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Abstract

This study examines the effect of technology stores—company-owned Apple and Microsoft retail stores—on mall configuration. We formulate a structural model that considers the endogenous location decisions of retail stores, taking into account both market characteristics and the spillover effects of co-location. As a byproduct, the study provides guidance on location choice to mall developers and retailers by examining the equilibrium outcome of mall configuration that affects retail sales. The results show that competitive effects dominate within and across store categories for traditional department stores, but agglomeration effects exist between technology stores and upscale department stores. The presence of an Apple store, for example, attracts high-income consumers, promoting the entry of upscale stores and the exit of midscale and discount stores. This study also introduces three key methodological innovations to the marketing literature. First, we address multiple equilibria by estimating equilibrium selection from the observed data. Second, we develop an efficient simulator that requires fewer random draws to evaluate the likelihood function for complete information games with multiple equilibria. Third, we overcome the remaining computational burden by utilizing the GPGPU technology, using multiple processing cores in a graphics-processing unit to increase computational speed.

Key words: Apple store, new anchor store, discrete game, complete information, multiple equilibria, GPGPU technology, simulator, Bayesian estimation, shopping mall, spillover.

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1. Introduction

The retail sector constitutes one of the largest segments of the U.S. economy, generating sizeable annual sales that considerably bolster total GDP. In 2017, retail sales surpassed $5 trillion in the U.S. alone (approximately 26 percent of GDP; Select USA, 2017) and nearly $23 trillion globally (eMarketer 2019), and the market continues to grow. Retail is the largest private employer in the United States, directly and indirectly contributing 42 million jobs, or one in four (National Retail Federation, 2014). Despite the recent e-tail surge, traditional brick-and-mortar stores still remain the core of the retail industry. In 2015, U.S. retail e-commerce sales accounted for only 7.3 percent of total U.S. retail sales. Furthermore, according to a recent survey of over 1,000 consumers, more than 70 percent would prefer to shop at a brick-and-mortar Amazon store versus on Amazon.com, and 92 percent of millennials planned to shop in-store in 2015 as often or more than they did in 2014 (Timetrade.com, 2015). A considerable proportion of brick-and-mortar retail involves a market structure typically referred to as a shopping mall or a shopping center.

Traditionally, big department stores such as Nordstrom and Macy's, with their recognized brand (from their large advertising budgets) and wide product portfolios, attracted people to the malls—and, thus, were referred to as anchor stores. Recently, though, technology stores such as the Apple and Microsoft stores have begun to draw foot traffic to the malls (Baig, 2018); therefore, we refer to these stores as the *new* anchor stores. Despite this shift, limited research has examined the role of these new retail establishments. Hence, this study seeks to gain insights into the way that these new anchors affect the shopping mall industry. Specifically, we examine how new and traditional anchor stores compete or agglomerate within and across store types to form the market structure. As a result, we provide guidance to both retailers and mall developers by predicting market structure, which can forecast retail profits, given market characteristics.

A typical shopping mall consists of a large cluster of retail stores located in physical proximity, sharing amenities such as restrooms, food courts, and customer parking. Naturally, the physical proximity of co-location has both benefits and costs. The benefits include an economy of scale achieved by sharing amenities, as well as increased overall demand from consumers' reduced transportation costs from one-stop shopping. The obvious cost comes from competition from other retail stores located in the vicinity.

The U.S. retail industry has been in a state of consolidation over the past several years as online shopping has accounted for a larger portion of consumer spending. For example, traditional anchor stores such as Nordstrom and J.C. Penney have witnessed a decline in per-square-foot revenue (Gray & Yuk, 2019). Although traditional department stores are struggling, shopping mall sales productivity rose from $383 per square foot in 2009 to $513 in 2018 (International Council of Shopping Centers). The media have speculated that technology tenants, mainly Apple stores, are a reason for the increase in mall performance. Because many Apple product owners need to go to a physical store to get their products serviced, Apple stores naturally increase foot traffic. As new anchors for the mall, they increase customer traffic, thus benefiting other mall tenants (Whelan, 2015; Lodge, 2017).

Apple opened its first physical store in 2001. As of 2018, Apple had 506 retail stores across 25 countries, including 272 in the U.S. (Apple.com). **Figure 1** shows the number of Apple stores in the U.S. by year. One can see a steep increase, which has stabilized in recent years. The presence of an Apple store increases mall traffic and, thus, increases mall value, which allows malls to increase other tenants' rent (Lodge, 2017). As a result, Apple can negotiate favorable terms with the mall while creating upward pressure on other tenants' leases. Hence, it is important to understand the factors that determine Apple's choice of location and its effect on the profits of other stores co-located in the mall.

To examine the formation of market structure and the possible spillover effects among firms, we utilize a simultaneous-move discrete game of complete information in which a firm's profit (and, thus, its entry decision) is a result not only of market characteristics, but also of the spillover effects generated by other firms' entry decisions. We refer to these spillovers as *strategic effects* because they result from the endogenous entry decisions of other co-locating firms.

This framework has several advantages. First, this approach does not require revenue or price data because the observed actions of entry—the equilibrium outcome—can be mapped onto firms' profits. Second, by allowing flexible strategic effects, we are able to capture both negative (competitive) and positive (agglomeration) effects of co-location. Finally, because our data are cross-sectional, it is fair to assume that the observed equilibrium outcome is a result of a steady-state, long-term equilibrium in which firms have made adjustments with regard to their choices (of entry). The complete information structure of the game fits this setting. Because of technical complications, researchers typically have refrained from using the complete-information setting, although the empirical context (such as the one in this study) suits this setting. We do not shy away from the complete-information framework, despite the challenges of both multiple equilibria and heavy computational burden. Sections 3 and 4 discuss the methods that we use to address these challenges.

The focus of this research is on anchor stores (both traditional and new) because they are, by definition, the key tenants in a mall, occupying most of the mall's gross leasable area (GLA) and generating much of the foot traffic (see **Figure 2** for an example of a mall layout in terms of GLA). We collect data from the Directory of Major Malls, a data provider that supplies information about U.S. shopping centers and their tenants, and utilize information from 1,196 malls with 6,753 anchor stores.

There are several challenges involved in the modeling and estimation of market structure in a complete-information discrete-game framework. First, as is the case with most discrete games, we face the problem of multiple equilibria, which makes it difficult to either define a likelihood for estimation or conduct accurate counterfactual policy simulations. As a result, past research has scaled back the problem (Bresnahan & Reiss, 1990; Berry, 1992); specified the sequence of moves (Berry, 1992; Mazzeo, 2002b); made arbitrary assumptions related to equilibrium selection (Hartmann, 2010); or adopted a partial identification approach—i.e., estimated a range of parameters instead of point estimates (Ciliberto & Tamer, 2009). In this research, we address multiple equilibria by implementing the selection function method of Bajari, Hong, and Ryan (2010) to empirically *estimate* the equilibrium selection rule from the observed data.

Second, estimating discrete games of complete information with multiple players, especially in a setting that involves equilibrium selection, requires immense computational processing power. The empirical setting for this study has 11 players in 1,196 markets, and the model, which includes marginal effects on market-firm characteristics and spillovers, has more than 100 parameters. Hence, to search over the parameter space, the estimation needs to evaluate equilibria numerous times. For example, to perform 3,000,000 posterior draws for parameter inference using 1,000 random draws for probability integration, we would need to evaluate $2^{11} \times 1{,}000 \times 1{,}196 \times 3{,}000{,}000 = 2{,}449{,}408{,}000{,}000{,}000$ cases for equilibria, which would not be feasible using conventional computational methods.

To overcome the computational burden, we propose two new approaches. First, we develop an efficient simulator that requires fewer random draws for numerical integration. The integration involves evaluating the number of random draws that generate an observed outcome as an equilibrium. Our new simulator relies on the fact that it is relatively easy, in a complete-information discrete-game setting, to avoid random draws that will not be included in the evaluation of the likelihood. In a discrete game of complete information with 11 players, there are 2^{11}=2,048 types of choice outcomes, and, thus, it is unlikely that a random draw generates the observed outcome out of the 2,048 possible equilibria. All the random draws from our simulator include the observed outcome as possible equilibria and, thus, convey information to the evaluation of the likelihood. We show that only 64 random draws from our new simulator achieve higher accuracy than 1,000 draws from a traditional simple simulator.

Second, we use a state-of-the-art technology, the general-purpose computing on graphics processing units (GPGPU) that uses multiple processing cores in a GPU of a graphics card to increase computation speed—the estimation process runs more than 10,000 times faster than traditional methods. Scholars have used GPUs for parallel computing in the estimation of random coefficient demand models (Kim, Song & Xu, 2017) and dynamic programming (Aldrich et al., 2011) but have not yet applied them in the estimation of a simultaneous-move discrete game of complete information. However, using GPUs is much more effective in complete-information discrete games than in other applications. Evaluating the likelihood of these discrete games involves many random draws; and for each draw, one needs to evaluate equilibria. For example, in 1,196 markets with 64 random draws, one needs to solve 63,388 ($=1{,}196 \times 64$) games for equilibria to evaluate the likelihood at a given parameter value. These games are completely independent and can be solved in parallel by implementing single instruction multiple data (SIMD) processing, using many cores in a GPU. The SIMD processing feature fits well with solving complete-information discrete games in which the same computational operations are performed on multiple games. Because all possible mall configurations are checked for equilibrium, the computational operations (e.g., checking 2,048 configurations for an 11-player setting) are exactly the same across games.[1] In addition, using GPUs for solving complete-information discrete games does not require high precision. The procedure requires evaluating only whether each mall configuration is an equilibrium and whether the entry payoff is positive. Hence, one does not need to compute the payoffs in double precision (15 decimal digits) but can compute them only in single precision (7-8 decimal digits) or even half precision (3-4 decimal digits). As such, our estimation procedure can benefit particularly from the use of modern GPUs, which operate faster with low precision.[2, 3]

The results of this study indicate that population and income are the key factors that drive retail stores' profits: both new anchors (Apple and Microsoft) and traditional upscale anchors locate in affluent and populated areas, whereas other traditional anchors (discount and midscale stores) locate in lower-income and less-populated areas. Although the results of the new anchors resemble those of traditional upscale anchors, there are some differences. Traditional upscale anchors locate in high-income areas where the average age is also high, likely in traditionally affluent areas, whereas new anchors locate in high-income regions with a younger demographic. In addition, the new anchors locate in areas in which the household size is small, likely in urban areas.

The strategic spillover effects indicate that, for traditional anchors, competition is the primary effect within and across store categories, except for within midscale and within upscale stores, where

[1] In contrast, if the application requires solving a non-linear equation for each market (as in a random coefficient demand model), the number of iterations needed to solve the equation may differ across markets, which does not fit well with SIMD processing. If a computation core solves the equation in one market, it needs to wait until other cores solve their equations in other markets, causing an inefficient allocation of computing power. In our application with 11 players, each core checks for equilibrium in 2,048 mall configurations, the same number of iterations for all markets.
[2] In contrast, if the application requires solving a non-linear equation, computing in double precision is necessary to obtain a precise solution. Furthermore, such an application needs to numerically optimize an objective function computed from the solutions of the equations (e.g., GMM), which makes double precision even more necessary.
[3] For example, a professional graphics card, NVIDIA Tesla V100, computes twice as fast in single precision as in double precision.

positive agglomeration effects of co-locating exist. Among the new anchors, Apple seems to have a profound effect on various players. Apple has a negative spillover to discount stores but a positive spillover to upscale and Microsoft stores. However, no player, including both traditional and new anchors, affects Apple, but Apple has a significant effect on many players, proclaiming its status as today's ultimate anchor store.

Regarding equilibrium selection, we find no evidence that the highest joint-payoff equilibrium is more frequently selected, an assumption commonly used in the literature in both estimation and counterfactual policy simulations.

Counterfactual policy simulations show that some stores would not enter a market because of the competitive entry of other stores, even under favorable market conditions. In addition, counterfactuals reveal changes in market structure due to the entry of new anchor stores. Specifically, the entry of Apple substantially increases the profit (and, thus, the entry probability) of upscale department stores, but decreases the profit of discount stores. Malls want to lure new anchor stores to increase foot traffic. As a way, malls are offering favorable terms (in rent and location) to attract these stores (Kapner, 2015). However, malls may increase the rent to other stores due to the increase in foot traffic, putting upward pressure on cost, especially to stores that rely on discounted goods. Furthermore, by luring new anchor stores, malls can adversely affect their main constituents by attracting the wrong types of customers to their focal stores. Hence, malls whose main constituents are not high-end customers should think carefully before actively luring a new anchor store, as the presence of such stores may substantially change mall configuration.

In terms of empirical context, this paper shares similarities with Vitorino (2012), which also examines the entry behavior of anchor stores in a shopping mall. However, there are four key differences, which are as follows. Vitorino (2012): 1) incorporates an incomplete-information framework; 2) uses the MPEC (mathematical problem with equilibrium constraints) method (Su and Judd, 2012) for estimation; 3) does not explicitly address multiple equilibria; and 4) examines only traditional anchor stores.

The data used in this study, like those in Vitorino (2012), are cross-sectional, and, thus, it is fair to assume that the observed equilibrium outcome is the result of a steady-state, long-term equilibrium, which the complete-information structure captures more closely to reality than an incomplete-information setting does. In addition, while the MPEC method can estimate model parameters without directly addressing multiple equilibria, counterfactual analyses cannot be performed because there is no information about the selected equilibrium among multiple equilibria. Conversely, we estimate the equilibrium selection function and consider all equilibria in both parameter estimation and counterfactual simulation analyses. Finally, technology stores are the new attractions of a mall and, thus, defined as new anchor stores. In this research, we examine how these new anchors, together with traditional anchors, compete and agglomerate to affect mall configuration.

The remainder of the paper is organized as follows. Section 2 discusses the data and industry details. Sections 3 and 4 present the model and estimation, respectively. Section 5 discusses the empirical results and counterfactual analyses. Section 6 concludes.

2. Data and Industry Details

The mall configuration data come from the Directory of Major Malls, a data provider that supplies information about shopping centers and their tenants operating in the U.S. Information is available on 7,411 malls operating as of December 2015. A typical shopping mall consists of a large cluster of retail stores sharing amenities such as restrooms, food courts, and customer parking facilities. Sometimes, retail stores also share logistical facilities, such as loading docks and warehouses. General-purpose shopping centers are organized by size and trade area into the following categories: strip mall/convenience center; neighborhood center; community center; regional mall; and super-regional mall (see **Table 1** for the definition of different types of shopping hubs by The International Council of Shopping Centers—ICSC, 2016).

According to the definition in **Table 1**, shopping hubs, generally referred to as shopping malls, are either regional or super-regional shopping malls. Because these malls are independent shopping hubs with the space and capacity to provide a wide range of goods and services, operating in a large and separate geographical trade area, we define these malls as separate markets in which anchor stores locate.

In addition to mall configuration, we obtain demographic data from the Scan/US demographic database, which includes population, size of household, and average household income within five miles of each shopping mall. Furthermore, we collect the location of each anchor store's headquarters and compute the distance to every shopping mall in which it has a store. After data cleanup by excluding unusable observations that are missing information, we end up with 1,196 regional and super-regional shopping malls including 6,753 anchor stores for our empirical analysis. **Table 2** shows the summary statistics of the key variables.

Traditional anchor stores are large chain department stores that drive customer traffic to a shopping mall. These retailers are typically classified into three broad categories—discount, midscale, and upscale—based on target customer segments (Levy & Weitz, 2012). Focusing on price rather than service, discount department stores, such as Sears and Target, sell a variety of merchandise at lower prices than typical retail stores offer. Midscale department stores, including Macy's and Dillard's, offer a wide selection of both brand- name and non-brand-name merchandise, seeking to offer good value to their customers. Upscale department stores sell goods at above-average prices; their customers typically prefer exclusive designer brands and value customer service over low price. Examples include Nordstrom and Bloomingdale's (see **Table 3** for a detailed categorization of each department store).

Aside from traditional anchor stores, technology stores—or what we refer to as new anchor stores— have recently gained attention for increasing malls' foot traffic. The focal store of interest among the new anchors is the Apple store. First opened in 2001, the Apple store is the retail establishment owned and operated by Apple Inc., selling and servicing Apple products. Although the media initially speculated that the Apple store would fail (Useem, 2007), it has, instead, been highly successful, with more than $16 billion in total revenue in 2011 (Segal, 2012). By attracting consumers, the Apple store not only makes revenue for Apple Inc., but also potentially increases sales of others stores in the mall. Similar to the concept of the Apple store, the Microsoft store is a retail store owned and operated by Microsoft; it opened in 2009 to sell and service Microsoft products.

Table 4 presents the number of malls in the data that house Apple and Microsoft stores along with stores in various traditional categories. Out of 1,196 malls, Apple and Microsoft stores are present in 168 and 84 malls, respectively. Classifying the malls that have Apple and Microsoft stores into different categories reveals some interesting patterns. Both Apple and Microsoft tend to co-locate with upscale stores: 59.5 percent of Apple and 36.3 percent of Microsoft stores are co-located with upscale stores, while only 9.5 percent of Apple and 4.1 percent of Microsoft stores are co-located with discount stores.

A key reason that research on shopping centers tends to be scarce is the paucity of data; statistics on mall/store profitability, such as rent and prices, are particularly difficult to obtain. The only available data are on market structure—that is, data on retail store configuration in a specific market. To properly examine market formation, one would need to supplement the limited data with economic theory. Thus, a structural model of firm entry is suitable to address the research question of this study.

3. Model

In order to examine the formation of market structure, we model the location (entry) decisions of firms in a specific market as a simultaneous-move discrete game of complete information. The model takes into account a firm's decision to enter a particular market in which a firm's payoff depends not only on firm and market characteristics, but also on the entry decisions of other firms.

3.1. Discrete Game of Firm Entry

There is a sequence of markets, indexed by $m = 1, \dots, M$, where a market in the empirical context is defined as a retail shopping mall. In each market, there are J potential entrants (i.e., anchor stores), and the profit of firm j when entering market m is defined as

$$\pi_{mj}\left(a_m\right) = \pi_{mj}\left(a_{mj} = 1, a_{m(-j)}\right) = \beta_j x_{mj} + \sum_{j' \neq j}^{J} \delta_{j'}^{j} a_{mj'} + \varepsilon_{mj} , \qquad (1)$$

where $a_m = (a_{m1}, \dots a_{mJ}) \in \{0,1\}^J$ is the vector of action profiles of all firms in market m, with $a_{mj} = 1$ if firm j enters and $a_{mj} = 0$ otherwise. Similarly, $a_{m(-j)}$ is the vector of action profiles for all firms in market m other than firm j. The vector x_{mj} represents the characteristics of firm j in market m, which include market-level characteristics such as population, average income, and household size.

The vector of parameters $\beta_j = (\beta_{j1},...,\beta_{jK})$ represents the marginal effect of firm and market-level characteristics on firm *j*'s profit, and $\delta^j = (\delta^j_{j'})^J_{j'=1,j'\neq j}$ represents the vector of strategic effects of other firms' entries on firm *j*'s profit. Notice that we do not restrict the strategic effects to be negative but also allow them to be positive—that is, we allow negative competitive effects and positive agglomeration effects (Ciliberto & Tamer, 2009; Vitorino, 2012).

The last term ε_{jm} in **Equation (1)** is the firm-market specific idiosyncratic shock that is unobserved by the econometrician but observed by the firms. The standard distributional assumption applies—independently and identically distributed (from a standard normal distribution) across firms and markets. A firm's profit from not entering the market is normalized to zero.

3.2. Multiple Equilibria

In each market, we assume that market structure is a result of a pure strategy Nash equilibrium. Firm j enters market m if and only if $\pi_{mj}\left(a_{mj} = 1, a_{m(-j)}\right) > 0$. It is generally the case that a pure strategy Nash equilibrium is not unique in discrete games. **Figures 3a** and **3b** offer an illustrative example similar to that shown in Bresnahan and Reiss (1990). Suppose that two firms, Apple and Microsoft, are playing a simultaneous-move entry game of complete information. For simplicity, assume that each player's payoff is dependent only on the strategic effect (entry choice) of the other player and an idiosyncratic shock. Thus, the profit function in **Equation (1)** has only the second and the last component. In such a case, the profits for Apple in market m would be $\pi_{mA} = -\delta^A_M a_{mM} + \varepsilon_{mA}$, and the profits for Microsoft would be $\pi_{mM} = -\delta^M_A a_{mA} + \varepsilon_{mM}$. If the other firm's entry is competitive ($\delta > 0$), there would be a region in the $(\varepsilon_{mA}, \varepsilon_{mM})$ plane where one would observe more than one equilibrium outcome (shaded region in **Figure 3a**). Similarly, if the other firm's entry is complementary—that is, the profit function for Apple is $\pi_{mA} = \delta^A_M a_{mm} + \varepsilon_{mA}$ and that of Bloomingdale's is $\pi_{mM} = \delta^M_A a_{mA} + \varepsilon_{mM}$ ($\delta > 0$)—there would be a region in which an equilibrium outcome could be either all firms entering or none entering (shaded area in **Figure 3b**).

There are two potential problems associated with the multiplicity of equilibria. First, because there are specific regions (shaded regions in **Figures 3a** and **3b**) where no unique outcome exists, the model is termed incomplete (Tamer, 2003)—that is, a researcher cannot define the likelihood of certain types of outcomes. Second, counterfactual policy simulations cannot accurately predict an outcome because one cannot determine the equilibrium that is selected. To overcome this problem, researchers typically have simplified the scale of the problem (e.g., used the number of firms rather than their identities (Bresnahan and Reiss, 1990)); postulated a structure on the sequence of moves (Berry, 1992; Mazzeo, 2002b); set arbitrary assumptions with regard to equilibrium selection (Hartmann, 2010); or relied on a partial identification framework that estimated a range of parameters instead of point estimates (Ciliberto and Tamer, 2009). We mitigate the problem of multiple equilibria by empirically estimating—from the observed data—the selection rule proposed by Bjorn and Vuong (1984) and formalized by Bajari, Hong, and Ryan (2010).

The detailed process is as follows. Let Γ be the set of pure strategy Nash equilibria given the discrete game payoffs. Thus, the probability that profile a_m is played is

$$\rho\left(a_m;\Gamma\right)=\begin{cases}\dfrac{\exp\left(\kappa z(a_m)\right)}{\sum_{a'_m\in\Gamma}\exp\left(\kappa z(a'_m)\right)} & \text{if } a_m\in\Gamma\\[2ex] 0 & \text{otherwise,}\end{cases} \tag{2}$$

where

$$z\left(a_m\right)=\begin{cases}1 & \text{if } \Psi_m\left(a_m\right)=\max\limits_{a'_m\in\Gamma}\Psi_m\left(a'_m\right)\\[2ex] 0 & \text{otherwise.}\end{cases}$$

The joint payoff of firms taking action profile a_m is represented as $\Psi_m\left(a_m\right)=\sum_j \pi_{mj}\left(a_m\right)$, and the parameter κ captures how often the highest joint-payoff equilibrium is selected. For example, if $\kappa>0$, the highest joint-payoff equilibrium is more likely to be selected instead of other equilibria. A discussion about the identification of κ will follow in the next section.

It is worth noting that the existing literature typically does not explicitly address equilibrium selection and makes arbitrary assumptions—e.g., that the highest total payoff equilibrium is always selected. As specified earlier, this research seeks to provide projections about market structure—

firm entry in the presence of other potential entrants—in markets with specific characteristics. Performing such a task requires counterfactual analyses—that is, simulations of future discrete-game outcomes where an equilibrium selection rule should be specified to choose an equilibrium and predict the market structure.

4. Estimation

For estimation of the model parameters, we adopt a Bayesian approach because it provides a unified methodology for inference and decision. Through the Bayesian approach, we can properly reflect the parameter uncertainty, including the equilibrium selection when evaluating the desirability of a firm's location choice. In addition, because the model proposed in Section 3 accompanies more than 100 parameters in our empirical context, the Bayesian approach turns out to be more feasible.

In this section, we discuss the computation of the posterior distribution for parameter inference. We use the Metropolis algorithm, one of the Markov Chain Monte Carlo (MCMC) methods that are common in Bayesian analyses when direct sampling from the posterior distribution is not feasible.

4.1. Likelihood Evaluation for Parameter Inference

For parameter inference, the computation of the likelihood (the probability of observing the data given parameter values) is necessary. Because the likelihood in **Equation (1)** does not have a closed-form solution, one may use a simple frequency simulator to compute the likelihood (Ciliberto & Tamer, 2009). To augment the simple simulator, we develop an efficient simulator that computes the likelihood with a smaller number of random draws. The simple frequency simulator evaluates the number of draws that generate the observed mall configuration as an equilibrium. A game with 11 players leads to 2^{11}=2,048 possible configurations; however, most draws from a simple frequency simulator will be incompatible with the observed configuration. Our new simulator is designed to avoid random draws that are not compatible with the observed configuration.

For notational simplicity, subscripts are omitted whenever the meanings are clear. The probability of observing firms' entry decisions $a \in \{0,1\}^J$ in a specific market is

$$p\left(a \mid \theta, x\right) = \int \rho\left(a; \Gamma(\varepsilon)\right) \cdot \phi(\varepsilon) d\varepsilon \,, \tag{3}$$

where $\Gamma(\varepsilon)$ is the set of equilibria with explicit dependence on ε. Because there is no closed-form solution for the set of equilibria $\Gamma(\varepsilon)$, one has to rely on simulations to conduct the integration. **Equation (4)** shows a simple frequency simulator to conduct such a task.

$$p\left(a \mid \theta, x\right) \approx \frac{1}{R} \sum_{r=1}^{R} \rho\left(a; \Gamma(\varepsilon^r)\right), \tag{4}$$

where $\varepsilon^1, \dots, \varepsilon^R$ are J-dimensional independent standard normal draws. While the simulator in **Equation (4)** can approximate the integral in **Equation (3)**, it is not computationally efficient because a majority of the draws may not provide any information to help determine the likelihood.

For example, if one of the following conditions holds for at least one $j = 1, \dots, J$ —

i) $\varepsilon_j < -\left(\beta_j x_j + \sum_{j' \neq j} \delta_{j'}^j a_j\right)$ and $a_j = 1$; or

ii) $\varepsilon_j > -\left(\beta_j x_j + \sum_{j' \neq j} \delta_{j'}^j a_j\right)$ and $a_j = 0$—

then it is the case that $\rho\left(a; \Gamma(\varepsilon)\right) = 0$ because neither i) nor ii) is true in equilibrium and, thus, is not compatible with observation a. In other words, $\rho\left(a; \Gamma(\varepsilon)\right) = 0$ represents the event that a firm enters when profits are negative or does not enter when profits are positive. Hence, to improve computational efficiency, we define a more efficient simulator than the one in **Equation (4)** such that

$$\begin{aligned} & p\left(a \mid \theta, x\right) \\ &= \Pr\left(E^c\right) \int \rho\left(a; \Gamma(\varepsilon)\right) \cdot \phi(\varepsilon \mid E^c) d\varepsilon + \Pr\left(E\right) \int \rho\left(a; \Gamma(\varepsilon)\right) \cdot \phi(\varepsilon \mid E) d\varepsilon \\ &= \Pr\left(E^c\right) \int \rho\left(a; \Gamma(\varepsilon)\right) \cdot \phi(\varepsilon \mid E^c) d\varepsilon \\ &\approx \Pr\left(E^c\right) \frac{1}{R} \sum_{r=1}^{R} \rho\left(a; \Gamma(\varepsilon^r)\right), \end{aligned} \tag{5}$$

where E is the event in which either condition i) or ii) holds for some $j = 1, \dots, J$; E^c is the complement of E; and $\varepsilon^1, \dots, \varepsilon^R$ are drawn from the density $\phi(\varepsilon \mid E^c)$. The second equality holds because $\rho\left(a; \Gamma(\varepsilon)\right) = 0$ when ε lies in E. Note that $\phi(\varepsilon \mid E^c)$ is the density of a truncated standard independent multivariate normal distribution. Hence, to simulate ε^r for $r=1,\ldots,R$ from $\phi(\varepsilon \mid E^c)$, one can draw each ε_j independently from a truncated standard univariate normal distribution, where the truncation level is set at $-\left(\beta_j x_j + \sum_{j' \neq j} \delta^j_{j'} a_j\right)$, and the truncation direction (left or right) is determined by a_j. The term $\Pr\left(E^c\right)$ is computed by the following product:

$$\Pr\left(E^c\right) = \prod_{j=1}^{J} \left[\Phi\left(-\beta_j x_j - \sum_{j' \neq j}^{J} \delta^j_{j'} a_{j'}\right)\right]^{1-a_j} \left[1 - \Phi\left(-\beta_j x_j - \sum_{j' \neq j}^{J} \delta^j_{j'} a_{j'}\right)\right]^{a_j},$$

where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution. We refer to the simulator in **Equation (4)** as the *simple simulator* and that in **Equation (5)** as the *augmented simulator*.

By avoiding simulation draws that give an obvious $\rho\left(a;\Gamma(\varepsilon)\right)=0$, the augmented simulator performs more efficiently than the simple simulator. For example, assume that $\beta_j x_j + \sum_{j' \neq j} \delta^j_{j'} a_j = 0$ for all $j=1,\ldots,J$ with $J=11$—that is, the entry decisions of 11 firms depend only on the draws of each ε. In addition, assume that $a=(1,\ldots,1)$ is observed—that is, all firms enter. Thus, the event E^c is mapped onto the positive orthant of the J-dimensional Euclidean space of ε. Via the simple simulator, a draw falls in E with probability $1-\frac{1}{2^{11}} \approx 0.9995$. Hence, fewer than one out of 1,000 draws, on average, will lie in E^c, and so the possibility of multiple equilibria is explored in fewer than one case out of 1,000 to determine the value of the likelihood. With the augmented simulator, however, all 1,000 draws lie in E^c, and, thus, all cases are used to find multiple equilibria.

Figure 4 illustrates the advantage of the augmented simulator over the simple simulator. For comparison, we use the two simulators to compute the probability that all players enter a given market. The details of the computation exercise are as follows. The total number of firms is set to 11 (the same number of firms as in the empirical application), with each firm's profit function set to **Equation (1)** with $\beta_j x_j = 0$, $\delta^j_{j'} = 1/J$ for each $j \neq j'$. The number of simulated errors is set as R=4, 8, 16, ..., 1024 for comparison; and the probability that all players enter is computed 100 times, with each point (the circle and triangle points for the simple and augmented simulators, respectively) in **Figure 4** representing a computed probability. With a small number of errors (e.g., R=4, 8, 16), the computed probabilities may coincide due to the discrete nature of the simulator; thus, not all computed probabilities are distinctly indicated in the figure. Note that because there is no closed-form solution for **Equation (1)**, we do not precisely know the true probability of all firms entering a market. However, from the simulation results of both the simple and augmented simulators, the true probability is about ten percent.

The probabilities computed by the simple simulator vary dramatically across 100 trials, especially when the number of simulated draws is small. Even in the case with more than 1,000 simulated draws, the standard deviation of the computed probabilities is close to one percentage point (10% of the true value). A ten-percent deviation would lead to a sizable bias in computing the likelihood for the MCMC posterior-parameter draws and, thus, model inference. In contrast to the simple simulator, our augmented simulator is relatively stable and shows little deviation. Even with only 64 simulated draws, it shows a standard deviation of less than 0.2 percentage point.

Next, we discuss the computation of $\Gamma(\varepsilon^r)$, the set of all pure strategy Nash equilibria. To find all equilibria, we check whether each strategy profile is in equilibrium. For each market and each draw of ε^r, there are 2^J strategy profiles to check for equilibrium. For example, the empirical setting in this study has 11 players in 1,196 markets. If we use R=64 random draws of ε^r for probability computation to perform three million MCMC iterations, we would need to check $2^{11}\times 64\times 1{,}196\times 3{,}000{,}000=470{,}286{,}336{,}000{,}000$ cases for equilibria, which would not be feasible using conventional computational methods. Because it is possible to evaluate equilibria by many markets and simulation draws within each MCMC iteration in parallel, we capitalize on the parallel-processing power of the GPGPU, a state-of-the-art technology that uses a graphics-processing unit and its many cores to compute the probability of the observed data.[4]

[4] The estimation (using Matlab) with GPGPU technology runs more than 10,000 times faster than that without it. While the MCMC iterations for our estimation took approximately three hours, a simple Matlab code without parallel processing would produce the same result in well over three years—that is, 1,250 days.

The use of GPUs significantly increases the computational efficiency in a discrete game of complete information compared to other applications. As discussed in Section 1, evaluating outcomes for equilibria fits the SIMD design of GPUs, where the same computational operations of checking 2,048 (=2^{11}) configurations for 11 players are performed simultaneously over multiple games. In addition, using GPUs to solve complete-information discrete games works well with low precision, as it requires evaluating only whether each configuration is in equilibrium and whether the entry payoff is positive. Hence, the use of a GPU for SIMD processing can substantially increase the computational efficiency of our empirical application. See the Appendix for the details of the estimation procedure.

4.2. Identification

This section presents an informal discussion of identification—the intuition on the variation in the data that helps one make inferences on the model parameters. For detailed and formal arguments, see Bajari, Hong, and Ryan (2010). The idea is based on identification at infinity. For brevity, we omit the market index m in this section. For each a_{-j}, we can find large values of x such that store j playing a_{-j} is a dominant strategy with probability close to one. For these x values, a small variation in x_j identifies β_j. Then, find x and x' such that $\beta_j x = \beta_j x'$ and a_{-j} differ only on the decision of store j'. The observed distribution of a_j on such x and x' identifies $\delta^j_{j'}$, the strategic spillover effect of store j' on store j. Given values of the parameters (β, δ), observations of markets with multiple equilibria will identify the selection probability $\rho\left(a_m;\Gamma\right)$—in particular, κ in **Equation (2)**.

Aside from the above arguments, we have numerically verified parameter identification with a dataset randomly generated according to the model in **Equation (1)**. An adequate number of observations led to mean posterior-parameters close to the true parameter values.

5. Results

First, we discuss the results of each firm's profit function in **Equation (1)**. Then, we conduct several counterfactual policy simulations to address the main research question of interest: how the new anchor stores affect the co-location decisions of other anchor stores (both traditional and new) to form the market structure.

5.1. Firm Profits

Table 5 shows the parameter estimates with regard to market- and firm-specific effects, and **Table 6** shows estimates of the strategic spillover effects of the discrete game of firm entry; thus, combined, they represent a retail store's profit function in **Equation (1)**. There is clearly a substantial degree of heterogeneity via stores. First, we discuss in detail some noticeable patterns of the traditional anchor stores by store category (discount, midscale, and upscale). Then, we discuss the results for the new anchor stores.

For traditional anchor stores, the effect of population is positive for upscale stores, indicating that these store types prefer to locate in populated areas. In contrast, discount and midscale stores locate in less-populated areas. Their offerings typically consist of products at affordable prices with limited service. Hence, discount and midscale stores would find it too costly (due to high labor and rental costs) to effectively operate in densely populated areas.

For upscale stores, such as Nordstrom and Bloomingdale's, the inclination to enter populated areas is not surprising. Upscale stores, by definition, serve upper-income segments of the population, which exist in critical mass only within highly populated areas. Correspondingly, the parameters associated with average income (a proxy for purchasing power) indicate that Nordstrom and Bloomingdale's prefer to locate in wealthy neighborhoods. On the other hand, the negative effect on average income implies that most discount and midscale stores prefer to locate in less-affluent areas because they cater to low- to middle-income customers. Macy's is the exception, as many consider it a higher-end store in the midscale category (Wahba, 2015).

The effect of household size is positive for most of the discount and midscale stores, suggesting that large households with many family members appreciate the good value-per-price of these stores. The effect of site size is positive for most store types. Customers who shop in shopping malls value not only merchandise shopping, but also other amenities such as restaurants, cafes, movie theaters, valet parking, etc. Larger shopping malls have the space to provide more of such amenities.

The results of new anchor stores closely resemble those of upscale department stores. They prefer to operate in large malls located in populated and high-income areas. However, there are two distinguishing factors. First, the traditional upscale department stores locate in high-income areas where the average age is also high—likely traditionally affluent areas. In contrast, new anchors stores locate in high-income regions with a younger demographic. Second, the new anchors locate in areas in which the household size is small, likely urban areas.

The coefficient regarding equilibrium selection is negative and statistically insignificant, providing no evidence that the highest joint payoff equilibrium is more frequently selected. This finding contradicts the previous literature that commonly assumes that the highest joint-payoff equilibrium is chosen in both estimation and counterfactual policy simulations. In fact, our results show suggestive evidence (negative but insignificant parameter estimate with regard to equilibrium selection) that the highest joint-payoff equilibrium is less commonly selected compared to other equilibria, implying that firms do not coordinate to achieve the highest joint payoff.

The parameter estimates for the strategic effects of firm entry, shown in **Table 6**, are consistent with the earlier inference regarding market- and firm-specific effects—for example, discount stores' reluctance to enter populated areas due to high operating costs. One can see that competition is the dominant effect within these stores. Furthermore, both discount and midscale stores suffer from the entry of upscale stores, indicating competitive effects not only within, but also across, store categories. In contrast, there is limited competitive effect and rather a positive agglomeration effects within both midscale and upscale stores.

In terms of the strategic effect regarding new anchor stores, Apple seems to have a profound effect on various players. First, Apple has a negative spillover and positive spillover effect on discount and upscale department stores, respectively. Apple's clientele overlaps with that of upscale stores, likely increasing the foot traffic of these customers. Second, Apple positively affects Microsoft's profits. Again, Microsoft's clientele resembles that of Apple, so positive agglomeration is not surprising. Microsoft, however, negatively affects the profits of discount stores but does not directly affect Apple. In fact, no player, including either traditional or new anchor stores, seems to have any effect on Apple's profits, but Apple seems to have a profound effect on the profits of many players, proclaiming its status as the ultimate anchor store in the current era. We will discuss these strategic effects in more detail in the next section.

5.3. Counterfactual Analyses

Using the structural parameters estimated in the previous section, we perform several counterfactual analyses to predict market structure. First, we examine the marginal effect of market characteristics on market structure to guide the developer. Second, we investigate the change in market structure regarding the entry of technology stores. When entering the market, a firm chooses its location based not only on market characteristics, but also on the expected strategic location choices of other firms.

A developer needs to select a site to construct a new shopping mall. The choice of a site is summarized as x, where x contains site characteristics such as population and average income. An important piece of information for a site selection is the joint distribution of the market structure $a = \left(a_1, \ldots, a_J\right)$. Formally, the probability of firm j entering a given mall is

$$E\left[a_j \mid x\right] = \iint E\left[a_j \mid x, \theta, \varepsilon\right] d\Phi(\varepsilon) dp(\theta \mid data),$$

where $\Phi(.)$ is the cumulative distribution function of an independent multivariate standard normal random vector, and $p(\theta | data)$ is the posterior distribution of the model parameters. Here *data* represents all the data used in the model estimation. To compute the inner integral, given θ, we simulate ε^r for $r = 1, \ldots, R$. For each ε^r, we compute the set of all pure strategy Nash equilibria $\Gamma(\varepsilon^r)$. If there exist multiple equilibria, entry decisions of potential entrants, a^r, are drawn according to the equilibrium selection rule $\rho\left(a; \Gamma(\varepsilon^r; x, \theta)\right)$. This step gives the inner intergral:

$$\int E\left[a_j \mid x, \theta, \varepsilon\right] d\Phi(\varepsilon) \approx \frac{1}{R} \sum_{r=1}^{R} \sum_{a \in \Gamma(\varepsilon^r; \theta)} a_j \rho\left(a; \Gamma(\varepsilon^r; x, \theta)\right). \qquad (6)$$

Finally, recall that we have samples of θ, $\{\theta_1, \ldots, \theta_S\}$, drawn from the posterior distribution, $p(\theta | data)$, through the MCMC draws in the model estimation. Because each sample of θ gives one value of **Equation (6)**, we can compute the entry probability, given market characteristics x, as

$$E\left[a_j \mid x\right] \approx \frac{1}{S}\sum_{s=1}^{S}\int E\left[a_j \mid x, \theta_s, \varepsilon\right] d\Phi(\varepsilon) \approx \frac{1}{SR}\sum_{s=1}^{S}\sum_{r=1}^{R}\sum_{a\in\Gamma(\varepsilon^r;\theta_s)} a_j \rho\left(a; \Gamma(\varepsilon^r; x, \theta_s)\right).$$

Figure 5 shows the probability of selected firms entering, conditional on different levels of site size. Consistent with the results of firms' profit function in **Table 5**, the entry probability of most stores increases with site size. However, Target's entry probability starts decreasing at a certain value of site size. What explains this phenomenon? A firm's entry probability is a function of three components: the main effect from firm- and market-specific characteristics (**Table 5**); the within-category spillover effects (diagonal elements in **Table 6**); and the cross-category spillover effects (off-diagonal elements in **Table 6**). In Target's case, the within- and cross-category spillover effects are all negative. As a result, even though the main effect of site size on Target's entry is positive, the effect of site size on other stores is also positive and, thus, encourages Target's competitors to enter the market. Higher competition decreases Target's likelihood of entry.

Similarly, the entry decisions of Apple and Microsoft depend not only on the main effect of site size, but also on within- and cross-category spillover effects. The presence of Apple stores encourages the entry of Microsoft. Moreover, cross-category spillover effects are mostly positive for both Apple and Microsoft. Hence, as shown in **Figure 5**, one can see an amplifying effect reflected in the convex relation between site size and the entry probabilities of Apple and Microsoft.

To examine the spillover effect in more detail, **Figure 6** separates the effect of site size on Target's profits into the direct (main) effect and the indirect (spillover) effect from other firms. The thick upward-sloping dotted line represents the main effect of site size on Target's profits, and the thin lines represent the ten spillover effects from other firms—that is, the change in Target's profits due to the entry of other firms. The thick downward-sloping dashed line shows the aggregate of all spillover effects. Finally, the thick solid line represents the sum of the main and overall spillover effects. Even though the main effect is positive, the overall effect of site size on Target's profits (and, therefore, its probability of entry) is negative at larger malls because the negative spillover effects are greater than the positive main effect.

Having explained all the working parts of the model, **Table 7** shows a realistic scenario that a developer faces in choosing a mall location. Site M possesses the average values of population and income, as well as the average values of other variables in the data. The population of site A is ten-percent higher than that of site M (with the same average income as site M). Similarly, the average income of site B is ten-percent higher than that of site M (with the same population as site M). Other market characteristics in sites A and B are set to the mean values in the data. We compare the effects of these differences in population and income to determine the market structure in sites A and B. The results show that more upscale and technology stores enter site B, the site with lower population but higher average income.

To increase customer traffic, malls are trying to lure new anchor stores by providing favorable terms on rent and location. Thus, the next counterfactual analysis depicts the hypothetical scenario in which a mall attracts new anchor stores to its retail location. **Table 8** shows the results of this counterfactual. The second column shows the entry probability of each store at the average values of all independent variables in the data (i.e., a market with average characteristics). The third, fourth, and fifth columns show firms' entry probabilities with Apple entering, Microsoft entering, and both entering. The entry of new anchor stores increases the profit (and, thus, the entry probability) of upscale department stores, but decreases the profit of discount stores. Because of the increase in traffic that an Apple store brings, malls tend to increase the rent for other stores, putting upward pressure on cost (Kapner, 2015), which considerably affects stores that sell discounted goods. In addition, by luring new anchor stores, malls attract high-income customers who are in search of high-end goods. Thus, in a mall that has low-income customers as its main constituents, luring a new anchor store can negatively affect its business operations by 1) attracting the wrong types of customers for its existing stores and 2) driving away its major retailers (discount stores). Hence, malls should carefully consider the dynamics of the location choice of retail stores and its effect on market structure.

6. Conclusion

Despite the recent surge in e-commerce, brick-and-mortar retail, specifically in the form of large-scale shopping malls, is still the dominant venue for consumer purchases in the developed world. In the past, brand-name department stores (traditional anchor stores), with their large advertising budgets and wide product portfolios, attracted consumers to the mall. Presently, however, many believe that technology stores such as Apple and Microsoft (referred to as new anchor stores in this study) attract consumers to the mall. Yet there is little research on the dynamics that the technology stores create in the formation of the retail cluster—mall configuration.

This paper develops a structural model of retail configuration with multiple equilibria to examine the complex dynamics between new and traditional anchor stores. The analyses help to assess the types of stores that will join a shopping hub with the presence of a technology store.

The results show that population and income are the key drivers of retail stores' profit. The upscale and new anchor stores locate in highly populated, affluent areas, whereas midscale and discount stores locate in less-populated, lower-income areas. Furthermore, new anchor stores locate in high-income regions with younger demographics and smaller household size—likely urban areas. The analyses of strategic effects suggest that the negative effect of competition is the dominant force within and across store categories, especially for discount stores, but positive agglomeration effects exist within store categories (midscale and upscale). No store directly affects Apple, but Apple affects many players, signifying its status as the anchor store of present-day retail. Apple negatively affects discount stores but positively affects upscale and Microsoft stores.

The counterfactual simulations suggest that some stores would decide not to join a mall, despite favorable market conditions, due to the expected competitive entry of other stores. Regarding equilibrium selection, we find no evidence that the highest joint-payoff equilibrium is more frequently selected. In fact, we find suggestive evidence that the highest joint-payoff equilibrium is less commonly selected than other equilibria, challenging the common assumption used in the prior economics and marketing literature.

Through our empirical application, we introduce three important methodological innovations. First, we provide one of the first empirical implementations of Bajari, Hong, and Ryan (2010) and consider all equilibria to estimate the equilibrium selection rule from the data. Second, we develop and use an augmented simulator that incorporates all information from each simulation draw for numerical integration. Finally, we utilize a state-of-the-art technology, GPGPU, using multiple processing cores of a graphics-processing unit to significantly increase computational speed to consider and solve all equilibria, an effort that would not have been feasible with conventional computational methods.

In summary, this research provides a rigorous yet practical framework to understand and evaluate why new and traditional anchor stores join a shopping mall and how their decisions affect mall configuration. Although our empirical application is in the retail shopping mall domain, our model can be extended and applied to other settings in which a decision maker must choose among alternative sites—for example, transportation hubs such as airports or train stations. In addition, our modeling framework can be applied to assess the impact of regulatory factors on firms' entry decisions to gauge their implications on consumer welfare. We believe that these substantive areas will be exciting venues for future research.

Appendix: Estimation Procedure

This appendix provides the details of the Bayesian estimation procedure used in this study. To obtain the posterior distribution, we draw samples of θ by the Metropolis algorithm. At each iteration t, the Metropolis algorithm draws θ' from a proposal distribution and determines if θ' is accepted as a posterior sample θ_t with probability $\max\left\{1, p\left(\theta'\right) / p\left(\theta_{t-1}\right)\right\}$, where $p\left(\theta\right)$ is the posterior distribution of parameters. If θ' is not accepted, we set $\theta_t = \theta_{t-1}$.

Recall that $p\left(\theta\right) \propto \left(\text{prior density at } \theta\right) \cdot \left(\text{likelihood at } \theta\right)$. The prior distribution for all parameters is set as the independent joint normal distribution with mean 0 and standard deviation 10. Because the likelihood does not admit a closed form, we rely on the simulated likelihood, explained in **Section 4**.

The proposal distribution is set as a random walk. The proposal distribution at iteration t is normal with mean vector θ_t and variance matrix $s^2 V$, where s is a positive number and V is a positive definite matrix. We tune the variance matrix to improve the performance of the Metropolis algorithm, a variation of Roberts and Rosenthal (2009) and Haario, Saksman, and Tamminen (2001). For s, we set our target acceptance probability between 0.1 and 0.3. If the number of accepted proposals in the last 100 iterations is below 10 or above 30, we adjust s accordingly. We set

$$V = \frac{\left(2.4\right)^2}{\left(\text{dimension of } \theta\right)} \left(\text{covariance of } t-1 \text{ samples}\right) + e\left(\text{identity matrix}\right)$$

at iteration t. Here, e is a small positive number such that the second term guarantees positive definiteness of V. During the initial tuning stage, we run two million Metropolis iterations. To evaluate the simulated likelihood, R=64 errors are generated once, and the same errors are used throughout the entire Metropolis iterations.

During the main MCMC stage, s and V are fixed. We set the matrix V equal to the one obtained from the initial tuning stage, and set s to 0.6, determined by trial and error. For the main MCMC stage, we simulate R=64 errors (that are fixed throughout the Metropolis iterations) and conduct one million Metropolis iterations, where every 100th sample is recorded with the first half discarded as burn-in. Thus, we obtain 5,000 samples for parameter inference and counterfactual analyses. We have experimented with various numbers of iterations and sets of simulated errors. The results were not qualitatively different.

We run the estimation procedure on Google Cloud Platform using Matlab R2017a, Windows Server 2019 64 bit, and a graphics card NVIDIA Tesla V100 SXM2. The graphics card has 5120 CUDA (Compute Unified Device Architecture) cores. The graphics card executes our OpenCL kernel code to compute the simulated likelihood in single precision on these cores in parallel. The OpenCL kernel code execution is programmed to be controlled by our C++ code, which is called by our Matlab code when evaluating the likelihood.

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Table 1: U.S. Shopping Center Classification and Characteristics

Type of Shopping Center	Concept	Average Size (Sq. Ft.)	Typical GLA* Range (Sq. Ft.)	Typical Number of Tenants	Trade Area Size
Super-Regional Mall	Similar in concept to regional malls, but offering more variety and assortment.	1,255,382	800,000+	NA	5-25 miles
Regional Mall	General merchandise or fashion-oriented offerings. Typically, enclosed with inward-facing stores connected by a common walkway. Parking surrounds the outside perimeter.	589,659	400,000-800,000	40-80 stores	5-15 miles
Community Center ("Large Neighborhood Center")	General merchandise or convenience-oriented offerings. Wider range of apparel and other soft-goods offerings than neighborhood centers. The center is usually configured in a straight line as a strip, or may be laid out in an L or U shape, depending on the site and design.	197,509	125,000-400,000	15-40 stores	3-6 miles
Neighborhood Center	Convenience oriented.	71,827	30,000-125,000	5-20 stores	3 miles
Strip Mall/ Convenience	Attached row of stores or service outlets managed as a coherent retail entity, with on-site parking usually located in front of the stores. Open canopies may connect the store fronts, but a strip center does not have enclosed walkways linking the stores. A strip center may be configured in a straight line, or have an "L" or "U" shape. A convenience center is among the smallest of the centers, whose tenants provide a narrow mix of goods and personal services to a very limited trade area.	13,218	<30,000	NA	<1 mile

Source: The International Council of Shopping Centers, January 2017

* GLA: Gross leasable area

Table 2: Variable Summary Statistics

Variables		Mean	S.D.
Sears		0.491	0.500
Target		0.193	0.395
Other Discount		0.362	0.481
Dillard's		0.221	0.415
Macy's		0.467	0.499
Other Midscale		0.635	0.482
Nordstrom		0.116	0.321
Bloomingdale's		0.025	0.156
Other Upscale		0.074	0.263
Apple		0.140	0.348
Microsoft		0.070	0.256
Population		205,091	208,830
Age		40.577	3.604
Household Size		2.568	0.302
Household Income ($)		76,290	23,156
Site Size (square feet)		913,580	364,763
Open (1 if opened in 1991 or later)		0.285	0.452
Distance to Headquarters (km)	Sears	1,343	889
	Target	1,545	700
	Dillard's	1,386	768
	Macy's	1,296	1,032
	Nordstrom	2,891	1,016
	Bloomingdale's	1,701	1,352
	Apple	2,787	1,248
	Microsoft	2,879	1,011

N = 1,196

Table 3: Department Store Categorization

Type	Definition	Stores
Discount	With a focus on price rather than on service, discount department stores sell a variety of merchandise at a lower price than typical retail stores. Many discount stores can be categorized as big-box stores, which offer a wide selection of products and groceries.	Kmart, Sears, Target, and Walmart
Midscale	Midscale department stores offer a wide selection of both brand-name and non-brand-name merchandise, seeking to offer good value to their customers.	Dillard's, JCPenney, Kohl's, and Macy's
Upscale	Upscale department stores sell goods at above-average prices; their customers are more interested in exclusive designer brands and value customer service over low price.	Bloomingdale's, Neiman Marcus, Nordstrom, and Saks Fifth Avenue

Source: J.D. Power and Associates (2007); Levy & Weitz (2011)

Table 4: Location of New and Traditional Anchor Stores

	N	With Discount	With Midscale	With Upscale
All	1,196	950	936	190
Apple Only	92	54 (5.7%)	92 (9.8%)	49 (25.8%)
MS Only	8	3 (0.3%)	7 (0.7%)	5 (2.6%)
Apple & MS	76	36 (3.8%)	75 (8.0%)	64 (33.7%)
All Apple	168	90 (9.5%)	167 (17.8%)	113 (59.5%)
All MS	84	39 (4.1%)	82 (8.8%)	69 (36.3%)

Discount, Midscale, Upscale: At least one of the three stores in each type is present.

Table 5: Parameter Estimates—Profit Function (Market- and Firm-Specific Effects)

	Sears	Target	Other Disc	Dillard's	Macy's	Other Mid	Nordstrom	Bloomingdale's	Other Up	Apple	MS
Constant	0.612***	-0.709***	-0.228***	-1.004***	0.170**	0.546***	-1.832***	-3.345***	-2.041***	-1.896***	-3.390***
	(0.088)	(0.091)	(0.085)	(0.095)	(0.082)	(0.083)	(0.224)	(0.379)	(0.234)	(0.349)	(0.425)
Ln Population	-0.421***	-0.006	0.050	-0.108*	0.031	-0.518***	0.562***	0.832***	0.217**	0.188**	0.288**
	(0.054)	(0.051)	(0.045)	(0.061)	(0.053)	(0.048)	(0.083)	(0.179)	(0.095)	(0.088)	(0.144)
Age	0.021	0.028	0.036	-0.176***	0.203***	-0.101*	0.044	0.541***	0.281***	-0.033	-0.185
	(0.052)	(0.057)	(0.049)	(0.061)	(0.053)	(0.052)	(0.087)	(0.166)	(0.093)	(0.080)	(0.142)
Size HH	0.068	0.106*	0.101**	-0.226***	0.122**	0.034	-0.116	0.052	-0.021	-0.207***	-0.368***
	(0.052)	(0.056)	(0.048)	(0.069)	(0.057)	(0.048)	(0.071)	(0.117)	(0.088)	(0.076)	(0.114)
Ln Income	-0.117**	0.098*	-0.087*	-0.167***	0.108**	-0.245***	0.352***	0.344***	0.297***	0.445***	0.095
	(0.050)	(0.052)	(0.048)	(0.060)	(0.053)	(0.049)	(0.076)	(0.124)	(0.081)	(0.077)	(0.126)
Ln Site Size	0.727***	0.095*	-0.133**	0.429***	0.813***	0.477***	0.424***	0.241*	0.412***	0.680***	0.645***
	(0.062)	(0.056)	(0.052)	(0.058)	(0.059)	(0.052)	(0.091)	(0.129)	(0.094)	(0.119)	(0.176)
Open	-1.210***	0.551***	0.608***	-0.056	-1.084***	-0.444***	0.259*	-0.022	0.321**	0.078	-0.028
	(0.104)	(0.096)	(0.089)	(0.108)	(0.108)	(0.094)	(0.151)	(0.306)	(0.162)	(0.154)	(0.239)
Ln Distance to HQ	0.118**	0.031		-0.479***	0.130***		-0.262***	0.039		-0.081	-0.018
	(0.047)	(0.047)		(0.058)	(0.047)		(0.054)	(0.078)		(0.055)	(0.078)
Equilibrium Selection	-7.219										
	(5.386)										

Note: Standard errors are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Table 6: Parameter Estimates—Profit Function (Spillover Effects)

	To discount	To midscale	To upscale	To Apple	To MS
From discount	-0.202***	-0.050	-0.171	-0.174	-0.224
	(0.034)	(0.047)	(0.133)	(0.150)	(0.197)
From midscale	-0.066	0.100***	-0.107	0.218	0.301*
	(0.043)	(0.034)	(0.094)	(0.149)	(0.161)
From upscale	-0.385***	-0.247**	0.152*	0.201	0.504**
	(0.133)	(0.106)	(0.085)	(0.186)	(0.234)
From Apple	-0.349**	0.264	0.702***		1.354***
	(0.169)	(0.180)	(0.177)		(0.321)
From MS	-0.430**	-0.115	0.271	0.585	
	(0.216)	(0.134)	(0.198)	(0.394)	

Note: Standard errors are reported in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

Table 7: The Effect of Population and Income on a Firm's Entry Probability

		Site M	Site A	Site B
Population		151,578	166,736	151,578
Average Income		73,264	73,264	80,591
Entry Probability of	Sears	20.7%	19.4%	19.3%
	Target	34.6%	34.5%	35.6%
	Other discount	54.5%	54.8%	52.9%
	Dillard's	15.3%	15.1%	14.1%
	Macy's	18.6%	18.7%	19.6%
	Other midscale	54.5%	52.0%	51.2%
	Nordstrom	4.5%	5.1%	5.8%
	Bloomingdale's	0.1%	0.1%	0.1%
	Other upscale	3.7%	3.9%	4.7%
	Apple	4.7%	4.8%	6.0%
	MS	0.6%	0.7%	0.8%

Note: Site M has average values of population and income, as well as the average values of other variables in the data. The population of site A is ten-percent higher than that of site M (with the same average income as site M). Similarly, the average income of site B is ten-percent higher than that of site M (with the same population as site M). Other market characteristics in sites A and B are set to the mean values in the data.

Table 8: Predicted Entry Probability with the Entry of Technology Stores

Entry Probability	None	Apple	MS	Both
Sears	20.1%	11.7%	11.4%	5.5%
Target	36.1%	23.7%	21.7%	13.1%
Other discount	57.5%	42.4%	41.0%	27.7%
Dillard's	14.2%	21.1%	12.9%	17.5%
Macy's	17.6%	24.9%	15.8%	20.8%
Other midscale	52.3%	60.5%	48.5%	55.8%
Nordstrom	3.4%	15.3%	9.6%	23.6%
Bloomingdale's	0.0%	0.9%	0.4%	1.4%
Other upscale	2.7%	13.1%	8.5%	20.7%
Apple	0.0%	100.0%	14.3%	100.0%
MS	0.0%	6.0%	100.0%	100.0%

Note: The market characteristics for the simulation are set to the mean values in the data.

Figure 1: The Number of Apple Stores in the United States by Year

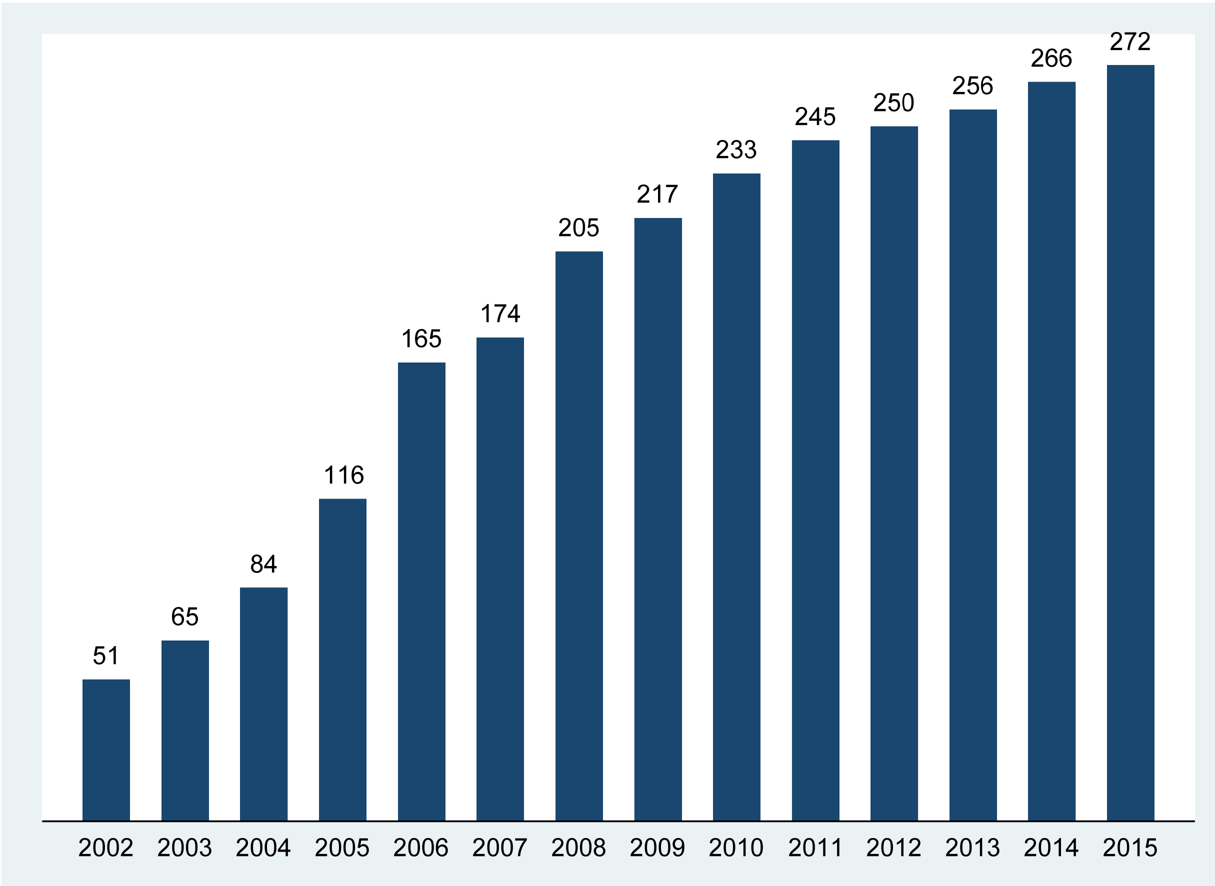
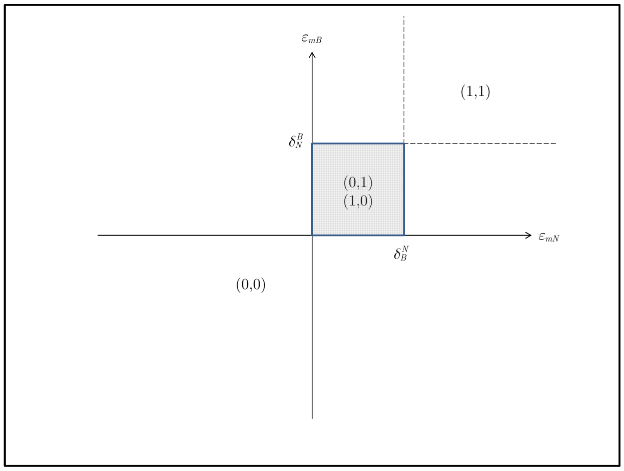


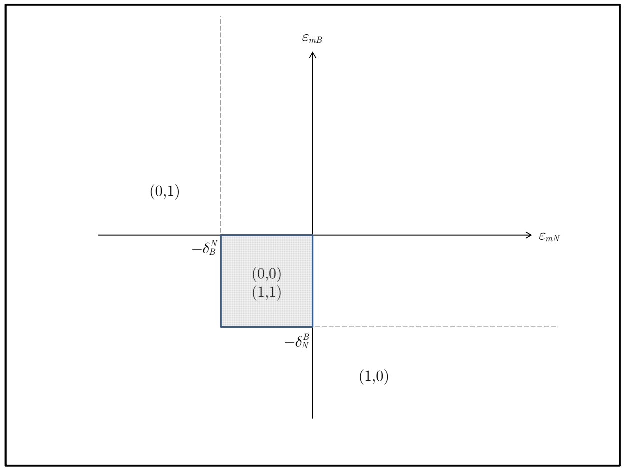
Figure 2: An Example of a Mall Floor Plan

Source: South Coast Plaza, Costa Mesa, CA 92626, http://www.southcoastplaza.com/directory/.

Figure 3: Multiple Equilibria—Illustrative Example

a) Competitive Entry (Negative Spillover) **b) Complimentary Entry (Positive Spillover)**

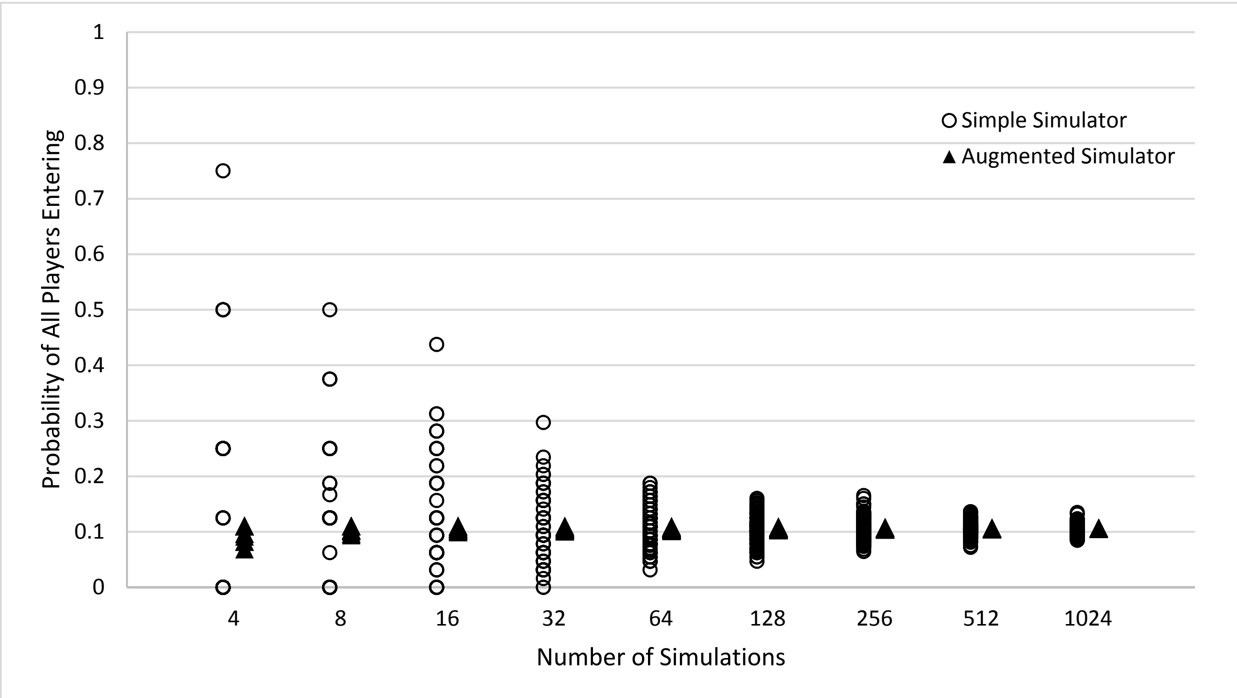




Profits of Apple in market m are $\pi_{mA} = -\delta_M^A a_{mM} + \varepsilon_{mA}$, and those of Microsoft are $\pi_{mM} = -\delta_A^M a_{mA} + \varepsilon_{mM}$ $(\delta > 0)$.

Profits of Apple in market m are $\pi_{mA} = \delta_M^A a_{mM} + \varepsilon_{mA}$, and those of Microsoft are $\pi_{mM} = \delta_A^M a_{mA} + \varepsilon_{mM}$ $(\delta > 0)$.

Figure 4: Simulator Comparison (Simple vs. Augmented)

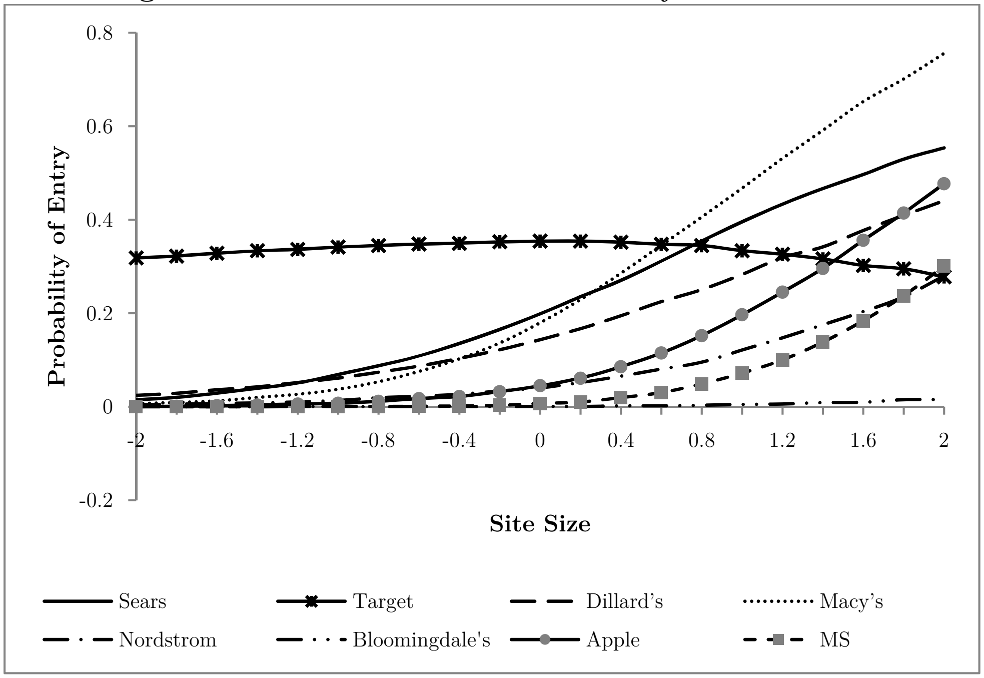


Standard Deviation

# of Simulations	4	8	16	32	64	128	256	512	1024
Simple Simulator	0.1547	0.1074	0.0856	0.0540	0.0370	0.0253	0.0201	0.0138	0.0097
Augmented Simulator	0.0084	0.0045	0.0030	0.0022	0.0018	0.0013	0.0009	0.0006	0.0004

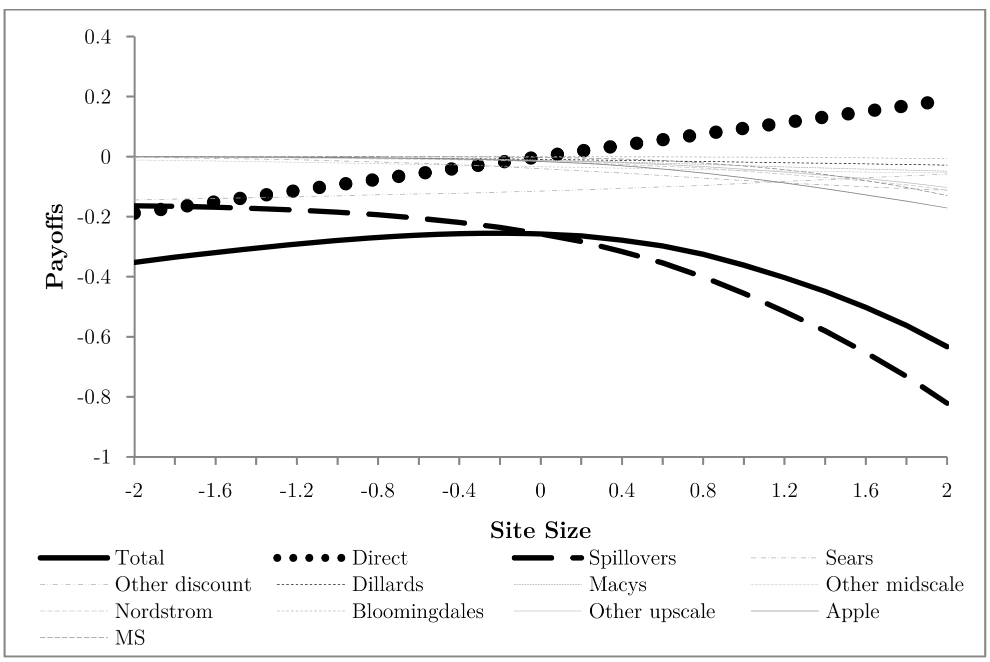
Note: the total number of firms is set to 11, with each firm's profit function set to $\pi_{mj} = \sum_{j' \neq j}^{J} \delta_{j'}^{j} a_{mj'} + \varepsilon_{mj}$. The strategic parameter $\delta_{j'}^{j}$ is set to $1/J$. The probability that all players enter is computed 100 times, with each point (the circle and triangle points for the simple and augmented simulators, respectively) in the Figure representing a computed probability.

Figure 5: Relation between Firm Entry and Site Size



Note: Site Size is standardized value of log (site size). That is, the x-axis represents standard deviations from the mean.

Figure 6: Main Effect vs. Spillover Effect of Site Size (Target)



Note: The thick, upward-sloping dotted line represents the main effect, and the thick, downward-sloping dashed line represents the aggregate spillover effect. The thick solid line is the sum of the main and the aggregate spillover effects. The eight thin lines are spillover effects from other firms. Site size is the standardized value of log (site size). That is, the x-axis represents standard deviations from the mean.