

Empirical Analysis of Competition between Wal-Mart and Other Retail Channels

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Abstract

This paper quantifies the degree of competition between Wal-Mart and different retail channels by exploiting a unique dataset that describes a consumer's choice of store. Using a discrete choice model, I estimate a consumer's choice of retailer in the sales market for DVDs among online, mass merchant, electronics, video specialty, and music stores. Wal-Mart competes more intensely with other mass merchants, and conditional on price and distance, the average consumer still prefers Wal-Mart over most other stores. I also consider a counterfactual experiment regarding the entry of Wal-Mart into 15 proposed store sites in California.

JEL classification: C25, L81

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1 Introduction

In 2002, the retail sector in the U.S. accumulated \$3,173 billion in sales and rivaled the manufacturing sector with a total employment of approximately 15 million workers. Currently, a dramatic transformation is reshaping the retail industry as stores differentiate across formats, pricing, and location. At the forefront of this change is the expansion of Wal-Mart. Over the past decade, Wal-Mart has grown from a modest, family-run business to the leading U.S. retailer with approximately \$250 billion in revenues in 2002. Dubbed the “Beast from Bentonville”, Wal-Mart’s phenomenal growth has revolutionized retailing by offering a wide assortment of products at discount prices; every week, Wal-Mart’s 4,750 stores attract nearly 138 million consumers, and an estimated 82% of U.S. consumers purchased at least one item from Wal-Mart in 2002.¹ Wal-Mart represents 9% of U.S. retail spending². Its reach extends into almost every major U.S. consumer-products company; Wal-Mart is also “Hollywood's biggest outlet, accounting for 15% to 20% of all sales of CDs, videos, and DVDs.”³

What attracts consumers to Wal-Mart? Does Wal-Mart maintain an advantage in the retail sector solely due to lower prices, increased proximity, or the convenience of one-stop shopping? This paper examines the source of the Wal-Mart advantage by investigating the nature of retail competition. To uncover a consumer’s preferences over Wal-Mart, I estimate a model of consumer choice over stores that controls for differences in prices and locations across stores within the consumer’s choice set. My discrete choice model allows for unobserved heterogeneity in consumers’ tastes over different store types, since the extent to how people feel about Wal-Mart will depend upon substitution patterns across different store types – mass merchants, specialty, and online. For instance, the rise of e-commerce has added a new dimension to retail

competition by reducing search and travel costs; Amazon.com has emerged as the leading online retailer by attracting \$1.39 billion in sales during 2004.

Retail competition with Wal-Mart is an important public policy issue because of the expansion of Wal-Mart in recent years. The rapid growth of Wal-Mart across the country and its aggressive plans to expand the number of its stores in California have raised concerns about the magnitude of business-stealing effects it could fuel. With my demand estimates, I simulate the effects of entry of Wal-Mart into additional locations in Southern California.

Research on cross-channel competition has been limited due to the lack of data on consumers' choices across retailers and distances traveled. Fortunately, I am able to exploit a detailed dataset on DVD purchases from Alexander and Associates. The DVD sales market offers an excellent opportunity to study cross-channel competition, since unlike certain retail products, DVDs are sold across a wide variety of retail channels. The top 15 retail chains for DVD purchases account for nearly 75% of total transactions and consist of many different types of stores: mass merchants, electronics, online, video specialty, and music. Moreover, Wal-Mart's position as the top-selling DVD retailer makes the home video market an attractive study of the interaction of Wal-Mart with its competitors. As shown in Table 1, Wal-Mart dominates the market with 41% of purchases among the top 15 retailers while Best Buy ranks second with 14%. Competition exists both within and across these different store types. In Video Store Magazine's 1996 Video Retailer Survey, video specialists cited competition from non-specialty outlets (such as Wal-Mart) among their top five concerns.

The dataset reports the store of purchase, title of the DVD purchased, item price, and demographics at the household-level from 2002 to 2003. For each household, I collect auxiliary information on the location and distance to nearby stores from the top 15 chains, using a chain's

online store locator form and Yahoo! Yellow Pages. I also identify the local sales tax rate charged by each store based on its zip code and data from Tax Data Systems.

I estimate a consumer's choice of store among the top 15 chains, conditional on purchasing a DVD, through a discrete choice model that allows for unobserved heterogeneity in preferences for store types and disutility of travel. I find that stores of the same type compete more intensely and are closer substitutes than stores of differing types. A striking result is that conditional on price and distance, the average consumer still prefers Wal-Mart over most other stores; any advantage that Wal-Mart maintains over its competitors cannot be solely due to lower prices or increased proximity. This advantage cannot be wholly attributed to one-stop shopping, since the model controls for preferences over other mass merchants – such as Target and Kmart. The price and distance to the nearest Wal-Mart exerts the greatest influence on the market shares of Target and Kmart.

My simulation results indicate that the entry of 15 proposed Wal-Mart stores in California during 2004 increases the predicted probability of choosing Wal-Mart for the affected households within my sample by 27%. These proposed sites are often located in urban regions with several existing Wal-Mart stores in adjacent cities; the average decrease in distance to the nearest Wal-Mart store falls by 2.6 miles.

This paper is directly related to the literature on cross-channel competition and consumer choice over stores. Empirical work in this area has been limited due to the lack of rich data on consumer choices across retailers. Goolsbee (2001) examines competition between online and offline stores and finds that the cross-price elasticity is in excess of one; he concludes that online and offline stores are not separate markets. In addition, Goolsbee (2000) looks at whether taxes affect a consumer's decision to purchase a computer online versus offline. Forman, et al. (2006)

examine how local competition, availability and selection of books, and prices affect a consumer's decision to purchase online versus offline, and Brynjolfsson et al. (2008) investigate how the number of local stores affect online and catalog demand. Ellison and Ellison (2006) also examine factors that drive a consumer's decision to purchase goods in-state instead of online. In contrast, I consider competition across a wide format of stores (not just offline versus online): mass merchants, video specialty, music, and online stores.

This paper also directly relates to a growing literature on Wal-Mart. Basker (2005a, 2005b, 2007) examine how the entry of Wal-Mart affects a county's employment, overall price level, and prices of supermarket items. Franklin (2001) examines how Wal-Mart's entry affects supermarket concentration. Jia (2007) looks at how the entry of Wal-Mart affects the entry/exit decisions of discount retailers, and she quantifies the size of scale economies within a chain. Holmes (2008) estimates the economies of density that Wal-Mart enjoys. Empirical work on Wal-Mart often faces limitations as Wal-Mart is known to be secretive about their data (Holmes, 2008). Fortunately, I am able to obtain data on purchases from Wal-Mart and other stores through a consumer survey. In contrast to previous studies, I focus on a slightly different question of how consumers substitute between Wal-Mart and other stores; moreover, I have individual-level data and directly estimate the decision of where to purchase a DVD.

This paper is indirectly linked to work on spatial differentiation (Davis 2006, Seim 2006, Thomadsen 2005) and the urban economics literature on traveling and distance (Weisbrod, et al. 1984, MIT Center for Real Estate 2004, Adler and Ben-Akiva 1976). It is also tied to the literature on online competition (Chevalier and Goolsbee 2003, Ellison and Ellison 2005, Smith and Brynjolfsson 2001).

The next section contains a brief background of the video retail industry, followed by a description of my data. Then I proceed with a description of my demand model and estimation results. Finally, I describe the simulation exercise with Wal-Mart entry into Southern California.

2 The Home Video Industry

The home video industry consists of two segments: rentals and sales (also called sell-through). My paper focuses on the sell-through market for DVDs which generates the most revenues within home video retail. The leading trade group, the Video Software Dealer's Association, reported that sales revenues for VHS and DVD format totaled \$12.1 billion in 2002, outweighing the \$8.38 billion accumulated from rental revenues. Video Business Research estimated that DVD sales accounted for 72% of all sell-through revenues in 2002 and totaled \$8.7 billion. In recent years, the increasing penetration of the DVD format into households has continued to fuel growth in the market for DVDs.

The DVD sell-through market is particularly well suited for a study of cross-channel competition, since unlike other retail goods (such as toothpaste or detergent), a variety of retail stores compete in the sales of DVDs. The top-selling stores can be categorized into online and traditional brick-and-mortar stores. The growth of online retailers has been more prevalent in the DVD market than VHS, and industry sources speculate that the demographics of early adopters of the DVD technology “[overlapped] considerably with Internet enthusiasts, the most likely group to be purchasing online” (Video Software Dealers Association, 1999). As seen in Table 1, the most popular online stores include Amazon.com, Bestbuy.com, and Columbiahouse.com; unlike the market for books, the online stores comprise a much smaller share of purchases for the DVD market.

The brick-and-mortar or “traditional” retailers can be further subdivided into mass merchants, video specialists, music stores, and electronics stores. For the past several years, mass merchants have dominated the sell-through market for videos. By offering a wide selection of products, ranging from household supplies and clothing to entertainment, these retailers provide one-stop, convenience shopping for consumers. The top mass merchants include Wal-Mart, Target, Costco, Sam’s Club, and K-Mart. Although video specialists, like Blockbuster Video, Hollywood Video, and Suncoast Video, sell an assortment of entertainment products (such as video games), they derive most of their revenues from the rental and sales of videos. Media Play and Sam Goody specialize in the sales of music CDs while also providing videos for sale. Finally, electronics stores, including Best Buy and Circuit City, devote most of their floor space to consumer electronics, such as personal computers, TVs, and cameras.

3 Dataset of Purchases and Store Locations

I utilize a unique dataset obtained from Alexander and Associates’ consumer surveys. From February 2002 to October 2003, 1000 households were selected and interviewed each week. The survey procedure used stratified random sampling to create a balanced sample of 3-digit telephone exchanges across the U.S., and within each exchange, respondents were chosen on a random-digit dialing method to be representative of the geographical, age, gender, and ethnic composition of the U.S. population. The survey recorded the title of the video purchased, the item price paid by the household, name of the store of purchase, and household demographics such as income, age, gender, and education.

I match each surveyed household to auxiliary data on video characteristics and location of neighboring stores from the top 15 chains. For each DVD title, I obtain information on the

video release date, genre, and theatrical box office revenues through the Titles Database from Adams Media Research. Since each household's telephone number was matched to a corresponding zip code through Melissa Data's zip code locator, I am able to recover the location of the nearest store from each of the top 15 chains by creating a program to query the store locator forms on the chains' websites and the Yahoo! Yellow Pages. When a chain's website did not report a distance, I calculated the zip code distance between the household and store locations using Spheresoft's Zip code distance calculator. Furthermore, I match the stores' zip codes to a list of local tax rates (effective for November 2003) that were provided by Tax Data Systems. To identify if a household resides in an urban area, I extract an indicator for whether the household's zip code lies within a Consolidated Metropolitan Statistical Area (CMSA) according to the 2002 Census.

As an example of the level of detail that my dataset provides, I observe that 108 households purchased the DVD of "Spider-Man". The average price they paid was \$18.26, and most households purchased the DVD from Wal-Mart. The households were located on average 5 miles away from the nearest Wal-Mart, and approximately 52% of these households had children under the age of 18. The theatrical box office revenues totaled approximately \$400 million for "Spider-Man".

I limit my sample to all videos of theatrical films that had a video release date during 2002 to 2003 and ranked among the Weekly Top 50 rentals of Video Store Magazine; the sample corresponds to a total of 4352 DVD transactions. The set of titles is meant to be representative of "popular" DVDs that will be available at most stores.⁴ After eliminating households with missing variables or who purchased a DVD more than 35 miles from their resident zip code, my final

sample consists of 3136 transactions that correspond to 2221 households with a complete set of demographic and purchase variables.

Tables 2, 3, and 4 provide some summary statistics. The demographics of the surveyed individuals resemble the overall U.S. population with the exception that they are slightly more well-educated. The purchased DVDs encompass a wide variety of films with varying box-office success in the theatrical market. Variation in prices exists across stores and videos; the average price paid for a DVD was \$17.56 with a standard deviation of 4.12. The typical consumer did not have to travel far to purchase a DVD; the average distance to the closest and second closest stores were 2.5 miles and 4.4 miles.

The dataset provides a rich set of variables on household choices and location of neighboring stores. The one dimension for which it lacks information is the set of prices across all stores that a consumer may potentially visit. The dataset contains prices for each transaction, so I observe the price of the DVD at the actual store of purchase but not at other stores. For instance, I can observe that a consumer buys “Shrek” at Wal-Mart for \$15, but I do not observe the price of “Shrek” at Best Buy, Kmart, or other stores that the consumers could have visited instead. I therefore construct estimates of prices that a consumer would face at each possible store. Taking the sample of all videos with observed prices, I regress the log of the price paid for each DVD on characteristics of the video, store, and location of purchase. Table 5 presents the results from this hedonic log-price regression. For each store in the consumer’s choice set, I calculate the predicted log of price using the estimated coefficients.⁵ Figure 1 graphs the ratio of the predicted price to the actual price for all transactions within my sample. The ratio lies between 0.8 to 1.2 for 80% of the transactions, and it has a mean of 1.02 and a standard deviation of 0.27. Some of the differences between the actual and predicted prices may be attributed to

misreporting by certain individuals or “focal” responses whereby surveyed individuals give round figures.

4 Model of Demand for Store Choice

Estimating demand is the first step towards investigating consumers’ preferences over Wal-Mart and other retailers. Using the data described in the previous section, I estimate a discrete choice model where consumers choose among retailers, conditional on buying a DVD title. This mixed nested logit model is equivalent to a standard mixed logit model with random coefficients on the attributes of alternatives and dummies for each nest (Train, 2003). The utility of purchasing a DVD at store j will depend on the price of the DVD at store j and the distance to store j as well as other store and consumer characteristics. I specify a random coefficient on the distance variable to allow heterogeneity across the population in the disutility of traveling. In addition, I group the stores into five nests and allow a consumer’s unobservable taste for stores to be correlated for stores within the same nest; the five nests coincide with the five store types: online, mass merchant, video specialty, electronics, and music store. McFadden and Train (2000) demonstrate that any random utility model can be “approximated to any degree of accuracy by a mixed logit model with the appropriate choice of variables” and distribution of the random coefficient.

While alternative models exist for estimating demand, I chose the nested logit model because of its discrete choice framework and its flexibility as well as tractability in capturing consumers’ substitution patterns. The alternative Almost Ideal Demand System assumes that consumers spend a fraction of their income at every store (Hausman and Leonard, 1997); moreover, since cross-price elasticities must be separately and directly estimated among all

stores, the number of parameters to estimate can be quite large. Under the logit model, consumers choose exactly one of the 15 stores to make their purchase, and consumer preferences are mapped to the characteristics of each alternative (store) in their choice set. The tastes over these characteristics are used to derive the own- and cross-price elasticities. The nesting allows for flexibility in consumers' substitution patterns as alternatives within the same nest may be closer substitutes, and the nested logit model has the additional advantage of yielding a closed form expression for the purchase probabilities.⁶ The nested logit model suits the data and question at hand by capturing richness in substitution patterns in a parsimonious way.

In the following sub-sections, I first describe the specific functional forms and distributional assumptions used to estimate the model, and then I briefly interpret the estimated parameters from the demand model.

4.1 Empirical Specification

Since I am interested in estimating substitution patterns across different stores, I define the relevant market as a geographic area and DVD title pair. Conditional on a purchasing a given DVD title, consumers choose which store to shop at. I condition on the particular DVD title and the decision to buy, so I may focus on substitution across different store types.⁷

Consumer i 's utility from traveling to store j to purchase video v in geographic area m during week t is given by:

$$U_{ijvmt} = \alpha_1 p_{vmjt} + \sum_{g=2}^4 \alpha_g p_{vmjt} * INC_{ig} + \delta TAX_{ij}$$

$$\begin{aligned}
& -\gamma_i DIST_{ij} + \sum_{g=2}^4 \phi_g DIST_{ij} * INC_{ig} + \psi DIST_{ij} * MSA_i \\
& + \beta DEMO_i * TYPE_{jh} + \xi_j + \varepsilon_{ijvmt}
\end{aligned} \tag{1}$$

where p is the price of the video, INC_{ig} is a dummy for whether consumer i lies within one of four income groups ($g = 1, \dots, 4$), TAX_{ij} is the sales tax charged at store j to consumer i , $DIST_{ij}$ is the distance between person i 's residence and store j , MSA_i is a dummy variable for whether consumer i resides in a metropolitan area, $DEMO_i$ contains observable household demographics (e.g., gender, age, education, presence of children) and a constant, $TYPE_{jh}$ is a dummy for one of the five store types ($h =$ mass merchant, video specialist, music, electronics, and online), and ξ_j is the coefficient on a store dummy that can be interpreted as an unobserved store quality or characteristic. The term ε reflects a consumer's idiosyncratic and unobservable taste for buying a video at a given store. Under a logit model, ε follows a Type I Extreme Value distribution.

By interacting the price variable with dummies for income group, I allow a consumer's price sensitivity to depend on income. The coefficient α_1 is the marginal utility of price for individuals in the lowest income bracket (group 1). Similarly, the coefficient $\alpha_1 + \alpha_2$ corresponds to the marginal utility of price for individuals in income group 2. The tax rate varies by the location of the brick-and-mortar store. Online stores, such as Bestbuy.com, are not required to collect sales tax unless the retailer has a physical presence in the state. I also interact demographic variables with dummies for each store type to allow the marginal utility of shopping at different store types to vary by age, education, gender, and the presence of children. The impact of price, interactions of price and income, the tax rate, and interactions of demographic variables with store type on utility are assumed to be constant among all individuals in the population.

In contrast, I introduce a random coefficient on distance, so the marginal disutility of distance can vary by individual. To estimate the demand model, I must specify a population distribution for the random coefficient. I assume that the marginal disutility of distance γ_i has a log-normal distribution, so γ_i attains only positive values. As seen in the utility equation, this implies that all consumers dislike distance. That is,

$$\gamma_i = \exp(b + su_i) \quad (2)$$

where u_i is a standard normal variable. I interpret u_i as a consumer's unobservable characteristic (e.g., number of cars, availability of public transportation, opportunity cost of time) that affects her disutility of distance. The parameters b and s are the mean and standard deviation of $\log(\gamma_i)$. By directly estimating the parameters b and s , I can recover the mean of γ_i :

$$E(\gamma_i) = \exp(b + (s^2/2)) \quad (3)$$

Conditional on the coefficients ($\alpha, \delta, \gamma_i, \beta, \phi, \psi, \zeta$) that enter utility, I want to allow for an individual's unobservable taste ε to be correlated by store types. The nesting of alternatives accomplishes this by introducing a correlation among idiosyncratic shocks to alternatives of the same nest. In this model, since stores are nested by store type, the idiosyncratic error ε can be decomposed into a component that is common among stores of the same nest ζ and an independent term η :

$$\varepsilon_{ijvmt} = \sum_{h=1}^S \zeta_{ih} TYPE_{jh} + \lambda \eta_{ijvmt} \quad (4)$$

For instance, consumer i will have a common valuation for Amazon.com and Bestbuy.com given by $\zeta_{i,online}$, but in addition, she also has independent valuations $\eta_{i,amazon}$ and $\eta_{i,bestbuycom}$ that may differ for each store. The common valuation $\zeta_{i,online}$ induces a correlation between her unobserved tastes for each online store, $\varepsilon_{i,amazon}$ and $\varepsilon_{i,bestbuycom}$.

More specifically, I assume that the unobservable tastes for store types ζ_{ih} are independent and follow the unique distribution as described by Cardell (1997).⁸ The distribution ζ_{ih} depends on a parameter λ to be estimated. This parameter λ is called the log-sum coefficient (also the dissimilarity coefficient or nesting parameter).

The log-sum coefficient is freely estimated, and it captures the degree to which alternatives in a nest are dissimilar. In other words, the log-sum coefficient reflects the degree of business-stealing among stores within the same nest. Values of λ that lie between 0 and 1 are consistent with random utility-maximization (McFadden, 1981). An estimated value of 1 indicates that consumers' tastes are not correlated among stores of the same nest, and business-stealing or substitution does not occur proportionately more among stores within the same nest. On the other hand, an estimated value near 0 indicates very little variation in idiosyncratic tastes among stores of the same nest; the idiosyncratic term ε drops out, since $\zeta \equiv 0$ when $\lambda = 0$. In this instance, consumers view stores in the same nest as very close substitutes.

I normalize the coefficient for the online store interactions with demographics and the constant term to zero, and within each nest, I normalize the coefficient ζ of one of the stores to zero. For each individual, I predict the probability of making her observed choice, and I estimate the model using Simulated Maximum Likelihood Estimation. Please refer to Appendix A for the details of the model and estimation.

4.2 Results

I now interpret the estimated coefficients of the benchmark demand model: the nesting parameter, consumers' tastes by demographics, disutility of distance, and travel costs. Then in the following Section 5, I will apply these results to directly investigate why people shop at Wal-

Mart, and I will use the estimated demand parameters to perform a counterfactual simulation of Wal-Mart entry into California.

Table 6 reports the estimated utility parameters of my benchmark demand model. Tables 7 and 8 present the estimated price and distance elasticities. The estimated nesting parameter indicates that competition occurs more intensely among stores of the same type. The log-sum coefficient is 0.74 and statistically significant, indicating that a consumer's unobserved tastes for stores are correlated by store types; in other words, nesting by store types matters. Wal-Mart competes more intensely with mass merchants than stores of other types.⁹ Recall that the nesting parameter is freely estimated and captures the degree of correlation of unobserved tastes among stores of the same type. An estimated log-sum coefficient of 1 indicates that unobserved tastes are not correlated among stores of the same nest; on the other hand, a log-sum coefficient close to 0 indicates very little variation in idiosyncratic tastes among stores of the same nest.

Shopping patterns vary significantly by demographics - gender and the presence of children in the household. A consumer's education plays an important part in explaining her decision to shop at Wal-Mart and mass merchants in general. The omitted store type is the online dummy, so all coefficients on the interactions between household demographics and store types dummies must be interpreted relative to the online store option. The estimated coefficient of -0.67 on the interaction between the dummy for female and electronic store indicates that men have a higher marginal valuation of electronics stores (over online stores) relative to women. In addition, the presence of children is associated with a higher marginal utility for music stores relative to online stores.

A consumer's willingness to travel to Wal-Mart will depend upon her disutility of traveling. The demand model allows the marginal disutility of distance to vary by unobservable

consumer characteristics (as captured by the random coefficient γ_i on the distance variable) and observable consumer characteristics (as captured by interactions of the distance variable with dummies for income bracket and residence in an urban region). As shown in Table 6, the estimated mean (b) and standard deviation (s) of the log of the random coefficient on distance are -2.415 and 0.127. Very little unobserved variation exists in consumers' attitudes toward traveling, since I cannot reject the hypothesis that $s = 0$. Also, the random coefficient on distance is given by $\gamma_i = \exp(b + su_i)$, where u_i is distributed as a standard normal. Using the estimated parameters b and s , I calculate the mean of the coefficient on distance according to the formula: $\exp(b+s^2/2) = \exp(-2.415 + 0.127^2/2) = 0.09$. Table 6 also reports the estimated utility coefficients for the interactions of the distance variable with income group dummies and a dummy for residing within an MSA. Consumers in the higher income groups have a lower marginal disutility of traveling and price, and consumers that live in urban areas face a higher disutility of distance. The magnitudes of the coefficients of these interactions account for most of the variation in tastes over traveling. As a result, the marginal disutility of distance for a low-income person in a rural and urban area are 0.09 and 0.14 ($= 0.09 + .047$), and the marginal disutility of distance for the average high-income person in a rural and urban area are 0.059 ($= 0.09 - 0.031$) and 0.109 ($= 0.14 - 0.031$).

In order to understand a consumer's preference for Wal-Mart, I need to investigate how price and distance motivated a consumer's choice of retailer. The estimates on the disutility of travel and price allow me to calculate two measures of consumer's tradeoff between distance and price. The first measure takes the ratio of the marginal disutilities of price and distance; this signifies the number of miles that a consumer is willing to travel to save \$1. As shown in Table 6, the marginal disutility of price and distance both decline as income rises. Since sensitivity to

price and distance varies by income and region, travel costs will as well. Table 9 reports the number of miles a consumer is willing to travel to save \$1. In urban areas, the average consumer in the lowest income bracket is willing to drive 1.59 miles to save \$1. Since his high-income counterpart has a marginal disutility of price of 0.08, he is only willing to drive 0.73 miles to save \$1. Similarly, the average low- and high-income consumer in a rural area would be willing to drive 2.43 and 1.31 miles to save \$1.

For the second measure, I calculate a consumer's marginal cost of traveling. Conditional on price, high-income consumers do experience a lower disutility of travel. However, because high-income consumers have a much lower marginal disutility of price than low-income consumers, high-income consumers possess a higher marginal cost of travel per mile. Since the marginal cost of travel can be calculated as the ratio of the marginal utility of distance to the marginal utility of price, the degree to which travel costs fall as income rises will depend on the relative sensitivity of consumers to distance and price. Table 9 reports the marginal cost of travel for high- and low-income consumers in rural and urban areas. The average low-income consumer in a rural area faces a marginal cost of 41 cents per mile while her counterpart in an urban area has a marginal cost of 76 cents per mile. Similarly, a high-income consumer experiences a higher marginal cost of travel of 63 cents and \$1.37 in rural and urban areas. The marginal costs capture a consumer's implied value of time as well as any costs of transport, which the U.S. General Services Administration estimates as 31 cents per mile in a privately owned vehicle.¹⁰

5 Wal-Mart

Using the demand estimates from my benchmark model in the previous section, I now examine the nature of consumer demand for Wal-Mart. First, I consider whether Wal-Mart's advantages in the retail sector are due solely to lower prices or increased proximity. Next, to illustrate the degree of business-stealing among stores and the magnitude of consumer substitution, I use the estimated demand parameters to simulate a counterfactual experiment of Wal-Mart entry into California.

5.1 The Wal-Mart Advantage

To understand Wal-Mart's dominance in the retail sector, I first consider substitution patterns between Wal-Mart and other retailers. Tables 7 and 8 present the price and distance elasticities across all 15 stores in my sample. Wal-Mart competes most intensely in price with Kmart and Target and to a lesser extent with Sam's Club. If Wal-Mart decreases its price by 1%, then the market shares of Kmart and Target fall by 1.69% and 1.57%. The distance elasticities exhibit a similar pattern to the price elasticities. If the distance to the nearest Wal-Mart decreases by 1% for all households, then the market shares of Kmart and Target decrease by 0.26% and 0.24%.

To quantify how consumer's value a shopping trip to Wal-Mart, I use my demand estimates to calculate a consumer's willingness to pay to shop at Wal-Mart. The estimated utility coefficients on store type and store dummies from the benchmark model imply that the average consumer prefers Wal-Mart to most other stores even conditional on price and distance. For instance, if all retailers charged the same price and were located in the same proximity, a consumer with "average" characteristics would still prefer to shop at Wal-Mart.

Several possible explanations exist for this finding. The average consumer's preference for Wal-Mart may reflect the convenience of one-stop shopping, the expectation of lower prices in other items in the consumer's shopping bundle, or an unobserved Wal-Mart "quality" effect. I investigate each possibility below.

First, differences in product assortment may account for why a consumer would prefer to shop at Wal-Mart (where they can purchase a variety of other goods in addition to DVDs) as opposed to Blockbuster (a video specialty store that mainly sells DVDs.) Recall that the benchmark model of demand contains store-type dummies, which can capture systematic differences in consumers' market baskets across different types of stores. However, product assortment cannot entirely account for the preference for Wal-Mart. Under the estimates from the benchmark model of model, consumers still prefer to shop at Wal-Mart even relative to other mass merchants that offer one-stop shopping (e.g., Target, K-Mart).

Secondly, it is possible that the average consumer's preference for Wal-Mart over other mass merchants may be due to systematically lower prices at Wal-Mart for other goods in the basket. I check for this possibility by considering an extension of my benchmark demand model. I allow for a Wal-Mart specific effect on price, distance, and all other explanatory variables. For instance, a one dollar increase in the price of DVD may not cause a consumer's utility of shopping at Wal-Mart to drop as much because of potential savings from other items in her shopping basket. By including an interaction between price and a Wal-Mart dummy into the demand model, I capture the fact that consumers may respond differently to DVD price changes at Wal-Mart because of the presence of other items in their shopping basket. A similar argument could be made for the effects of distance on a consumer's utility of traveling to Wal-Mart. Consequently, I interact all explanatory variables (e.g., price, distance, demographics) with a

Wal-Mart dummy to capture any systematic differences across stores that may be due to shopping bundles or prices for non-DVD items.

The results of the extension show that even after adjusting for a Wal-Mart specific effect, the average consumer still prefers shopping at Wal-Mart conditional on distance and price. Tables 11 and 12 report the estimated utility coefficients from this expanded model. I find that the Wal-Mart dummy is still highly significant and positive. Consumers with a higher education place a lower value on shopping at Wal-Mart while consumers with children place a higher value. Also, older consumers tend to dislike Wal-Mart relative to online stores.

A given consumer's preference for Wal-Mart will depend upon demographics such as gender, age, and presence of children in the household. However, for the average consumer, Wal-Mart remains the preferred store even relative to other mass merchants. For instance, a typical male consumer with the average characteristics of the sample (35-years old with kids under the age of 18, a college education, lives in an urban area, and income of \$40,000) favors Wal-Mart over all other mass merchants; he is willing to pay \$7.09, \$4.70, \$2.61, and \$2.37 to shop at Wal-Mart instead of Kmart, Sam's Club, Costco, and Target for a \$15 DVD, assuming both stores are located 5 miles away. His female counterpart also values Wal-Mart over other mass merchants; she would be willing to pay \$6.56, \$4.17, \$2.09, and \$1.85 to shop at Wal-Mart instead of Kmart, Sam's Club, Costco, and Target. In contrast, individuals with above average age or education levels experience a lower utility of shopping at Wal-Mart; a 55-year old male with kids under the age of 18, a graduate school education, lives in an urban area, and income above \$75,000 would actually prefer to shop at Target instead of Wal-Mart, and he is willing to pay \$1.74 to do so.

Finally, this striking result suggests that Wal-Mart's advantage might not solely be due to lower prices and increased proximity. A Wal-Mart "quality" effect still persists even when we allow for a Wal-Mart specific effect on prices, distance, and all other explanatory variables.¹¹

5.2 Simulation of Wal-Mart Entry into California

As previously discussed, the estimated demand coefficients indicate a strong preference for Wal-Mart by the average consumer, even conditional on price and distance. To quantify the magnitude of this preference, I examine a particular public policy issue of Wal-Mart's entry into California.

In 2004, Wal-Mart announced its intention to open 40 more store sites as part of its aggressive expansion plans into California, particularly in the Southern California region. Previous attempts to construct new store sites have met with "intensifying grassroots opposition", and many agree that Wal-Mart's "biggest barrier to growth is ... opposition at the local level".¹² In 2003, a fierce struggle ensued in Contra Costa County near San Francisco, as Wal-Mart collected signatures to compel a referendum over its entry. Wal-Mart has also met staunch local resistance at other California cities such as West Covina, Oakland, Bakersfield, and Inglewood by local merchants and labor unions. The United Food and Commercial Workers union has been a long-time opponent of the chain, and in 2003, it organized campaigns against Wal-Mart in 45 locations across the U.S.

The business-stealing effects of Wal-Mart are a hotly debated topic as Wal-Mart looks to expand its presence in California. Target and Kmart have already situated 184 and 163 stores within California, and as Wal-Mart's closest competitors, they stand to suffer from the entry of Wal-Mart. I simulate the effects of entry of Wal-Mart at 15 store sites in California, which

include 10 new stores constructed in 2004, 3 proposed store sites that were rejected by city votes (Inglewood, West Covina, and Oakland), and 2 proposed store sites that were approved by the city (Palm Springs and Rosemead). Table 13 lists each city and the corresponding zip code used for the simulation. As seen in Figure 2, the majority of these sites are located in Southern California.

A total of 37 households, that comprise slightly over 1% of my sample, are affected by the entry of these 15 new stores, and the average change in distance to the nearest Wal-Mart was 2.6 miles. I simulate the predicted probability of choosing each store before and after the entry of the 15 Wal-Mart stores. Table 14 reports the estimates and standard errors for the average predicted probability of choosing each store for the 37 households before and after the entry of Wal-Mart, and the table also shows the average change and percentage change in the predicted probabilities. The average change in probability of choosing Wal-Mart increased by 5.92 percentage points, which accounted for 27% increased probability, and the average change in probability of choosing Target and Kmart dropped by 1.45 and 0.19 percentage points.

The introduction of the 15 new store locations improves Wal-Mart's position relative to other mass merchants, and now the probability of choosing Wal-Mart is on par with Best Buy. However, it does not make Wal-Mart the overwhelmingly preferred store, since the entry occurs in regions with several existing Wal-Mart stores nearby. For instance, the Norwalk store which opened in 2004 lies within 2 miles of an existing store at Cerritos.

6 Conclusion

The retail sector contributes a significant portion of spending in the U.S. economy, yet empirical work on the nature of competition among retailers has been limited by the availability

of data. Wal-Mart's overwhelming presence dominates the retail landscape. Wal-Mart generates approximately \$250 billion in annual sales and attracts 20 million shoppers to its stores each day.¹³

My paper investigates the source of Wal-Mart's dominance by examining consumer preferences for store choice. My paper focuses on retail competition in the sales of DVD among a wide array of store types (i.e., online, mass merchants, video specialists, electronics, and music stores). I exploit a detailed dataset that combines household transactions with the locations of surrounding stores, and I apply a mixed nested logit that allows for heterogeneity in a consumer's dislike of distance and for correlation in a consumer's unobserved tastes for stores of the same type.

I find that substitution occurs proportionately more among stores of the same type. For instance, a change in the price or distance to a Wal-Mart store has the largest impact on the market shares of Target and Kmart. A striking result is that even conditional on the price of a DVD and distance, the average consumer still prefers to shop at Wal-Mart over most other stores. This result remains even after allowing for a Wal-Mart specific effect in my demand model, and it suggests that Wal-Mart's dominant market share may not be due solely to low prices and location. This preference cannot wholly be attributed to Wal-Mart's one-stop shopping convenience, since the average consumer prefers Wal-Mart even relative to other mass merchants, such as Kmart and Target.

To capture the magnitude of consumers' preferences for Wal-Mart, I consider a particular public policy issue. I use the estimates from my model of demand to simulate the effects of Wal-Mart's entry into several proposed locations in California. I find that the entry of 15 proposed Wal-Mart stores in California during 2004 increases the predicted probability of choosing Wal-

Mart for the affected households within my sample by 27%. These proposed sites are often located in urban regions with several existing Wal-Mart stores in adjacent cities; the average decrease in distance to the nearest Wal-Mart store falls by 2.6 miles.

The rise of Wal-Mart relates to a general shift away from traditional department stores and towards shopping at discount stores over the past decade, and consumers' strong preference for Wal-Mart has implications for the calculation of the Consumer Price Index (CPI). Hausman (2003) discusses how the failure to properly account for these shifts in shopping patterns leads to a first-order "outlet" bias in the CPI. Currently, when the Bureau of Labor Statistics rotates a retail good from a discount store into the CPI, it treats the discount store's product as new good instead of a reduction in the price of an existing good. The 2002 report from the National Research Council (Schultze and Mackie, 2002) supports the underlying assumption by the Bureau of Labor Statistics that stores such as Wal-Mart may not have a lower "service-adjusted" price. However, my results suggest the contrary: even conditional on store and consumer characteristics, Wal-Mart appears to be a desirable place to shop relative to most other stores for the average consumer. In fact, if Blockbuster Video can be thought of as the "traditional" place to purchase a video while Wal-Mart is the "new" discount retailer, then my results imply that an "average" 35-year old female who lives in an urban area and has a college education and children under the age of 18 is willing to pay \$6.06 to shop at Wal-Mart instead of Blockbuster Video (for a \$15 DVD if both stores are 5 miles away.)

Appendix A: Details of Demand Model and Estimation

A.1 Model

Following Berry, Levinsohn, and Pakes (1995), I model a consumer's choice of store as a function of store and consumer characteristics while allowing for unobserved heterogeneity in preferences over store characteristics and correlation in tastes among store of the same type. Consumer i 's utility from traveling to store j is given by:

$$U_{ij} = U(z_j, h_i, d_{ij}, p_j, \xi_j, \omega_i, \varepsilon_{ij}, \theta) \quad (5)$$

where z_j is a vector of observable store characteristics, h_i is a vector of observable consumer characteristics, d_{ij} is the distance to store j for consumer i , p_j is the price at store j , ξ_j captures any unobserved characteristics of store j , ω_i is a vector of unobserved characteristics of consumer i , ε_{ij} is individual i 's idiosyncratic taste for store j , and θ is a vector of parameters to be estimated.

The terms ω and ε capture the two sources of unobserved heterogeneity in consumer preferences over store types. Interactions of the unobservable consumer characteristics ω and observable store characteristics z allow tastes for store characteristics to differ among the population in unobservable ways. Furthermore, specifying an error structure that allows for correlations in the idiosyncratic taste ε over particular stores generates more flexible substitution patterns.

Each consumer will choose the store that maximizes her utility. More specifically, the set of values of the idiosyncratic error ε and unobservable consumer characteristics ω that induce consumer i to choose store j is given by:

$$A_{ij} = \{(\varepsilon, \omega) : U(z_j, h_i, d_{ij}, p_j, \xi_j, \omega_i, \varepsilon_{ij}, \theta) \geq \max_k U(z_k, h_i, d_{ik}, p_k, \xi_k, \omega_i, \varepsilon_{ik}, \theta)\} \quad (6)$$

where k indexes all possible stores in consumer i 's choice set. If ε has distribution $f_1(\varepsilon)$ and ω has distribution $f_2(\omega)$, then the probability of consumer i choosing store j is:

$$P_j(h_i) = \int_{\varepsilon \in A_{ij}} f_1(\varepsilon) f_2(\omega) d\omega d\varepsilon \quad (7)$$

To obtain the market shares of the stores, I need to integrate the individual choice probabilities over the distribution of observable consumer characteristics h in the population. If h has distribution $g(h)$, then store j has market share:

$$s_j = \int P_j(h)g(h) dh \quad (8)$$

A2. Simulated Maximum Likelihood

I estimate the demand model using Simulated Maximum Likelihood with a numerical gradient. In my numerical search, I employ the BHHH algorithm which applies the Information Identity to exploit the fact that the objective function being maximized is a sum of log likelihoods over a sample of observations (Berndt, et al. 1974).

To construct the log-likelihood function, I calculate the predicted probability (as a function of the utility parameters) for each consumer making his/her observed choice. A person chooses the alternative with the highest utility. For convenience, I drop the subscripts for v , m , and t , and re-write utility for consumer i purchasing a video at store j as $U_{ij} = X_{ij}\theta_i + \varepsilon_{nj}$ where $\theta_i = (\alpha, \delta, \gamma_i, \beta, \varphi, \psi, \xi)$.

Conditional on the utility parameters θ_i , the choice probabilities follow the conventional formulas for nested logit. The probability of consumer i choosing store j , conditional on his/her tastes θ_i is given by:

$$L_{ij}(\theta_i) = \frac{\exp(X_{ij}\theta_i / \lambda) \left(\sum_{k \in TYPE_g} \exp(X_{ik}\theta_i / \lambda) \right)^{\lambda-1}}{\sum_{h=1}^5 \left(\sum_{k \in TYPE_h} \exp(X_{ik}\theta_i / \lambda) \right)^{\lambda}} \quad (9)$$

where store j belongs in nest g . The first term in the numerator describes the utility from choosing alternative j , and the second term in parentheses weights the probability by the utility from all alternatives in nest g . The denominator is a function of the utility of all possible alternatives. The log-sum coefficient λ appears in the choice probability due to the nesting of alternatives. Note that if the log-sum coefficient equals one, then the formula reduces to the standard logit probability.

Consequently, the unconditional probability of person i 's choice is the integral of $L_{ij}(\theta_i)$ over all possible values of θ_i (Train, 2003):

$$P_{ij} = \int L_{ij}(\theta) f(\theta) d\theta \quad (10)$$

The integral does not have a closed form expression, so I evaluate it numerically by taking draws of θ from the population density $f(\theta)$ and calculating $L_{ij}(\theta)$. I do this R times and take the average:

$$\hat{P}_{ij} = \frac{1}{R} \sum_{r=1}^R L_{ij}(\theta^{(r)}) \quad (11)$$

By construction, this simulated probability is an unbiased estimator whose variance decreases as the number of draws R increases. It is smooth (twice-differentiable) and sums to one over all alternatives (Train, 2003). Since it is strictly positive, its logarithm is defined.

To calculate the simulated probability, I use Halton draws instead of random draws in order to increase efficiency (Halton, 1960). Halton draws achieve greater precision and coverage for a given number of draws than random draws, since successive Halton draws are negatively

correlated and therefore tend to be “self-correcting” (Train, 2003). In fact, Bhat (2001) demonstrates that for a mixed logit model, 100 Halton draws provided results that were more accurate than 1000 random draws. Consequently, the application of Halton draws allows a decrease in computation time without sacrificing precision. In addition, I apply the same set of draws to each iteration of the optimization routine in order to prevent chatter (McFadden, 1996); differences in the objective function at two different parameter values do not arise from different sets of draws.

Next, I use the simulated probabilities to form the log likelihood. I maximize the simulated log likelihood over the parameters $(\alpha, \delta, \beta, b, s, \varphi, \psi, \zeta)$ where b and s describe the mean and standard deviation of the population distribution of $\log(\gamma_i)$. In Table 6, I report demand estimates for 100 Halton draws. As a measure of goodness of fit, I find that the predicted market shares of each store do not differ by more than 3.5% from the actual market shares.

The Simulated Maximum Likelihood estimator is consistent, asymptotically normal and efficient. If the number of draws R increases at a rate faster than the square-root of the number of observations, then the Simulated Maximum Likelihood estimator is asymptotically equivalent to the Maximum Likelihood estimator (Hajivassiliou, 1993 and Hajivassiliou and Ruud, 1994).

I calculate own- and cross-elasticities for price and distance by taking the average percentage change in an individual’s predicted probability for each alternative from a 10% increase in price (or distance) and divide the measure by 0.10 (Train, 2003). The standard errors of the elasticities were obtained by a parametric bootstrap where I draw from the asymptotic distribution of the estimated parameters 100 times. For each draw, I calculate the elasticity matrix, and then I calculate the sample standard deviation of the elasticities over the draws.

In general, a mixed nested logit model relaxes the Independence of Irrelevant Alternatives (IIA) assumption among alternatives in a given nest; the ratio of the market shares of any two alternatives within a nest will depend on the characteristics of all other goods. The introduction of the random coefficient on distance implies that while substitution still occurs disproportionately among stores of the same type, substitution among alternatives in a nest will now depend on the characteristics of all other stores as well. This can be seen by taking the ratio of the formulas for the probabilities of any two goods within a nest; the denominators do not cancel because of the integral. On the other hand, since distance is defined as zero for online stores, the online stores exhibit the IIA property. As a result, the cross-elasticities of Amazon.com, Columbiahouse.com, and Bestbuy.com with each brick-and-mortar store will be identical.

For consumers with multiple purchases of DVDs, I assume that the demands for each DVD are independent.¹⁴ If the demands for multiple purchases are correlated, then my estimates will still be consistent but inefficient with incorrect standard errors (Train, 2003). Also, I restrict each consumer's choice set to stores within 35 miles of her zip code with the exception of Blockbuster Video (whose website only reports stores within a 20 mile radius of your zip code). I find that my qualitative results are not sensitive to whether I restrict the radius to 20, 25, 30, or 35 miles.

While the demand model presented is theoretically identified, I perform several checks to confirm that it is empirically identified by the data. In particular, Ben-Akiva, et al. (2001), Walker (2002), and Chiou and Walker (2007) emphasize the importance of checking the stability of the parameters with respect to the number of draws, since models may appear identified at lower numbers of draws when they are in fact not. The parameter estimates and standard errors

were stable with respect to different start values and to 200, 1000, and 4000 Halton or random draws.¹⁵

A.3 Unobserved Consumer and Store Characteristics

In the benchmark demand model, consumer tastes are correlated among stores of the same type in unobserved ways. The model also allows consumers to have an unobserved taste over distance and traveling. The store fixed effects capture a store's unobserved quality that is fixed over time.

One concern is that additional unobserved characteristics (not captured by the store dummies) may still exist and be correlated with price. I conduct a series of checks to implicitly test for the magnitude of any endogeneity bias.¹⁶ First, I examine whether the estimates from my benchmark model of demand suffer from the classic symptoms of endogeneity bias. Then, I consider a direct extension to my structural model to check for the extent of any endogeneity bias.

First, the results of my benchmark model do not appear to exhibit the classic symptoms of endogeneity bias. Although the model contains store dummies which control for aspects of (unobserved) store quality that are constant over time, any time-varying unobserved quality of a store could be correlated with price. A classic symptom of not accounting for this correlation and endogeneity is an upward-sloping demand curve. With this endogeneity bias, demand estimates and elasticities may mistakenly indicate that consumers prefer higher prices because these higher prices are correlated with higher (unobserved) quality. For my model, the estimated own-price elasticities in Table 7 are negative and with plausible magnitudes. Most estimates lie in the -2.0 range. Another implication of price endogeneity found by Chintagunta, et al (2005) is that

unmeasured brand characteristics could lead to an over-estimate of the variance of unobserved tastes; in my model, this would lead to an upward bias in the estimated coefficient on the variance of the random coefficient on distance. In Table 6, the estimated standard deviation of the log of distance coefficient is relatively small (0.127), as unobserved tastes do not play a large role in consumer's preferences over stores. Another direct consequence of endogeneity bias is that the estimated marginal disutility of price and distance will be biased, and the estimated marginal cost of traveling, which is the ratio of the two measures, will also be biased. The estimates from my demand model yield reasonable magnitudes for the marginal cost of travel (see Section 4.2).

Secondly, in addition for checking for symptoms of endogeneity bias, I take a more direct approach by considering an extension to my structural model. To clarify my approach, for convenience, suppose that consumer i 's utility from traveling to store j in week t is given by:

$$U_{ijt} = \alpha p_{jt} + \gamma d_{ij} + X_{ijt} \beta + \xi_{jt} + \varepsilon_{ijt} \quad (12)$$

where X contains demographics and store characteristics, p is the price at store j at time t , d is the distance of consumer i to store j , ξ is an unobserved store quality that may vary over time, and ε is an idiosyncratic error term. If store quality does not vary over time, then $\xi_{jt} = \xi_j$ for all t . Including store dummies in the utility specification will deal with the endogeneity problem (Nevo, 2000). The benchmark model of demand includes store fixed effects.

However, if store quality varies over time, then we can decompose the unobserved store quality into two components:

$$\xi_{jt} = \xi_j + \Delta \xi_{jt} \quad (13)$$

where ξ_j is the component of quality that does not vary over time, and $\Delta \xi_{jt}$ is the component that varies over time (Nevo, 2000). Endogeneity bias can arise through correlation changes in store

quality over time $\Delta\check{\zeta}_{jt}$ and variables such as price p and distance d . While including interactions of store and weekly dummies would control for the endogeneity, this requires a large number of parameters to be estimated, which is not computationally feasible.

To check for the extent of such bias, I modify and re-estimate my structural model; I include interactions of store type with quarterly dummies into the demand model to capture some aspect of the quality changes $\Delta\check{\zeta}_{jt}$ over time. If the endogeneity bias is large, then I would expect the results from this extended model to vary substantially from the benchmark model. On the other hand, if the bias is not large, then I would expect the results to be similar across the two specifications. The estimates from the extended model table indicate that the parameter estimates are similar to the benchmark model; the magnitude of any endogeneity bias does not appear to be large.

A.4 Bootstrapping to Adjust for Noise in Price Estimates

Since I use an estimate of the price variable in the utility specification, I need to adjust the standard errors of the demand coefficients to account for noise in the price estimates obtained in the first step. I employ the following procedure: I bootstrap the price regression 100 times. If N denotes the number of observations in the price dataset, then each bootstrapped sample consists of N observations drawn with replacement from the price data. For each bootstrapped sample, I re-estimate the price regression, use the results to calculate the estimates of price for each store in the consumer's choice set, and re-estimate the mixed nested logit model with the new price estimates. I add the variance in parameter estimates over the bootstrapped price samples to the variance in estimates from the original dataset. The standard errors were calculated using the BHHH approximation to the Hessian with a numeric gradient. The bootstrap procedure produces

a valid correction for the standard errors if the moment conditions from the price regression and the demand estimation are orthogonal (Newey, 1984). This is a plausible assumption, since my sample consists of individuals from several different markets dispersed across the U.S. A sampled individual's demand comprises a very small portion of the aggregate demand in each market and very little influence on market price.

References

- Adler, T. and M. Ben-Akiva, 1976, "Joint-Choice Model for Frequency, Destination and Travel Mode for Shopping Trips," *Transportation Research Record*, No. 569, 136-150.
- Basker, E., 2005a, "Job Creation or Destruction? Labor-Market Effects of Wal-Mart Expansion," *Review of Economics and Statistics*, 87, 174-183.
- Basker, E., 2005b, "Selling a Cheaper Mousetrap: Entry and Competition in the Retail Sector," *Journal of Urban Economics*, 58, 203-229.
- Basker, E. and M. Noel, 2007, "The Evolving Food Chain: Competitive Effects of Wal-Mart's Entry into the Supermarket Industry," University of Missouri Department of Economics Working Paper 07-12.
- Ben-Akiva, M., D. Bolduc, and J. Walker, 2001, "Specification, Estimation, and Identification of the Logit Kernel (or Continuous Mixed Logit) Model," mimeo, Department of Civil Engineering, MIT.
- Berndt, E., B. Hall, R. Hall, and J. Hausman, 1974, "Estimation and Inference in Nonlinear Structural Models," *Annals of Economics and Social Measurement*, 3/4, 653-665.
- Berry, S., J. Levinsohn, and A. Pakes, 1995, "Automobile Prices in Market Equilibrium," *Econometrica*, 63, no. 4, 841-890.
- Bhat, C., 2001, "Quasi-random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model," *Transportation Research B*, 35, 677-693.
- Brynjolfsson, E., J.Y. Hu, and M.S. Rahman, 2008, "Battle of the Retail Channels: How Product Selection and Geography Drive Cross-Channel Competition", mimeo.
- Cardell, N.S., 1997, "Variance Components Structures for the Extreme Value and Logistic Distributions with Application to Models of Heterogeneity," *Econometric Theory*, 13, 185-213.
- Chevalier, J. and A. Goolsbee, 2003, "Price Competition Online: Amazon versus Barnes and Noble," *Quantitative Marketing and Economics*, 1, no. 2, 203-222.
- Chintagunta, P., J. Dube, and K. Goh, 2005, "Beyond the Endogeneity Bias: the Effect of Unmeasured Brand Characteristics on Household-level Brand Choice Models," *Management Science*, 51, 832-849.
- Chiou, L. and J. Walker, 2007, "Masking Identification of Discrete Choice Models under Simulation Methods," *Journal of Econometrics*, 141, 683-703.
- Davis, P., 2006, "Spatial Competition in Retail Markets: Movie Theaters," *RAND Journal of Economics*, forthcoming.

Ellison, G. and S. Fisher Ellison, 2005, "Search, Obfuscation, and Price Elasticities on Internet," mimeo, MIT.

Ellison, G. and S. Fisher Ellison, 2006, "Internet Retail Demand: Taxes, Geography, and Online-Offline Competition," mimeo, MIT.

Forman, C., A. Ghose, and A. Goldfarb, 2006, "Geography and Electronic Commerce: Measuring Convenience, Selection, and Price," mimeo, Tepper School of Business Working Paper #2006-E95, Carnegie Mellon University.

Franklin, A., 2001, "The Impact of Wal-Mart Supercenters on Supermarket Concentration in U.S. Metropolitan Areas," *Agribusiness*, 17, no. 1, 105-114.

Goolsbee, A., 2000, "In a World Without Borders: The Impact of Taxes on Internet Commerce," *The Quarterly Journal of Economics*, 115, no. 2, 561-576.

Goolsbee, A., 2001, "Competition in the Computer Industry: Online versus Retail," *The Journal of Industrial Economics*, 49, n. 4, 487-499.

Hajivassiliou, V., 1993, "Simulation Estimation Methods for Limited Dependent Variable Models," *Handbook of Statistics*, 11, Ch. 19, 519-543, Amsterdam, Elsevier Science Publishers B.V.

Hajivassiliou, V. and P. Ruud, 1994, "Classical Estimation Methods for LDV Models using Simulation," *Handbook of Econometrics*, 4, Amsterdam, Elsevier Science Publishers B.V.

Halton, J., 1960, "On the Efficiency of Evaluating Certain Quasi-random Sequences of Points in Evaluating Multi-dimensional Integrals," *Numerische Mathematik*, 2, 84-90.

Hausman, J., 2003, "Source of Bias and Solutions to Bias in the Consumer Price Index," *Journal of Economic Perspectives*, 17, No. 1, 23-44.

Hausman, J. and G. Leonard, 1997, "Economic Analysis of Differentiated Products Mergers Using Real World Data," *George Mason Law Review*, 5, 321-343.

Holmes, T., 2008, "The Diffusion of Wal-Mart and Economies of Density," mimeo, University of Minnesota, Department of Economics.

Jia, P., 2007, "What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry," mimeo, Massachusetts Institute of Technology, Department of Economics.

Massachusetts Institute of Technology Center for Real Estate,
<<http://web.mit.edu/cre/students/curriculum/courses/11.433/fall04/Lecture6.ppt>>, accessed 10/30/2004.

- McFadden, D., 1981, "Econometric Models of Probabilistic Choice" in *Structural Analysis of Discrete Data with Econometric Applications*, Cambridge, MA, MIT Press.
- McFadden, D., 1996, "Lecture on Simulation-assisted Statistical Inference," mimeo, University of California, Berkeley.
- McFadden, D. and K. Train, 2000, "Mixed MNL Models of Discrete Response," *Journal of Applied Econometrics*, 15, 447-470.
- Nevo, A., 2000, "A Practitioner's Guide to Estimation of Random Coefficients Logit Models of Demand," *Journal of Economics and Management Strategy*, 9, 513-548.
- Newey, W., 1984, "A Method of Moments Interpretation of Sequential Estimators," *Economics Letters*, 14, 201-206.
- Petrin, A. and K. Train, 2006, "Control Function Corrections for Omitted Attributes in Differentiated Product Markets," mimeo, University of Minnesota, Twin Cities, Department of Economics.
- Schultze, C. and C. Mackie, 2002), *At What Price?*, Washington, D.C., National Academy Press.
- Seim, K., 2006, "An Empirical Model of Firm Entry with Endogenous Product-Type Choices," *RAND Journal of Economics*, 37, 619-640.
- Smith, M. and E. Brynjolfsson, 2001, "Brand Still Matters," *Journal of Industrial Economics*, 49, 541-558.
- Thomadsen, R., 2005, "The Effect of Ownership Structure on Prices in Geographically Differentiated Industries," *RAND Journal of Economics*, 36(4), 2005, 908-929.
- Train, K., 2003, *Discrete Choice Methods with Simulation*, Cambridge University Press, New York.
- Video Software Dealers Association, *1999 Annual Report on the Home Entertainment Industry*.
- Video Store Magazine, *1996 Video Retailer Survey*.
- Walker, J. L., 2002, "Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables," Ph.D. Dissertation, Department of Civil and Environmental Engineering, MIT.
- Weisbrod, G., R. Parcells, and C. Kern, 1984, "A Disaggregate Model for Predicting Shopping Area Market Attraction," *Journal of Retailing*, 60, No. 1, 65-83.

¹ Business Week Online, “Is Wal-Mart Too Powerful?”, October 6, 2003.

² The Los Angeles Times, “Wal-Mart Posts Modest Sales Gain”, September 7, 2004.

³ Business Week Online, “Is Wal-Mart Too Powerful?”, October 6, 2003.

⁴ My qualitative results are similar whether I restrict my sample to videos with total box office revenues greater than \$25 million, \$50 million, or \$75 million.

⁵ Suppose the hedonic regression is given by $\ln p = X\beta + \varepsilon$ where N = number of observations and k = number of independent variables. Then the equation for price is given by $p = \exp(X\beta + \varepsilon) = \exp(X\beta) \exp(\varepsilon)$, and

$E[p | X] = \exp(X\beta)E[\exp(\varepsilon)]$. If ε is normally distributed with variance σ^2 , then $E[\exp(\varepsilon)] = \exp(\sigma^2 / 2)$.

Consequently, predicted prices are calculated as $\hat{p} = \exp(X\hat{\beta}) \exp(s^2 / 2)$ where $s^2 = \sum_{i=1}^N e_i^2 / (N - k)$ is an unbiased and consistent estimate of σ^2 , and e is the residual from the hedonic regression.

⁶ In contrast, an analytic formula does not exist for the equivalent logit model with random coefficients on nest dummies.

⁷ A full model that examines the decision to purchase could be incorporated. However, the dataset only contains households that made a purchase during the sample period. A calculation of the full elasticity of substitution would include the decision to buy versus rent or neither.

⁸ The nesting can also be interpreted as introducing random coefficients on store type dummies (Berry, 1994).

⁹ Several reasons exist for why stores of the same nest may be closer substitutes. One possibility is that consumers themselves are different across stores; those who choose to shop at electronics stores may differ in unobservable ways from those who choose to shop at music stores. This difference among consumers may be due purely to taste differences or to the presence of other products in their shopping basket. Please see discussion in Section 5.1.

¹⁰ U.S. General Service Administration (GSA), May 23, 1996, Federal Register page 25802, Vol. 61, no. 101.

¹¹ Wal-Mart may not raise its price due to advantages in cost. Wal-Mart’s cost advantages stem from low labor costs and the retail chain’s logistics and distribution innovations (Emek, 2005b).

¹² Business Week Online, “Is Wal-Mart Too Powerful?”, October 6, 2003.

¹³ The New York Times, “Wal-Mart, a Nation Unto Itself”, April 17, 2004.

¹⁴ From the dataset, I find that nearly all households purchase no more than 1 DVD per member. If I divide the weekly number of DVDs purchased by a given household by the household size (number of members), the average weekly number of DVDs purchased by an individual is approximately 0.47 with 97% of households purchasing at most 1 DVD per member.

¹⁵ I tried more general specifications of the mixed logit model, e.g., a full correlation matrix for idiosyncratic tastes across store types, but the estimates were not stable with respect to the number of draws. For the creation of my optimization procedures, I am grateful for the insights illuminated in the estimation algorithm created by Kenneth Train, David Revelt, and Paul Ruud.

¹⁶ Note that the two common methods for correcting endogeneity are not applicable in the current context. Under the “fixed effects” approach of Berry, Levinsohn, and Pakes (1995), a contraction mapping is used to concentrate out the market-specific fixed effects. In my sample, a market consists of a DVD title and geographic pair; in most cases, I only have one observation per market. Consequently, I cannot calculate the market share or concentrate out the fixed effect for each market. On the other hand, the control function approach of Petrin and Train (2006) uses a two-part procedure. In the first stage, the endogenous variable (price) is regressed on all exogenous factors. In the second stage, the demand model is re-estimated with a function of the residual from the price regression explicitly included in the utility specification along with the price variable. In my model, my measure of price is already a predicted value from a hedonic price regression, which I used to estimate prices across all alternatives in a consumer’s choice set. Consequently, I cannot include a residual correction.