and beverage, cash and coupon, and rooms—are used in the regression analysis. On average, they account for over eighty percent of the total value of complimentaries awarded in Atlantic City each quarter. I interpolate monthly data from quarterly data by dividing values into three weighted parts according to the proportion of total dollars wagered in each month during the quarter by casino.

To the extent that the number of recipients and total dollar value of comps are a function of a casino's market share, these variables will not be exogenous to the model. Normalizing comp value by the number of recipients fixes this problem. For each type of comp, I construct a variable equal to the average comp value per recipient for food and beverage comps (*fb_comp_vpr)*, for cash and coupon comps (*cc_comp_vpr*), and for room comps (*rm_comp_vpr*). Although these variables measure how generously a casino comps on a per recipient basis, it is an incomplete picture of a casino's total comping policy. The reason is that a consumer's utility does not just depend on the size of the average comp per recipient, but on the likelihood of receiving a comp at all. In other words, a consumer may also care about the proportion of a casino's visitors who receive a comp. To measure this, I construct a second set of variables that indicate the ratio of comp recipients to casino visitors where casino visitors are computed by summing the product-specific quantities, q_{jt}, over all products within a particular casino (*fb_comp_rpv*, *cc_comp_rpv* and *rm_comp_rpv*).

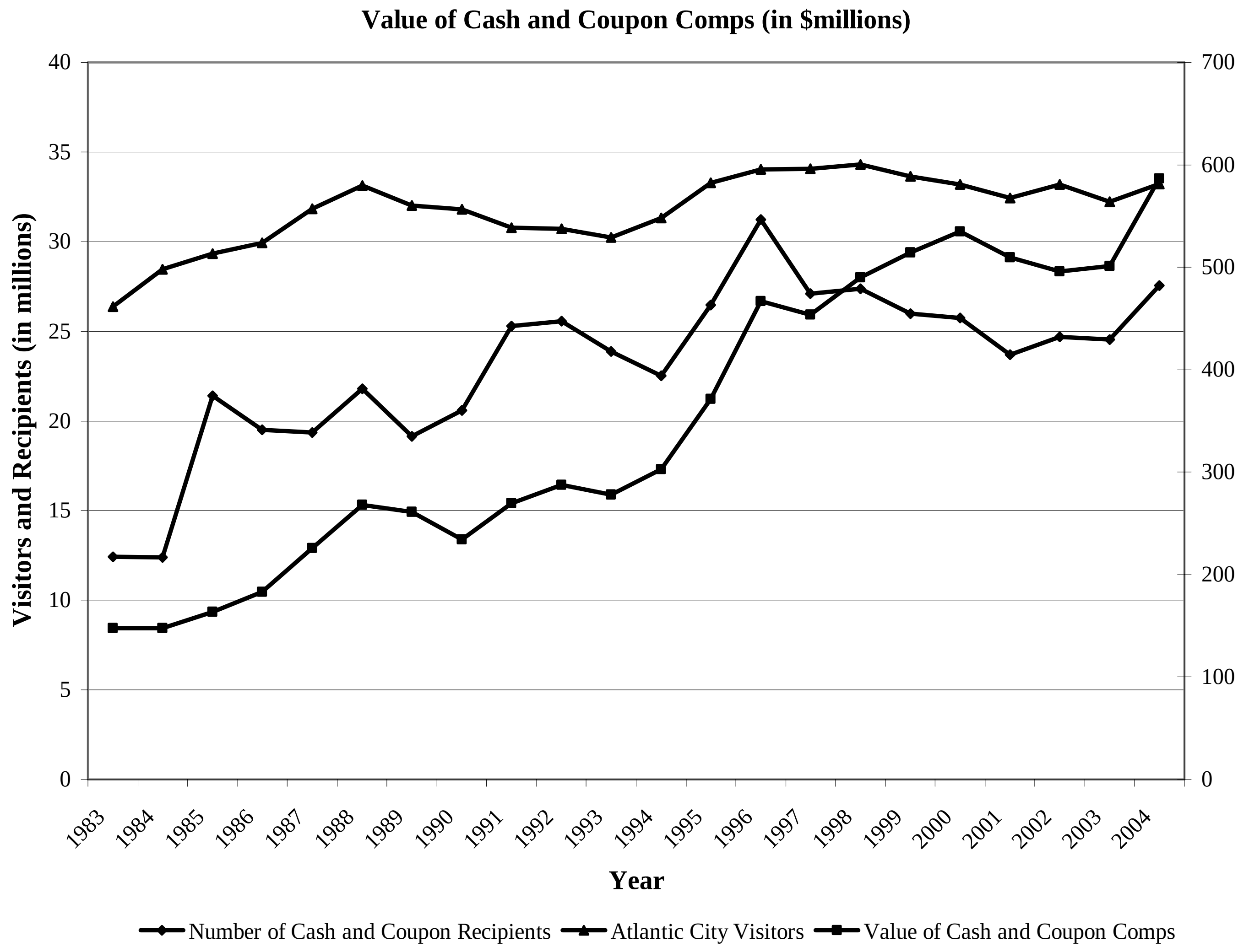
A couple of additional variables were constructed in order to capture technological and regulatory changes related to slot machines and are based on patterns observed in the monthly slot handle data. The first is a trend variable extending from January 1998 through the end of 2004, equal to 1 in the first month of the period, and interacted with a dummy for nickel slots (*technology5*). This variable is expected to capture the impact of technological advancements in nickel slot technology on consumer choice. Since 1998, the number of nickel slot machines has grown dramatically due to video and touch screen technology as well as multiple-line betting capabilities. Evolving consumer preferences for games has proven to be a major factor in the market for gaming (Perry, 1996). The second is an indicator variable equal to one in months where a restriction requiring casinos to maintain a minimum number of nickel slot machines on the casino floor was in effect (*nickel_min_ma*). A 12-month moving average is applied to the value of this variable in order to model any phase-out period following the change in policy. The CCC lifted the restriction in February, 1992. As a result, the number of nickel slot machines declined dramatically between the years 1993 and 1998.

4.3 Instruments for Price

As described in the section titled "Instruments for Price," the set of instruments I consider includes the observed product characteristics, means and sums of these characteristics for rival products sharing the same denomination, and means and sums of these characteristics for rival products within the same casino. I also consider the lagged price per unit. Characteristics that vary at the casino level include casino and simulcast floor space as well as comps. Means and sums of these variables are computed across rival products sharing the same denomination and enter the first stage regression as instruments. Characteristics that vary across both games and casinos include *gameratio*, *crowding* and the number of gaming units. Means and sums across rival products within the same casino, as well as for rival products sharing the same denomination, also enter the first-stage regression as instruments.

A first-stage F-statistic and second-stage Hansen's J-statistics were computed to verify that the set of instruments under consideration were both valid and relevant. A first-stage F-statistic is used to test whether the coefficients on instruments excluded in the second-stage regression are equal to zero in the first-stage regression, in other words whether or not the instruments are relevant to the model. In general, an F-statistic greater than or equal to 10 is considered adequate. The second-stage Hansen's J-statistic is used to test whether or not at least one of the instruments in the model is endogenous or correlated with the error term. If not, the set of instruments is considered valid. For all specifications of the model, a small subset of the full set of instruments was found to meet these criteria best.

Figure 2. Annual Industry Cash and Coupon Complimentaries with Atlantic City Visitor Counts



Chapter 5: Results

In terms of new casinos, the Atlantic City casino industry experienced its most rapid growth during its first three years between 1978 and 1981. During this period nine out of fourteen total casinos opened. Of the remaining five, only one—the Borgata—has opened within the last ten years. In spite of this fact, there has been considerable growth in industry's capacity due to expansions in floor space at existing casinos. This is illustrated by Figure 3, located at the end of the chapter, which shows the total floor space of each casino at their date of entry and at year-end 2004. As of December 2004, floor space expansions accounted for over 40 percent of total casino square feet in Atlantic City.

5.1 Descriptive Statistics

The successful opening of the Borgata in the summer of 2003 added over 100,000 square feet of casino floor space to the market proving that Atlantic City had not yet reached its capacity limit. The immediate popularity of the Borgata also demonstrated that the industry's potential for expansion depends on the ability of its participants to appeal to the changing tastes of consumers. By year-end 2004, the Borgata ranked second in terms of total annual table game drop plus slot handle, just behind the combined Bally's and Claridge casinos, as shown in Table 2, below.

Ten years earlier, in 1994, the top-ranked casino was the Taj Mahal, which also happened to be the newest casino at that time. The Tropicana and Caesars casinos ranked second and third. In both years, Harrah's and the Taj Mahal ranked among the top four.

Table 2. Combined Table Game and Slot Drop by Casino: 1994, 2004[a]

Casino	1994 Casino Drop (000s)	2004 Casino Drop (000s)
Taj Mahal	$4,085,093	$5,191,611
Tropicana	3,398,713	3,623,705
Caesars	3,235,823	5,002,843
Harrah's	3,216,548	5,352,967
Bally's	3,055,339	6,886,436
Claridge[b]	1,451,810	0
Showboat	3,047,445	4,211,482
Trump Plaza	2,478,786	3,387,568
Trump Marina	2,446,133	2,969,725
Resorts	2,401,026	2,742,327
Sands	2,381,223	2,049,458
Atlantic City Hilton	2,127,364	3,123,417
Borgata	0	6,841,056

[a] Excluding poker.
[b] Annexed by Bally's in 2003.

Table 3. Atlantic City Table Game and Slot Drop by Game: 1994, 2004

Casino	1994 Casino Drop (000s)	2004 Casino Drop (000s)
25-Cent Slots	$11,565,668	$15,844,467
1-Dollar Slots	7,646,273	8,189,149
Table Games[a]	6,855,679	7,809,418
50-Cent Slots	3,205,952	2,630,867
5-Dollar Slots	2,932,550	3,798,332
25-Dollar Slots	361,086	666,126
Other Slots	336,630	2,755,989
5-Cent Slots	162,779	8,566,139
100-Dollar Slots	144,811	543,586
Simulcast	113,875	123,921
Multi-Denom Slots	0	454,599

[a] Excluding poker

Similarly, Table 3 provides total annual table game drop and handle across all casinos by game. Together, these two tables are intended to give the reader a general idea about relative product rankings without listing each casino-game pair individually. Among games, quarter slots dominate the market in 1994 and 2004. Games that experienced the fastest growth in market share over this 10-year period include nickel slots, other slots and multi-denomination slots. This is primarily because of advances in slot-machine technology, such as multi-line betting and touch screen capabilities, which have increased the popularity of these types of machines among slot players. Of these three, however, the rate at which the market share of nickel slots has grown is most striking.

Table 4. Means and Standard Deviations of Key Product Characteristics: 1994, 2004

	1994		2004	
Product characteristics	Mean	Std Dev	Mean	Std Dev
Casino floor space (sqft)	69,990	20,400	105,361	36,360
Simulcast floor space (sqft)	7,363	6,925	14,182	14,895
Total table game units	115	38.393	120	54.887
Total slot machine units	2,253	556.747	3,467	1,083.476
Comp value per recipient:				
Cash and coupon	14.22	3.803	23.01	6.451
Food and beverage	6.08	2.272	6.15	2.259
Rooms	70.47	29.109	69.37	28.282
Comp recipients per visitor:				
Cash and coupon	0.76	0.304	0.85	0.308
Food and beverage	1.47	0.543	2.15	0.970
Rooms	0.07	0.030	0.13	0.033
Casino win percent				
25-cent slots	9.62%	0.82%	8.13%	1.06%
1-dollar slots	7.90%	0.40%	7.72%	0.87%
5-dollar slots	5.13%	1.05%	5.70%	1.71%
Table games	17.20%	2.83%	15.49%	2.47%
Percent of floor space dedicated to…[a]				
25-cent slot machines	38.99%	6.13%	29.68%	4.62%
1-dollar slots machines	13.73%	2.76%	8.86%	1.81%
5-dollar slot machines	2.01%	0.89%	1.92%	0.50%
Table games	26.08%	2.83%	23.78%	2.47%

[a] Based on 22 square feet per slot machine.

Additionally, a summary of the mean values and standard deviations of key product characteristics is provided in Table 4. Not surprisingly, total casino floor space increased 50 percent on average between 1994 and 2004 while total simulcast space increased nearly 100 percent. Although the increase in simulcast space does not correspond to a comparable increase in simulcast drop during this period, casinos were able to use this added space to accommodate table games, some of which may have been moved out of the main casino area to make room for additional slot machines.[18] This is supported by a lack of growth in the number of table game units as well as a small change in total simulcast drop over this ten-year period. From 1994 to 2004 total slot machines increased 50 percent, whereas the corresponding increase in table games was only 4 percent.

With regard to casino comps, differences in the 1994 and 2004 mean values for the variables provided suggest that there have been significant changes in comping policies across casinos. In particular, the average value of a cash and coupon award (derived from a combination of visitor statistics, market shares, and complimentaries data) has increased from approximately $14 to $23, while the average value of food and beverage comps and room comps has remained roughly the same. By contrast, the number of recipients per visitor increased only moderately for cash and coupon awards with roughly 3 out of 4 visitors receiving a cash and coupon award in 1994 and approximately 6 out of 7 receiving one in 2004. By contrast, the ratio of recipients to visitors experienced a much larger increase with respect to food and beverage and room comps. Whereas consumers received an average 1.47 food and beverage comps per visit in 1994, they received approximately 2.15 per visit in 2004, an increase of 46 percent. Likewise, the number of room comp recipients per visitor nearly doubled from 7 percent

---

[18] Conduct of authorized games in a casino simulcasting facility: NJAC 19:55-2.6.

of all visitors to 13 percent. Relative to comps, the price of gaming (i.e. casino win percent) remained relatively stable over the period from 1994 to 2004.

5.2 Estimates for the Traditional Logit Model

Table 5 presents the results of the discrete-choice estimation using a traditional logit model. For all three specifications the dependent variable is the log ratio of the share of the inside good relative to the outside good where market shares are computed as the number of units that were purchased divided by the size of the potential market. Recall that units are determined on a per-visit basis such that one unit of a given casino-game pair is equal to the average total dollars wagered per visitor in time t. Although data from 1978 are available, the specifications presented here are based on an observation period starting July, 1992, and ending December, 2004. This start date corresponds to a major change in how certain types of slot data are reported.[19]

Model 1 is estimated using an ordinary least squares (OLS) regression in which observed market shares depend on price, various product characteristics, fixed effects for the casino and game to control for unobserved product characteristics that remain constant over time, and fixed effects for month and year to control for seasonality. Standard errors are corrected for heteroskedasticity and autocorrelation using Stata's *prais* command with a robust option. The Durbin-Watson statistic does not reject autocorrelation among the error terms. Moreover, the model may be especially prone to heteroskedasticity since differences across both casinos and games can mean that characteristics vary a lot from one group of products to another.

[19] As of July 1992, monthly casino win and drop amounts for the "other" slot machines category were disaggregated into the following categories: 50-cent, 5-dollar, 25-dollar, 100-dollar and other slot machines.

Table 5. Traditional Logit Regression Results

Variable	Model 1: OLS with HAC-Corrected SEs		Model 2: 2SLS with AC-Corrected SEs[a]		Model 3: 2SLS with HAC-Corrected SEs[a]	
price_vst	-0.000***	0.000	0.009***	0.001	0.009	0.006
sqft_casino	0.000***	0.000	0.000***	0.000	0.000***	0.000
sqft_simul	0.000***	0.000	-0.000	0.000	-0.000	0.000
tbl_hhi	-0.000*	0.000	-0.000***	0.000	-0.000***	0.000
firm_count	-0.091***	0.019	-0.089*	0.050	-0.089**	0.039
age_mos	-0.004***	0.001	-0.003***	0.000	-0.003***	0.000
chng_sqft	-0.000**	0.000	0.000	0.000	0.000	0.000
chng_rooms	-0.000	0.000	0.000	0.000	0.000	0.000
technology5	0.495***	0.034	0.403***	0.011	0.403***	0.028
nickel_min_ma	0.829***	0.168	0.634**	0.288	0.634**	0.298
cc_comps_vpr	-0.000	0.000	0.000	0.000	0.000	0.000
fb_comps_vpr	-0.005	0.003	0.009	0.005	0.009	0.006
rm_comps_vpr	-0.000*	0.000	-0.002***	0.001	-0.002***	0.001
cc_comps_rpv	0.063***	0.020	0.536***	0.070	0.536***	0.071
x 100-doll	-0.081	0.099	-1.508***	0.101	-1.508***	0.179
x 1-doll	-0.032	0.026	-0.459***	0.093	-0.459***	0.076
x 25-doll	-0.112**	0.055	-1.512***	0.097	-1.512***	0.217
x 50-cent	-0.025	0.026	-0.360***	0.093	-0.360***	0.069
x 5-cent	0.253**	0.118	0.073	0.105	0.073	0.111
x 5-doll	-0.096***	0.027	-0.626***	0.093	-0.626***	0.074
x multi-denom	-0.609	1.026	-1.160**	0.591	-1.160	0.822
x other slots	-0.107**	0.054	-1.360***	0.100	-1.360***	0.121
x simulcast	-0.170***	0.058	-0.656***	0.117	-0.656***	0.084
x table games	-0.058**	0.026	-0.312***	0.093	-0.312***	0.098
fb_comps_rpv	-0.014	0.021	0.106***	0.040	0.106***	0.038
x 100-doll	-0.132	0.088	-0.376***	0.043	-0.376***	0.071
x 1-doll	-0.037	0.023	-0.121***	0.041	-0.121***	0.043
x 25-doll	-0.109**	0.050	-0.076*	0.041	-0.076	0.051
x 50-cent	-0.071**	0.028	-0.340***	0.042	-0.340***	0.049
x 5-cent	0.212***	0.075	-0.182***	0.046	-0.182***	0.063
x 5-doll	-0.070**	0.027	-0.152***	0.041	-0.152***	0.028
x multi-denom	-0.767	0.678	-0.436	0.299	-0.436	0.643
x other slots	0.062	0.039	0.142***	0.043	0.142***	0.040
x simulcast	0.013	0.047	-0.273***	0.043	-0.273***	0.043
x table games	-0.071***	0.026	-0.264***	0.043	-0.264***	0.065
rm_comps_rpv	-1.059***	0.257	-4.096***	0.649	-4.096***	0.447
x 100-doll	1.227	1.039	10.717***	0.774	10.717***	1.236
x 1-doll	0.053	0.266	-0.516	0.766	-0.516	0.394
x 25-doll	2.139***	0.641	6.474***	0.772	6.474***	0.840
x 50-cent	-0.045	0.283	0.035	0.768	0.035	0.378
x 5-cent	-0.456	1.164	2.416***	0.902	2.416***	0.586
x 5-doll	0.698**	0.329	1.635**	0.767	1.635***	0.373
x multi-denom	13.052	17.998	-9.610	6.316	-9.610	14.526
x other slots	0.797	0.584	4.859***	0.817	4.859***	0.697
x simulcast	0.134	0.571	0.322	0.858	0.322	0.537
x table games	0.390	0.301	-1.043	0.797	-1.043	1.207
game dummies						
100-doll slots	-4.192***	0.242	-3.064***	0.157	-3.064***	0.441
1-doll slots	-0.526***	0.061	0.169	0.134	0.169	0.190
25-doll slots	-3.668***	0.144	-2.479***	0.148	-2.479***	0.379
50-cent slots	-1.420***	0.070	-0.615***	0.132	-0.615***	0.135

5-cent slots	-5.488***	0.362	-4.154***	0.152	-4.154***	0.202
5-doll slots	-1.450***	0.075	-0.495***	0.143	-0.495	0.314
multi-denom slots	-3.196	2.251	0.486	0.892	0.486	1.778
other slots	-2.848***	0.145	-2.057***	0.153	-2.057***	0.349
simulcast	-4.661***	0.206	-3.526***	0.149	-3.526***	0.139
table games	-0.539***	0.065	-0.624***	0.143	-0.624**	0.318
casino dummies						
AC Hilton	0.393***	0.119	0.417***	0.055	0.417***	0.054
Bally's	0.521***	0.120	0.497***	0.056	0.497***	0.048
Caesars	0.309*	0.159	0.644***	0.044	0.644***	0.042
Claridge	-0.809***	0.210	-0.807***	0.051	-0.807***	0.057
Harrah's	0.493***	0.125	0.540***	0.046	0.540***	0.053
Resorts (Ref)						
Sands	0.056	0.117	0.133**	0.055	0.133**	0.056
Showboat	-0.433***	0.123	-0.313***	0.059	-0.313***	0.065
Trump Marina	-0.032	0.115	-0.116***	0.039	-0.116***	0.041
Trump Plaza	0.127	0.114	0.166***	0.045	0.166***	0.050
Tropicana	0.303***	0.116	0.253***	0.062	0.253***	0.055
Trump Taj Mahal	-0.038	0.132	0.028	0.057	0.028	0.063
month dummies						
January	-0.441***	0.014	-0.439***	0.031	-0.439***	0.043
February	-0.453***	0.014	-0.418***	0.035	-0.418***	0.034
March	-0.297***	0.013	-0.275***	0.031	-0.275***	0.030
April	-0.317***	0.011	-0.328***	0.032	-0.328***	0.035
May	-0.205***	0.010	-0.173***	0.031	-0.173***	0.031
June	-0.245***	0.008	-0.205***	0.029	-0.205***	0.030
July (Ref)						
August	0.006	0.007	0.037	0.027	0.037	0.030
September	-0.205***	0.009	-0.183***	0.031	-0.183***	0.031
October	-0.231***	0.011	-0.185***	0.030	-0.185***	0.037
November	-0.280***	0.012	-0.258***	0.031	-0.258***	0.035
December	-0.406***	0.013	-0.362***	0.030	-0.362***	0.038
year dummies						
1993	0.367***	0.033	0.167	0.103	0.167	0.115
1994	0.335***	0.053	0.189*	0.107	0.189	0.125
1995	0.401***	0.064	0.175	0.109	0.175	0.143
1996	0.250***	0.076	0.148	0.110	0.148	0.145
1997	0.282***	0.086	0.133	0.112	0.133	0.147
1998	0.488***	0.094	0.169	0.113	0.169	0.151
1999	0.539***	0.101	0.115	0.114	0.115	0.167
2000	0.553***	0.108	0.107	0.117	0.107	0.185
2001	0.553***	0.118	0.101	0.120	0.101	0.197
2002	0.453***	0.128	0.111	0.121	0.111	0.206
2003	0.352***	0.134	-0.071	0.126	-0.071	0.228
2004	0.500***	0.143	-0.129	0.130	-0.129	0.273
constant	-2.981***	0.273	-3.935***	0.642	-3.935***	0.743
Number of obs	16,347		16,254		16,254	
R-squared	0.621		0.788		0.788	
Rho	0.905		NA		NA	
First-Stage F-Stat	NA		38.65		1.82	
Hansen's J-Stat p-value	NA		0.435		.500	

[a] Excluded instruments include lagged price per unit and the sums and means of casino floor space at other casinos.

Note: * - 10% significance level; ** - 5% significance level; *** - 1% significance level.

Model 1 produced several significant coefficients, including a negative coefficient for price. The coefficients on total casino and simulcast square feet (*sqft_casino* and *sqft_simul*) were positive and significant, indicating that consumers tend to prefer larger casinos with more simulcast space. Other product characteristics that had a positive impact on demand include advancements in nickel slot technology (*technology5*) and the enforcement of a rule specifying the minimum allowable number of nickel slot machines on the casino floor (*nickel_min_ma*). By constrast, consumer response was negative with respect to casino age in months (*age_mos*), table game HHI (*tbl_hhi*), and current-period increases in casino floor space (*chng_sqft*). With the exception of changes in casino floor space, all variables mentioned above have the expected signs.

Recall that the model also contains two sets of comp variables. One set measures the value per recipient (VPR) for each of three types of complimentary goods: cash and coupon, food and beverage, and rooms. The other set measures the number of recipients per visitor (RPV) for the same three types of comps. This second set is interacted with game dummies in order to allow the impact of these variables to vary across games.[20] The interaction between these variables is designed to compensate for the fact that the comp data are reported at the casino level, rather than product level. Supposing consumers who prefer one denomination differ from consumers who prefer another in the way they experience or benefit from certain types of comps, these differences in terms of preferences can be captured through these interactions. A priori, both the comp value-per-

[20] The same interaction procedure was applied to the comp value-per-recipient variables without comparable success. No patterns emerged across game types and no additional information could be determined. Results for this specification are not shown.

recipient and comp recipients-per-visitor variables were expected to have positive coefficients.

Under Model 1, only the room comps value-per-recipient variable yields a significant, although negative, coefficient. The model yields several more significant coefficients among the recipients-per-visitor variables and interaction terms, which lead to reasonable conclusions regarding consumer behavior. To simplify the discussion of these variable and their interactions, I will refer the joint impact of the reference group (25-cent slots) and the interacted term.

First, the coefficient on cash and coupon recipients-per-visitor is positive and significant for 25-cent slots. This means, on average, the market share of 25-cent slots at a given casino is increasing with respect to the proportion of visitors who receive a cash and coupon award. This coefficient is also positive and significant for nickel slots; and it is positive, though not significant, for 50-cent slots, 1-dollar slots and table games. By contrast, the estimates indicate that shares of higher stakes games such as the 5-dollar slots, 25-dollars slots and other slots as well as simulcast betting are negatively and significantly affected by increases in the number of recipients per visitor.

Intuitively, consumers who play high stakes games will be less sensitive to the number of cash and coupon recipients per visitor because they are less affected by marginal changes in a casino's cash and coupon comping policy. This is reflected by the fact that a large percentage of a casino's visitors receive cash and coupon comps, as confirmed in Table 4. Assuming high stakes players are among the first to be comped, the number of cash and coupon recipients per visitor among this group of consumers will be higher than among low stakes players. As a result, changes in the number of recipients per visitor will not necessarily impact these high stakes consumers. Difficulty identifying the true impact of a casino's comping policies on different groups of consumers reflects the fact that comps, along with several other product characteristics, are defined at the casino rather than product level. If product-level comp data were available, then the expected sign on the recipients-per-visitor coefficients would be positive for all denominations.

The signs of the coefficients associated with the number of room recipients per visitor are opposite those for the number of cash and coupon recipients per visitor. An increase in the number of room recipients per visitor appears to have a negative impact on the market shares of 25-cent slot games but a positive impact on the market shares of 25-dollar and 100-dollar slots. This is consistent with the story developed above. Recall from Table 4 that a relatively small fraction of visitors receive room comps (just 7 percent in 1994 and 13 percent in 2004). If casinos give high stakes players priority when awarding comps, then marginal changes in a casino's policy regarding room comps will affect these players more than the rest.

Models 2 and 3 are variations on the traditional logit model that address potential endogeneity in prices by employing a two-stage least squares (2SLS) instrumental variables technique. Instruments for both models include all of the second-stage regressors, except for price, plus a lagged price variable and the sums and means of casino square feet at all other casinos. Although Models 2 and 3 both instrument for price, the results should be interpreted with care. Model 2 computes autocorrelation-corrected standard errors, but does not correct for heteroskedasiticy; whereas Model 3 corrects for heteroskedasticity but does not pass the first-stage F-test. Failure to pass this test indicates that the instruments used for price may not be relevant to the model, which could compromise the reliability of the reported standard errors.

Estimates for Models 2 and 3 are similar to Model 1, with a few notable exceptions. First, the coefficient on price changes from negative and significant to positive and significant in the case of Model 2;[21] and changes to positive and insignificant, i.e. not statistically different than zero, in the case of Model 3. An insignificant coefficient on price is not surprising considering that prices for casino gaming are learned rather than posted, as they are for most other goods. However, the expected value for the price coefficient is nonetheless negative because there is significant evidence based on the historic pattern of prices across casinos that this is one area in which firms compete (Perry, 2000). The second notable difference is that the coefficient on current-period changes in floor space becomes insignificant. Relative to the negative coefficient observed in Model 1, this is more in line with prior expectations of estimating a positive coefficient on this variable. Third, the year dummies become insignificant while several of the recipients-per-visitor variables, including the interaction terms, change from insignificant to significant without changing sign. Given the increased significance level of many of these estimates, this only serves to strengthen the conclusions drawn above with respect to consumer attitudes towards casino complimentaries.

As an extension, I estimate the traditional logit model for nickel slots, quarter slots, 25-dollar slots and table games separately. I summarize a few of the main findings

[21] Note that this same specification, when run with CPI-adjusted prices and complimentary values, produced a negative and insignificant coefficient on price while the overall conclusions of this model remained the same.

here. To start, with the exception of 25-cent slots, the estimated coefficients are mostly insignificant with respect to the comp variables. For 25-cent slots, however, the coefficients on the value of cash and coupon per recipient and the number of cash and coupon recipients per visitor are positive and significant while those on food and beverage as well as rooms are negative. Recall that this is consistent with the coefficients estimated for the cash and coupon recipients-per-visitor variable when interacted with lower denomination dummies in the pooled model.

Perhaps more interesting is the fact that the estimated coefficients for the casino dummies vary from one game-level regression to the next, which suggests that there may be unobserved characteristics of a casino that tend to attract players of certain games. For example, relative to Resorts (the reference casino), Caesars typically has a harder time attracting nickel-slot players, while Harrah's and Showboat typically have an easier time attracting quarter-slot players. By contrast, Caesars, Bally's and the Atlantic City Hilton have a greater tendency to attract consumers who prefer 25-dollar slots and table games while Claridge, Showboat, Harrah's and Trump Marina clearly do not.

In terms of the implied elasticities of demand, all of the patterns typically associated with the traditional logit model apply. That is, a single value describes the elasticity of demand for all products j with respect to changes in the "price" of a particular product k. As a result, elasticities defined between two products sharing the same casino or game type are no larger than elasticities defined between two relatively unrelated products. Moreover, because shares of all products are very small relative to the outside good, elasticities are determined primarily by price. In the case of price elasticities of demand, values associated with goods sharing the same game type are comparable because the casinos assign prices according to the denomination or game.

Demand elasticities computed with respect to the value-per-recipient variables are similarly "flat" since these data are reported at the casino level. As a result, the "price" component of elasticity is shared by all products located within the same casino. In both cases, the estimated elasticities are unrealistic because substitution patterns are expected to be stronger between product pairs having the most traits in common.

Relative to the value-per-recipient elasticities, a slightly richer pattern of demand is observed among the recipients-per-visitor elasticities of demand because these coefficients were interacted with game dummies. See Table 6. As a result, elasticities vary across both dimensions: casinos and denominations. We find that an increase in the number of cash and coupon recipients per visitor for any of the 100-dollar slot games, regardless of casino, is predicted to have a positive impact on the shares of all other gaming products while a comparable increase the number of cash and coupon recipients-per-visitor for any of the nickel slot games is predicted to have the opposite effect. Note that, in spite of the added variation in elasticities, it is still the case that each cell represents the recipients-per-visitor cross-price elasticity of demand for *all* products *j* with respect to a specific product *k*.

Table 6. Model 2 Elasticities of Demand for Cash and Coupon Recipients-per-Visitor Based on 2004 Prices and Shares

	Tables	Simul	Other	Multi	100D	25D	5D	1D	50C	25C	5C
AC Hilton	-0.17	0.09	0.63	0.48	0.75	0.75	0.07	-0.06	-0.14	-0.82	-0.47
Bally's	-0.22	0.12	0.81	0.62	0.96	0.97	0.09	-0.08	-0.17	-1.05	-0.60
Borgata	-0.12	0.07	0.45	0.34	0.53	0.54	0.05	-0.04	-0.10	-0.58	-0.33
Caesars	-0.09	0.05	0.33	0.25	0.39	0.39	0.04	-0.03	-0.07	-0.42	-0.24
Harrah's	-0.29	0.15	1.06	0.80	1.25	1.25	0.12	-0.10	-0.23	-1.36	-0.78
Resorts	-0.20	0.11	0.75	0.57	0.88	0.89	0.08	-0.07	-0.16	-0.97	-0.55
Sands	-0.15	0.08	0.55	0.42	0.65	0.65	0.06	-0.05	-0.12	-0.72	-0.41
Showboat	-0.20	0.11	0.73	0.56	0.87	0.87	0.08	-0.07	-0.16	-0.94	-0.54
Tr. Marina	-0.17	0.09	0.64	0.49	0.76	0.76	0.07	-0.06	-0.14	-0.83	-0.47
Tr. Plaza	-0.29	0.16	1.06	0.81	1.26	1.26	0.12	-0.10	-0.23	-1.38	-0.78
Tropicana	-0.16	0.08	0.58	0.44	0.68	0.69	0.06	-0.05	-0.12	-0.75	-0.43
Taj Mahal	-0.17	0.09	0.62	0.47	0.73	0.73	0.07	-0.06	-0.13	-0.80	-0.45

* Each cell represents the recipients-per-visitor cross-price elasticity of demand for all products j with respect to the casino-game pair identified by the row and column headers.

5.3 Estimates for the Nested Logit Model

Recall that the benefit of using the nested logit model is that it relaxes the assumption of independence of irrelevant alternatives by allowing consumer preferences to be correlated within pre-defined product groups, or nests. For the purpose of this study, groups are defined by the type of game. That means up to twelve products (one for each casino) fall into each group in any given month. Table 7, below, reports the results of the discrete-choice estimation using a nested logit model. Like Model 1, Model 4 is estimated using OLS with the same set of regressors plus an additional group-share variable. The coefficient for this variable should take a value from 0 to 1, which indicates the degree of correlation across products within the same group. Recall that values close to 1 indicate the highest degree of correlation while values close to 0 indicate the lowest.

Models 5 and 6 are variations on the basic nested logit model that use a two-stage instrumental variable technique to control for potential endogeneity in either prices (Model 5) or the group-share term (Model 6). In both cases, instruments include all the regressors from the second-stage regression plus the sums and means of casino floor space at other casinos and the sums and means of simulcast floor space at other casinos. Both models compute heteroskedasticity and autocorrelation-corrected standard errors.

Table 7. Nested Logit Regression Results

Variable	Model 4: OLS with HAC-Corrected SEs		Model 5: 2SLS (IV-price) with HAC-Corrected SEs[a]		Model 6: 2SLS (IV-group share) with HAC-Corrected SEs[a]	
price_vst	-0.000	0.000	-0.013**	0.007	-0.001**	0.001
sqft_casino	0.000**	0.000	0.000***	0.000	0.000**	0.000
sqft_simul	0.000***	0.000	-0.000	0.000	-0.000	0.000
tbl_hhi	-0.000***	0.000	0.000	0.000	-0.000**	0.000
firm_count	-0.060***	0.006	0.001	0.037	-0.108	0.073
age_mos	0.000	0.000	-0.000	0.000	-0.003**	0.002
chng_sqft	-0.000**	0.000	-0.000	0.000	-0.000	0.000
chng_rooms	0.000	0.000	0.000	0.000	0.000	0.000
technology5	0.389***	0.007	0.371***	0.031	0.373***	0.031
nickel_min_ma	0.736***	0.094	0.213	0.209	0.398	0.250
cc_comps_vpr	0.000	0.000	-0.000	0.000	0.000	0.000
fb_comps_vpr	-0.002*	0.001	0.002	0.005	0.007	0.006
rm_comps_vpr	0.000	0.000	-0.000	0.001	-0.002**	0.001
gamevisits_shr	0.978***	0.008	0.761***	0.087	-0.118	0.517
cc_comps_rpv	0.011	0.014	0.070*	0.040	0.568**	0.285
x 100-doll	0.023	0.050	-0.019	0.135	-1.460**	0.692
x 1-doll	-0.004	0.020	-0.016	0.032	-0.445**	0.218
x 25-doll	-0.023	0.021	-0.001	0.103	-1.431**	0.670
x 50-cent	0.001	0.021	-0.074*	0.040	-0.391**	0.192
x 5-cent	0.011	0.031	0.150	0.109	0.363	0.231
x 5-doll	-0.004	0.018	-0.210**	0.084	-0.745**	0.351
x multi-denom	0.017	0.388	-0.310	0.626	-1.343	1.051
x other slots	-0.021	0.021	-0.205**	0.100	-1.386**	0.623
x simulcast	-0.047*	0.026	-0.201***	0.076	-0.807**	0.382
x table games	-0.006	0.020	-0.240**	0.106	-0.467**	0.227
fb_comps_rpv	-0.028*	0.014	-0.056**	0.025	0.074	0.057
x 100-doll	-0.053	0.039	0.132*	0.068	-0.345	0.223
x 1-doll	-0.020	0.020	0.039	0.038	-0.065**	0.029
x 25-doll	-0.019	0.022	-0.043	0.052	-0.132	0.089
x 50-cent	-0.024	0.021	-0.018	0.035	-0.293***	0.111
x 5-cent	0.031	0.019	0.123*	0.069	-0.021	0.047
x 5-doll	-0.016	0.019	-0.006	0.013	-0.145**	0.070
x multi-denom	-0.207	0.204	0.691	0.451	-0.032	0.583
x other slots	0.061**	0.031	0.211***	0.034	0.170***	0.038
x simulcast	0.001	0.029	-0.006	0.027	-0.225**	0.093
x table games	-0.041**	0.020	0.070	0.057	-0.180**	0.075
rm_comps_rpv	-0.236	0.152	-1.745***	0.456	-4.500**	1.767
x 100-doll	0.015	0.470	6.341***	1.460	11.220***	2.900
x 1-doll	-0.065	0.192	-1.347***	0.230	-0.709*	0.423
x 25-doll	0.300	0.258	1.916***	0.523	6.571***	2.454
x 50-cent	-0.139	0.205	-1.966***	0.292	0.190	1.253
x 5-cent	-0.183	0.257	0.133	0.494	2.171	1.483
x 5-doll	0.078	0.202	0.477**	0.228	1.859**	0.902

x multi-denom	-2.631	4.593	-5.039	4.793	-3.201	15.011
x other slots	0.660**	0.286	6.173***	0.714	5.664***	0.661
x simulcast	0.308	0.294	-0.088	0.395	0.750	0.850
x table games	0.018	0.211	1.711	1.407	1.074	1.143
game dummies						
100-doll slots	-3.924***	0.105	-5.501***	0.401	-3.681***	0.519
1-doll slots	-0.536***	0.049	-0.745***	0.176	-0.092	0.173
25-doll slots	-3.421***	0.060	-4.308***	0.358	-3.013***	0.321
50-cent slots	-1.496***	0.053	-1.362***	0.106	-0.754***	0.226
5-cent slots	-4.115***	0.061	-3.905***	0.128	-4.285***	0.185
5-doll slots	-1.463***	0.049	-2.045***	0.300	-0.951***	0.265
multi-denom slots	-2.183***	0.740	-3.670***	0.874	-1.510	1.909
other slots	-2.787***	0.135	-3.959***	0.322	-2.550***	0.419
simulcast	-4.839***	0.088	-4.618***	0.082	-3.565***	0.518
table games	-0.581***	0.051	0.241	0.370	-0.060	0.232
casino dummies						
AC Hilton	0.115**	0.048	0.072	0.048	0.413**	0.185
Bally's	0.003	0.053	0.130**	0.063	0.562**	0.270
Caesars	-0.019	0.061	0.085	0.058	0.667**	0.338
Claridge	0.085*	0.047	-0.152**	0.067	-0.900**	0.426
Harrah's	0.031	0.056	0.028	0.042	0.515**	0.244
Resorts (Ref)	0.050	0.050	-0.033	0.050	0.077	0.051
Sands	0.063	0.050	-0.001	0.059	-0.337*	0.178
Showboat	0.003	0.060	-0.005	0.035	-0.099**	0.050
Trump Marina	0.006	0.064	-0.041	0.042	0.123*	0.073
Trump Plaza	0.017	0.060	0.014	0.049	0.248*	0.141
Tropicana	-0.017	0.058	0.080	0.061	0.061	0.059
Trump Taj Mahal	0.115**	0.048	0.072	0.048	0.413**	0.185
month dummies						
January	-0.437***	0.006	-0.412***	0.048	-0.424***	0.022
February	-0.448***	0.006	-0.460***	0.032	-0.430***	0.025
March	-0.300***	0.006	-0.318***	0.033	-0.296***	0.023
April	-0.322***	0.005	-0.279***	0.035	-0.300***	0.021
May	-0.204***	0.004	-0.231***	0.034	-0.209***	0.024
June	-0.240***	0.003	-0.270***	0.031	-0.238***	0.018
July (Ref)	0.005*	0.003	-0.034	0.031	0.012	0.016
August	-0.218***	0.004	-0.246***	0.030	-0.199***	0.024
September	-0.239***	0.005	-0.304***	0.041	-0.228***	0.023
October	-0.284***	0.005	-0.313***	0.033	-0.277***	0.023
November	-0.404***	0.006	-0.475***	0.040	-0.415***	0.021
December	-0.437***	0.006	-0.412***	0.048	-0.424***	0.022
year dummies						
1993	0.323***	0.015	0.056	0.075	0.140	0.107
1994	0.249***	0.026	0.217**	0.090	0.212**	0.106
1995	0.314***	0.032	0.378***	0.120	0.255**	0.104
1996	0.117***	0.037	0.376***	0.117	0.224**	0.106
1997	0.165***	0.041	0.472***	0.112	0.239**	0.109
1998	0.362***	0.044	0.456***	0.132	0.273**	0.106
1999	0.380***	0.047	0.460***	0.155	0.269**	0.111
2000	0.367***	0.051	0.517***	0.183	0.318***	0.120
2001	0.328***	0.054	0.514**	0.200	0.340**	0.140
2002	0.231***	0.058	0.538**	0.212	0.364**	0.150
2003	0.153**	0.062	0.536**	0.229	0.216*	0.124
2004	0.285***	0.066	0.661**	0.287	0.246*	0.131
constant	-1.070***	0.101	-0.944	0.702	-2.994***	0.641
Number of obs	16,347		16,347		16,347	

R-squared	0.920	0.764	0.891
Rho	0.917	NA	NA
First-Stage F-Stat	NA	1.53	1.49
Hansen's J-Stat p-value	NA	0.803	0.144

[a] Excluded instruments include the sums and means of casino floor space at other casinos and the sums and means of simulcast floor space at other casinos.
Note: * - 10% significance level; ** - 5% significance level; *** - 1% significance level.

Note that when instruments are employed for the group-share term in Model 6 the value of σ, which was close to 1 in Model 4 (0.978) and Model 5 (0.761), is not significantly different from 0. This seems to imply that there is very little correlation among consumers types who choose products in the same product group, which is consistent with the fact that the regression results for Model 6 are quite similar to those of Model 3, which is estimated using a traditional logit model. One notable difference between the two models is that the coefficient on price is now positive and significant. As was the case with Model 3, the results for Models 5 and 6 should also be interpreted with caution because both models fail the first-stage F-test indicating that the chosen set of instruments may not be relevant to the model. It should be noted that this set of instruments did pass a second test, which confirmed that the instruments were at least valid, i.e. not correlated with the second-stage error term.

Ideally, the nested logit model would have allowed for more complex and realistic patterns of substitution. However, this is lost if the value of σ is zero. Recall that own-price elasticities are computed according to

$$\varepsilon_{jj} = \alpha_j p_j \left(s_j - \frac{1}{1-\sigma} + \frac{\sigma}{1-\sigma} s_{j/g} \right),$$

and cross-price elasticities are computed according to

$$\varepsilon_{jk} = \begin{cases} \alpha_k p_k s_k, & (k \neq j, k \notin g) \\ \alpha_k p_j \left(s_k + \dfrac{\sigma}{1-\sigma} s_{k/g} \right), & (k \neq j, k \in g) \end{cases}.$$

To illustrate the expected pattern for σ close to 1, the price elasticities of demand for Model 5 are provided below.

In general, the elasticities predicted by the nested logit model are an improvement over those estimated using a traditional logit model and reflect the model's added flexibility. For example, elasticities based on the estimates from Model 5 vary across products *j* within a group *g* relative to a particular product *k* in the same group. Among the patterns observed, elasticities between products within the same group appear to be larger in magnitude than elasticities between products in two different groups. Moreover, the within-group elasticities suggest that, for a given game type, certain casinos-pairs make better substitutes than others. See Table 8, below.

Table 8. Model 5 Price Elasticities of Demand Based on 2004 Prices and Shares

	Quantity: 25-Cent Slots			Quantity: 25-Dollar Slots			Quantity: 5-Cent Slots		
Price	BA	SH	TT	BA	SH	TT	BA	SH	TT
25-Cent									
BA	-6.2774	0.7401	0.8277	0.0235	0.0235	0.0235	0.0235	0.0235	0.0235
SH	0.6542	-6.0371	0.6892	0.0185	0.0185	0.0185	0.0185	0.0185	0.0185
TT	0.5370	0.5058	-6.8754	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169
25-Dollar									
BA	0.0004	0.0004	0.0004	-4.1897	0.2249	0.2534	0.0004	0.0004	0.0004
SH	0.0001	0.0001	0.0001	0.0790	-3.1159	0.0626	0.0001	0.0001	0.0001
TT	0.0004	0.0004	0.0004	0.4069	0.2862	-3.2513	0.0004	0.0004	0.0004
5-Cent									
BA	0.0136	0.0136	0.0136	0.0136	0.0136	0.0136	-7.7942	0.9589	0.8239
SH	0.0132	0.0132	0.0132	0.0132	0.0132	0.0132	0.6942	-9.1830	0.6909
TT	0.0097	0.0097	0.0097	0.0097	0.0097	0.0097	0.5930	0.6869	-7.9909

Where BA = Bally's, SH = Showboat, TT = Trump Taj Mahal

These relationships correspond with the information we learned from looking at the coefficients on casino dummies estimated in the game-level regressions using the traditional logit model. Note that it is still the case that elasticities remain constant across all products j not in group g relative to a specific product k in group g. For example, neither 25-dollar slots nor 5-cent slots belong in the same product nest as 25-cent slots. As a result, the estimated elasticity between 25-cent slots and 25-dollar slots at Bally's is equal to the estimated elasticity between 25-cent slots and 5-cent slots at Bally's. Clearly there is still room for improvement in the model's specification since ideally there would be some variation here.

5.4 Conclusions

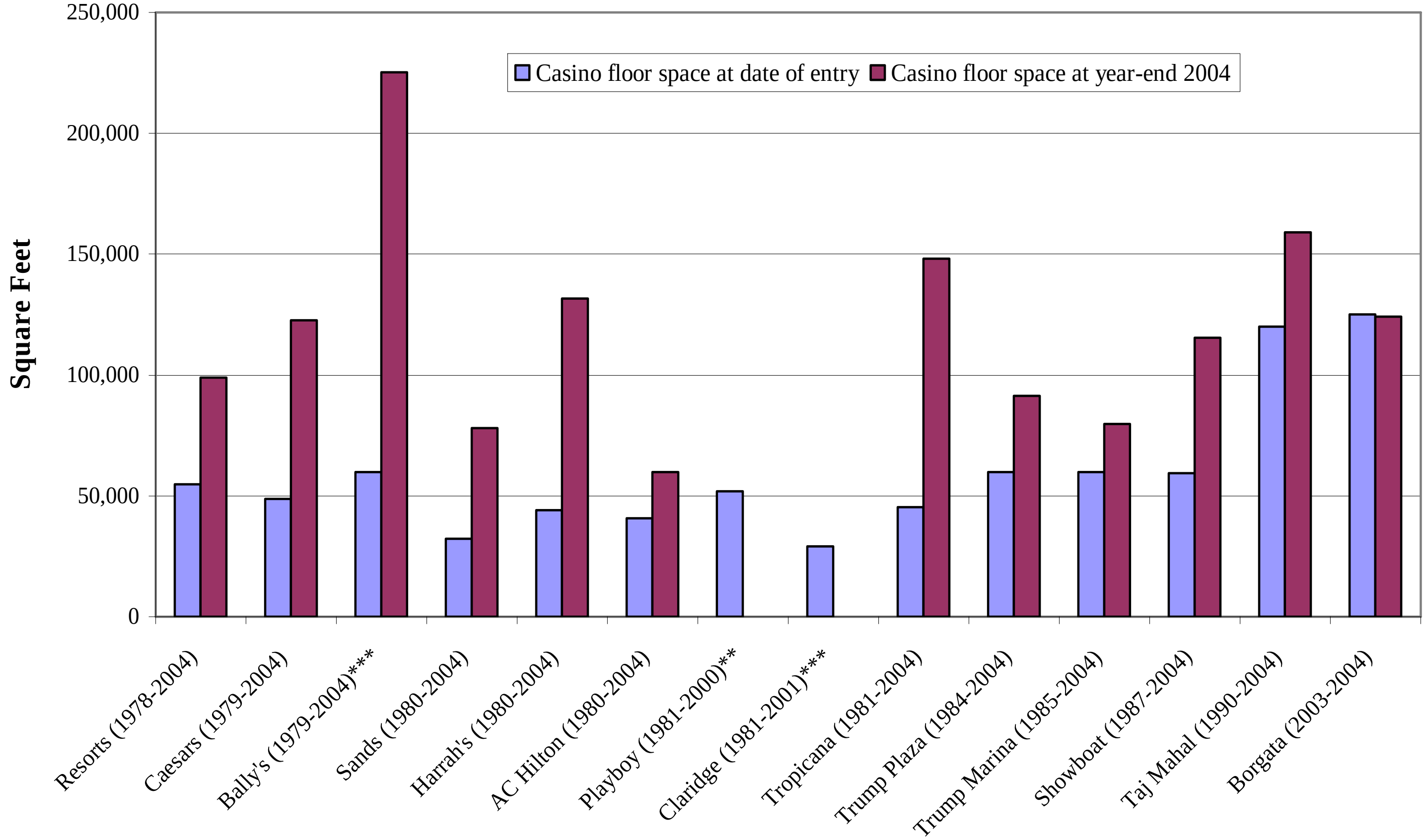
What do the results tell us about which competitive policies will work best for casinos in Atlantic City in the rapidly expanding regional market for gaming? Overall, it is clear that product differentiation is the most promising strategy. In general, that means casinos in Atlantic City must take advantage of the characteristics unique to their ocean-side location and to the variety of choices that come from having such a large number of casinos in one location. It is clear from recent expansions in the city, especially in terms of retail and restaurant offerings, that the casinos have already recognized and begun to address this need. More specifically, the regression results suggest that a casino's comping policies may also have a significant impact on market share—and this potential may not yet be fully realized. Furthermore, the results suggest that comping policies can be refined so as to attract a particular type of consumer, one who will be most responsive to the particular qualities that Atlantic City has to offer.

To start, a negative coefficient associated with the room comps value-per-recipient variable suggests that quantity, rather than quality, may be the right approach for a successful comping policy for rooms. Alternatively, it could mean that casinos with more affordable rooms attract more consumers. In either case, it appears that making rooms more widely available to consumers may be a successful strategy for gaining market share. Indeed, given the number of hotel rooms in Atlantic City, overnight accommodations is one area in which Atlantic City has an advantage compared to many of the gaming alternatives in the region, such as racinos, which tend to attract more daily than overnight visitors.

The optimal comping policy appears to be reversed with respect to food and beverage awards. Recall that the coefficient on the food and beverage comp variable is negative for almost every type if game. It follows that a positive coefficient associated with the variable's value-per-recipient counterpart may be an indication that consumers are more responsive to the size, or total value, of food and beverage awards than the frequency with which they receive them. These observations are completely in accord with the theory of product differentiation. While food and beverage comps are not unique to the casinos in Atlantic City, fine dining increasingly is. The results of the model suggest that casinos might realize even more value from their new dining alternatives by awarding a greater share of the food and beverage budget to a smaller number of consumers.

Consumer loyalty programs have given casinos the information they need to develop very targeted comping programs. Since casinos gained the ability to track consumers' play, the trend in cash and coupon awards has been toward increasing the value of each award without necessarily increasing the number of recipients. The impact of increasing the value of each cash award is unclear from the regression results, which produce an insignificant coefficient for the value-per-recipient variable. Instead, the conclusion that can be drawn is that increasing the number of recipients per visitor appears to have a positive impact on market share among those who play smaller denomination slots, such as nickel slots and quarter slots. To the extent that casinos wish to remain attractive to this highly profitable segment of their consumer population, they should consider expanding the reach of their cash and coupon awards.

Figure 3. Atlantic City Casino Floor Space at Date of Entry and Year-End 2004*



* Including simulcast space.

** The Playboy casino closed in 2000 as the Trump World's Fair Casino.

*** Claridge was acquired by Park Place Entertainment in 2001 and annexed by Bally's in 2003.

Chapter 6: Alternative Specifications and Extensions

Results from the traditional and nested logit model provided interesting insights into the preferences of consumers with respect to various gaming characteristics, especially casino complimentaries. However, the patterns of substitution that could be deduced from the computed elasticities were not entirely credible. There are a couple of estimation techniques that could provide additional flexibility to the model and produce more realistic elasticities of demand.

6.1 The Principles of Differentiation Generalized Extreme Value Model

In addition to estimating a nested logit model in which groups were defined according to type of game, I estimated a model in which nests are defined according to casino. This specification produced a σ very close to 1, even after applying instruments for the group-share term, which suggests a strong correlation in consumer preferences across products within the same casino. This result is not very surprising in light of the fact that products within in the same casino share all of the traits associated with that casino and are only differentiated by game-level attributes. While the sign of the price coefficient was not stable and various coefficients on key variables became insignificant, the overall results of this model did not change the general conclusions presented in Chapter 5. The obvious potential for grouping by either casino or game suggests that a less rigid method for grouping products might be appropriate. A reasonable extension of the model for casino gaming would be to apply the principles of differentiation extreme value approach used by Bresnahan (1997), which allows consumer tastes to be correlated across two different aspects of a product without having to specify which of the two takes priority.

6.2 The Full Random Coefficients Discrete-Choice Model

Beyond this, one could try a full random-coefficients approach in which consumer types are interacted with product characteristics. There are several options with respect to picking a distribution to describe consumer types. One is to assume that unobservable consumer traits have a multivariate normal distribution. Another is to use data on income, education, and other demographic variables to derive a nonparametric distribution of consumer traits. Data can be obtained from the Consumer Population Survey data available on the BLS website and also through NBER. One downside to using population survey data is that it requires making certain assumptions about the correlation between the characteristics of the general population, those of the gaming population, and those of the product units purchased. Insight into which consumer characteristics matter most can be found in Morrison’s 1996 article “A Profile of the Casino Resort Vacationer.” Finally, I think it would also be interesting to explore whether or not a non-parametric distribution of the consumer population could be derived from annual visitor transportation data available from the South Jersey Transportation Authority.

Part II

The Nature of Energy Conservation in California During the Deregulation Crisis

Chapter 7: Introduction

In May of 2000 California's Independent System Operator (ISO), the agency responsible for the physical exchange of the state's electricity, announced that energy reserves had fallen below five percent and declared a Stage II emergency.[22] In the months that followed, reports of a growing energy crisis became increasingly prominent in the media, and the ISO kept the public informed about the status of the state's electricity distribution system through timely Power Watch alerts. These alerts have the dual purpose of announcing critical shortages in the power supply and urging the public to take immediate action to conserve energy.

Data confirm that energy consumption did, in fact, diminish as the public's awareness about the seriousness of the situation grew. The change in same-month peak demand from 2000 to 2001 appears in Table 9. Reductions in demand from one year to the next reached as high as 14 percent.[23] This occurred in spite of the fact that consumers had little financial incentive to reduce their energy consumption during this period. Not only were they protected from soaring wholesale prices by retail price caps, California utilities did not begin offering incentive-based rebates until the summer of 2001.[24]

---

[22] The ISO defines a Stage II emergency as a situation in which utilities may interrupt service to select customers, on a voluntary basis, in order to avoid more serious conditions.
[23] Comparing June 2000 and June 2001.
[24] Price caps for retail sales were set at 10% below 1996 levels and held constant until mid-2001, San Diego excepted.

Table 9. Monthly Peak Electricity Demand (Megawatts)

	Megawatt Difference (2000-2001)	Percent Difference (2000-2001)
January	-2,091	-6.2
February	-2,578	-8.0
March	-2,967	-9.2
April	-2,866	-9.0
May	-3,595	-10.4
June	-5,570	-14.1

Source: California Energy Commission

In the absence of a simple price-quantity explanation, conservation is an explanation for the observed reductions in demand. Households and firms made a socially responsible, possibly altruistic, effort to reduce their overall demand toward achieving a socially optimal outcome. The combination of ISO alerts and news reports that dominated the media during this period may have generated both the awareness and the sense of urgency required to convince people to turn off the lights. In this paper, I attempt to quantify the extent to which ISO alerts, as opposed to other factors, explain the changes in energy consumption observed among households and firms. Toward this goal, I construct an econometric model of electricity demand that includes among its regressors the frequency of Stage I, II, and III ISO Power Watch alerts. The results of this model will be interpreted with eye toward specific policy and economic applications. Of particular interest will be the extent to which reductions in the demand for electricity can be explained by conservation.

Previous studies on the subject of altruistic behavior and social responsibility have been conducted with respect to over-compliance—a phenomenon wherein a firm reduces their pollution emissions below the legal limits. The difficulty in conducting these studies comes primarily from the burden of separating the effects of socially responsible, or altruistic, behavior from other influences, especially financial. The current study differs from previous studies in a couple of important ways. First, agents do not face a penalty for noncompliance (i.e. customers do not pay a fine for failing to reduce energy consumption to below-normal levels).[25] This eliminates the burden of having to account for any influence that such a penalty may have on observed behavior. By the same reasoning, this study benefits from the fact that retail prices are held constant over the period of observation.

Second, the data used in this study allow for a separate examination of each market sector: residential, commercial and industrial. A comparison of the model's estimates across the three sectors provides an interesting opportunity to test for firm accountability. Accountability is a concept introduced in previous writings on the subject of social responsibility, particularly in the area of over-compliance. It refers to the pressure firms face to act according to public or consumer expectations. To illustrate, consider two ways in which Power Watch alerts may influence firm behavior. First, the alerts produce an immediate conservation response from both households and firms. Second, the alerts shape household expectations regarding the way in which firms in the commercial and industrial sectors ought to respond to the emergency. As a result, Power Watch announcements may indirectly be responsible for how firms react to these changing household expectations. The proposed model tests this theory by letting residential behavior represent consumer expectations while differences between

[25] Compliance in the context of energy conservation refers to any reduction in energy consumption to below normal levels.

commercial and industrial behavior reflect the level, or intensity, of firm accountability. It is assumed that households are better able to observe the behavior of commercial firms than that of industrial firms.

The layout of this study is as follows. Chapter 8 provides a review of the related literature and gives both the theoretical and empirical motivation behind this study. Chapter 9 introduces a model for the econometric analysis of the panel data. Chapter 10 provides a description of the data set. The results of the econometric analysis are provided in Chapter 11, and a conclusion follows in Chapter 12.

Chapter 8: Social Responsibility and Conservation

With prices held constant throughout much of California's energy crisis it is tempting to attribute acts of energy conservation to altruistic behavior on the part of households and firms. After all, if we assume all parties were maximizing profits before the crisis then, all else equal, a reduction in energy consumption would be costly. To be certain, all else is not held equal during the period of observation. Yet, after accounting for weather effects, price effects, and macroeconomic factors such as employment, what remains to influence the behavior of energy consumers? What factors, beyond these basics, cause the consumer to reduce consumption and how do they affect economic well-being? Earlier studies may provide some clues.

Previous literature has done a lot to explain seemingly altruistic behavior and has specified conditions under which firms achieve socially beneficial outcomes by acting in their own interest. Baron (2001) calls this phenomenon Corporate Social Performance (CSP). He distinguishes between CSP and Corporate Social Responsibility (CSR) by stating that "both motivation and performance are required for actions to receive the CSR label," whereas performance alone is sufficient for CSP. [26] Throughout this paper I use the term *social responsibility* to refer to any behavior by a household or firm that benefits society. In other words, any level of conservation, whatever the motivation, will be considered socially responsible behavior. This is due, at least in part, to the difficulty of empirically distinguishing between CSP and CSR, both in the context of energy conservation and given the limitations of the available data.

---

[26] In the context of Baron's work, motivation is the desire to improve the social outcome.

Households and firms may conserve energy in times of crisis for many different reasons. Lutzenhiser (2002) conducted a survey in which utility customers in Southern California were asked to rank various factors according to the extent to which each motivated them to conserve energy. Respondents rated “keeping bills down, avoiding blackouts, [using] energy wisely and stopping overcharging by suppliers as most important.” Whereas “[qualifying] for a utility rebate, protecting the environment and seeing how low the bill could go were ranked as less important.” For the most part, goals that consumers consider most important can be characterized as socially responsible, if not altruistic. Many of these motives mirror those mentioned in previous papers on over-compliance (e.g., Arora and Gangopadhyay, 1995, and Harford, 1997). Raising the costs of competitors is not a motive that was addressed in Lutzenhiser’s (2002) survey results, although it is a theory proposed by Salop and Scheffman (1983).

Recognizing that purely altruistic behavior among firms should be rare, Arora and Gangopadhyay (1995) develop a theoretical model of voluntary over-compliance based on data observed through the EPA 33/50 Program. The EPA 33/50 Program was designed by the Environment Protection Agency to encourage firms to voluntarily reduce emissions in exchange for public recognition. Their theory provides an explanation for empirical evidence that suggests competition actually increases efforts towards the cleanup of emissions in spite of the fact that more concentrated markets would be better able to pass the costs along to consumers. In particular, they find that the program was effective because “market forces are important if information on the environmental records of firms is publicly available.” As a result, a segmented market develops in which some of the firms serve consumers with a high willingness to pay for environmentally friendly products while other firms emit more pollutants but offer a less expensive product. In essence, firms in this model are able to differentiate otherwise homogeneous products by reducing emissions because of information made available to the public by the EPA. Arora and Cason (1995) provide an empirical counterpart to the above theoretical study. These main conclusions can be applied to a study of energy conservation and its motivation among firms. Although there is no formalized mechanism for informing consumers about the energy conservation habits of particular firms, consumers can observe directly whether, in times of crisis, a particular store has turned off the lights or shut off the air conditioning. A consumer is less likely to observe these same activities within the industrial sector since direct physical interaction between the consumer and firm is less common.

In this study, aggregated data prevents an examination of behavioral differences between competitive and non-competitive markets. Still, differences between the industrial and commercial sectors may be observable. Note that information about a particular firm's level of energy conservation is neither documented by a government agency, nor made accessible through other means of observation. As a result, commercial firms such as hotels, grocery stores, and bookstores that are easily observed by the end-consumer may be more motivated to differentiate their products through conservation than less conspicuous industrial firms. They may also be more likely to use overt methods of conservation such as turning out lights and cutting back on air conditioning rather than buying energy efficient equipment or insulating the building. Unfortunately, data regarding which types of conservation methods were used by which firms were not available for this report. There is, however, a study being funded by the state of

California that will use surveys to collect this type of data at the household and firm level. See Lutzenhiser (2002).

Further support for a theory that is not dependent on purely altruistic motivations comes from Becker and Barro (1988). These authors show how a dynamic utility function can describe the altruistic relationship between parents and children. A reasonable extension of this idea might be to apply a similar function to describe the “altruistic” relationship between energy consumers and their state government. In the case of California, households and firms may be able to increase the likelihood that the state government endures an energy crisis with minimal financial strain simply by conserving energy. In return, a healthier government could mean lower taxes and fewer restrictions on energy use in the future. Indeed, during the California energy crisis, there was significant strain on the government as the state was forced to pay tens of millions of dollars per day to energy producers in order to keep the energy markets functioning during times when supply was short and neither consumers nor utilities could compensate for discrepancies in wholesale and retail prices.

Images on national TV showing grocery stores in California with their lights turned out during shopping hours suggest that conservation really happened. The question we try to answer here is why. To obtain the answer, I develop a model of electricity demand that accounts for more than just climate, prices, and major macroeconomic variables. The model also accounts for the influence of crisis-related media announcements as well as the availability of rebates. Demand is analyzed across all of these variables for the residential, commercial and industrial sectors. Estimates from this model are intended to facilitate a better understanding of what generates a public response in a crisis situation. Potential public policy applications include the development of optimal communications and incentive programs designed to motivate households and firms to conserve energy in times of crisis. More generally, insights gained from the model could lead to a better understanding of how to motivate the general public to engage in socially responsible behavior in a variety of situations.

Chapter 9: Econometric Procedure

I examine a model of electricity demand as a function of ISO Power Watch alerts, macroeconomic variables, climate, retail electricity prices, a rebate dummy and a shock variable. The goal of the model is to fully account for all of the variables that affect the demand for electricity so that the influence of ISO Power Watch alerts can be accurately measured. By sector we estimate:

$$\text{DEMAND}_{u,t} = \alpha_u + \eta\left(\text{ISO POWERWATCH}\right)_t + \delta\left(\text{ECON}\right)_t + \phi\left(\text{CLIMATE}\right)_{u,t} + \beta\left(\text{PRICE}\right)_{u,t} + \lambda\left(\text{REBATE}\right)_{u,t} + \varepsilon_{u,t} \qquad (2)$$

The subscripts *u* and *t* represent variation across utility and time, respectively. A single, non-specific shock ε is included in the model. Climate, price per kilowatt hour, and the availability of rebates are variables that vary across both utility and time. The macro-economic variables (including new building permits and the unemployment rate) and the count of ISO Power Watch alerts (Stages I, II and III) are factors that vary over time only. Descriptive statistics for each of these variables appear in Table 10.

Estimates generated for the initial specification using OLS were poor, and a closer examination of the relationship between the dependent and explanatory variables revealed that the ISO Power Watch variable may be endogenous to the model. To solve this problem, I find an instrument for the ISO Power Watch variable and use 2SLS to re-estimate the model. California monthly precipitation is a good candidate for the instrument because (a) rainfall does not influence energy demand, and (b) rainfall is an important determinant of the number of Stage I, II, and III Power Watch alerts. The reason is that California relies heavily on hydroelectric power generation, and shortages in power generation lead to shortages in supply and, consequently, to crisis situations.

Table 10. Descriptive Statistics of the Electricity Market

Variable	Minimum	Maximum	Mean	Std. Dev.
Demand/Consumer (kWh)				
Residential	360.37	1,139.95	575.09	156.95
Commercial	1,158.40	7,187.03	4,164.83	2,056.64
Industrial	4,710.5	827,582.6	207,096.7	261,571.2
ISO Power Watch Alerts[a]	0	63	4.7	12.3
Building Permits	5,875	17,888	10,847	2,112
Unemployment Rate (%)	4.4	7.4	5.6	0.7
Cooling Degree Days	0.0	446.2	116.1	132.6
Heating Degree Days	0.0	640.0	165.2	165.4
Fixed Price ($/mo.)				
Residential	0.00	5.00	0.66	1.03
Commercial[b]	4.00	14.88	8.62	4.46
Industrial[c]	50.00	299.00	144.67	110.37
Variable Price (¢/kWh)[d]				
Residential	9.63	15.16	12.24	1.74
Commercial[b]	7.29	21.04	10.04	2.28
Industrial[c]	4.57	12.12	6.08	1.54
Demand (kWh x 1,000)				
Residential	232,361	3,072,033	974,779	793,661
Commercial	54,470	3,372,493	1,184,518	994,115
Industrial	183,292	2,493,352	871,989	831,124
Consumers				
Residential	433,099	3,873,163	1,812,252	1,427,162
Commercial	45,735	496,934	233,961	182,679
Industrial	2,954	41,925	11,139	9,602

[a] Total Stage I, II, and III Emergency announcements per month
[b] Commercial Class I
[c] Industrial Class I
[d] Variable Rate Type I

The revised 2SLS model for electricity demand can be written as:

$$\text{DEMAND}_{u,t} = \alpha_u + \eta\left(\text{ISO POWERWATCH}\right)_t + \delta\left(\text{ECON}\right)_t + \phi\left(\text{CLIMATE}\right)_{u,t}$$

$$+\beta\left(\text{PRICE}\right)_{u,t} + \lambda\left(\text{REBATE}\right)_{u,t} + \chi\left(\upsilon_{t,estimated}\right) + \varepsilon_t \qquad (3)$$

$$\left(\text{ISO POWERWATCH}\right)_t = \alpha_u + \gamma\left(\text{PRECIPITATION}\right) + \delta\left(\text{ECON}\right)_t + \phi\left(\text{CLIMATE}\right)_{u,t}$$
$$+ \beta\left(\text{PRICE}\right)_{u,t} + \lambda\left(\text{REBATE}\right)_{u,t} + \upsilon_t \qquad (4)$$

A discussion of the estimates generated for this model follows a description of the data.

Chapter 10: Data

Monthly panel data were compiled for the period beginning February of 1997 and ending December of 2001. All observations are unique at the sector, utility, and date level.

The dependent variable for the proposed model is defined as average monthly sales per consumer. It is computed by dividing monthly sales totals by the corresponding number of consumers.[27] Sales figures were obtained from the Energy Information Administration (EIA) database titled "Monthly Electric Utility Sales and Revenue Data."[28] These data are aggregated at the level of utility and sector and include total monthly revenue (in thousands of dollars) and sales (in thousands of Kilowatt hours) for the residential, commercial, industrial, and *other* sectors. Four utilities are represented by the survey: the Los Angeles Department of Water and Power (LADWP), Pacific Gas & Electric (PGE), Southern California Edison (SCE), and the Sacramento Municipal Utility District (SMUD). The EIA considers these four to be a "statistical sample" of all California utilities as they represent nearly the entire population of electricity consumers in California.

Exposure to crisis-related news reports and public announcements through the media is probably the biggest determinant of consumer awareness regarding the need to conserve energy. A variable that perfectly captures the intensity of this coverage would be a useful addition to the model. To derive such a variable in a way that captures every

[27] Annual consumer counts for each sector-utility pair were obtained from Forms EIA-861. Monthly dummies compensate for the missing monthly values.
[28] Data originate from Forms EIA-826.

type of coverage (news reports, public announcements, debates) across every form of media (newspapers, television, radio) would not be feasible. Fortunately, the events most likely to have generated news stories (e.g., power shortages and blackouts) are the very events reported in press releases that were issued by the ISO through their Power Watch program. Because the ISO maintains a complete record of these press releases, I am able to derive a variable that represents the total number of ISO Power Watch alerts per month including all Stage I, II, and III emergency alerts.[29] Non-emergency ISO announcements are not included.

Two macroeconomic variables also appear in the model. These include the monthly rate of statewide unemployment and the number of new building permits issued in California each month.

A climate variable is constructed using monthly Cooling Degree Day (CDD) and Heating Degree Day (HDD) data obtained from the National Climatic Data Center website. A Cooling Degree Day is an absolute measure of how much the average daily temperature exceeds a base temperature of 65 degrees Fahrenheit. Likewise, a Heating Degree Day is an absolute measure of the extent to which the temperature falls below a base temperature of 65 degrees Fahrenheit. These measurements are a good indication of how much energy would be required to keep the indoor environment at a comfortable temperature and, therefore, are likely to be important components in any model of energy demand.

[29] Stage 1 announcements urge consumers to reduce their use of electricity voluntarily to avoid more severe conditions; Stage 2 alerts inform consumers that voluntary interruption of service to select customers is required to avoid more severe conditions; and Stage 3 alerts advise consumers that rotating outages are possible.

The NCDC data provides monthly CDD and HDD totals for each NCDC weather station within a county. With the exception of four counties in the sample, there are between one and ten stations per county. Monthly CDD and HDD totals for each county are computed by averaging over the weather stations in that county. One last transformation is required to link climate data to their respective observations since consumption data is aggregated by utility. I derive a utility-specific climate variable by again taking an average, this time over all of the counties located within the service area of a given utility, weighting it according to county population. The California Department of Finance website provides a table of estimated county populations, by year, based on California 1990 and 2000 census data. Monthly population estimates are derived from the annual figures.

The CDD and HDD variables enter the model's final specification as the square of their- difference. They do not enter the model separately because neither variable is able to capture the full range of climate-related changes that affect demand due to the fact that each variable is bounded below by zero. To illustrate, consider that a very high CDD generally corresponds to higher energy consumption due to an increase in the use of air conditioners while a very low CDD will not necessarily correspond to the increase in energy consumption caused by an increase in the use of electric heaters. Instead, a low CDD may coincide with both periods in the middle of winter (when energy use is peaking) as well as periods of very pleasant weather, such as in the fall or spring, when energy use is relatively low. The same phenomenon is true for HDD. One solution is to take the difference between CDD and HDD. Large differences between CDD and HDD can be associated with extreme weather (very hot or very cold) while small differences can be associated with pleasant weather (neither hot nor cold). The climate variable is then squared because plots of the transformed variable against demand suggest this more accurately describes the relationship between climate and demand.

The model also includes a dummy variable equal to one if the utility is participating in the state-run 20/20 Program. This program offers rebates of 20 percent to all consumers reducing energy usage by at least 20 percent relative to the same-month, year-2000 levels. Only two of California's four main utilities offered the 20/20 Program to their consumers over the observation period. These are the investor-owned utilities PGE and SCE. The program was made available during the summer months of 2001. Details regarding the number of consumers that were eligible for rebates are available, but were not obtained for use in this study.

Each of the utilities provided monthly fixed and variable electricity rates, or tariffs, by sector. For the purposes of this study, I make certain simplifying assumptions with respect to the price data. Most notably, I use only the most common pricing schedule for each sector. This was necessary due to the aggregated nature of the sales data. As a result, estimates must be interpreted as though the consumer population is homogenous in spite of the fact that the typical rate sheet suggests otherwise. Rates typically vary according to quantity and time of usage, as well as need for financial assistance. Residential rates were chosen based on statistics that suggest a "typical American home uses about 840 Kilowatt hours per month."[30] This level of consumption typically coincides with second-tier rates that fall just above the baseline. It should be noted that retail prices were capped at 10 percent below 1996 levels in order to protect

[30] Based on information on the California Independent System Operators website: www.caiso.com.

consumers during the deregulation of California's energy market. They remained capped until mid-2001. Only San Diego, not covered in this study, uncapped prices as early as 1999, only to reinstate a price cap soon after as a result of rapidly increasing retail market prices.

Rainfall and reservoir storage data for California, Washington, and Oregon were obtained from the United States Department of Agriculture - National Resources Conservation Service - National Water and Climate Center.[31] Of these, only California monthly precipitation is included in the final model. It enters in the first-stage estimation as an explanatory variable for the number of ISO Power Watch alerts. Declining rainfall has been reported as an important contributing factor to the shortage of power during the crisis due to the fact that California relies heavily on hydroelectric power. Precipitation enters the model as a deviation from the monthly average.[32]

---

[31] California data is located at http://www.wcc.nrcs.usda.gov/cgibin/precip.pl?state=california, for example.
[32] Based on the average same-month rainfall from 1961 to 1990.

Chapter 11: Results

Coefficient estimates for the model described in Equation 4 are generated for each sector using a total of 177 observations, comprising 59 months of data for three of California's four major utilities. The fourth utility, PGE, is not represented in the analysis because adequate price data could not be obtained. The main objective of this model is to measure each sector's response to ISO Power Watch alerts. The magnitude of the response will be interpreted as the tendency of each consumer class to engage in socially responsible behavior (i.e., to conserve energy). This makes sense as long as ISO alerts are a suitable proxy for the level of consumer awareness with respect to the need for conservation. Estimates generated for the commercial and industrial sectors are of particular interest. As part of the secondary objective of the model, they will be analyzed to determine whether or not they provide new evidence to validate or discount the theory of firm accountability. The theory asserts that market forces explain most of the socially responsible behavior exhibited by firms. The final objective of the model is to generate insight into what factors motivated the conservation response observed in California. Ultimately, these lessons may be applied to developing optimal strategies for directing a large-scale public response to an emergency situation.

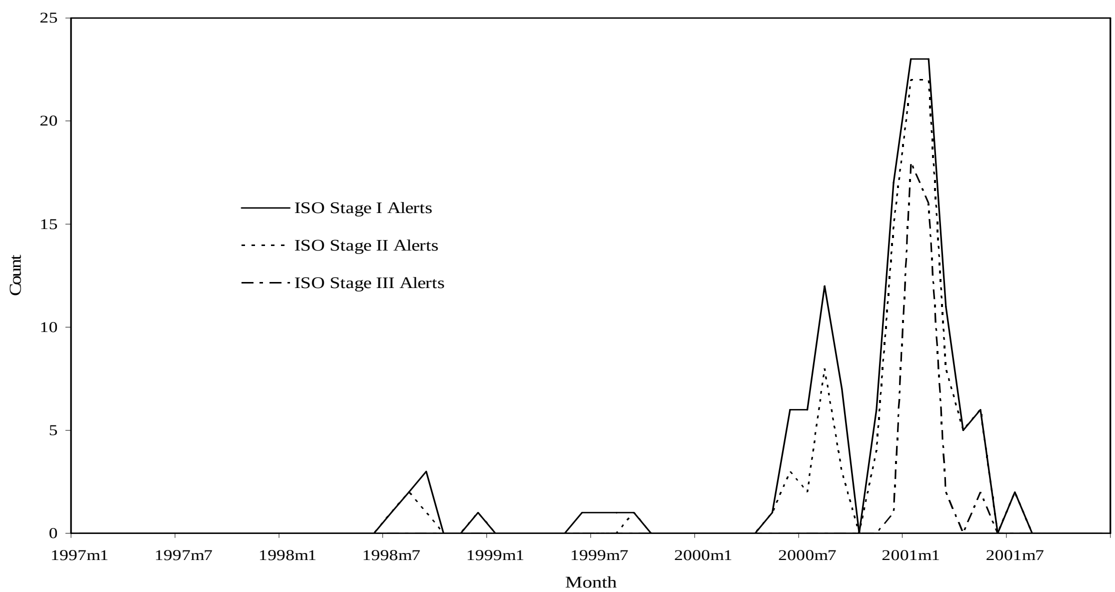
Table 11. 2SLS Estimates for Electricity Demand per Consumer (kWh x 1000)

	Residential Sector		Commercial Sector		Industrial Sector	
Parameter	Estimate	t-value	Estimate	t-value	Estimate	t-value
Constant	0.3204**	2.19	5.3047***	6.06	17.1804	0.18
ISO Power Watch Alerts	-0.0011	-1.41	-0.0047	-1.05	-0.3711	-0.57
Building Permits	2.36×10^{-6}	0.36	0.0001	1.60	0.0141**	2.50
Unemployment Rate	-0.0205	-0.98	-0.1239	-1.01	-38.6741**	-2.17
Degree Days, difference squared	7.24×10^{-7}***	4.97	8.95×10^{-7}	1.08	0.0002*	1.73
Rebate	-0.0573	-1.56	0.8715**	2.57	125.18***	3.73
Fixed Price, \$/mo	-0.0007	-0.10	0.0740	0.50	--	--
Variable Price, ¢/kWh	0.8882	0.71	0.6471	0.17	173.9599	0.44
Dummies						
dutility2	0.0687	1.27	-1.7871	-1.15	543.44***	47.65
dutility3	0.2504***	9.17	-4.8842***	-10.01	24.5209**	2.09
dmonth2	0.1620***	6.06	0.6933***	4.49	19.7908	0.88
dmonth3	0.0260	0.83	-0.0104	-0.06	-37.4888	-1.42
dmonth4	0.0422	1.07	0.1790	0.76	52.0628	1.52
dmonth5	0.0978***	3.04	0.2832	1.51	22.0061	0.80
dmonth6	0.1447***	4.80	0.5872***	3.32	22.5399	0.87
dmonth7	0.0729**	2.37	0.2693	1.50	-25.6866	-0.96
dmonth8	0.0360	1.49	-0.0189	-0.14	14.3486	0.70
dmonth9	0.0102	0.43	0.1353	0.98	9.2958	0.46
dmonth10	0.0036	0.14	0.2751*	1.85	3.7119	0.17
dmonth11	0.0818	1.48	0.4476	1.35	-53.7916	-1.12
dmonth12	0.1490***	5.41	0.6833***	4.29	35.1613	1.51
RISO[a]	0.0003	0.37	0.0018	0.39	1.1765*	1.79
Number of Obs	177		177		177	
R-squared	0.8494		0.9721		0.9612	
F	41.63		256.76		193.33	

[a] Residual from Stage 1 Least Squares Estimation.
Note: * - 10% significance level; ** - 5% significance level; *** - 1% significance level.

The estimated coefficients on the PowerWatch variable are insignificant for all three market sectors suggesting that PowerWatch alerts had little or no measurable impact on the behavior of households or firms. It is possible, however, that the difficulty in measuring a demand response is due to the limited sample size, and that the significance level would increase if price data for PGE, for example, became available. Allowing for a relaxed level of significance, such as at the 20% significance level, would yield the following conclusions. Results of the empirical analysis suggest that ISO alerts have the biggest impact on household sales. The model predicts (at a significance level of 16.1 percent) that the average residential consumer will reduce their energy consumption by 1.9 percent for every 10 additional ISO alerts.[33] To put that in perspective, consider that the number of ISO alerts exceeded 50 during a single month at the height of the deregulation crisis. Refer to Figure 4, below.

Figure 4. Frequency of Stage I, II, and III Power Watch Alerts from California's Independent System Operator



Among the two remaining sectors, commercial firms appear to have a greater tendency toward conservation than industrial firms. For every 10 additional ISO alerts, the model

[33] Figures reflect a percentage change in average sales per consumer based on the estimated ISO coefficient.

predicts that electricity sales per commercial consumer will decrease by 1.1 percent at a significance level of 29.4 percent while sales per industrial consumer will decrease by 1.8 percent at a significance level of just 56.7 percent. See Table 11 for estimates and their t-values.

From a policy perspective, it is encouraging that ISO alerts appear to be effective in reducing energy demand among households. Although questions remain regarding the ability of ISO alerts to generate a conservation response among commercial and industrial firms, the fact that households and firms responded differently to the crisis may be informative. Acts of social responsibility are most likely to be performed by the party who can do it at least cost (altruism) or maximum benefit (CSR). Households make an excellent target for energy conservation campaigns because a large percentage of the electricity they consume is allocated to nonessential amenities such as air conditioning, lighting (especially during daylight hours), and hot water. As a result, they can significantly decrease their energy consumption by making small, costless changes in their regular routine.

In addition to feeling satisfied about having helped alleviate the crisis, households can look forward to savings on their next electricity bill. Firms, on the other hand, may face an entirely different set of consequences. Many firms allocate the majority of the energy that they consume to the actual production process. For these firms, conservation could disrupt their ability to provide goods and services and consequently have a negative impact on the bottom line. In these cases, the decision to conserve makes sense only in the context of a rebate program which guarantees future savings to the firm or cash rewards in exchange for current reductions in demand, especially during peak hours or emergency situations.

In a theoretical sense, the fact that households appear to be sensitive to ISO alerts may be an indication of more than just a willingness to conserve. It may also signal that, as consumers, they have certain expectations regarding the responsibility of firms to conserve. To test this idea, we must ultimately determine whether or not these expectations have any observable influence on firm behavior. Based on the theory of firm accountability, firms in the commercial sector are expected to be more susceptible to market forces originating from consumer expectations. This is true because 1) conservation efforts must be observable, 2) observations are most likely to take place during store visits, and 3) store visits usually occur in the context of the relationship between households and the commercial, rather than industrial, establishments. It follows that ISO alerts should have a greater impact on demand among commercial firms than among industrial firms. Estimates are more or less inconclusive in this regard. On one hand, the results suggest that industrial firms are more sensitive to ISO alerts, at least in terms of the magnitude of the coefficient. On the other hand, the estimated coefficient for commercial firms is statistically more significant. In brief, the test neither confirms nor rules out the possibility that consumer expectations increased conservation rates among firms.

The number of ISO alerts would, of course, be a poor predictor of commercial and industrial demand if firms simply did not conserve. However, there may be alternative explanations for the low t-values associated with this variable. One is unaddressed heterogeneity among firms. Firms differ from one another in two critical ways. First, they consume different quantities of electricity; and second, they face a different set of consequences (or costs) in the event that they choose to conserve electricity. Unfortunately, the aggregate nature of the data prevents us from incorporating these factors into the model. Instead, we must rely on a representative consumer approach. Another consideration with respect to low t-values is that different firms may be responding to different, and opposing, consumer expectations. For example, a local purveyor of hemp clothing might appeal to their socially minded customers by turning out the lights and turning off the air conditioning, whereas a local grocer may benefit as much or more from keeping the lights on and the food frozen. It comes down to what adds the most value to the product or service being provided. Although both firms are responding to consumer expectations, each makes a different choice about whether or not to conserve energy. The combined effect could lead to inconclusive results regarding the true role of consumer expectations with respect to a firm's decision to conserve energy.

In general, the model seems to fit the data well and produces estimates which have the expected signs. For example, the estimated coefficient for ISO Power Watch Alerts is negative for all three sectors. Similarly, the estimated coefficient for Building Permits is positive, while the one for Unemployment Rate is negative and the one for climate (Degree Days) is positive. Of these, the estimated coefficients for Building Permits and Unemployment Rate appear to be more significant with respect to industrial demand than residential demand. Alternatively, the estimated coefficient for the climate variable is most significant with respect to residential demand. These results are encouraging since one would expect macroeconomic variables to be a stronger determinant of industrial demand for electricity, just as one would expect changes in temperature to be a stronger determinant of household demand. After all, heating and cooling account for a greater proportion of a household's energy consumption.

Interpreting the estimates derived for the rebate and price variables is not as straightforward. For the residential sector, the coefficients on rebate and fixed price are both negative, as expected, but the estimate for variable price is positive, though not significant. For both the commercial and industrial sectors, coefficient estimates for all three variables are positive. However, only the coefficient for the rebate variable is significant. A positive rebate coefficient is hard to interpret since there is no obvious economic explanation for why demand should increase in response to the availability of a rebate program, especially one that is designed to reward consumers for conserving energy. There are, however, alternative explanations. For one, SCE is the only utility to offer the rebate during the observation period, which means the variable could be capturing something specific to that utility. For another, the period during which the rebate program was in effect coincides with the peak of the energy crisis in the summer of 2001. This could be a sign that the rebate variable is endogenous.

Further exploration of this topic would benefit from four items not available for the purpose of this study. First, two additional instrumental variables are required in order to address the fact that variable price and rebate may be endogenous in the model. Second, monthly consumer population data would minimize measurement errors inherent in the dependent variable as a result of its being derived from annualized population data. Third, disaggregated consumer-level data would extend the econometric scope of the model and increase the likelihood of obtaining estimates that would better characterize the role of market forces on socially responsible behavior among firms. Finally, obtaining accurate price data for PGE would increase the number of observations by 33 percent and improve the overall quality of the estimates.

Chapter 12: Conclusions

Unstable market conditions in California during the deregulation crisis meant that even small shortfalls in the supply of electricity ended up costing the state millions of dollars. This has obvious implications with respect to public policy for states that may yet face the uncertainty of their own deregulation process. The message can also be applied more broadly. Officials preparing for any type of situation that would require an immediate response by the public should give serious consideration to preparing a public announcement program that is capable of keeping everyone informed about the immediate status of the situation (such as a weather emergency, natural disaster, civil unrest, or terrorist attack) and to focus any requests for action on the group that can respond at the lowest cost. When possible, a program that compensates individuals or firms for the cost of responding should be considered. Finally, neglecting to develop a multi-pronged approach could have serious consequences. After all, commercial and industrial firms in California consume roughly two thirds of all the electricity sold in that state.[34]

Table 12. Sales by Utility and Sector, Year 2000

	LADWP	SCE	SMUD	PGE
Total Sales (Millions of kWh)	22,852	82,813	9,620	81,014
Residential (% of Total)	29.3	31.9	43.0	35.4
Commercial (% of Total)	57.3	36.4	8.5	43.5
Industrial (% of Total)	11.6	30.9	47.7	20.3
Other (% of Total)	1.8	0.8	0.8	0.8

Source: EIA Form 826

[34] The relative sizes of each consumer class appear in Table 12.

Appendix A

The general formula for price elasticities of demand under the traditional logit model can be written as

$$\eta_{jk} = \frac{\partial \ln s_j}{\partial \ln p_k} = \frac{\partial s_j}{\partial p_k} \cdot \frac{p_k}{s_j}$$

where s_j are the aggregate shares of product *j*, and the subscript denoting time t is suppressed. Recall that the expression for s_j using the traditional logit model is

$$s_j = \frac{e^{\delta_j}}{\sum_{m=0}^{J} e^{\delta_k}}.$$

To derive the own-price elasticity, let $j = k$ and substitute the expression for s_j, given above, into the first term of the formula for price elasticity:

$$\frac{\partial s_j}{\partial p_j} = \frac{\partial}{\partial p_j}\left[\frac{e^{\delta_j}}{\sum_{m=0}^{J} e^{\delta_m}}\right]$$

$$= \left(e^{\delta_j}\right) \cdot \frac{\partial}{\partial p_j}\left(\sum_{m=0}^{J} e^{\delta_m}\right)^{-1} + \left(\sum_{m=0}^{J} e^{\delta_m}\right)^{-1} \cdot \frac{\partial}{\partial p_j}\left(e^{\delta_j}\right)$$

$$= -\left(\frac{e^{\delta_j}}{\left(\sum_{m=0}^{J} e^{\delta_m}\right)^{-2}}\right) \cdot \frac{\partial}{\partial p_j}\left(\sum_{m=0}^{J} e^{\delta_m}\right) - \alpha_j\left(\frac{e^{\delta_j}}{\sum_{m=0}^{J} e^{\delta_m}}\right)$$

$$= \alpha_j\left(\frac{\left(e^{\delta_j}\right)^2}{\left(\sum_{m=0}^{J} e^{\delta_m}\right)^{-2}} - \frac{e^{\delta_j}}{\sum_{m=0}^{J} e^{\delta_m}}\right).$$

Next, make the same substitution for s_j in the second term of the formula for elasticity:

$$\frac{p_j}{s_j} = p_j \cdot \frac{\sum_{m=0}^{J} e^{\delta_m}}{e^{\delta_j}}.$$

Finally, take the product of the two terms and simplify to get the elasticity:

$$\eta_{jj} = \alpha_j \left(\frac{\left(e^{\delta_j}\right)^2}{\left(\sum_{m=0}^{J} e^{\delta_m}\right)^{-2}} - \frac{e^{\delta_j}}{\sum_{m=0}^{J} e^{\delta_m}} \right) \cdot p_j \frac{\sum_{m=0}^{J} e^{\delta_m}}{e^{\delta_j}}$$

$$= -\alpha_j p_j \left(1 - s_j\right).$$

This is the expression used to compute own-price elasticity in the traditional logit model. A comparable calculation, assuming $j \neq k$, gives the following formula for the cross-price elasticity: $\eta_{jk} = \alpha_k p_k s_k$.

Appendix B

The following derivation of the inverse market share function for the nested logit model has been adapted from the detailed description given by Berry (1994). The procedure involves the following basic steps.

First, Berry (1994) specifies the market share equation for product j. This is determined jointly by the share of product j with respect to other products in the nesting group $g \in G$, $G = \{0,1,...,\bar{G}\}$, and the market share of group g with respect to the rest of the market as follows. Given

$$\bar{s}_{j/g}(\delta,\sigma) \quad = \quad \frac{e^{\delta_j/(1-\sigma)}}{D_g} \text{ where } D_g \equiv \sum_{j \in g} e^{\delta_j/(1-\sigma)}$$

and

$$\bar{s}_g(\delta,\sigma) \quad = \quad \frac{D_g^{(1-\sigma)}}{\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}},$$

it follows that

$$s_j(\delta,\sigma) \quad = \quad \bar{s}_{j/g}(\delta,\sigma)\bar{s}_g(\delta,\sigma) \quad = \quad \frac{e^{\delta_j/(1-\sigma)}}{D_g^{\sigma}\left[\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right]}.$$

Note that since $\delta_0 = 0$, it is also the case the $D_0 = 1$ and so

$$s_0(\delta,\sigma) = \frac{1}{\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}}.$$

Based on this model, we can derive an analytic expression for mean utility, δ, in terms of the observed market shares S_j by taking the log of both sides:

$$\ln\left(S_j\right) = \frac{\delta_j}{(1-\sigma)} - \ln D_g{}^{\sigma} - \ln\left[\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right].$$

Subtracting $\ln S_0$ from both sides, we see that

$$\ln(S_j) - \ln(S_0) = \frac{\delta_j}{(1-\sigma)} - \ln D_g{}^{\sigma}$$

$$= \frac{\delta_j}{(1-\sigma)} - \sigma\left[\frac{\delta_j}{1-\sigma} - \ln(\bar{S}_{j/g})\right] = \delta_j - \sigma \ln(\bar{S}_{j/g}).$$

The mean utility can then be expressed as

$$\delta_j(S,\sigma) = \ln(S_j) - \ln(S_0) + \sigma \ln(\bar{S}_{j/g}).$$

Setting $\delta_j = x_j\beta - \alpha p_j + \xi_j$, we can rearrange terms to yield a linear expression similar to the one estimated under the traditional logit model, but with a nested term on the right hand side:

$$\ln S_j - \ln S_0 = x_j\beta - \alpha\, p_j + \sigma \ln \bar{S}_{j/g} + \xi_j\,.$$

This equation can be estimated using standard OLS and 2SLS regression methods.

Appendix C

The expressions from Appendix B can be used to derive price elasticities of demand under the nested logit model. According to the inverse market share function, we know

$$\ln(s_j) - \ln(s_0) = \frac{\delta_j}{(1-\sigma)} - \sigma \ln D_g \,.$$

Elasticities can therefore be expressed as

$$\eta_{jk}(k \neq j\,;\, j,k \in g) = \frac{\partial \ln(s_j)}{\partial p_k} \cdot p_k = p_k \cdot \frac{\partial}{\partial p_k}\left[\frac{\delta_j}{(1-\sigma)} - \sigma \ln D_g + \ln(s_0)\right].$$

This partial derivative can be evaluated in three pieces, the first term being equal to 0:

$$\frac{\partial}{\partial p_k}\left(\frac{\delta_j}{(1-\sigma)}\right) \quad = \quad \left(\frac{1}{(1-\sigma)}\right)\frac{\partial}{\partial p_k}\left(x_j\beta - \alpha_j p_j + \varepsilon_j\right) \quad = \quad 0\,.$$

Solving for the second term yields:

$$\frac{\partial}{\partial p_k}\left(-\sigma \ln(D_g)\right) \quad = \quad -\sigma \frac{\partial}{\partial p_k} \ln\left(\sum_{j \in g} e^{\delta_j/(1-\sigma)}\right)$$

$$= \quad -\sigma\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right)^{-1} \frac{\partial}{\partial p_k}\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right) \quad = \quad -\sigma\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right)^{-1} \frac{\partial}{\partial p_k}\left(e^{\delta_k/(1-\sigma)}\right)$$

$$= \quad -\sigma\left(\frac{e^{\delta_k/(1-\sigma)}}{\sum_{j\in g} e^{\delta_j/(1-\sigma)}}\right)\frac{\partial}{\partial p_k}\left(\delta_k/(1-\sigma)\right)$$

$$= \quad \frac{\alpha_k \sigma}{(1-\sigma)}\left(\frac{e^{\delta_k/(1-\sigma)}}{\sum_{j\in g} e^{\delta_j/(1-\sigma)}}\right) \quad = \quad \alpha_k \frac{\sigma}{(1-\sigma)} \bar{s}_{k/g}\,.$$

Solving for the third term of the elasticity expression yields:

$$\frac{\partial}{\partial p_k}\ln s_0 \quad = \quad -\frac{\partial}{\partial p_k}\ln\left(\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right)$$

$$= \quad -\left(\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right)^{-1} \frac{\partial}{\partial p_k}\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right)^{(1-\sigma)}$$

$$= \quad -(1-\sigma)\left(\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right)^{-1}\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right)^{(-\sigma)} \frac{\partial}{\partial p_k}\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right)$$

$$= \quad \alpha_k\left(\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right)^{-1} \frac{e^{\delta_k/(1-\sigma)}}{\left(\sum_{j\in g} e^{\delta_j/(1-\sigma)}\right)^{\sigma}} \quad = \quad \alpha_k\left(\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}\right)^{-1} \frac{\bar{s}_{k/g} D_g}{D_g{}^{\sigma}}$$

$$= \quad \alpha_k \frac{D_g^{(1-\sigma)}}{\sum_{i=0}^{\bar{G}} D_i^{(1-\sigma)}}\bar{s}_{k/g} \quad = \quad \alpha_k \bar{s}_g \bar{s}_{k/g} \quad = \quad \alpha_k s_k$$

Finally, putting the three terms together yields the complete formula for elasticities:

$$\eta_{jk}(k \neq j\ ; j,k \in g) \quad = \quad \alpha_k p_k\left[s_k + \frac{\sigma}{1-\sigma}s_{k/g}\right].$$

The own price elasticity of demand and the cross price elasticity of demand, where $k \neq j$, $j \in g$ and $k \notin g$, can be similarly derived.

References

Allenby, Greg M. and Rossi, Peter E. "Quality Perceptions and Asymmetric Switching between Brands," *Marketing Science*, Summer 1991, 10(3), pp. 185-204.

Allenby, Greg M.; Shively, Thomas S.; Yang, Sha and Garratt, Mark J. "A Choice Model for Packaged Goods: Dealing with Discrete Quantities and Quantity Discounts," *Marketing Science*, Winter 2004, 23(1), pp. 95-108.

Arora, Seema and Cason, Timothy N. "An Experiment in Voluntary Environmental Regulation: Participation in EPA's 33/50 Program," *Journal of Environmental Economics and Management*, May 1995, 28(3), pp. 271-286.

Arora, Seema and Gangopadhyay, Shubhashis. "Toward a Theoretical Model of Voluntary Overcompliance," *Journal of Economic Behavior and Organization*, 1995, 28(3), pp. 289-309.

Baron, David P. "Private Politics, Corporate Social Responsibility, and Integrated Strategy," *Journal of Economics & Management Strategy*, 2001, 10(1), pp. 7-45.

Becker, Gary S. and Barro, Robert J. "A Reformulation of the Economic Theory of Fertility," *Quarterly Journal of Economics*, February 1988, 103(412), pp. 1-25.

Berry, Steven T. "Estimating Discrete-Choice Models of Product Differentiation," *Rand Journal of Economics*, Summer 1994, 25(2), pp. 242-262.

Berry, Steven T.; Carnall, Michael and Spiller, Pablo T. "Airline Hubs: Costs, Markups and the Implications of Customer Heterogeneity." In *Advances in Airline Economics, Vol. 1: Competition Policy and Anti-Trust*, D. Lee, ed. Elsevier Press, 2006, pp. 183-214. (An earlier version is NBER Working Paper #5561, May 1996.)

Berry, Steven T.; Levinsohn, James and Pakes, Ariel. "Automobile Prices in Market Equilibrium." *Econometrica*, July 1995, 63(4), pp. 841-890.

_____. "Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market." *Journal of Political Economy*, 2004, 112(1), pp. 68-105.

Bjorner, Thomas B.; Togeby, Mikael and Jensen, Henrik H. "Industrial Companies' Demand for Electricity: Evidence from a Micropanel," *Energy Economics*, 2001, 23(5), pp. 595-617.

Bresnahan, Timothy F. and Schmalensee, Richard. "The Empirical Renaissance in Industrial Economics: An Overview." *The Journal of Industrial Economics*, June 1987, 35(4), pp. 371-378.

Bushnell, James and Mansur, Erin. "The Impact of Retail Rate Regulation on Electricity Consumption in San Diego," Report PWP-082, University of California Energy Institute, March 2001.

Conlisk, John. "The Utility of Gambling" *The Journal of Risk and Uncertainty*, 1993, 6(3), pp. 255-275.

Davis, Peter. "Spatial Competition in Retail Markets: Movie Theaters," *RAND Journal of Economics*, Winter 2006, 37(4). (An earlier version is mimeo, MIT Sloan School of Management, December 2001.)

Domencich, Thomas and McFadden, Daniel. *Urban Travel Demand: A Behavioral Analysis*. Amsterdam: North-Holland Publishing Company, 1975.

Friedman, Milton and Savage, L. J. "The Utility Analysis of Choices Involving Risk," *The Journal of Political Economy*, August 1948, 56(4), pp. 279-304.

Harford, Jon D. "Firm Ownership Patterns and Motives for Voluntary Pollution Control," *Managerial and Decision Economics*, 1997, 18(6), pp. 421-431.

Hausman, Jerry A. and Wise, David A. "A Conditional Probit Model for Qualitative Choice: Discrete Decisions Recognizing Interdependence and Heterogeneous Preferences." *Econometrica*, March 1978, 49(2), pp. 403-426.

Hunsaker, Julie. "The Impact of Riverboat Casinos on the Demand for Gambling at Casino Resorts: A Theoretical and Empirical Investigation." *Managerial and Decision Economics,* January – May 2001, 22(1/3), pp. 97-111.

Konar, Shameek and Cohen, Mark A. "Information as Regulation: the Effect of Community Right to Know Laws on Toxic Emissions," *Journal of Environmental Economics and Management*, 1997, 32(1), pp. 109-124.

Lutzenhiser, Loren. "Consultant Report – An Exploratory Analysis of Residential Electricity Conservation Survey and Billing Data: Southern California Edison, Summer 2001." Sacramento, California: California Energy Commission. Publication number 400-02-006F, 2002.

Mas-Colell, Andreu; Whinston, Michael D. and Green, Jerry R. *Microeconomic Theory*. New York: Oxford University Press, 1995.

McFadden, Daniel L. "Conditional Logit Analysis of Qualitative Choice Behavior," in P. Zarembka, ed., *Frontiers in Econometrics*, New York: Academic Press, 1974, pp. 105-142.

Morrison, Alastair M.; Braunlich, Carl G.; Cai, Liping A. and O'Leary, Joseph T. "A Profile of the Casino Resort Vacationer." *Journal of Travel Research*, May 1996, 35(2), pp. 55-61.

Nevo, Aviv. "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand." *Journal of Economics & Management Strategy*, Winter 2000, 9(4), pp. 513-548.

____. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica*, March 2001, 69(2), pp. 307-342.

Perry, Martin K. "Report on the Fifty Percent Rule and Competition in the Market for Slot Machines," a report prepared for the Casino Association of New Jersey for submission to the New Jersey Casino Control Commission, February 1996.

Perry, Martin K. "Second Report on Competition in the Hotel/Casino Industry of Atlantic City, New Jersey," a report prepared for the New Jersey Division of Gaming Enforcement of the Department of Law and Public Safety for submission to the New Jersey Casino Control Commission, October 2000.

Przybylski, Michael and Littlepage, Laura. "Estimating the Market for Limited Site Casino Gaming in Northern Indiana and Northeastern Illinois." *Journal of Urban Affairs*, 1997, 19(3), pp. 319-333.

Salop, Steven C. and Scheffman, David T. "Raising Rivals' Costs," *American Economic Review*, May 1983, 73(2), pp. 267-271.

Shonkwiler, J. S. "Assessing the Impact of Atlantic City Casinos on Nevada Gaming Revenues." *Atlantic Economic Journal*, June 1993, 21(2), pp. 50-61.

Skolnick, Jerome H. *House of Cards: The Legalization and Control of Casino Gambling*. Boston: Little, Brown and Company, 1978.

Stone, Richard. "Linear Expenditure Systems and Demand Analysis: An Application to the Pattern of British Demand." *The Economic Journal*, September 1954, 64(255), pp. 511-527.

Von Neumann, John and Morgenstern, Oskar. *Theory of Games and Economic Behavior*. Princeton NJ: Princeton University Press, 1944.

Walker, Ian. "The Economic Analysis of Lotteries," *Economic Policy*, October 1998, 13(27), pp. 357-402.

Curriculum Vita

Maria Lauve

1993-1998	University of Oklahoma, Bachelor of Science, Mathematics
1993-1998	University of Oklahoma, Bachelor of Arts, French
2000-2002	Rutgers, The State University of New Jersey, Master of Arts, Economics
2002-2007	Rutgers The State University of New Jersey, Doctor of Philosophy, Economics
1998-1999	Netherland Sewell & Associates, Inc. – Dallas, Texas Petroleum Analyst
1999-2000	Madison Capital Management, LLC – New York, NY Financial Analyst (Oil & Gas)
2003-2004	Rutgers, The State University of New Jersey – New Brunswick, NJ Instructor
2003-2004	Microeconomic Consulting and Research Associates, Inc. – Washington, DC Economist
2003-2005	Princeton Economics Group, Inc. – Princeton, NJ Research Economist
2006-2007	Analysis Group, Inc. – Montreal, Quebec Economist