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Two Essays on Retailing and Political Advertising Strategy

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Two Essays on Retailing and Political Advertising Strategy

By

Ravi Kumar Shanmugam

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Committee in charge:

Professor Ganesh Iyer, Chair
Professor J. Miguel Villas-Boas
Professor Zsolt Katona
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Abstract

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Essay A ("Anchor Store Quality and Competition in Shopping Malls"): The ability of shopping centers to attract customers and increase sales depends in part on their anchor stores, the small number of large-sized, high-profile tenants located in every mall. In this paper, I develop a theoretical model of competition between anchor and non-anchor stores in a shopping mall, with the goal of explaining an observed pattern of choices of anchor-store quality levels made by mall developers. In particular, I examine the relationship between a mall's anchor-store quality levels, size, and measures of mall performance (visitor traffic and revenues). I find that mall size, because of its relationship to the probability that consumers will find a "fit" between their preferences and the non-anchor store's goods, has varying effects on price competition between the stores, visitor traffic, mall revenues, and anchor quality levels chosen by mall developers. The primary analytical result is that mall size has a positive and concave, i.e. inverse U-shaped, relationship with the probability that the developer chooses a high-quality anchor over a low-quality one. I then validate the predictions of this model using a data set containing information about key strategic variables for major North American malls, showing that the proposed relationships are robust to the inclusion of inter-mall competitive effects and additional relevant controls.

Essay B ("Negative Advertising and Voter Choice"): Negative advertising in political campaigns has been especially timely in recent years, given the increased presence of negative advertising with each successive U.S. election cycle. Using data containing detailed information from both voter surveys and automated ad monitoring, we model choices made by both voters and candidates in U.S. House and Presidential elections in 2000. On the voter side, we model and estimate both voter candidate choice as well as voter turnout, and find that negative advertising has a positive effect both on voter turnout and on the likelihood of voting for the candidate sponsoring the ad. We then examine the campaign's choice of negative advertising and the manner in which it is related to various voter and market characteristics. The key findings are that negative advertising is more likely to be chosen when the cost of advertising is low, when races are closer, when the candidate is a "challenger" rather than an incumbent, and when the voter market is less educated, which makes it less likely that there will be greater scrutiny of candidates by voters.

Dedication

This work is dedicated to Mom, Dad, Kannon, Senthil, and Sakthi, in grateful recognition of the unending support they have given me throughout this process.

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Essay A

Anchor Store Quality and Competition in Shopping Malls

1 Introduction

Investigating research questions in the shopping center industry has always been of interest to marketers and real estate professionals, especially given the significant role played by shopping centers in American commerce; the International Council of Shopping Centers estimates that shopping centers account for 14% of non-automobile U.S. retail sales. Strategic analysis of the industry will become even more important as the industry currently faces a cyclical contraction after a period of over-development and in response to a challenging retail climate. According to a recent *Wall Street Journal* article, there exist 84 "dead malls", centers with sales per square foot below $250, in the United States in early 2009 - up from 40 at the end of 2006. In response to these conditions, mall management companies are now forced to make increasingly strategic decisions regarding redevelopment of struggling properties such as Santa Monica Place in downtown Santa Monica, California, a once-successful enclosed mall which closed in 2008 and is slated to re-open as an open-air center with new tenants in 2010.

Competition between malls and between stores within malls is also of interest to academic researchers in marketing as well as industry professionals, because analysis of shopping center development patterns can provide insight into the nature of how firms, i.e. individual stores within a mall, compete when agglomerated together in close proximity. In addition, shopping centers represent a theoretically interesting variation of the traditional manufacturer-retailer model from vertical control theory, in which the mall developer plays the role traditionally assumed by an upstream manufacturer. Analyzing competitive interactions within this framework can yield insights that generalize beyond shopping malls to any centrally-planned cluster of retail stores, including central business districts in cities and towns.

The goal of this research is to develop a model with testable predictions about mall developers' decisions regarding one key aspect of a shopping center: the "quality" level of its anchor stores. Malls vary widely in their choices of anchor stores, the small number of large-sized tenants in a mall that, because of their range of offerings and brand recognition, attract shoppers to malls and boost sales of a mall's tenant base as a whole. Anchor stores are valued by mall developers for their ability to generate positive demand externalities - as modeled by Brueckner (1993), Benjamin et al. (1992) and Gould et al. (2005) - and attract non-anchor mall tenants in turn; the high profile of most anchor stores relative to non-anchors introduces asymmetry between retailers to the traditional multiple-retailer vertical model. One area in which anchor stores differ among themselves is their quality levels; anchors are often categorized into tiers based on the quality of the goods they sell as well as the prestige of their brand names, both of which affect consumers' willingness to pay for their goods. On these dimensions, there are significant differences between upscale anchors (Bloomingdale's, Nordstrom), mid-level anchors (Macy's, Dillard's), and lower-tier or discount anchors (Target, Sears, J.C. Penney and others). While non-anchor stores also vary in quality level, the smaller number and "marquee" status of a mall's anchors make anchor quality in particular an important strategic variable.

The actual quality levels of anchor stores observed in the mall industry reflect profit-maximizing decisions made by mall developers, who, during the mall planning process, choose whether to attempt to attract high-, mid-, or low-tier anchor stores to their projects. Mall developers' profits, in turn, are often at least partially determined by the profits made by anchor and non-anchor stores in the mall, as well as the cost associated with attempting to attract a higher-quality anchor. Store profits depend on consumers' decisions as to whether to visit the mall, i.e. whether their expected utility from a mall trip, which incurs costs of time and transportation, is positive. Factors that determine how many consumers are attracted to the mall include the quality of the anchor stores, the prices chosen by anchor and non-anchor stores, and the size of the mall, which determines the breadth of merchandise offerings carried within.

Given this setup, the economic question of interest is: What anchor store quality level is optimal for the profit-maximizing mall developer to choose? In particular, when this choice is made conditional on mall size (which is typically determined first in the mall development process as a result of site size limitations and characteristics of a market), how does the developer use the anchor-quality decision to influence competition between mall stores in a way that maximizes its profits?

I model the above competitive framework as a game played by a mall's developer, anchor and non-anchor stores, and consumers, in which the probability that consumers consider purchasing from non-anchor stores, i.e. find a "fit" with the goods available at those stores, is directly related to mall size. In doing so, I find that at a given anchor quality level, there exists a positive and concave relationship, i.e. an "inverse U-shaped" relationship, between mall size and the dependent variables of mall traffic and store profits. I identify two effects that contribute to this concave relationship. At higher mall sizes, the expected value of a mall visit for a representative consumer increases due to the increased fit probability. However, as this probability reaches high values, stores (because they do not know consumers' price expectations) increase their prices by progressively larger amounts, which has a negative effect on consumers' expected utility of purchasing from each store and from the mall visit overall, and drives down mall traffic and store profits.

Regarding the central issue of interest, the developer's decision about which anchor quality level to choose to maximize its own profits, I find that there exists a similarly positive yet concave relationship between mall size and anchor quality, i.e. that the likelihood of the developer choosing high quality over low quality increases and then decreases as mall size increases. Up to a certain point, an increase in mall size causes mall profits to grow faster at higher anchor quality levels than at lower quality levels, as the high anchor quality acts in conjunction with the increased probability of fit to attract more visitors to the mall. However, when mall size increases beyond a certain point, the stores' resulting price increases as described in the previous paragraph, and their negative effects on mall traffic and combined store profits, are greater at higher anchor quality levels than at lower levels, causing the developer to choose low quality as a means to control the negative demand externalities generated by the stores' pricing decisions.

I then develop an empirical framework to test the predictions of this theory and further investigate the relationship between mall size, anchor quality, mall traffic, and mall profits, using a data set containing information about 1,391 malls across the U.S. and Canada. I correct for potential endogeneity of mall size in relation to anchor quality via the control function method with an instrumental variable. I then show how the developer's anchor-quality decision is influenced not only by mall size but also by the expected anchor-quality choice probabilities of competing malls in each market, using a nested fixed-point algorithm within a maximum likelihood procedure to estimate the equilibrium choice probabilities for each group of competing malls. I also control for mall- and market-level demographic variables (income, age, population density) not included in the theory model and observe how additional significant relationships discovered in this analysis are related to the predicted theoretical results.

The remainder of this paper proceeds as follows. Section 2 describes how previous work provides a foundation for this research problem. Section 3 introduces the data set and presents some preliminary empirical insights. Sections 4 and 5 outline the theoretical model and predictions it yields about the behavior of mall developers, individual mall stores, and consumers. Section 6 presents a more detailed empirical discussion that further analyzes the determinants of developer's anchor quality decision. Section 7 concludes the paper.

2 Related research

There exists a considerable body of literature that has studied the economic reasons behind the co-location of firms - as seen in shopping centers and other centralized retail clusters - starting with the basic Hotelling (1929) prediction that a single firm in a cluster of homogeneous retailers cannot gain monopoly power by reducing price (because of factors such as quality and reputation). This principle favors the agglomeration of similar retailers at a single location, a result that has been confirmed even when factors such as consumer uncertainty (Webber 1972) and slight heterogeneity of products and consumer tastes (DePalma et al. 1985, Konishi 2005) are incorporated. Wernerfelt (1994) and Dudey (1990) conclude that firms may find it optimal to co-locate to facilitate search by consumers because it signals to them that competition will keep prices reasonable, thus attracting consumers to the joint location and away from other competitors.

Given the time and travel costs of visiting a mall, the incentive of an increased chance of finding desirable goods as a result of multiple retailers in one space is also necessary for the mall to attract visitors. Datta et al. (2008) isolate the positive effect on the profits of each firm in a cluster resulting from the benefits of agglomeration, as well as the negative effect from competition. Vitorino (2008) is one of the few studies to investigate agglomeration-related issues specifically within the context of the shopping center industry by constructing and empirically verifying a strategic model of entry for mall stores, in which certain stores' entry decisions have "spillover" effects on the profits of other stores. I aim to contribute to this stream of literature by examining how one strategically critical aspect of a mall, the quality of its anchor stores, creates a spillover effect on demand for non-anchor stores' goods and using this to explain the observed empirical relationship between mall size and anchor quality.

Investigating the nature of competition between stores in a mall, because of how this competition can be influenced by the mall developer, is akin to a vertical control problem as outlined by Tirole (1988) and Katz (1989). In the theoretical framework proposed in this paper, the mall developer and mall stores are the equivalents of the upstream manufacturer and downstream retailers, respectively, in the traditional model used in much of the vertical control literature. A key variation from the traditional vertical-control paradigm is that the mall developer does not supply retailers with a product to sell to consumers at a markup; instead, developers sell retail space, which can be viewed as a complementary "product" necessary for retailers to operate in the mall.

While this eliminates the traditional negative vertical externality resulting from double marginalization in the traditional manufacturer-retailer model, the lack of integration between the developer and retailers, i.e. the free will of the latter to set prices competitively, results in horizontal externalities as described by Jeuland and Shugan (1983), Matthewson and Winter (1984), and Dixit (1983). Each store's actions represent a balance between the goals of maximizing its own profit per consumer by raising prices, and maximizing all stores' profits by lowering prices and attracting more consumers to the mall; the latter mechanism allows the stores to exert externalities on each other through their pricing decisions. In this setup, the developer's choice variables do not include price (unlike in the typical vertical integration model) but include the type and size of anchor and non-anchor stores chosen to occupy the mall. These choice variables can be thought of as a means to regulate competition and horizontal externalities in a way that maximizes the profits of stores in the mall, which in turn maximize the profits the developer can extract through store rents.

With the exception of studies such as Vitorino (2008) and Konishi and Sandfort (2003), who model the joint profit-maximization problem faced by a mall developer and tenant stores, the majority of research related to the shopping-center industry is dependent on reduced-form empirical methods. While many of these papers, such as those mentioned in the introduction, use these methods to explain rents charged by shopping-center developers to anchor and non-anchor tenants, others address determinants of mall traffic and profit unrelated to tenant mix and intra-mall price competition, such as the influence of competing centers. Smith and Hay (2005) establish that "converting" retail clusters into malls and allowing developers to internalize economic benefits of agglomeration results in intensified competition between developers, while other researchers (Eppli and Shilling 1996, Mejia and Eppli 2003) empirically model the effect of competing malls on a center's sales. Other studies examine how mall sales and traffic are influenced by non-retail mall attractions such as movie theaters (Ooi and Sim 2007). In the empirical analysis section of this paper, I consider these factors and how they relate to my proposed theory of anchor store quality.

3 Data and empirical measures

To examine the relationship between anchor quality, non-anchor size, and measures of a mall's success (visitor traffic and profits), I utilize a data set published by the Directory of Major Malls (DMM), consisting of approximately 5,000 malls across all regions of the United States and Canada. Based on their size and tenant mix, these malls are separated into categories, which are listed in Appendix 1.

I restrict the data to malls in the regional, super-regional, value-retail, and lifestyle categories. The categories of regional and super-regional malls are primarily defined by size, including all malls of greater than 500,000 square feet. These malls are well suited to model the proposed competitive framework because malls of this size or larger tend to have multiple stores in categories such as apparel and gifts, implying that the benefits of agglomeration to consumers are more likely to be evident in these malls relative to their smaller counterparts. Lifestyle centers and value retail centers tend to have a retail mix similar to that of regional and super-regional malls, while community centers, power centers, and entertainment centers tend to have a significantly different retail mix and less competition between anchors and non-anchors relative to malls in the categories included in this data set.

To further refine this data set, I checked all malls in these categories for missing or erroneous data and eliminated errant observations, resulting in a data set consisting of a representative cross-sample of 1,391 malls. It is also important to note that while most variables are available for all malls in this subset, data on mall traffic and store sales is only available for 445 and 532 malls in the final data set, respectively; the remaining malls did not provide this data to DMM, as data specifically related to mall performance is often more sensitive and confidential than other mall data.

In addition to variables specific to each mall, the DMM data provides lists of tenants for each mall, including anchor stores, but does not provide any classification of individual anchor stores as it does for entire malls. I divide all department-store mall anchors in this data set into 3 discrete categories as illustrated in Figure 1. To do so, I use a classification scheme in a report by the U.S. Equal Employment Opportunity Commission (2004), which represents the most objective and comprehensive attempt to classify department store anchors in U.S. malls. The EEOC report first identifies a group of upscale "bridge" and mid-tier "better" brand names in the women's apparel and accessories industry based on an analysis of fashion publications and price points. A statistical cluster analysis of the number of high- and mid-tier designers represented in the stores of the various chains, which yields two significant clusters; the chains are then categorized based on how many of their locations fall into these clusters.

The resulting department-store classification is consistent with how these stores are commonly categorized in retail-industry publications, which not only consider the quality level of the goods offered by these stores across multiple categories but also their perceived value, which is a function of the stores' brand equity. As most malls used in the data analysis for this paper have multiple anchors, I define the overall mall anchor quality level for each mall as being equivalent to the quality level of its highest-quality anchor, as it is this anchor-quality "ceiling" (i.e. whether at least one anchor of a higher quality level is available within the mall) that has the greatest implications for consumers' overall "valuation" of a visit to the mall.

Also, even though non-department store anchors are common in shopping malls (albeit to a limited extent in this data set because of their relative prevalence in the omitted mall categories), I categorize them as low-quality anchors. The majority of non-department-store anchors in this data set are restaurants or entertainment destinations, not retailers, and do not compete with non-anchor stores across the same merchandise categories. Furthermore, in instances where a non-department-store anchor exists that offers the equivalent of "high quality" as well as merchandise that overlaps with the mall's non-anchors, such a store is virtually always accompanied by at least one high-quality department-store anchor, which already ensures that the mall's overall anchor-quality rating will be "high" as defined earlier.

Quality level	Description	Stores included in classification
q_H	Upscale department store	Barney's, Bloomingdale's, Holt Renfrew, Neiman Marcus, Nordstrom, Saks Fifth Avenue
q_M	Mid-tier department store	Carson Pirie Scott, Dillard's, Lord & Taylor, Hudson Bay, Macy's, Parisian, Von Maur
q_L	Discount department store or non-department store anchor	All other department stores (including Target, Sears, J.C. Penney) and non-department store anchors

Figure 1: Classification of anchors in data set into 3 distinct quality levels: high, medium, and low.

Using the above categorization scheme, preliminary analysis of the data shows that across the entire data set, malls with an anchor-quality rating of medium comprise roughly half of all malls, with low-anchor-quality malls the next most popular category and high-anchor-quality malls a distant third. To further examine the distribution of anchor quality, I divide the data set into quartiles based on the general leasable area (GLA) of each mall's non-anchor stores, which is closely correlated ($\rho = 0.8055$) to overall mall GLA or "mall size", a variable identified in the introduction as being of interest; the significance of non-anchor GLA in particular will be discussed later. The breakdown of anchor quality by GLA quartile is shown in Figure 2, in which higher-quality malls become more prevalent when "mall size" as represented by this variable increases.

Quality level	Total	Q1	Q2	Q3	Q4
q_H	192 (13.8%)	17 (4.9%)	24 (6.8%)	53 (15.2%)	98 (28.7%)
q_M	673 (48.3%)	111 (31.8%)	211 (60.1%)	204 (58.5%)	147 (43.0%)
q_L	526 (37.8%)	221 (63.3%)	116 (33.0%)	92 (26.4%)	97 (28.4%)

Figure 2: Distribution of malls by anchor quality rating (equivalent to anchor quality rating of mall's highest anchor).

However, it is worth pointing out that the relative percentage of low-anchor-quality malls slightly increases when moving from quartile 3 to quartile 4, and that the relative rate at which medium quality is chosen over low quality decreases. This is even more noteworthy in light of the fact that larger malls tend to have more anchors, which should increase the likelihood that at least one anchor will be high- or medium-quality and that the mall's anchor quality rating as defined here will be high or medium. Based on this table, it is worth considering not only whether a theoretical explanation exists for the likelihood of choosing a high- and/or medium-quality anchor level over a low-quality anchor level increasing with non-anchor GLA (which Figure 2 seems to suggest) but also whether that same likelihood decreases with anchor size for high non-anchor GLA levels (which is not strongly evident in Figure 2 but may be in evidence when the appropriate controls are included in the empirical analysis). The model described in the following section addresses these questions.

4 Theoretical framework: Overview

In this section, I analyze the relationship between mall size and anchor quality by presenting a model of a mall which consists of two stores, an anchor store and a non-anchor store.

Both stores in this model are assumed to sell a single type of item. Valuation of each store's version of this good varies among consumers; consumers' relative preference for the anchor and non-anchor version is represented by a variable v with a uniform unit distribution. The inclusion of this variable allows the model to represent a type of consumer heterogeneity which motivates the agglomeration of anchor and non-anchor stores in malls, as including both store types allows the mall to better appropriate consumer surplus.

Consumers' purchase decisions are also influenced by whether the good offered at either the anchor or non-anchor store "fits" with their product preferences, which occurs with probability α or β, respectively. Only if there is a fit does the consumer consider buying from that store. As anchor stores are usually more widely-known and consumers tend to have more information about their goods prior to visiting the store, the anchor fit probability is normalized to $\alpha = 1$. However, the analysis in this paper generalizes to any case where $\alpha > \beta$. The fit parameter β is linked to the breadth of offerings of the non-anchor store, which for malls in the data set can be associated with the size of the non-anchor component of the mall's retail space. As mentioned in the introduction, this size is usually determined before the developer chooses anchor quality; therefore, the associated fit parameter β is treated as exogenous.

Given this specification, the game played by the developer, the stores, and consumers involves the following stages, in which each party makes choices to maximize its own profit or utility as appropriate:

- *Stage 1*: The developer chooses q.
- *Stage 2*: The anchor and non-anchor stores endogeneously and simultaneously set prices p_A and p_N.
- *Stage 3*: Consumers decide whether to visit the mall, based on their expected utility upon visiting the mall. This decision is made based on fit probability, expected valuation and prices.
- *Stage 4*: Consumers decide whether to purchase from the anchor store or non-anchor store based on fit, actual valuation and prices.

Stores' ability to set prices independently in stage 2 is a central feature of this model. While many mall stores are part of chains and are somewhat constrained by corporate-level decisions, they still have leeway in terms of price promotions, "clearance" discounts and the choices of specific brands and items to stock at each location.

At the conclusion of stage 4, the developer acts as the "residual claimant" on all profit earned by the anchor and non-anchor stores. In actuality, the store profits claimed by the developer represent all profits beyond a pre-determined reservation profit level for each store; the developer extracts all surplus economic rent from each store. This setup reflects the fact that many contracts between mall developers and tenants are at least partially based on sales. As a result, the developer's choice of q in stage 1 is intended to induce the anchor and non-anchor stores and consumers to act in such a way that combined store profits are maximized. In the remainder of this section, I further examine the behavior of the various players at each stage of the game, using backwards induction to compute the subgame-perfect Nash equilibria at each stage.

4.1 Developer- and store-level model details

In the typical shopping center development process, the act of securing lease commitments from anchor tenants is a complex procedure. This step often takes place in conjunction with determining the feasibility of a center and securing funding for its construction, due in large part to anchor tenants' importance to the success of the center. However, it is usually the case that the mall developer must have a good sense of many of a center's details - including its estimated size - before making a sales pitch to prospective anchor tenants. For the purposes of this model, the developer's choice of a discrete anchor quality level $q \in \{q_L, q_H\}$, implicit in its choice of which quality level of retail store fills the single anchor store space in the mall, is a necessary yet reasonable simplification of this process.

In this model, the developer's profits depend on the maximum rents he can extract from the anchor and non-anchor stores as a residual claimant. For each store, this is equal to the store's total profits, which will be defined in the following section. As mentioned in the introduction, the developer also incurs a cost based on the chosen level of anchor quality q. This cost represents the resources a developer must expend to attract a relatively high-quality anchor to the mall, primarily consisting of increased spending on common areas within the mall but outside the individual stores.

The developer's profit function is represented by the following specification in which c is a cost parameter:

$$\Pi_D = \Pi_A + \Pi_N - c(q - q_L)$$

The developer's goal in stage 1 is to choose the value of $q \in \{q_{L,} q_H\}$ that maximizes this profit function, given his anticipation of store and consumer behavior in subsequent stages.

Conditional on the anchor quality parameter q, the anchor and non-anchor stores set their prices simultaneously in stage 2 to maximize their individual profits[1], which are specified as follows:

$$\Pi_A = p_A P(A)\overline{M}$$
$$\Pi_N = p_N P(N)\overline{M}$$

These profits are a function of:

- p_A and p_N: prices chosen by each store
- $P(A)$ and $P(N)$: probability that a representative consumer chooses to buy from either store
- $\overline{M}$: expected number of consumers who visit the mall.

Closed-form expressions for $P(A)$, $P(N)$, and M and the equilibrium prices are derived in Appendix 2 and 4.

4.2 Consumer-level model details

Once the anchor quality level is chosen and prices are set in stages 1 and 2, consumers then decide whether to visit the mall, which is conditional on their expected decision about which store to purchase from once they visit the mall. I describe the latter decision first and then examine the consumer's mall-visit decision.

Consumer valuation for the good offered by either store (defined as V_A and V_N) is a function of two components: an unconditional "base" valuation, and the consumer's realized value of the preference variable v. The base valuation represents the value that a consumer who has the strongest possible preference for one store would have for that store's good. For the anchor store good, this base valuation is equal to the anchor quality choice variable q; for the non-anchor store, base valuation is normalized to 1. In this setup, the fit probability β can be thought of as a "horizontal" variable affecting whether a consumer's preferences match with a store's offerings, whereas the anchor quality variable q can be thought of as a "vertical"

[1]Although stores have cost functions as well, this model only considers stores' revenues, given that cost function data is unavailable.

variable affecting consumer's actual valuation of one of the stores' goods conditional on such a match.

Consumer valuation is also dependent on the consumer's value of v, involving a travel cost similar to that from the traditional Hotelling model, based on the following:

- Distance between the consumer's position on the 0-1 range of v and the value of v that represents maximum preference for that store (at which valuation is equal to the base valuation)
- A parameter t which represents the level of differentiation between the anchor and non-anchor stores, i.e. the "travel cost" deducted from maximum possible valuation as a result of being at a value of v other than 0 or 1.

For the anchor and non-anchor stores, the maximum preference occurs at $v = 0$ and $v = 1$, respectively, at which $V_A = q$ and $V_N = 1$. Valuation decreases from these levels as v or $(1 - v)$ increases, as shown graphically in Figure 3 for the cases in which consumers consider both stores and the anchor store only.

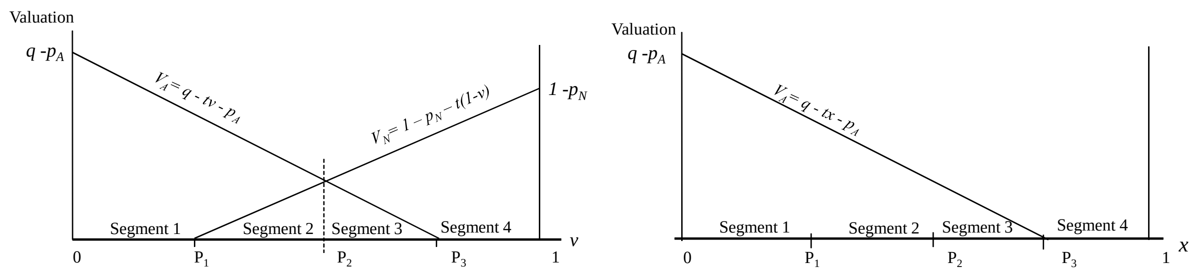

Figure 3: Valuation of both stores as a function of v, q, and firms' prices, for 2 cases: (1) Consumer considers both stores, (2) Consumer considers only anchor store.

Once the consumer visits the mall, she finds out whether she finds a fit with the non-anchor store's good, which is determined by the fit probability parameter β. The consumer's purchase decision then depends on the consumer's valuation of the goods of whichever store(s) are in her consideration set at that point. These valuations are a function of the consumer's relative-preference variable v, the mall's anchor quality variable q, and the endogenously determined prices p_A and p_N. If consumers consider both stores, they purchase from the store for which valuation net of price is greater.

These rules can be used to estimate how many consumers choose to visit the mall. Although it is not known until a consumer visits the mall whether a fit with the non-anchor store is found or not, the value of β is known *a priori* by consumers. V_A and V_N are also known in advance, as they are a function of the mall anchor's value of q as well as the consumer's own relative preference v. Consumers decide whether to travel the mall based on their expected utility of such a trip, which is a function of the probability of purchasing from one store or the other conditional on visiting the mall (i.e. in stage 4) as well as the expected utility from doing so.

$$EU = P(N)E(U \mid N) + P(A)E(U \mid A)$$

These purchase probabilities for a given consumer depend on that consumer's value of v as well as whether that consumer's consideration set includes both the anchor and non-anchor store or just the anchor store. As shown in Figure 3, the entire consumer base can be divided into four distinct segments based on their individual values of v.

Figure 4 depicts the anticipated purchase decisions made by consumers for each possible consideration set as a function of v. Closed-form expressions for the boundary points P_1, P_2, and P_3 are derived in Appendix 3.

	v interval	Fit with A+N	Fit with A only
		P $= \beta$	P $= (1-\beta)$
1, 2	$v \in [0, P_2]$	A	A
3	$v \in [P_2, P_3]$	N	A
4	$v \in [P_3, 1]$	N	none

Figure 4: Anticipated purchase decisions for consumers for various combinations of consideration set and preference level v.

These anticipated purchase decisions conditional on fit, as well as the probability of each "fit" scenario (as shown in the second row of the table), lead directly to an expression for the unconditional purchase probabilities $P(A)$ and $P(N)$ associated with each v interval, as shown in Figure 5.

	v interval	$P(A)$	$P(N)$
1, 2	$v \in [0, P_2]$	1	0
3	$v \in [P_2, P_3]$	$1-\beta$	β
4	$v \in [P_3, 1]$	0	β

Figure 5: Unconditional purchase probabilities for consumers for various intervals of v, equal to 0 for certain intervals.

These unconditional purchase probabilities can be used to calculate expected utility for a representative consumer in each of the four intervals of v shown in the table. Assuming consumers' reservation utility (which reflects a combination of transportation cost and utility from shopping at the nearest competing mall or retail area) has a uniform unit distribution, these expected utilities are equal to the probabilities that a given consumer in each segment will visit the mall; the consumer will do so if his expected utility of a mall visit is greater than his reservation utility. Calculations of expected utility by segment as well as expected mall traffic are shown in Appendix 4.

5 Theoretical framework: Predictions

Having outlined the model in stages, I next present testable propositions of how prices, mall traffic, store profits, and developer's choices of anchor-quality level depend on the exogenous value of non-anchor size, which affects consumer behavior via the non-anchor "fit" probability β. I do so by examining the equilibrium behavior of the players at each stage of this model, culminating in the primary result in stage 1, in which the developer chooses a profit-maximizing level of mall anchor quality q given the exogenous value of β.

5.1 Store-level predictions: Price equilibrium

I first examine stores' pricing decisions with respect to the developer's choice variable q

(referred to as a "parameter" for this part of the analysis) and the exogenous fit parameter β. It is important to observe that higher levels of q "favor" the competitive position of the anchor store, as this results in higher consumer valuation of that good for all values of v, and greater consumer surplus for the anchor good. Likewise, higher levels of β favor the non-anchor store, as this increases the probability that consumers will find a fit with that store's good and consider that store.

It is also necessary to consider the economic intuition behind two effects that balance each other equally at each firm's price equilibrium: a "price effect", equivalent to the additional profit the firm would gain from the share of consumers (segments 1, 2, and 4 in Figure 3) who continue to buy from a store if it raised its price from the equilibrium value, and a "probability change effect", equivalent to the profit lost from the share of consumers (segment 3) who no longer buy from that store as a result of the higher price.

A higher value of q results in a new equilibrium in which the anchor store charges a higher price while the non-anchor store charges a lower price. Considering the anchor store first, an intuitive explanation for this result is that higher anchor quality results in higher consumer valuation and demand for the anchor store's good for all consumers regardless of their relative preference v; the anchor store can increase its price while still preserving higher demand and ending up with higher profit than at the previous equilibrium. As a direct result of this, the share of consumers who buy from the non-anchor store (as calculated in Appendix 2) decreases. The non-anchor store therefore has more to gain from reducing price rather than increasing it - the profit lost via the "price change" effect comes from a smaller consumer base.

At higher levels of non-anchor fit probability β, both stores charge higher prices. The non-anchor store, which is "favored" by the increase in this parameter, is able to increase price at higher values of this parameter and still earn higher profits. However, in contrast to the non-anchor store in the previous case, the anchor store has more to gain from increasing price along with the non-anchor store, choosing a strategy of making more profit from a consumer share that increases as a result of the non-anchor's price increase. This reveals that stores, who do not know consumers' price expectations, respond to an increase in mall size with a mutual strategy of increasing prices to maximize the expected profit per consumer who visits the mall.

5.2 Store-level predictions: Mall traffic and store profits

The preceding discussion of how an increase in β results in reduced price competition is necessary to set up the model's first prediction, about the effect these same parameters (as well as their resulting effects on prices) have on the market size, i.e. the number of expected mall visitors.

Proposition 1. The comparative statics of the model with respect to equilibrium mall traffic (number of consumers who decide to visit the mall) are as follows:

- An increase in anchor quailty (q) results in greater mall traffic.
- An increase in non-anchor fit probability (β) causes mall traffic to increase and then decrease, i.e. the relationship is positive and concave (inverse U-shaped).

To consider the comparative statics with respect to mall traffic in this model, it is necessary to decompose the effect of a parameter increase on mall traffic into two sub-effects: a "direct" effect, corresponding to the effect of the parameter increase on mall traffic independent of price (i.e. with price remaining fixed), and a "price" effect, corresponding to the effect of the parameter increase on mall traffic via its effect on either of the stores' prices. These sub-effects correspond to the first term and the remaining terms, respectively, in the decomposition below:

$$\frac{dM}{dq} = \frac{\partial M}{\partial q} + \frac{\partial M}{\partial p_A}\frac{\partial p_A}{\partial q} + \frac{\partial M}{\partial p_N}\frac{\partial p_N}{\partial q}$$

The direct effect, price effects, and overall effect on mall traffic for changes in each parameter are summarized in Figure 6. Considering first the comparative statics for anchor quality q, the direct effect of a higher anchor quality level on mall traffic is positive: ignoring the effect it has on prices, a higher-quality anchor store increases valuation of the anchor store good and makes expected utility higher for at least some consumers. The second, third, and fourth columns depict effects of the changes in p_A and p_N outlined in the previous section as well as the combined effect. An increase in q leads to an overall positive effect on mall traffic because the positive direct effect is stronger than the negative price effect, i.e. the increase in quality drives additional consumers to the mall despite the negative effect of the resulting changes in stores' prices.

	Direct	p_A	p_N	$p_A + p_N$	*Overall*
$\frac{dM}{dq}$	+	-	+	-	+
$\frac{dM}{d\beta}$	+	-	-	-	+/-

Figure 6: Signs of direct, price, and overall effects on mall traffic in response to changes in q and β.

A similar explanation holds as non-anchor fit probability β increases at relatively low values, but the effect on mall traffic of an increase in β eventually becomes negative. As β approaches sufficiently high levels, the price increases chosen by both firms grow increasingly large, resulting in a negative price effect that gradually overtakes the positive direct effect in magnitude; the economic implication is that increases in non-anchor fit probability, beyond a certain point, cause firms to overreact in their price increases, which creates a negative effect on mall's ability to draw visitors. I next examine how changes in parameters translate to changes in store-level profits.

Proposition 2. The comparative statics of the model with respect to store-level profits are as follows:

- An increase in anchor quality (q) results in greater profits for each store.
- An increase in non-anchor fit probability (β) causes non-anchor store profit to increase, but causes anchor store profit to increase and then decrease, i.e. the relationship is positive and concave (inverse U-shaped).

It is somewhat surprising that an increase in q not only benefits the anchor but also the non-anchor, mainly because of the increased mall traffic and in spite of a lower probability that consumers purchase from the non-anchor and a lower non-anchor price. Not only does the increase in mall traffic appear to be the key driver of increases in both stores' profits when q increases, but the non-anchor store's price cut contributes to the increase in mall traffic, generating a demand externality that benefits the anchor as well.

The result of greatest interest pertains to increases in non-anchor fit β; while this results in an increase in the favored non-anchor store's profits as expected, anchor store profit varies in the same way that mall traffic varies as described in Proposition 1, first increasing and then decreasing as β increases. Recall that store profit, as defined in Section 4.1, is a function of three things: probability of purchase from a store, the store's price, and mall traffic. The increase in non-anchor fit probability is accompanied by a higher price charged by the anchor store, which have negative and positive effects on the anchor store's profit, respectively, but the overall effect on anchor profit is primarily driven by the effect on mall traffic described in Proposition 1.

In addition, the combined profits of the anchor and non-anchor store also have a similarly concave relationship with non-anchor fit β. While the non-anchor store's profit always increases with β, the decrease in the anchor store's profit eventually offsets this increase and results in lower combined profit. This finding sets up the key prediction of the theoretical model, relating to the developer's choice of q.

5.3 Developer-level predictions

To examine the behavior of the model at the developer's level, I first define q_H and q_L as a function of β and t in such a way that all four segments in Figure 3 exist (i.e. such that the two stores are guaranteed to "cover" the market completely)[2]. To define the relative attractiveness to the mall developer of q_H and q_L, the gap between developer's profits at the two levels of q, $\Pi_D(q_H) - \Pi_D(q_L)$ is considered. It is by examining the derivative of this gap with respect to non-anchor fit probability that one can answer the following question: What impact does this parameter have on whether the developer chooses high or low anchor quality q?

Proposition 3. An increase in non-anchor fit probability (β) causes the relative attractiveness of the high anchor quality level to increase and then decrease, i.e. the relationship between non-anchor fit probability and anchor quality is positive and concave.

In this result, the "horizontal" non-anchor fit probability has an effect on the "vertical" choice variable, the developer's profit-optimizing choice of anchor quality. Proposition 2 predicted an increase in combined store profits, which are equivalent to developer profits, [3] as a result of higher consumer valuation, mall traffic, and store profits as non-anchor fit probability increases from 0 to a certain point; by examining how the gap between developer profits at high and low quality levels changes, I observe that this effect is amplified at higher anchor quality levels, causing the developer to favor higher anchor quality. This is a result of increasing non-anchor fit and higher anchor quality acting in conjunction to attract enough new consumers to the mall to outweigh the effect of both stores' price increases.

Similarly, what was observed as the non-anchor fit probability increases beyond a certain point - a negative effect on mall traffic and profits as a result of the stores' increasingly large price increases - is also amplified at higher anchor quality levels, causing the developer to favor lower anchor quality. The implication is that as mall size grows large enough, the

[2]The results generalize to all constraint-compliant definitions of q_H and q_L.

[3]While Proposition 2 was actually concerned with the effect on combined store profits, this is treated as equivalent to developer profits in the discussion of Proposition 3, as the developer's cost term does not affect this analysis.

developer is forced to use his control over anchor quality (in particular, by choosing lower anchor quality) to manage the negative externalities generated by the stores' price increases.

The preceding results discuss how the developer's likelihood of choosing high or low anchor quality is affected; as to the actual choice itself, it is possible for certain values of the cost parameter c for observed anchor quality levels to change from low quality to high and back to low as the non-anchor fit parameter β increases from 0 to 1. In other words, this suggests that high-quality anchors would be found in mid-sized malls. This prediction raises a question for the empirical analysis of the predictions of this model: Is this pattern actually observed in the data when the appropriate controls are added? Even in the absence of data on store prices and mall contracts, market structure alone (i.e. observed mall sizes and quality levels) can be used to test the predictions of Propositions 1, 2, and 3: this analysis is the subject of the following section.

6 Econometric model

In this section, I develop an empirical model to verify the proposed relationships between the mall developer's anchor-quality decision and the other variables mentioned in the previous section: mall size, mall traffic, and store profits. Using the data setup described in section 3, I begin by testing the intermediate predictions in Propositions 1 and 2. I then use a simple multinomial logit choice model to present evidence for the main result in Proposition 3. Finally, I develop a more advanced econometric model to incorporate between-mall competitive effects and provide further evidence for Proposition 3.

6.1 Determinants of mall traffic and sales profit

I first construct a basic ordinary least-squares (OLS) regression to test the relationships between the dependent variables of mall traffic and non-anchor store sales[4], and the independent variables of anchor quality and non-anchor size, as proposed in Propositions 1 and 2.

The OLS model is specified as follows:

$$Y_i = \alpha_i + \beta_1 GLA_{Ni} + \beta_2 GLA_{Ni}^2 + \beta_3 q_{Hi} + \beta_4 q_{Mi} + \beta X_i + \varepsilon_i$$

in which:

- Y_i = Dependent variable for mall i, defined as either (1) mall traffic, i.e. number of annual mall visitors, or (2) non-anchor store sales per square foot
- GLA_{Ni} = Total non-anchor GLA
- q_{Hi} = Binary variable equal to 1 if the mall's highest-quality anchor has a quality rating of q_H, 0 otherwise
- q_{Mi} = Binary variable equal to 1 if the mall's highest-quality anchor has a quality rating of q_M, 0 otherwise
- X_i = Vector of additional mall-specific regressors (described in Appendix 5)

[4]Sales figures for anchor stores are unavailable in this data set.

- ε_i = Mall-specific unobservables (error term)

The results for the first regression in which mall traffic is the dependent variable, as shown in Figure 7, display evidence for a positive relationship between higher-than-minimum levels of mall anchor quality and number of mall visitors. I also find that there exists a positive yet concave relationship between non-anchor size and visitor traffic; the coefficient for the non-anchor size term is positive and significant, and the coefficient for the quadratic term is negative and significant.

Variable	**Coefficient (std. error)**	**T statistic (significance)**
Intercept	$8.88 \times 10^5 (5.04 \times 10^7)$	0.18 (0.86)
NA (non-anchor) size effect	**14.32 (4.83)**	2.19 (0.029)
NA size^2 effect	**-5.29×10^{-6} (3.27×10^{-6})**	-1.62 (0.107)
Effect of "anchor quality = H"*	**2.38×10^6 (1.07×10^6)**	2.23 (0.027)
Effect of "anchor quality = M"*	**1.85×10^6 (8.43×10^5)**	2.19 (0.029)
Population (10 mile radius)	**1.289 (0.530)**	2.43 (0.016)
Income (10 mile radius)	19.17 (16.66)	1.15 (0.251)
Age (10 mile radius)	-8.49×10^4 (1.05×10^5)	-0.80 (0.422)
Herfindahl index	8.36×10^6 (9.70×10^6)	0.86 (0.389)
# of seats in food court	**2680.69 (735.99)**	3.64 (0.000)
# of mall levels	4.21×10^5 (3.67×10^5)	1.15 (0.252)
Years since last renovation	-2.80×10^4 (4.60×10^4)	-0.61 (0.543)
Outparcel space	5.66×10^5 (5.60×10^5)	1.01 (0.313)
Distance to nearest mall	1.97×10^4 (1.99×10^4)	0.99 (0.324)
Distance to nearest city	-1478.71 (6537.25)	-0.23 (0.821)
Mall classification: value retail	-2.57×10^7 (2.45×10^7)	-1.05 (0.294)
Mall classification: lifestyle	-2.19×10^7 (1.48×10^7)	-1.48 (0.141)
Outdoor center	**1.68×10^7 (1.02×10^7)**	1.64 (0.101)
Effect of "region = South"**	**1.67×10^6 (8.34×10^5)**	2.01 (0.045)
Effect of "region = Midwest"**	3.75×10^5 (8.66×10^5)	0.43 (0.665)
Effect of "region = West"**	8.02×10^5 (8.50×10^5)	0.94 (0.346)
MSA mean anchor quality	-4.43×10^5 (8.23×10^5)	-0.54 (0.591)
MSA mall count	1920.76 (2.38×10^4)	0.08 (0.936)

Figure 7: Results from OLS regression of visitor traffic on non-anchor size and anchor quality. Coefficients that are significant are shown in **bold**. See Appendix 5 for a definition of all regressors included in this figure and the following figure.
* - Relative to base case in which anchor quality = L (low)
** - Relative to base case in which region = East

The regression in which non-anchor sales per square foot is the dependent variable reveals that there is a positive relationship between this variable and high and medium anchor quality levels as well as non-anchor size, as shown in the results of this regression in Figure 8. As discussed in the previous sections, the effect of non-anchor size on the developer's anchor-quality choice follows directly from its effect on mall traffic and store profits; hence the importance of these results, which verify the behavior predicted by the theoretical model in Propositions 1 and 2 for each of the intermediate stages of the game.

In addition to demonstrating that the predicted relationships between the intermediate variables (mall traffic and profits) and the key strategic variables of interest (anchor quality and non-anchor size) are robust to the inclusion of multiple relevant control variables, Figures 7 and 8 also show that some of these controls - including the distance from the subject mall

Variable	Coefficient (std. error)	T statistic (significance)
Intercept	**208.65 (92.59)**	2.25 (0.025)
NA size effect	**1.14 x 10^{-4} (3.25 x 10^{-5})**	3.51 (0.001)
Effect of "anchor quality = H"	**166.69 (19.02)**	8.76 (0.000)
Effect of "anchor quality = M"	**61.13 (14.53)**	4.21 (0.000)
Population (10 mile radius)	**6.11 x 10^{-5}(1.08 x 10^{-5})**	5.66 (0.000)
Income (10 mile radius)	**7.87 x 10^{-4}(3.30 x 10^{-4})**	2.38 (0.018)
Age (10 mile radius)	-1.785 (2.007)	-0.89 (0.374)
Herfindahl index	**295.08 (162.06)**	1.82 (0.069)
# of seats in food court	9.11 x 10^{-3}(0.16)	0.57 (0.570)
# of mall levels	-6.14 (7.066)	-0.87 (0.385)
Years since last renovation	**-2.33 (0.887)**	-2.63 (0.009)
Outparcel space	-16.199 (10.479)	-1.55 (0.123)
Distance to nearest mall	**0.667 (0.375)**	1.78 (0.076)
Distance to nearest city	**-0.194 (0.114)**	-1.69 (0.092)
Mall classification: value retail	4.619 (71.65)	0.06 (0.949)
Mall classification: lifestyle	10.714 (25.154)	0.43 (0.670)
Outdoor center	**60.42 (18.20)**	3.32 (0.001)
Effect of "region = South"	-13.85 (16.23)	-0.85 (0.394)
Effect of "region = Midwest"	-19.51 (16.22)	-1.20 (0.230)
Effect of "region = West"	2.649 (16.84)	0.16 (0.875)
MSA mean anchor quality	16.95 (16.09)	1.05 (0.293)
MSA mall count	**-1.158 (0.474)**	-2.44 (0.015)

Figure 8: Results from OLS regression of non-anchor sales per square foot on non-anchor size and anchor quality.

to the nearest competing mall and city - have statistically significant relationships with mall traffic and profits as well.

Of greatest interest is a calculated variable containing a Herfindahl index of mall size allocation, which represents the extent to which the square footage of the mall is concentrated in a relatively small number of stores. I calculate the Herfindahl index for each mall in the data set using the following equation:

$$H_i = \sum_{a=1}^{A} (\frac{GLA_a}{GLA})^2 + N(\frac{GLA_n}{GLA})^2$$

in which:

- H_i = Herfindahl index for mall i
- GLA_a = GLA of anchor store a
- GLA_n = GLA of a "representative" non-anchor store[5]
- GLA = Total mall GLA
- N = Total number of non-anchor stores

[5]GLA for individual non-anchor stores is not available in the data set.

The positive and significant coefficient associated with the Herfindahl index variable demonstrates that an increasing degree of dominance of a mall's retail space by a small number of anchor stores (with non-anchor GLA being held constant) has a positive effect on non-anchor store profits, providing additional empirical evidence for the general theory that anchor stores generate positive demand externalities.

Furthermore, it is also interesting to note the positive relationship between mall traffic, profits and a group of variables including population and number of food court seats. These variables can influence the utility that consumers expect to receive as part of a trip to the mall. Higher population density in the surrounding area as well as a higher number of mall levels are typical of malls in large urban areas, which tend to be surrounded by additional shopping and entertainment options in close proximity. These additional options may in turn add to consumer's expected utility from a mall visit: according to a survey conducted by Christiansen et al. (1999), "mall locations where there were multiple opportunities for the consumer to engage in diversionary activities were felt to provide greater entertainment value." Likewise, the size of a mall's food court (a centrally-located cluster of quick-service restaurants located within many regional malls), as measured by number of seats, represents another potential source of consumer utility from a mall trip not captured by the theoretical model.

6.2 Determinants of mall's anchor store quality decision

I now consider the determinants of the anchor quality choice variable itself. I examine whether non-anchor store size has a positive and concave relationship with the likelihood of a mall developer choosing a high or medium anchor quality level instead of the default low level, as predicted in Proposition 3 in the theoretical model.

There exists the possibility that the exogeneity of non-anchor GLA presumed by the theoretical model may not hold in actuality, given that the iterative process of mall development may result in limited adjustments to total non-anchor size once anchor stores are chosen, and that non-anchor size may be dependent on unobserved market conditions. I correct for potential endogeneity using the control function approach developed by Villas-Boas and Winer (1999) and Petrin and Train (2006). I use the number of parking spaces in the mall as an instrument: of the variables in the data set, this variable has the strongest correlation with non-anchor GLA (even when controlling for anchor GLA), but is considerably less likely to be plausibly correlated with unobserved market conditions that may affect anchor quality. Thus, I run a regression of non-anchor size on the instrument variable of parking space ($GLA_{Ni} = \alpha + \beta ParkSpaces_i + \varepsilon_i$) and include the residuals ε_i from this regression in the following step.

I use a multinomial logit choice model specification to model the developer's choice between the three anchor store quality levels described in section 3. The index of each choice is represented by $j \in \{H, M, L\}$, with the low quality level as the default choice. The payoff function for each move (anchor-store quality choice j) taken by each mall (i) is specified as follows:

$$\Pi_{ij} = \alpha_j + \beta_{j1} GLA_{Ni} + \beta_{j2} GLA_{Ni}^2 + \beta_j X_i + \xi_i + \varepsilon_{ij}$$

in which:

- GLA_{Ni} = Total non-anchor GLA

- X_i = Vector of mall-specific regressors (same as in previous regression) including endogeneity correction residuals
- $\xi_i \sim (0, \sigma^2)$ = Market-specific error term (observable to all firms)
- ε_{ij} = Mall-specific unobservables affecting utility for mall i from choice j

Since each mall developer's private information ε_{ij} is independent and identically distributed across firms and anchor-quality choices with a type 1 extreme value distribution, the equilibrium probability of firm i choosing quality level q_H or q_M in market n is as follows:

$$P_{inj} = \frac{exp(\alpha_j + \beta_j X_i + \xi_n)}{1 + \sum_{k \neq j} exp(\alpha_k + \beta_k X_i + \xi_n)}$$

The probability of choosing the default quality level q_L is as follows:

$$P_{inj} = \frac{1}{1 + \sum_{k \neq j} exp(\alpha_k + \beta_k X_i + \xi_n)}$$

The coefficient estimates for the non-anchor size effect linear and quadratic terms, which are positive and negative, respectively, show that non-anchor size has a positive and concave relationship with the likelihood of choosing high or medium anchor quality, as predicted by Proposition 3. This result is similar to the positive and concave relationship shown in the previous section between non-anchor size and mall traffic. The coefficient estimates for the effects of selected variables on the likelihood of choosing high (H) or medium (M) anchor quality are shown in Figure 9; the full regression results, including additional significant controls, are shown in Appendix 6.

Variable	**Coefficient (std. err.)**	**Z-statistic (significance)**
Intercept (H)	**-9.07 (2.44)**	-3.71 (0.000)
Intercept (M)	**-3.34 (1.88)**	-1.78 (0.075)
NA size effect (H)	**1.76 x 10^{-5} (2.49 x 10^{-6})**	7.07 (0.000)
NA size effect (M)	**1.36 x 10^{-5} (2.06 x 10^{-6})**	6.61 (0.000)
NA size^2 effect (H)	**-5.52 x 10^{-12} (1.58 x 10^{-12})**	-3.49 (0.001)
NA size^2 effect (M)	**-5.23 x 10^{-12} (1.39 x 10^{-12})**	-3.75 (0.000)
MSA mean anchor quality (H)	-0.7049 (0.4651)	-1.52 (0.130)
MSA mean anchor quality (M)	-0.0275 (0.3397)	-0.08 (0.935)
PS residual effect (H)	**-1.27 x 10^{-5} (1.85 x 10^{-6})**	-6.83 (0.000)
PS residual effect (M)	**-1.12 x 10^{-5} (1.58 x 10^{-6})**	-7.12 (0.000)

Figure 9: Results from multinomial logit regression of anchor quality on non-anchor size with endogeneity correction residuals ("PS residual effect") included.

One independent variable shown in Figure 9 that was omitted from the previous regressions is "MSA mean anchor quality", which represents the mean anchor quality rating of all other malls in the same MSA (U.S. Census Bureau-defined "metropolitan statistical area"), in which anchor quality ratings of high, medium, and low are coded as 1, 2, and 3, respectively. The coefficient estimate for this variable's effect on the likelihood of choosing high quality is negative and relatively significant, suggesting that the presence of other high-quality anchor malls (which may be indicative of unobservable factors within the MSA other than the included controls which influence demand for high-quality goods) increases the likelihood that a mall will choose a high-quality anchor. However, this explanation does not account for the effect of having nearby malls that compete for the same upscale segment of consumers; it seems necessary to consider the effects not just of all malls in the MSA, but of the nearest competing mall. This analysis is the subject of the following section.

6.3 Full model with competitive effects

In this section, I extend the basic multinomial logit choice model described in the previous section to account for competitive interactions between neighboring centers. This extended model is based on previous work by Seim (2006), Zhu and Singh (2007), Orhun (2009), and Shen and Villas-Boas (2009).

The data can be partitioned into N markets $(1....N)$ with 2 competing malls ("firms") in each market, using n and i to denote the indices of each market and mall, respectively: $i\in \{1,2\}$. The payoff function for each move (anchor-store quality choice j) taken by each mall (i) in each market (n) is specified as follows:

$$\Pi_{inj} = \alpha_j + \beta_1 GLA_{Ni} + \beta_2 GLA_{Ni}^2 + \beta_j X_{in} + \sum_{j'=1}^{J} \delta_{jj'} E(A_{i'j'}) + \xi_n + \varepsilon_{inj}$$

in which:

- GLA_{Ni} = Total non-anchor GLA
- X_{in} = Vector of mall-specific regressors (from previous regression)
- $A_{i'j'}$ = Binary variable equal to 1 if other mall in market (i') chooses quality level j', 0 otherwise
- $\delta_{jj'}$ = Coefficient that captures effect of other mall's choice of j' on utility if current mall chooses j
- $\xi_n \sim (0, \sigma^2)$ = Market-specific error term (observable to all firms)
- ε_{inj} = Mall-specific unobservables affecting utility for mall i from choice j

Again, as each firm's private information ε_{inj} is I.I.D. across firms and anchor-quality choices with a type 1 extreme value distribution, the equilibrium probability of firm i choosing quality level q_H or q_M, or quality level q_L, respectively, in market n is as follows:

$$P_{inj} = \frac{exp(\alpha_j + \beta_j X_{in} + \sum_{j'=1}^{J} \delta_{jj'} E(A_{i'j'}) + \xi_n)}{1 + \sum_{k \neq j} exp(\alpha_k + \beta_k X_{in} + \sum_{j'=1}^{J} \delta_{kj'} E(A_{i'j'}) + \xi_n)}$$

$$P_{inj} = \frac{1}{1 + \sum_{k \neq j} exp(\alpha_k + \beta_k X_{in} + \sum_{j'=1}^{J} \delta_{kj'} E(A_{i'j'}) + \xi_n)}$$

In the above model, the parameters to be estimated are (α,β,δ). To simplify the parameter space, $\delta_{jj'} = 0$ if either j or j' is equal to the low quality level q_L.

The parameters are estimated using the maximum-likelihood approach. During each iteration, the probability terms (P) are calculated for each market using a fixed-point algorithm that converges to a Bayesian Nash equilibrium in which each of the two malls in that market has choice probabilities that represent a best response to each other's probabilities. To estimate this model, I consider the subset of the data in which two malls can be identified as mutually "competing" with each other. Using a field in the data set which identifies each mall's closest competitor, I observe that a total of 293 pairs of malls mutually identify each other as such, thus defining 293 unique markets with two firms in each market.

Figure 10 shows the results of the estimation for the likelihood model with competitive effects included. These results show that the positive and concave relationship between anchor quality and non-anchor size observed in the previous models exists even when competitive effects are accounted for, as the coefficient estimates for the non-anchor size linear terms are again positive and significant and the coefficient for the quadratic terms are negative and significant. Furthermore, there is evidence that the anchor quality choices of competing malls has an effect on a mall's likelihood of choosing the high anchor quality level (though not the medium anchor quality level). The probability of choosing high anchor quality is affected positively by the rival mall's choice of medium anchor quality, but negatively by the rival mall's choice of high anchor quality. This suggests that the presence of another high-quality-anchor mall acts as a deterrent against choosing high anchor quality, perhaps due to the possibility that two such malls in close proximity oversaturates the limited market for expensive goods offered by high-quality anchors. However, the positive coefficient for the effect of medium anchor quality on the rival's choice of high anchor quality may be explained as follows: if a mall chooses medium anchor quality, this establishes that at least some demand for goods other than those offered by low-quality anchors exists in the area, while still presenting the rival mall with an opportunity to differentiate itself by choosing high anchor quality.

The results of this empirical analysis demonstrate that an inverse-U-shaped relationship between anchor quality and non-anchor size not only exists in a cross-section of U.S. malls, but that this relationship is robust to the inclusion of multiple mall-specific and market-specific control variables, an endogeneity correction, and inter-mall competitive effects.

Variable	**Coefficient (std. err.)**	**T-statistic (significance)**
Intercept (H)	**1.3475 (0.3960)**	3.4028 (0.001)
Intercept (M)	0.0031 (0.3487)	0.0089 (0.993)
NA size effect (H)	**2.0422 (0.7025)**	2.9073 (0.004)
NA size effect (M)	**1.0173 (0.2831)**	3.5939 (0.001)
NA size^2 effect (H)	**-0.2455 (0.0223)**	>10 (0.000)
NA size^2 effect (M)	-0.1681 (0.1184)	-1.4205 (0.156)
Competitive effect (H→H)	**-0.7383 (0.0633)**	>10 (0.000)
Competitive effect (H→M)	-0.1450 (3.5821)	-0.0404 (0.968)
Competitive effect (M→H)	**1.8180 (0.1919)**	9.4759 (0.000)
Competitive effect (M→M)	2.8457 (4.5633)	0.6236 (0.533)
PS residual effect (H)	**-1.7219 (0.4155)**	-4.1442 (0.000)
PS residual effect (M)	**-2.4812 (0.4385)**	-5.6580 (0.000)

Figure 10: Results from multinomial logit regression of anchor quality on non-anchor size with endogeneity correction and competitive effects included. "Competitive effect (M→H)" represents the coefficient that determines the effect that the probability of a competing mall choosing anchor quality level q_M has on a mall choosing quality level q_H.

7 Conclusion and future work

The goals of this paper have been to present a theoretical model capturing competitive interactions between anchor and non-anchor stores in a developer-controlled mall, to propose a relationship between mall size, anchor quality, and variables relating to mall performance (traffic and store profits), and to verify it empirically using data from the shopping-center industry. The results have important implications for mall developers, particularly those who are currently faced with the task of redeveloping an existing mall or replacing vacated anchor spaces. In doing so, they must consider how the retail mixes of their properties - as influenced by the quality of their anchor stores and the number and variety of non-anchors - impact price competition and shopper behavior. The relationships demonstrated by this paper must be taken into account in conjunction with other analyses that are typically part of the shopping-center development process, such as analysis of the income patterns and alternate shopping options in the center's trade area, which can alter the extent to which consumers act in ways predicted by this model.

This paper has also aimed to present a non-trivial variation on the traditional upstream manufacturer and downstream retailer paradigm from the vertical control literature. Analyzing the effects of mall size as well as additional market-level and store-level factors on the various parties' competitive actions within the shopping-center framework should yield insights that generalize beyond malls. A major goal of this paper is to demonstrate how stores in a "retail cluster" - of which a shopping mall is one example - balance the need to compete with each other for their share of the cluster's aggregate profits with the need to attract as many consumers to the cluster in the first place, increasing profits for all stores. Modeling the choices made by a central planner in other settings (i.e. a city planner in charge of developing a central business district, or proprietor of an online "virtual mall") to manage these two components of intra-cluster competition may be of further interest to the field of vertical control theory.

This framework presents multiple directions for additional research. The theoretical model can be expanded to include more flexible contracts similar to those mentioned elsewhere in the vertical control literature, in which stores are able to negotiate arrangements other that one in which the developer acts as a residual claimant. A potential stream of research identified in the empirical section of this paper that may result in enhancements to the theory model relates to non-traditional anchors such as restaurants and entertainment destinations; as numerous struggling malls are currently being redeveloped, such anchors are steadily growing in number, the most notable being the Nickelodeon Universe amusement park that occupies the center of the largest mall in the United States, the Mall of America in Bloomington, Minnesota. While the current theoretical model defines consumer utility from a mall shopping trip in terms of valuation of goods and price, it could be extended to include utility from food- and entertainment-oriented anchors and non-anchors alike. What makes it challenging to both theoretically model and empirically validate these effects is formally defining the value of "entertainment" in a shopping-center context; Christiansen et al. (1999) define entertainment in a shopping context as "some activity or behavior that provided a diversion or relief from normal day-to-day activities" including shopping, and attempt to quantify the appeal of various mall entertainment options using a 38-question survey. Further advances in research related to this specific aspect of malls could lead to meaningful extensions of the model proposed in this paper.

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Appendix 1: List of mall classifications in data set

The following is a list of all shopping-center categories included in the data set provided by the Directory of Major Malls (DMM):

- **Super-regional centers**: Retail centers (typically enclosed malls) with general leasable area (GLA) of above 1,000,000 square feet.
- **Regional centers**: Retail centers (typically enclosed malls) with GLA between 500,000 and 1,000,000 square feet.
- **Community centers**: Centers with GLA between 100,000 and 350,000 square feet.
- **Lifestyle centers**: Centers with an "emphasis on lifestyle" (typically outdoor malls with upscale amenities).
- **Power centers**: Centers with at least 2 big-box chain retail stores.
- **Value retail centers**: Outlet- and off-price-focused centers.
- **Entertainment centers**: Centers which mix retail with theatres and entertainment attractions, with an emphasis on the latter.

Appendix 2: Derivation of price equilibrium

As stated in Section 4.1, the stores' profit functions are specified as follows:

$$\Pi_A = p_A P(A) M$$
$$\Pi_N = p_N P(N) M$$

The probability terms $P(A)$ and $P(N)$ are calculated by integrating the probabilities from Figure 5 across the four intervals of v (similar to the EU calculation in Appendix 4), yielding the following expressions:

$$P(A) = \frac{1}{2t}[-2p_A + 2q + \beta(-1 + p_A + p_N - q + t)]$$
$$P(N) = \frac{1}{2t}[\beta(1 + p_A - p_N - q + t)]$$

Solving first-order conditions for the stores' profit functions (after substituting p_A and p_N for the price expectation variables $\overline{p_A}$ and $\overline{p_N}$ in the M term, which are equal to actual prices in equilibrium under the rational-expectations assumption) yields the following equilibrium prices:

$$p_A = \frac{\beta - 4q + 3\beta q - 3\beta t}{5\beta - 8}$$
$$p_N = \frac{\beta(3 - q + t) + 2(q - 2(1 + t))}{5\beta - 8}$$

Throughout the model, these equilibrium prices can be substituted for the actual price variables p_A and p_N. By making these substitutions, closed-form expressions for the various components of the model ($P(A)$, $P(N)$, M, Π_A, Π_N) can be derived solely in terms of t, β and q.

Appendix 3: Boundary points

Given that v is uniformly distributed from 0 to 1, the point P_2 in Figure 3, representing the value of v at which a consumer would be ambivalent between purchasing from either store is defined as follows:

$$P_2 = \frac{1}{2t}(q - p_A + p_N + t - 1)$$

Similarly, the points P_1 and P_3, representing the values of v at which non-anchor and anchor valuation are 0, respectively, are as follows:

$$\begin{aligned} P_1 &= 1 + \frac{p_N}{t} - \frac{1}{t} \\ P_3 &= \frac{q - p_A}{t} \end{aligned}$$

Appendix 4: Calculation of expected mall traffic

As described in Section 4.2, expected utility can be calculated for each of the 4 segments of consumers as defined by their values of v. In the following calculations, $E(U \mid N)$ and $E(U \mid A)$ are simply equal to valuation net of price as shown in Figure 3. Note that price expectation variables ($\overline{p_N}$ and $\overline{p_A}$) replace actual prices, which are unknown to consumers at this stage of the game.

$$\begin{aligned} EU_1 = EU_2 &= (q - v - \overline{p_A}) \\ EU_3 &= (1-\beta)(q - v - \overline{p_A}) + \beta(v - \overline{p_N}) \\ EU_4 &= \beta(v - \overline{p_N}) \end{aligned}$$

Since v is uniformly distributed on the unit interval across the population, the total expected number M of visitors to the mall can be calculated by integrating EU across the four intervals of v as follows:

$$\begin{aligned} M &= \int_0^{P_1} EU_1 dv + \int_{P_1}^{P_2} EU_2 dv + \int_{P_2}^{P_3} EU_3 dv + \int_{P_3}^{1} EU_4 dv \\ &= \frac{1}{4t}[2(\overline{p_A} - q)^2 - \beta(-1 + \overline{p_A}^2 - \overline{p_N}^2 + 2q + (q-t)^2 - 2t + 2\overline{p_N}(1 - q + t) \\ &\quad + 2\overline{p_A}(-1 + \overline{p_N} - q + t)] \end{aligned}$$

Appendix 5: Description of variables used in econometric models

The following list includes a description of all variables included in the regressions in Sections 6.1 and 6.2.

- **NA size**: Combined general leasable area (GLA) of the mall's non-anchor stores.
- **Effect of "anchor quality = H/M"**: Binary variable equal to 1 if the mall's highest-quality anchor has a quality rating of H(igh) or M(edium), 0 otherwise. (Base case: anchor quality = L(ow))
- **Population (10 mile radius)**: Total population within a 10-mile radius of the mall.
- **Income (10 mile radius)**: Mean income of population within a 10-mile radius of the mall.
- **Age (10 mile radius)**: Mean age of population within a 10-mile radius of the mall.
- **Herfindahl index**: Measure of the degree to which a mall's GLA is concentrated in a small number of stores, calculated as described in Section 6.1.
- **# of seats in food court**: Total number of seats in the mall's "food court", a centralized group of food-service establishments. Variable contains 0 if the mall does not have a food court.
- **# of mall levels**: Number of floors in the mall on which stores are found.
- **Years since last renovation**: Number of years since the mall was last renovated.
- **Outparcel space**: Amount of GLA devoted to "outparcel" stores, which are located in the mall's parking lot or in another location not physically connected to the main part of the mall.
- **Distance to nearest mall/city**: Distance from the mall to the nearest competing mall or to the nearest "city" as defined by the U.S. Census.
- **Mall classification - "value retail"/"lifestyle"**: Binary variable equal to 1 if mall is in the "Value Retail" or "Lifestyle" categories as defined in Appendix 1, 0 otherwise.
- **Outdoor center**: Binary variable equal to 1 if the mall is an outdoor mall, 0 if the mall is enclosed.
- **Effect of "region = South/Midwest/West"**: Binary variable equal to 1 if the region of the mall is South, Midwest or West, 0 otherwise. (Base case: region = East)
- **MSA mean anchor quality**: Mean anchor quality rating of all other malls in the subject mall's MSA (metropolitan statistical area).
- **MSA mall count**: Number of malls in the subject mall's MSA.
- **PS residual effect**: Residuals from regression of GLA on number of parking spaces, included as part of the endogeneity correction described in Section 6.2.

Appendix 6: Complete anchor-choice multinomial logit regression

Variable	**Coefficient (std. err.)**	**Z-statistic (significance)**
Intercept (H)	**-9.07 (2.44)**	-3.71 (0.000)
Intercept (M)	**-3.34 (1.88)**	-1.78 (0.075)
NA size effect (H)	**1.76×10^{-5} (2.49×10^{-6})**	7.07 (0.000)
NA size effect (M)	**1.36×10^{-5} (2.06×10^{-6})**	6.61 (0.000)
NA size^2 effect (H)	**-5.52×10^{-12} (1.58×10^{-12})**	-3.49 (0.001)
NA size^2 effect (M)	**-5.23×10^{-12} (1.39×10^{-12})**	-3.75 (0.000)
Population (10 mile radius) (H)	-1.71×10^{-7} (2.49×10^{-7})	-0.68 (0.494)
Population (10 mile radius) (M)	-2.69×10^{-7} (2.24×10^{-7})	-1.20 (0.231)
Income (10 mile radius) (H)	**3.24×10^{-5} (8.12×10^{-6})**	3.99 (0.000)
Income (10 mile radius) (M)	5.29×10^{-6} (7.25×10^{-6})	0.73 (0.465)
Age (10 mile radius) (H)	0.205 (0.0518)	0.40 (0.693)
Age (10 mile radius) (M)	-0.023 (0.039)	-0.60 (0.551)
# of seats in food court (H)	**0.0012 (0.00049)**	2.41 (0.016)
# of seats in food court (M)	**0.00088 (0.00045)**	1.97 (0.048)
# of mall levels (H)	**1.023 (0.1905)**	5.37 (0.000)
# of mall levels (M)	**0.6113 (0.1714)**	3.56 (0.000)
Years since last renovation (H)	-0.00366 (0.0227)	-0.16 (0.872)
Years since last renovation (M)	-0.00633 (0.0177)	-0.36 (0.720)
Outparcel space (H)	**-0.9908 (0.2814)**	-3.52 (0.000)
Outparcel space (M)	**-0.5972 (0.2309)**	-2.59 (0.010)
Distance to nearest mall (H)	-0.000419 (0.0212)	-0.02 (0.984)
Distance to nearest mall (M)	**0.054 (0.0143)**	3.78 (0.000)
Distance to nearest city (H)	-0.00159 (0.00366)	-0.43 (0.664)
Distance to nearest city (M)	-0.000973 (0.00266)	-0.36 (0.715)
Mall classification: value retail (H)	-0.952 (1.1165)	-0.85 (0.394)
Mall classification: value retail (M)	**-2.877 (1.093)**	-2.63 (0.009)
Mall classification: lifestyle center (H)	-0.4903 (0.6163)	-0.80 (0.426)
Mall classification: lifestyle center (M)	0.2583 (0.4414)	0.59 (0.558)
Outdoor center (H)	**-0.88312 (0.400)**	-2.20 (0.027)
Outdoor center (M)	**-1.87823 (0.3203)**	-5.87 (0.000)
Effect of "region = South" (H)	0.096 (0.406)	0.24 (0.813)
Effect of "region = South" (M)	0.354 (0.316)	1.12 (0.262)
Effect of "region = Midwest" (H)	**-0.693 (0.413)**	-1.68 (0.093)
Effect of "region = Midwest" (M)	**-0.922 (0.321)**	-2.87 (0.004)
Effect of "region = West" (H)	0.1217 (0.422)	0.29 (0.773)
Effect of "region = West" (M)	-0.1657 (0.356)	-0.47 (0.642)
MSA mean anchor quality (H)	-0.7049 (0.4651)	-1.52 (0.130)
MSA mean anchor quality (M)	-0.0275 (0.3397)	-0.08 (0.935)
MSA number of malls (H)	-0.0043 (0.0119)	-0.36 (0.716)
MSA number of malls (M)	-0.0107 (0.0104)	-1.02 (0.308)
PS residual effect (H)	**-1.27×10^{-5} (1.85×10^{-6})**	-6.83 (0.000)
PS residual effect (M)	**-1.12×10^{-5} (1.58×10^{-6})**	-7.12 (0.000)

Figure 11: Complete results from multinomial logit regression of anchor quality on non-anchor size with endogeneity correction residuals ("PS residual effect") included.

Essay B

Negative Advertising and Voter Choice [1]

1 Introduction

Negative advertising in political campaigns is a particularly important and timely issue in U.S. politics. It can be defined as advertising used by a campaign to provide negative and adverse information about either an opposing candidate's stand on issues, or about the opponent's personal characteristics. Recent years have seen a marked increase in the amount of negative advertising, and analysts have pointed out its adverse effects in keeping voters away from elections (Ansolabehere and Iyengar 1995). Despite these effects, negative advertising is on the rise: the 2006 midterm Congressional election was marked by especially high amounts of negative advertising, as 90% of advertisements run in the final 60 days of all House and Senate campaigns nationwide were negative (Page 2006). Meanwhile, while campaigns have used increasing amounts of negative advertising, U.S. voter turnout rates have remained relatively low; the voter turnout rate was estimated at 37% for the 2006 midterm Congressional election (McDonald 2006).

This paper has two objectives: First, it examines how voter turnout (the decision to vote) and choice (the decision about whom to vote for) are affected by negative advertising. Second, it analyzes the campaign's choice of advertising strategy, i.e. whether to run negative or non-negative ads, and the manner in which it is influenced by voter, market and campaign characteristics. We use data containing information about advertising airings and voter survey responses from the 2000 U.S. House and Presidential elections to model voter behavior and the choice of negative advertising by campaigns.

We begin with analysis of voter candidate choice and estimate a nested-logit model to explain the effect of negative advertising on both voter turnout and candidate choice decisions. This is important for two reasons: first, unlike the existing literature which focuses only on turnout, our paper jointly analyzes both turnout and choice and shows that negative advertising positively affects not only turnout but also the likelihood of voting for a given candidate. A decomposition of the effects shows that the effect of negative advertising on candidate choice (approximately 80% of the total effect) is much larger than its effect on voter turnout (approximately 20%). This uncovering of the relatively high impact on voter candidate choice as compared to that on turnout is missing in existing political advertising studies (see Lau, Sigelman, and Heldman 1999). Second, this analysis allows us to obtain the own- and cross-demand elasticity estimates of negative advertising for voter choices and turnout, which are essential for our subsequent analysis of campaigns' advertising strategy decisions.

The empirical analysis on candidates' advertising strategy choices addresses the above predictions by estimating how advertising content choice and quantity are determined by market, voter and campaign characteristics. The empirical study shows that campaigns are more likely to choose negative advertising in closer races and when the cost of advertising is low. We also find that campaigns are less likely to choose negative advertising in markets

[1] This essay is part of a co-authored work with Hai Che and Ganesh Iyer.

with a more educated electorate, and that Presidential candidates are more likely to deploy negative advertising than House candidates. We also find that campaigns' decisions to air negative advertisements are sensitive to demand elasticities in a direction that is intuitively appealing, thus providing validity for our voter choice model estimates. Furthermore, advertising choices are sensitive to competitors' airing of negative advertising, and the time (e.g. primetime) that the ads are aired. In our empirical analysis, we also investigate relationships between the choice of negative advertising and several candidate and voter characteristics that are available in the data, such as incumbency status, pre-existing voter goodwill for candidates, and voter-level measures of campaign interest, media exposure, and partisanship.

1.1 Related research

The existing literature in political science has examined the effects of negative advertising on voter turnout (Finkel and Geer 1998, Ansolabehere et al. 1994, Freedman and Goldstein 1999, Kahn and Kenney 1998). These studies have proposed two opposing effects: a demobilization effect and a stimulation effect, which correspond to negative and positive effects of negative advertising on voter turnout, respectively. The arguments proposed in the literature for the demobilization effect are two-fold: First, negative advertising may reduce an individual voter's belief about "political efficacy" - the belief that her individual vote can impact the outcome of the election. Second, negative advertising can create disillusionment which leads to reduced turnout. The arguments for a stimulation effect include that negative advertising raises voters' perception of the importance of an election and increases voter knowledge, both of which are indicated in the literature to encourage participation. Ansolabehere and Iyengar (1995) indicated that negative advertising might reduce voter turnout; however, Lau et al (1999) find no support for such a demobilization effect[2]. Our study investigates the stimulation vs. demobilization debate from the political science literature to ask whether negative advertising has a positive or negative effect on not only voter turnout, but also on voter candidate choice. By studying the effects of campaigns' negative advertising on voters' candidate choice decisions, we are able to better understand the campaigns' decisions to deploy negative advertising in response to anticipated voter reaction.

In the marketing literature, there are some experimental studies that consider the effects of negative advertising on consumer brand choice decisions. James and Hensel (1991) suggest an explanation for a negative main effect of negative advertising on brand choice. Other papers conduct analysis of the interaction of factors. For example, Shiv, Edell, and Payne (1997) suggest that negative information from advertisements has a positive effect on product choice, which is stronger if the purchase decision is characterized by low involvement levels of information processing. As consumers become more involved in processing information, they tend to question more of the tactics behind negative advertising and respond to it negatively. There have been relatively few empirical studies on creative execution and the content of advertising. However, an exception is seen in the work of Tellis, Chandy, MacInnis, and Thaivanich (2005), which estimates the effectiveness of the advertising as a function of its creative characteristics.

Recent analytical work on advertising strategy is also relevant to our study. In the context of product advertising, Chen, Joshi, Raju, and Zhang (2007) discuss combative advertising

[2]In addition to studies on U.S. elections, Rosenthal and Sen (1977) study voter behavior in French elections. They find evidence of the effects of candidate information on voter participation, and find higher voter participation in close races.

which involves the use of advertising in changing voters' ideal preferences. Soberman and Sadoulet (forthcoming) analyze the effect of campaign spending limits on the advertising strategies of candidates, and find that tight spending limits evoke aggressive advertising on the part of competing parties, while generous budgets often lead to parties acting defensively. Lovett and Shachar (2008) provides a knowledge-based explanation to why there is more negative advertising in closer races. In our paper we examine how a campaign's use of negative advertising content can be explained through a strategic communication rationale. Polborn and Yi (2006) develop a model of informative campaigns, both positive and negative. They argue that information about a candidate can be transmitted more efficiently by his opponent, and that a negative advertising campaign, on average, could facilitate a more informed choice by voters.

The remainder of the paper proceeds as follows. In Section 2 we present the empirical model of voter turnout and choice decisions in the 2000 U.S. Presidential and House elections. We describe the data, empirical measures, and then present the results on the voter side. In Section 3, we develop a similar empirical study of campaigns' advertising content choices and quantity decisions. Section 4 summarizes our findings and discusses topics for future research.

2 Analysis of voter choice and turnout

In this section, we present an empirical study of voters' response to campaign advertising in terms of their turnout and candidate choice decisions. This analysis is motivated by several objectives: first, as already mentioned, existing studies on negative advertising have focused primarily on its effect on voter turnout. Investigating the role of negative advertising on candidate choice not only helps to provide us with a more complete picture of the effects of negative advertising, but also helps us to model a candidate's choice of negative advertising. Second, for our subsequent empirical analysis of the campaign's advertising decisions, we require the own- and cross-elasticity estimates of negative advertising from the voter choice model, which we identify in this section. We propose an individual-level voter candidate choice model and estimate it using voter survey data and observed advertising data in either congressional districts or media markets, as applicable.

2.1 Data and empirical measures

To investigate the effects of negative advertising on voter behavior, we need detailed information on voters' candidate choice and turnout decisions, as well as information on different types of advertising deployed in election markets. We obtain individual-level voter survey data from the American National Election Studies (ANES) project. This data contains questions asked of a cross-section of 1807 voters in 48 states both before and after the 2000 elections. Each observation corresponds to a distinct voter and contains that voter's response to pre- and post-survey questions; summary statistics for this data are included in Figure 1.

From the 1807 voters in the ANES survey, we select 482 voters for the Presidential election data set and 614 voters for the House election data set by using the following criteria: voters must be from a congressional district or media market for which we have advertising data, and the sample turnout rates in a congressional district or media market with the selected voters match closely with the actual turnout rates in that area. We select voters based

		House	Presidential
Total number of observations (voters)		614	482
Voter choice	Democrat	27%	30%
	Republican	32%	28%
	Other (3rd party)	2%	1%
	None	39%	41%
Interest in election	Not interested	0.21 (0.01)	
	Somewhat interested	0.50 (0.01)	
	Extremely interested	0.29 (0.01)	
Media exposure	TV News (days/week)	3.10 (2.81)	
	Newspaper (days/week)	3.67 (2.97)	
Partisanship		0.57 (0.34)	
Goodwill towards candidate	Unfavorable (D)	0.11	0.34
	Unfavorable (R)	0.10	0.34
	Favorable (D)	0.30	0.52
	Favorable (R)	0.36	0.51
	Indifferent (D)	0.59	0.14
	Indifferent (R)	0.54	0.16
Demographic variables	White	84%	80%
	Minority	16%	20%
	Years of education	0.804 (0.142)	0.801 (0.200)
	Income score	0.216 (0.126)	0.227 (0.145)

Figure 1: Summary statistics of voter data. Standard deviations are shown in parentheses where applicable.

on the above criteria because the ANES data and other voter data may be subject to the problem of "vote over-reporting". However, for this problem to bias our estimation results of the voter choice model, the over-reporting (but not the probability of voting) would have to be negatively correlated with exposure to negative advertising (Goldstein and Friedman 2002). Although existing studies which use the ANES data or voter data do not indicate this negative correlation to be likely, we take the precaution of selecting a sample to ensure there is a closer match between the sample and actual turnout rates. The actual turnout rates of the congressional districts in the 2000 House election are obtained from the U.S. House of Representatives data archive. We then aggregate their turnout rates to the media market level for the Presidential election.

The summary statistics of the voter survey data show that the sample turnout rate in our Presidential election voter data set is 59.9% (the actual turnout rate in these media markets is 59.4%), and the sample turnout rate in our House election voter data set is 61.2% (the actual turnout rate in these congressional districts is 57.4%). In addition to turnout and candidate choice data, we also obtain the following information for each voter from the survey: voter-specific attitudinal variables such as interest, media exposure, partisanship, and goodwill for candidates, and voter demographics such as income, education, and race.

As can been seen in Figure 1, voters are similar across the two elections on measures such as interest, media exposure, and partisanship. These measures are elicited as general voter characteristics, and they are not specific to the type of elections. However, we have a measure of voter-reported goodwill towards candidates, which is candidate-specific and significantly different across the two elections. The goodwill measure captures voter opinion on candidate credibility, as well as voters' level of involvement in the election. Consistent with what political theory suggests, we find that in the House election, the proportion of voters who do not have any opinions on the candidates' credibility is significantly higher than that in the Presidential election.

To measure the effects of negative advertising, we obtain advertising data tracked by the Campaign Media Analysis Group (CMAG). The CMAG data contains information on political advertising shown in different election districts or media markets, which covers 80% of the U.S. population, by different candidates during the 2000 House and Presidential elections. Each observation corresponds to a unique airing of a campaign advertisement on one of the broadcast or cable networks; summary statistics for this data are shown in Figure 2.

		House	**Presidential**
Total number of observations (ads)	Democrat	73,276	93,096
	Republican	71,342	94,114
Total number of character-focused ads	Democrat	28,408	24,731
	Republican	31,052	16,964
Orientation of ads	Negative (D)	51.2%	58.6%
	Negative (R)	51.5%	55.1%
	Non-negative (D)	47.9%	41.4%
	Non-negative (R)	48.5%	44.9%
Timing of ads	Primetime (D)	92.9%	83.8%
	Primetime (R)	86.5%	84.4%
	Non-primetime (D)	7.1%	16.2%
	Non-primetime (R)	13.5%	15.6%
Advertising cost	Democrat	735.21 (1363.25)	690.89 (972.81)
	Republican	689.52 (1074.47)	757.02 (1289.51)

Figure 2: Summary statistics of ad data. Standard deviations are shown in parentheses where applicable.

By analyzing satellite-captured audio and video storyboards, CMAG researchers coded a set of 25 traits for each political advertisement including the negative, positive, or contrast orientation of the ad. To simplify the analysis, all contrast advertisements were reclassified by an independent researcher as either positive (non-negative) or negative advertising[3]. While all advertisements originally classified as contrast advertisements (10-20% of advertisements across elections) devote some airtime to the opposing candidate, they can be classified into three distinct groups based on the nature of content:

- For a first group of advertisements, the content is significantly and primarily negative.
- For a second group, the content simply consists of defending the candidates by asserting that the opposing candidate's negative attack about the favored candidate is untrue.
- For a third group, the favored candidate explicitly claims that he/she would not respond negatively even though the opponent had previously used attack advertisements.

Contrast ads that fall into the first group were reclassified as negative, while the remaining contrast ads were reclassified as positive.

Lastly, to study the effects of negative advertising on voter choice decisions, we join the advertising data with the previously described voter survey data. To do this, we aggregate the counts of negative and non-negative advertisements run by each party in each market[4].

[3]In political science studies, contrast advertisements are classified as negative advertisements (Goldstein and Freedman 2002). This classification method might be somewhat crude for our analysis and we therefore develop a finer classification based on the actual content of the advertisements.

[4]For the House elections, a market is defined as a congressional district, while for the Presidential election, a market is defined as a "media market", which can include voters across several congressional districts.

Since negative advertising counts are the same for all voters in any given market, we account for differences in voter response by estimating voter-level parameters of negative advertising, which we will explain in the following section detailing the econometric model. In addition, we also interact the advertising amount with a voter-specific media exposure measure from the ANES survey to obtain a better measure of each individual voter's negative advertising consumption (Freedman and Goldstein (2002) used a similar measure for individual exposure to negative advertising). This measure can be thought of as the upper bound of the number of advertisements that a voter could have seen, and as a relative measure among different voters in our sample. By joining advertisement counts to each individual voter observation in a market, we create an augmented voter data set containing information on the number of advertisements of each type and party to which each voter may potentially have been exposed.

2.2 Econometric model

We model an individual voter's decision in a market, in which campaigns try to influence voters through advertising. For each voter i ($i = 1...I$), we observe a binary outcome variable y_i that takes the value 1 if the voter votes in the election and 0 otherwise. For those voters who decide to vote (i.e. $y_i = 1$), they can choose to vote for one of j ($j = 1...J$) candidates, which correspond to Democratic, Republican or independent/third-party candidates. This vote outcome is a multinomial choice variable denoted by y_i^*. Our goal is to model the outcome variables (y_i, y_i^*) on the basis of observed levels of negative and positive advertising run by the campaigns. We develop the joint model of voter turnout and choice using a nested logit model.

To model the binary outcome y_i, let u_i denote the deterministic part of the indirect utility of voter i from voting in the election. This utility is modeled as a function of the voter's demographic and social-economic characteristics denoted by X_i, and the attractiveness to the voter of the candidates in the election, which in the nested logit formulation, is captured by an inclusive value variable ϕ_i. More specifically, $u_i = \gamma_{i0} + \gamma_{i1}X_i + \lambda\phi_i$, where $\lambda\phi_i$ measures the expected utility that voter i receives from choosing the best candidate in the election, in addition to the average utility from voting (and picking any candidate) in the election, and $\phi_i = ln(\sum_{j=1}^{J} exp(v_{ij}))$, where v_{ij} stands for the deterministic component of voter i's indirect utility for candidate j. The parameter λ reflects the degree of independence among the candidate choices, as used in McFadden (1978); $\lambda = 1$ indicates complete independence among candidate choices, and $\lambda = 0$ indicates perfect correlation. The vector X_i includes demographic and attitudinal variables, e.g. race, education, and income as well as interest, media exposure, and partisanship. In addition, X_i includes the closeness of the election and the market competitiveness measures as described in the data section. Voter turnout is expected to be higher for closer elections. Indeed, Shachar and Nalebuff (1999) find that voter turnout is a positive function of the predicted closeness of the race.

When $u_i > 0$, the vote turnout outcome $y_i = 1$. In other words, voters vote when the current utility of voting in the election exceeds the reservation utility (normalized to zero for identification purposes). Under the assumption of error terms being of a Type I extreme value distribution with scale parameter 1, the probability of voting in the election for voter i is $Pr(y_i = 1) = \frac{exp(u_i)}{1+exp(u_i)}$.

We model a voter's candidate choice decision using a voter-level conditional multinomial logit model. In this specification, the dependent variable is the voter's decision as to whom to vote for. This is modeled as a choice among three options: Democratic, Republican, or independent/third-party candidates. The probability of a voter i ($i = 1...I$) voting for one of J available candidates (denoted by $j = 1...J$, which corresponds to Democratic, Republican or independent candidates) is given by $\theta_{ij} = \frac{exp(v_{ij}/\lambda)}{\sum_{k=1}^{J} exp(v_{ik}/\lambda)}$, where v_{ij} is specified as $v_{ij} = \alpha_{ij} + \beta_{1i} NegAds_j + \beta_{2i} X_j + \xi_j$ for Democratic and Republican candidates; $v_{ij} = \alpha_{ij}$ for independent candidates, and α_{i0} is normalized to 0 for identification purposes. Note that α_{ij} denotes voter i's intrinsic preference for candidate j in the current election, $NegAds_j$ is the amount of negative advertising shown by candidate j, and β_{1i} denotes the corresponding response coefficient. X_j represents other candidate-specific variables (such as the amount of non-negative advertisements, incumbent status, candidate-specific goodwill, etc.), and ξ_j denotes a composite (stochastic) measure of unobserved characteristics of candidate j. It refers to common shocks that affect all voters (such as candidates' personal appearances and macro-economic conditions in the election district) that are not recorded in the data and unobservable to researchers, but observable by the voters and candidates (Berry, Levinsohn, and Pakes 1995). Finally, the voting outcome y_i^*, i.e. whether voter i votes for candidate j ($y_i^* = j$), is determined by the principle of maximum utility.

The voter-specific model coefficients follow a multivariate-normal distribution whose mean is a function of the voter-specific demographic variables. This allows us to capture the effects of voter heterogeneity (Gonul and Srinivasan 1993) on voter response to negative advertising. For the demographics and attitudinal variables, we again include minority status, education, and income as well as interest, media exposure, and partisanship measures. By including these variables again in the heterogeneity specification, we can test for the interaction between negative advertising amounts and the group of demographics and attitudinal variables, e.g. media exposure, as discussed in the previous section[5].

Since there exists a distinct possibility that the amounts of advertising chosen by the campaigns are based on unobserved market conditions ξ_j (Villas-Boas and Winer 1999), we use the control function approach proposed by Petrin and Train (forthcoming) to control for endogeneity. We first run a regression in which negative (or non-negative) advertising shown by a particular party in a specific market is the dependent variable, and the corresponding total cost of these advertisements paid by that party in that district is the independent variable (market subscript is omitted here for exposition simplicity, but accounted for in estimation): $NegAds_j = \psi_0 + \psi_1 COST_j + \eta_j$. Total cost serves as a valid instrument because it is highly correlated with the amount of advertisements a campaign airs, but is less correlated with the error terms since this cost is charged by the TV stations and is usually fixed for a specific time slot. The average R^2 of the quantity regressions is 0.74, and the F-statistics are highly significant.

2.3 Empirical results

We obtain the voter-level coefficient estimates through simulated maximum likelihood. Figure 3 presents the results for the effects of negative and positive advertising on voter turnout and candidate choice in the House and Presidential elections. From these estimation results, we find the intercept terms between House and Presidential elections are both negative and significant. These negative parameters suggest a general disinclination towards voting, which is consistent with the trend of low voter turnout levels from the 1980s through the present

[5]We only include demographics and attitudinal variables in the β coefficient for negative advertising, due to the cross-sectional nature of the data sets and subsequently the small number of observations. We also tested the models which do not include these additional demographics and attitudinal variables, and found the estimates of negative advertising and all other variables do not change significantly.

day. The coefficient estimates for the inclusive values are both positive and significant, with a magnitude of 0.31 for the House race and 0.38 for the Presidential race. This finding suggests a high correlation between turnout and candidate attractiveness.

	House				**Presidential**			
	Mean		Standard dev.		Mean		Standard dev	
	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
Intercept (Democrat)	**1.086**	3.26	*-0.426*	-1.89	**0.697**	2.03	0.064	0.23
Intercept (Republican)	**0.968**	3.21	-0.352	-1.54	**0.695**	1.89	0.134	0.44
Negative advertising	**0.010**	2.10	**-0.004**	-2.04	**0.029**	2.27	-0.004	-0.35
Neg ad interaction: Education	0.051	1.51			0.006	0.16		
Neg ad interaction: Income	-0.019	-0.63			-0.047	-1.05		
Neg ad interaction: Minority	0.003	0.33			-0.010			
Neg ad interaction: Partisanship	*0.018*	1.64			**0.004**	2.23		
Neg ad interaction: Interest	-0.023	-0.89			0.003	1.41		
Neg ad interaction: Media exposure	-0.001	-0.34			-0.003	-1.60		
Non-negative advertising	-0.006	-0.66	**0.024**	2.21	-0.002	-0.37	-0.006	-0.38
Incumbent					*0.181*	1.80	-0.175	-0.72
Incumbent interaction: Neg ads					*-0.010*	-1.72	0.014	0.75
Goodwill interaction: Neg ads	**-0.001**	-2.05	**-0.003**	-2.46	**-0.010**	-2.22	*0.017*	1.95
Badwill interaction: Neg ads	0.014	1.42	-0.006	-0.44	*-0.017*	-1.92	0.002	0.13
Intercept (turnout)	**-1.106**	-3.11	-0.336	-1.43	**-0.930**	-2.10	0.069	0.21
Education	**3.574**	3.57	-0.253	-0.28	**2.799**	2.62	0.399	0.42
Income	**1.852**	2.33	0.672	1.22	*1.132*	1.71	0.775	0.62
Minority	-0.245	-1.19	**0.977**	1.95	-0.282	-1.32	0.163	0.30
Partisanship	**0.360**	2.23	1.433	1.12	*0.405*	1.65	0.163	0.68
Interest	**1.415**	2.24	-0.102	-1.31	0.041	1.51	-0.086	-1.02
Media exposure	0.007	0.21	**4.084**	3.04	**-0.336**	-2.41	-0.006	-0.11
Closeness of election	**0.544**	2.25	0.992	1.61	*0.723*	1.87	0.838	1.22
Inclusive value	**0.306**	2.31			**0.377**	2.22		
Residual neg ads: Democrat	**-0.080**	-3.58			*-0.008*	-1.85		
Residual neg ads: Republican	**-0.070**	-2.00			*-0.051*	-1.68		
Residual non-neg ads: Democrat	0.011	1.38			-0.024	-1.18		
Residual non-neg ads: Republican	0.015	0.12			0.026	1.00		
Number of observations	482				614			
Log likelihood value	-520.19				-565.21			

Figure 3: Empirical results from voter model. Coefficients that are significant at the 95% and 90% levels are shown in **bold** and *italics*, respectively.

Demographics and attitudinal factors are found to have significant effects on voter turnout decisions. In both elections, we find voters with high education, high income and strong party identification are more likely to vote. Minority voters are less likely to vote, although the effects are less significant. Higher interest leads to higher turnout in House elections, while higher media exposure actually leads to lower turnout among voters in the Presidential election. The effects of the closeness of the election measure on voter turnout are positive and at least 90% significant in both elections, verifying that voters are more likely to come out and vote in closer races (Shachar and Nalebuff 1999).

The results in Figure 3 also show, as expected, that voters prefer Democratic and Republican candidates to independent candidates in both elections. In terms of the effect of negative advertising, we find that a candidate's negative advertising on his opponent has a positive effect on voter choice in both House ($\hat{\beta} = 0.029$) and Presidential ($\hat{\beta} = 0.010$) elections. In other words, we find the stimulation effect of negative advertising dominates the backlash effect in voters' candidate choice decisions. For each campaign, sending out more negative ads helps their candidate to attract more votes.

The above stimulation effects are obtained when we use the subject campaign's amount of negative advertising on its opponent as the regressor. We also substitute it with the opponent's amount of negative advertising on the subject campaign as the regressor, in order to understand the effects of negative advertising from the opponent on voters' preference for a given candidate. We find the effect is negative. This suggests that the opponent's negative advertising on the candidate results in a reduced probability of voting for that candidate. This is consistent with the net stimulation effect we find when using the subject campaign's negative advertising on its opponent as the regressor. We also find the effects of non-negative advertising amounts to be insignificant in all of the above model estimates. With an endogeneity correction, we find, as expected, that negative advertising is more effective and has a higher positive effect[6].

The analysis includes two regressors related to incumbency status in the House elections. The first regressor is incumbency status, a dummy set to 1 for all incumbent candidates and 0 for others. The second regressor is an interaction term, set to the product of the incumbency term and the amount of negative advertising. The incumbency term is not applicable for the Presidential election, as the 2000 Presidential race had no incumbent. We observe that the coefficient for incumbency for the House elections is positive. Meanwhile, the coefficient for the interaction term between incumbency status and negative advertising is negative (-0.010), and is smaller in magnitude than the main positive effect of negative advertising (0.029). This indicates that while negative advertising helps candidates, the effect is relatively smaller for the incumbent.

We add demographics and attitudinal variables as additional controls in the heterogeneity specification for the negative advertising parameter. They do not have any significant interaction effects with negative advertising in either election. In addition, we include two interaction terms between negative advertising and voter-stated candidate goodwill (both positive goodwill and negative goodwill, or "badwill"[7]). Goodwill coefficient estimates are negative and significant for both elections. Since strong positive goodwill could indicate high voter "involvement" in a candidate, this finding is consistent with the results reported in the experimental work done by Shiv, Edell and Payne (1997).

Based on the parameter estimates, we report the elasticity estimates of negative advertising on voter turnout and choices for the Democratic and Republican parties. As already mentioned, computing these elasticity estimates is one of the key objectives of this section, given that these estimates are necessary for the analysis pertaining to candidates' strategic choices of negative advertising levels. The turnout elasticity is computed using the following formula:

$$\frac{dPr(y=1)}{dNegAds_j}\frac{NegAds_j}{Pr(y=1)} = \frac{NegAds_j}{1+exp(u)}\frac{exp(v_j)}{\sum_{j=1}^{J} exp(v_j)}\gamma_1\beta_1$$

The candidate choice elasticity is computed using the following formula:

[6] A Hausman test (Hausman 1978) rejects the null hypothesis that the amounts of negative advertising chosen by campaigns are exogenous ($\chi^2_{(1)} = 2.78$ for the House model, and $\chi^2_{(1)} = 2.93$ for the Presidential model, both rejecting exogeneity at a 90% significance level).

[7] The measures of "badwill" are transformed into absolute values. Note it is not appropriate to only include a continuous measure of goodwill, which can either be positive or negative. Many more voters in our House data are "indifferent" or have "no opinion" towards either candidate, which increases the mean of the goodwill measure for the House races, so it is necessary to have separate measures of positive and negative goodwill.

$$\frac{d\theta_j}{dNegAds_j}\frac{NegAds_j}{\theta_j} = \left[1 - \frac{exp(v_j)}{\sum_{j=1}^{J} exp(v_j)}\right] NegAds_j\beta_1$$

These elasticity estimates are computed using the parameter estimates from our voter turnout and choice model. We find that negative advertising has positive effects on both voter turnout and choice in the House and Presidential elections. This indicates that negative advertising has positive primary demand effect on voter turnout, and also positive secondary demand effect on candidate choice. To see which effect is stronger, we carry out a decomposition exercise (Gupta 1993). In both House and Presidential elections, negative advertising has a consistently larger effect on voter candidate choice than on voter turnout, as shown in Figure 4.

	House		**Presidential**	
	Democrat	Republican	Dem. (Gore)	Rep. (Bush)
Turnout	0.016 (19%)	0.018 (19%)	0.026 (16%)	0.023 (11%)
Candidate choice	0.068 (81%)	0.077 (81%)	0.140 (84%)	0.190 (89%)

Figure 4: Summary of elasticity measures of negative advertising and decomposition between turnout and choice (shown as percentage in parentheses).

This finding is useful since existing studies on negative advertising have focused on its effect on voter turnout, while our findings suggest that negative advertising plays a more important role in affecting voters' candidate choice. Examining the own- and cross-advertising elasticities on voters' candidate choice can potentially act as a building block for us to build theory models of campaign negative advertising choice.

In summary, the estimation results from the voter choice model show negative advertising has a positive net stimulation effect, and this effect is stronger on voter candidate choice than on voter turnout. Negative advertising has a smaller stimulation effect for an incumbent, and it interacts with goodwill, a measure of voter involvement in a candidate.

3 Campaign choice of negative advertising

In this section we provide an empirical analysis of a campaign's choice of negative advertising and how it is affected by market characteristics, advertising costs and voter and campaign characteristics.

3.1 Empirical measures and econometric model

We have described the campaign advertising data used in our study in the previous section (Figure 2). In addition to the nature of the advertising content, our data also contains the candidate's name, incumbency status, the time and the program that a specific advertisement was aired, the number of days before the election that it was aired, and the cost charged by the TV station for airing each ad. The cost data can be used to test whether or not a campaign is more likely to choose negative advertising when the cost of advertising is lower.

The summary statistics in Figure 2 indicate that the 2000 Presidential candidates, Republican George W. Bush and Democrat Al Gore, showed a greater proportion of negative advertisements relative to the House candidates. The difference is quite significant (for example, 68.2% of Bush's character advertisements are negative; while only 49.1% of the Republican House candidates' character advertisements are negative). The difference in the amount of negative advertising may be linked to the difference of voter valuations of candidates across these two elections. Since the stakes in a presidential race are likely to be higher, average voter valuations for Presidential candidates relative to the House candidates are also likely higher. This may explain why a greater incidence of negative advertising occurs in the Presidential election.

Another issue is whether or not candidates in closer races (i.e., with more undecided voters) are more likely to choose negative advertising. In order to test this, we require a measure of the closeness or the competitiveness of the election. We obtained one such measure from the Cook Political Report, produced by an independent/non-partisan election analysis consulting firm. The Cook Report classifies different congressional districts (for 2000 House races) as well as different media markets (for the Presidential race) into four categories: non-competitive, non-competitive but potentially competitive in the future, more competitive, and toss-ups (i.e. most competitive). This classification can be seen as a measure of the closeness of the election and has also been used by other researchers (Lovett and Shachar 2008). The distributions of this measure across markets during the last week of the race for both House and Presidential elections are shown in Figure 5[8].

	House	**Presidential**
Non-competitive	67	8
Potentially competitive	18	10
More competitive	15	4
Most competitive (toss-up)	13	17
Total districts/markets	**113**	**39**

Figure 5: Distribution of competitiveness measure across districts/markets.

We next describe our empirical model of campaign's advertising choice. We are interested in how the closeness of the election, market (voter) and candidate-specific characteristics, and competitor behavior affect a campaign's decisions about type and quantity of advertising. To model the choices made by Democratic and Republican campaigns to run negative advertising as opposed to non-negative advertising (which includes positive and contrast advertisements which do not have negative content), we use a binary logit choice model specification and estimate the model for each candidate in the Presidential and House elections. The probability of a candidate j (j = Democrat or Republican) choosing one of k available types of advertising (k = negative or non-negative) in a given week t is given by:

$$\theta_{jkt} = \frac{exp(V_{jkt})}{\sum_{l \in K} exp(V_{jlt})}$$

where V_{jkt} is given by:

$$\begin{aligned} V_{jkt} &= \alpha_{jk} + \beta_1 OwnElasticity_{jk} + \beta_2 CrossElasticity_{jk} \\ &\quad + \beta_3 CostOfAdAmounts_{jkt} + \beta_4 CompetitorAdAmounts_{jk(t-1)} \end{aligned}$$

[8]In addition, we obtain state-level voter pre-election polls for the 2000 presidential election from SurveyUSA and Pollingreport.com, and compute the polls ratio as a variable that measures the closeness of the race in each media market. We find that the poll ratio, used as a measure of the closeness of the election, also has a positive effect on campaign choice of negative advertising. Unfortunately, it is impossible to obtain any reliable poll data for the 2000 House elections.

$$+\gamma_{1k} ClosenessOfElection_{jt} + \gamma_{2k} Incumbent_j$$
$$+\gamma_{3k} DemographicsVariables_j + \gamma_{4k} CampaignVariables_{jt}$$

for a negative or non-negative ad chosen by candidate j. As noted earlier, the advertising choice regression includes the own- and cross- elasticity estimates that were obtained from the voter choice model in the previous section. The intuition is that higher positive own-elasticity (from a net stimulation effect) makes negative advertisements more favorable, as more of that type of advertising leads to more votes for one's own candidate, while higher cross-elasticity makes negative advertisements less favorable because they help the other candidate. To test whether or not campaigns run more negative advertisements in closer races and when the cost of advertising is lower, we also include the following two variables: closeness of the election and costs paid to the TV station for the ad. We include a variable representing the incumbency status of the candidate.

Demographic variables include market-level income, education and race information, which we collect from the 2000 U.S. Census. In addition, we include a set of time-varying campaign-specific variables, such as the number of days before the election and a dummy variable for prime-time airing of an ad. $CompetitorAdAmounts_{jk(t-1)}$ (k = negative or non-negative) is added as a control variable to investigate how the competitor's amount of negative advertising in the previous period affects the subject campaign's advertising choice in the current period. We estimate the models using maximum likelihood methods.

3.2 Empirical results

Figure 6 reports the advertising choice model results that describe a campaign's decision on whether or not to run negative advertising.

	House				**Presidential**			
	Democrat		Republican		Democrat (Gore)		Republican (Bush)	
	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
Intercept	0.28	1.14	**-2.04**	-8.05	**2.86**	11.55	*0.33*	1.66
Own elasticity	**3.23**	55.51	**2.97**	52.74	**0.23**	3.76	-0.03	-0.42
Cross elasticity	**-3.19**	-52.60	**-4.04**	-51.67	**-0.35**	-4.84	**-0.07**	1.66
Race (minority)	**0.35**	4.52	-0.03	-0.31	-0.06	-0.64	**-1.08**	14.10
Years of education	**-5.63**	-14.15	*-0.55*	-1.69	**-5.02**	-19.33	0.18	0.68
Income score	**-8.23**	-22.10	*-0.70*	1.84	**-7.64**	-14.06	0.32	0.65
Days before election	**-0.06**	-10.39	**-0.03**	-51.96	**-0.75**	-60.46	**0.35**	39.93
Incumbency	**-0.88**	-43.94	**-0.93**	42.10	N/A	N/A	N/A	N/A
Primetime airing	0.02	0.55	**0.24**	9.22	**0.06**	2.70	**0.13**	6.18
Cost of ad	**-0.11**	-11.83	**-0.20**	-20.33	*-0.02*	1.93	**-0.04**	4.79
Positive ads run by competitor	**-0.05**	15.65	**-0.03**	12.63	**-0.07**	39.28	**-0.05**	27.14
Negative ads run by competitor	**0.01**	4.04	**0.05**	20.09	**0.05**	27.85	**0.07**	-51.76
Closeness of election	**0.61**	3.73	**0.92**	5.62	**0.68**	6.15	**0.39**	3.65
Number of observations	73276		71342		93076		94114	
Log likelihood value	-42679.90		-43093.50		-52413.20		-58774.10	

Figure 6: Empirical results from advertising choice model. Coefficients that are significant at the 95% and 90% levels are shown in **bold** and *italics*, respectively.

As described in the model section, we include a measure of how close the election is. This measure is obtained from the Cook Political Report in both House and Presidential elections in the advertising choice model. We find the coefficient estimates are positive and significant in both models, for both parties in both elections, suggesting that candidates have a greater chance of choosing negative advertising when the race becomes closer.

In terms of the demographic variables, we find that education level has a strong negative effect on candidates' negative advertising choice. More educated voters could be more interested and involved in the elections and may scrutinize information more carefully. Our estimates show that campaigns send out less negative ads in such markets, perhaps to avoid incurring a negative "backlash effect" if a more educated electorate successfully discerns the untruthfulness of the candidate's negative advertising. We find the cost coefficients are negative in all four advertising choice models; as the cost of negative advertising decreases, campaigns are less likely to choose negative advertising.

We test the effect of incumbency on negative advertising and find the incumbency status estimates to be negative in the House elections. This is also consistent with our finding in the voter choice models that incumbents' negative advertising hurts incumbents in terms of votes and helps non-incumbent candidates relatively more compared to incumbents.

We also find consistent and significant results for other additional voter-, campaign- and advertising-specific factors. First, we expect the coefficients for the own- and cross- voter choice elasticity terms to be positive and negative, respectively. We observe the expected signs for seven out of eight own- and cross-elasticity terms in the ad choice model. These results provide strong validation of coefficient estimates from the voter regressions, and suggest campaigns choose negative advertising because it generates more votes for their candidates. Second, we find that as the number of days before the election decreases, i.e. as the election date draws near, negative advertising is favored more. This suggests that campaigns tend to go more negative as the election draws closer. This finding is consistent with the observations in Ansolabehere and Iyengar (1995), who find that as the election date draws closer, candidates in House elections show more negative advertisements. Last, we include the amount of negative and non-negative advertising run by the opponent in the previous week as regressors in the choice model. We find most coefficients (except for the coefficient for the Republican in the Presidential race) for the competitors' negative advertising are positive and significant, while all coefficients for the competitors' positive advertising are negative and significant. These results imply that campaigns are more likely to go head-to-head with their opponents in terms of the choice and quantity of negative advertising.

3.3 Advertising quantity choice

In addition to advertising choice, the amount of negative advertising campaigns choose can also be affected by the closeness of the race and other voter- and campaign-specific factors as identified in the previous section. To examine these effects, we also estimate an advertising quantity model, which illustrates how much negative advertising a campaign will choose. The amount q_{jt} of negative advertising shown by candidate j (j = Democrat or Republican) at time t conditional on running a positive number of negative ads, is assumed to be a discrete positive value (Kalyanam and Putler 1997) and follow a zero-truncated Poisson distribution, i.e., campaign j's probability of choosing q_{jt} showings of negative advertisements is given by:

$$Pr(q_{jt} = q) = \frac{(V'_{jt})^q}{(exp(V'_{jt}) - 1)q!}$$

In the above formula, $V'_{jt} = exp(\alpha'_{jk} + \beta' X_{jkt})$.

For X_{jkt}, we include the same set of co-variates as those in the advertising choice model.

The parameter estimates in the quantity model provide insights on the effects of these market-specific, campaign-specific, and competitor-specific factors in determining the quantity of negative advertising that is chosen by a campaign (in addition to their effects on which type of advertising a campaign chooses).

	House				**Presidential**			
	Democrat		Republican		Democrat (Gore)		Republican (Bush)	
	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
Intercept	**3.03**	19.15	**2.14**	12.71	**3.64**	23.33	**2.85**	18.45
Own elasticity	**4.22**	92.93	**3.59**	78.89	**2.95**	46.27	**3.64**	35.38
Cross elasticity	**-3.37**	-76.39	**-4.30**	-70.46	**-3.09**	-37.38	**-4.10**	-32.44
Race (minority)	**0.45**	8.20	**0.73**	13.34	**-0.18**	-2.97	**0.40**	7.78
Years of education	**-1.90**	-7.65	0.26	1.02	**-0.30**	-2.10	**-0.67**	-4.03
Income score	**4.01**	15.48	**1.47**	5.31	**3.41**	9.90	**1.18**	3.69
Days before election	**-0.10**	-44.08	**-0.18**	-71.85	**-0.11**	-73.84	**-0.16**	-130.61
Incumbency	**-1.21**	-3.87	**-1.73**	-4.18	N/A	N/A	N/A	N/A
Primetime airing	**1.52**	16.13	**0.64**	5.98	**-1.63**	-14.18	0.13	1.21
Cost of ad	**-0.00025**	-24.67	**-0.00015**	-14.32	**-0.00012**	-8.12	**-0.00004**	-5.47
Positive ads run by competitor	**-0.01**	-10.92	**-0.03**	25.51	**0.05**	51.65	**-0.01**	5.41
Negative ads run by competitor	**0.01**	7.32	**0.02**	19.27	**0.04**	24.26	**0.01**	6.55
Closeness of election	**0.78**	18.87	**0.97**	45.22	**0.64**	8.47	**0.24**	3.44
Number of observations	446		491		584		596	
Log likelihood value	-13820.37		-17003.79		-18006.99		-13872.05	

Figure 7: Empirical results from advertising quantity model.

As seen in Figure 7, the parameter estimates show that these factors have similar effects to those in the advertising choice models on campaigns' ad quantity decisions. Consistent with the findings in Lovett and Shachar (2008), we also find that larger amounts of negative ads were deployed in closer races.

4 Conclusion and future work

The results described in this paper cast light on negative advertising in U.S. elections, which has been increasing with each successive U.S. election cycle. In our empirical analysis we model the choices made by both voters and candidates in House and Presidential elections in 2000. On the voter side, we model and estimate both voter candidate choice as well as voter turnout. Negative advertising positively affects both the turnout and the likelihood of voting for the subject candidate in House and Presidential elections. A decomposition of the effects shows that the effect of negative advertising on candidate choice is much larger than its effect on voter turnout, demonstrating the value of jointly studying both turnout and choice. This analysis allows us to obtain consistent own- and cross-demand elasticity estimates of negative advertising for voter choices and turnout, which aids in conducting analysis of the candidate's advertising strategy decisions.

On the advertising strategy side of this framework, we provide an empirical analysis of the choice of negative advertising by candidates. The main empirical analysis of the paper examines advertising strategy choices by estimating how advertising content choice, as well as advertising quantity, is determined by market, voter and campaign characteristics. We find that negative advertising is more likely to be chosen when education levels (a measure of voter scrutiny or the probability that they will know the "truth") or the cost of advertising is low. Negative advertising is more likely to be deployed in closer election races where the market is less heterogeneous as well as when the election date draws nearer. We find that incumbents choose relatively less negative advertising. Finally, Presidential candidates run more negative advertising than House candidates. Voter valuations (all else being equal) are likely to be higher in the Presidential race, which can lead to a greater incentive to send out negative advertising.

There are several possibilities for further research in this area. On the empirical side, it would be interesting to collect data from multiple elections, which would allow one to test for potential interacting factors that vary between election cycles. Time series data for voters and campaigns would also allow us to look at the dynamics of voter turnout and choices over time, and how they are affected by negative advertising from campaigns. It would be also be useful to investigate additional election-specific interacting factors based on ad traits, such as the percentage of negative advertising aired during prime time or the specific issues mentioned in advertisements. On the analytical side, an interesting issue will be to examine understand how negative advertising could generate media bias (Xiang 2006). Thus, negative advertising in political markets can present a rich set of additional research issues.

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