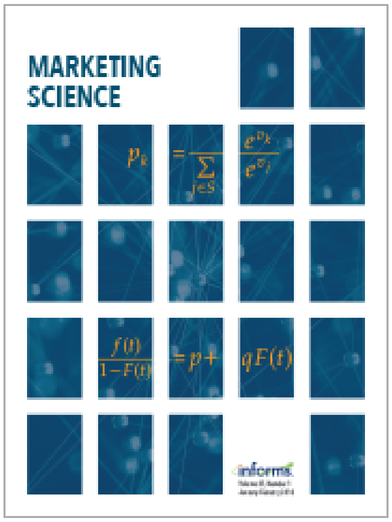

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Inferring the Economics of Store Density from Closures: The Starbucks Case

Ali Umut Guler[a]

[a] Koç University, 34450 Sariyer Istanbul, Turkey
Contact: umutguler@ku.edu.tr, http://orcid.org/0000-0003-0093-7568 (AUG)

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Abstract. This paper proposes a method that makes use of firms' mass store closures to measure the store network effects of cannibalization and density economies. I calculate each store's contribution to chain-level profits via one-store perturbations on the set of retained stores, and map these onto the firm's closure choices. To separate the demand- and supply-side store network effects, I exploit the fact that the business-stealing effect intensifies with local network density, whereas the supply-side disadvantage prevails at sparse regions of the network. I apply the method to study the Starbucks chain. The average rate of cannibalization imposed by a neighbor outlet is 1.2% within one mile and 0.4% within one to three miles. For remote outlets, operation costs increase by 0.3% of revenues for each mile of distance from the network. Counterfactual analyses suggest that income level is a more important determinant of demand than population count at low levels of store penetration, whereas high-population regions can sustain denser store networks because of the softening of the cannibalization effect.

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1. Introduction

Store location is generally considered to be one of the most important determinants of profitability for retail businesses. For chains, which account for an increasingly large part of the U.S. retail sector,[1] store location decisions essentially become choices of store density over a given area, with confounding consequences. A dense store network helps the firm to capture more business. Additionally, the firm benefits from scale economies in costs related to distribution and management when its outlets are located close together (density economies). At the same time, each additional store serving the same area competes for business with the firm's existing outlets. This may result in considerable cannibalization, given that stores belonging to the same chain are not differentiated much, except spatially.

Two stylized cases demonstrate how these factors play out in chains' location choices.[2] At one extreme, the firm could choose to open a new store at a remote location far away from its existing outlets. In this case, cannibalization would not be a concern, and all business generated at the new location would be incremental. On the other hand, it would be costlier for the firm to manage and supply to this store because of its remote location. At the other extreme, the new store could be located at an already dense region of the network. In this case, the firm would incur minimal additional costs to cater to the new outlet with its existing infrastructure. However, the question then becomes how much incremental business the new store would generate net of cannibalization. Accordingly, estimating the profitability at the new location would require figuring out (i) how demand would respond to the firm's increasing store density, that is, how much additional demand the firm would capture through operating several outlets rather than a single outlet in a given area; (ii) how much incremental business the new location would generate (net of cannibalization); and (iii) how operation costs would increase in the incremental distance the firm would need to cover to supply to the outlet (density economies). This study uses mass store closures as an empirical experiment to quantify these effects.

The straightforward approach to measuring the extent of cannibalization and density economies within a store network would involve analyzing the change in outlet-level revenues and costs as the store network evolves. However, such data, especially pertaining to costs, are rarely available to the researcher at a level of richness that would reflect the impact of variations in network configuration. Besides, standard accounting data may not give a good indication of the economic value, that is, the marginal cost and benefit of operating a given location. The solution to these limitations is the use of a revealed preference argument that makes use of firms' observed store entry choices to infer about determinants of profitability (Bresnahan and Reiss 1990, 1991; Berry 1992). This discrete choice approach has been widely used in empirical studies to model the entry decisions of independently profit-maximizing outlets, with extensions that account for vertical (Mazzeo 2002) and horizontal (Seim 2006, Zhu and Singh 2009, Orhun 2013) product differentiation and agglomeration effects (Vitorino 2012, Datta and Sudhir 2011).

In the context of a retail chain, entry decisions regarding individual outlets are linked through the network effects I aim to measure, so the network entry problem must be considered as a whole. Ideally, this would involve analyzing which specific network configuration the firm chooses to operate, given the potential locations that could be considered. However, it is difficult to set up and estimate this model: First, with n potential locations, there are 2^n different network configurations the firm could choose from. For instance, even with 20 potential locations, that would create more than a million different network options. Because of this combinatorial complexity, the discrete choice approach in its standard form becomes intractable. Second, while the chosen locations are observed in the form of active outlets, data on the nonchosen locations in the firm's consideration set are not readily available.

The method proposed in this paper circumvents these challenges via a perturbation approach that exploits the firm's simultaneous store elimination choices as revealed in a mass closure setting.[3] Given that the firm holds on to the profit-maximizing subset of locations, I posit that any one-store perturbation on this retained store set that involves removing a kept store or adding back a closing store must be profit reducing. The difference in the total chain profits resulting from these perturbations gives the incremental profits related to operating each location, and these can be estimated based on the firm's closure choices.

The perturbation method, which transforms the network choice problem to the choice of keeping versus closing an outlet and thereby circumventing the inherent combinatorial complexity, parallels the moment inequality–based analyses (Pakes et al. 2015) on retail networks in the discount retail (Holmes 2011, Ellickson et al. 2013) and automotive industries (Albuquerque and Bronnenberg 2012). The difference is that, under the moment inequality approach, the profit-reducing counterfactual actions that are used to bound profits have to be artificially generated, whereas here, the difference equation obtained via perturbation has a structural interpretation that maps directly onto the firm's observed decisions and can be estimated within a simple choice probability framework.

Existing store network models identify the nonchosen locations in the firm's consideration set based on the absence of (further) entry, either within an arbitrarily specified market (Jia 2008, Albuquerque and Bronnenberg 2012, Nishida 2014, Ellickson et al. 2013) or for a given location at a specific time (Holmes 2011). A caveat of this indirect approach is that the absence of entry may not necessarily be reflecting the firm's choice, when, for instance, outside constraints such as zoning restrictions or the unavailability of suitable retail space inhibit entry in an otherwise profitable region.[4] Potential correlations between these unobserved constraints and profitability factors could then lead to the misidentification of model variables (Datta and Sudhir 2012). The approach I take rules out this issue by making use of ex post data relating to closures, where the firm's location preferences are more conclusively revealed.

The model formulation aims to capture the specifics of the quick service business, which involves the sale of immediate consumption food and drink products. The majority of the largest U.S. retailers in terms of store count are quick service chains (Schulz 2015), suggesting that in this industry, the economics of store density take on a different character compared to the big-box retail format studied in previous network entry models (Jia 2008, Holmes 2011, Ellickson et al. 2013). Specifically, because of high operating leverage and the small-ticket nature of the transactions, the profitability of these businesses is highly dependent on customer traffic.[5] At the same time, purchases are discretionary and often unplanned, with a wide range of potential substitutes for any particular product. With demand thus tending to be spontaneous and elusive, store density plays a key role in capturing customer traffic.

This type of demand behavior may not accord well with the usual demand formulation in spatial models, where customers are assumed to make a premeditated outlet choice among nearby options, factoring in the disutility from travel.[6] Instead, I adopt a less stylized formulation, taking the firm's local store density to be a spatially differentiated quality attribute increasing the customer's visit likelihood. The demand model derives the visit probability of a given customer as a function of the local number of outlets and a reduced-form specification of the outside utility. Chain-level profits are defined to be the total number of customer visits generated by the network multiplied by a uniform marginal profit per visit, net of any fixed costs.

On the supply side, the model captures density economies in an inverse manner, by quantifying the disadvantage to the remoteness of a location within the network. The measure of remoteness is the store's distance from its closest network neighbor. The larger this distance, the costlier it is for the firm to manage and supply to this store. This is consistent with a "traveling salesman"–type distribution system, where two closest neighbor outlets are served consecutively within one route. In this respect, the approach differs from the previous literature that documents density economies without specifying an underlying mechanism. An exception is the work of Holmes (2011), who, in analyzing the Walmart network, considers a setup where each delivery from the distribution center targets a single store.

The model jointly estimates demand and supply parameters from closure data. To separate the demand- and supply-side network effects, I differentiate between nonremote stores, whose trade areas overlap with at least one other outlet in the network and hence could be impacted by cannibalization, and remote stores, for which the cannibalization effect is irrelevant but there would be a supply-side disadvantage due to the absence of density economies.

I apply the method to analyze the Starbucks network, based on the firm's mass closure of its 800 unprofitable outlets (7.2% of the U.S. store portfolio), announced around the recession year of 2008. The results quantify how customers' probability of visiting a Starbucks store increases with the number of local outlets and decreases with population density. While initial store additions make the average customer as much as 60% more likely to visit the chain, the effect diminishes to less than 10% for more than 10 stores within five miles. There is a positive, significant effect of income and wealth levels on demand.

In terms of store network effects, the rate of cannibalization imposed on the average store is estimated to be 4.8%. Because of a nearby outlet, the store's incremental business decreases by 1.2% and 0.4%, respectively, within one mile and one to three miles. On the supply side, the firm incurs an additional fixed cost equivalent to 0.30% of the average store's revenues, for each mile a store is farther away from its closest neighbor.

In a model application, I estimate that a 10% decline in housing wealth reduces the firm's demand by 3.8%. This estimate agrees with the findings of Mian and Sufi (2014) on the effect of wealth drops on nontradable sector employment during the Great Recession. Another application studies the response of demand to changes in store density under varying levels of income and population. I find that compared to population size, income level is a more important determinant of demand, especially at low levels of store penetration. On the other hand, population density softens the cannibalization effect, and additional stores in a high-income region may not generate as much in incremental sales if population density is low. Together, these insights indicate that a firm that benchmarks on the actual (accounting) rather than the incremental (economic) sales levels of the existing outlets could make suboptimal store entry choices. In a third application, I show that the model estimates can be used to predict the revenue implications of a hypothetical store expansion policy.

The proposed method of using mass closure data to study a chain's network entry problem could have practical use in cases where data availability is a concern. For example, an industry observer with no access to the firm's proprietary financial data could employ the method to assess the profit implications of closures and new store openings. Insights derived from the analysis of an incumbent chain could be of use to entrant firms in planning their network expansions. The Starbucks case examined provides a demonstration of such applications. The empirical analysis also contributes to the literature on the Great Recession, as I use recession-induced housing wealth shifts to identify wealth effects on consumption behavior.

The plan of this paper is as follows: Section 2 describes the model and its estimation based on closure data. Section 3 presents background information on Starbucks and introduces the data used in the analysis. Section 4 discusses the results and model applications. Section 5 includes a critical overview of the study and concluding remarks.

2. Model and Estimation

2.1. Model

Let J denote the set of stores the firm operates, where $j \in J$ is a store in the network. Let $i \in I(J)$ denote a customer unit within the firm's trading area, given the store set J. Customers make a choice as to whether to visit the chain.

I start by specifying the outside utility. The set of substitutes for a quick service product such as a fast food meal or ready-made drink may be varied and hence difficult to pin down. Accordingly, I do not explicitly account for competition, and instead, following Holmes (2011), measure the strength of the outside option indirectly through population density. The assumption here is that the firm would face stronger competition in more densely populated areas.[7] In the empirical application, I allow factors such as the customer's age group, income, and wealth level and the size of wealth shifts induced by the 2008 recession to affect demand. I write the outside utility as

$$u_i^o = \beta_0 + \beta_{\text{popd}} \ln(popd_i) + \beta_{\text{popdsq}}(\ln(popd_i))^2 + x_i \beta^{\text{demog}} + \varepsilon_0, \tag{1}$$

where $popd_i$ denotes the local population density around customer i; x_i denotes a vector of demographic variables; β_0 represents the gross mean utility from the outside option (net of the gross mean utility from visiting the chain, which cannot be identified separately); and ε_0 denotes the logit error term.

Having more outlets in the vicinity would increase the convenience of a visit and might also enhance the chain brand, thereby increasing its value to the customer. I assume the firm's local store density to be a quality attribute capturing these effects. The utility customer i derives from visiting the chain is specified as

$$u_i(J) = f(\ln(n_{ib}(J)+1)) + \varepsilon_i, \tag{2}$$

where $n_{ib}(J)$ is the number of outlets the firm operates within a distance of b from customer i's location. Thus, the model allows for full spatial differentiation in the store density variable across the customer units. I augment $n_{ib}(J)$ by one to avoid the ln(0) incidences. The empirical application presents results with several different specifications of $f(\cdot)$ that allow for quadratic effects, multiple concentric distance bands, and interaction terms of the store density measure with outside utility variables such as population density and income. With ε_i denoting the logit error term, the probability that on a given choice occasion customer i chooses to visit the chain takes the standard logit form

$$s_i(J) = \frac{\exp(\bar{u}_i(J))}{\exp(\bar{u}_i^o(J)) + \exp(\bar{u}_i(J))}, \tag{3}$$

where $\bar{u}_i$ and $\bar{u}_i^o$ denote the deterministic parts of u_i and u_i^o, respectively.

The model defines the firm's variable profits to be the total volume of customer visits generated throughout the chain multiplied by a uniform marginal profit per visit. I denote by $FC(J)$ the total fixed costs due to operating the set of stores J. The firm's profit function is then given by

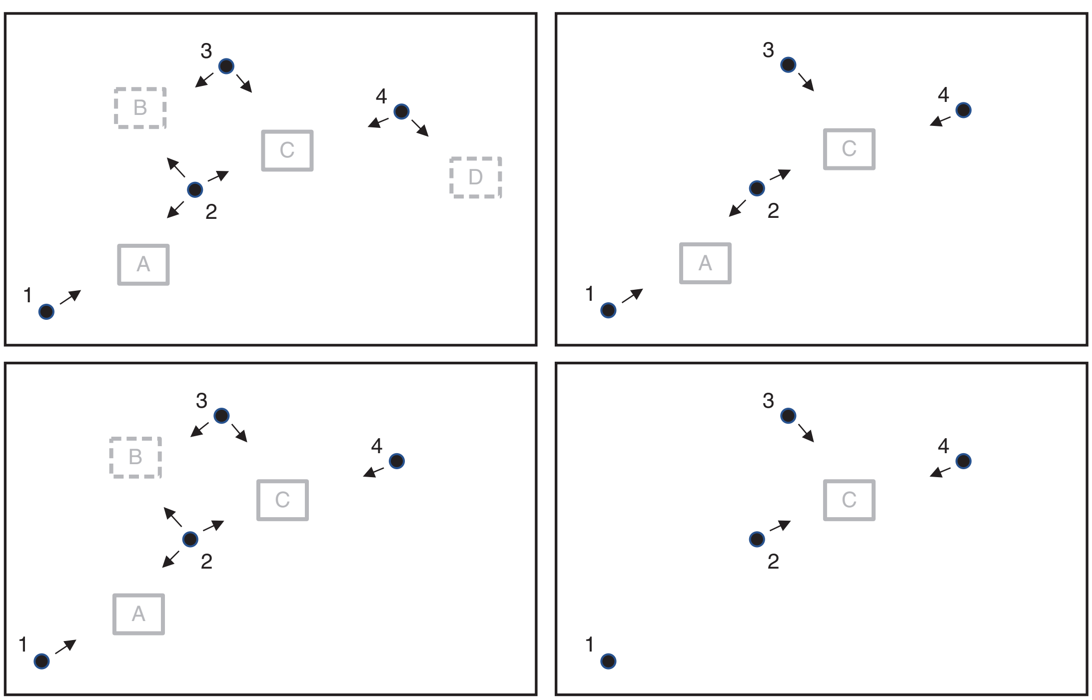
$$\pi(J) = m \cdot \sum_{\tilde{I}(J)} (pop_i \cdot s_i(J)) - FC(J). \tag{4}$$

In this expression, $pop_i \cdot s_i(J)$ gives the quantity of visits by customer unit i, where pop_i denotes the size (population) of i, and $s_i(J)$ is the visit probability as derived in the demand model. Total customer volume for the chain is obtained via summing over all customer units $i \in I(J)$, where $\tilde{I}(J)$ represents the cardinality of the set $I(J)$. The uniform marginal profit per customer visit is denoted by m. As is common for structural models estimated without quantity data (e.g., Gowrisankaran and Krainer 2011), the frequency of the choice occasion determines the time interval for the profit function. For instance, if the visit choice were assumed to take place weekly, the above expression would give the chain's weekly profits.

2.2. Inferring Stores' Incremental Profits from Mass Closure Data

2.2.1. Demonstration of the Method. This section demonstrates with a stylized example how closure data are used by the method to make inferences about a store's incremental contribution to total firm profits (Figure 1). In this example, ABCD is the firm's

Figure 1. (Color online) Demonstration of the Method



Notes. The squares (denoted by letters) indicate the stores, and the circles (denoted by numbers) indicate the customer units. Arrows denote the number of local stores for a given customer. From the top left to the bottom right, the panels demonstrate (i) the set of initial stores, (ii) the set of retained stores, (iii) a perturbation involving the readdition of a closing store (store B), and (iv) a perturbation involving the removal of a retained store (store A).

initial store set (top left panel in Figure 1). The firm's objective is to maximize aggregate profits. The firm announces B and D for closure and retains the subset AC. I assume that, of all feasible subsets of the initial store set ABCD (each of which corresponds to a different network structure that the firm could have alternatively retained), the subset the firm chooses to retain (AC) is the profit-maximizing (optimal) subset. By optimality, any network that is obtained by either adding back any one of the closing stores (B or D) to AC or removing any one of the remaining stores (A or C) must yield lower profits. These one-store perturbations on AC, the set of retained stores, give each location's contribution to chain-level profits as a difference term that is estimated based on the store's closure status.

For example, in the case of a closing store, say, B, the perturbation involves its readdition to the retained set. The counterfactual network thus obtained is ABC (bottom left panel in Figure 1), and B's incremental profit is the difference in chain-level profits when the active store set is ABC rather than AC. Likewise, I get at the profit contribution of a retained location, say, A, by comparing the firm's profits under the retained set AC versus the counterfactual set formed by A's removal, the singleton set C (bottom right panel in Figure 1). Table 1 summarizes the inferences generated through these perturbations.

2.2.2. Advantages of Closure Data. Note the difference between the proposed approach and the moment inequality method: To bound profits, the moment inequality method compares the firm's observed actions, which are presumed optimal, to actions not observed. It is assumed that these unobserved actions were feasible, considered by the firm, but foregone, as they were suboptimal. In the context of entry models, suboptimal actions correspond to entries that have not taken place. Yet, equating the absence of entry with that entry being suboptimal may be problematic. It may be that the firm did not consider that particular location at all, or ex ante miscalculated its profitability. Especially, the feasibility assumption may be violated, if outside constraints such as availability of suitable rental space or zoning restrictions limit entry in an otherwise profitable location. Since such limitations likely indicate high demand potential, not accounting for them can lead to biased estimates of the profit parameters. The main advantage of observing closure choices is that they provide data on exact locations that actually proved unprofitable to operate. In this regard, the closing locations are, not by assumption but literally, the firm's foregone options.

Entry models generally define the firm's actions based on a market demarcation, and this has some potential shortcomings. First, because the structure of available data (usually census data) dictates the demarcation, resulting markets may do a poor job of matching customer units with their relevant store sets. This issue becomes especially prevalent in metropolitan areas, which are usually left out of the analysis, even though they are highly important from an economic perspective, or studied as a whole, without partitioning. A second problem is that a market-level analysis, especially when markets span large areas, lacks precision and does not allow for a sensitive measurement of the spatial parameters that characterize the store network effects I aim to measure. Closure data bypass the need for a market demarcation, conditioning the analysis on the exact locations that the firm experimented with.

2.2.3. Accounting for the Demand- and Supply-Side Network Interdependencies. Demand-side interdependencies across the stores are automatically accounted for by the demand model, as stores with overlapping trade areas jointly determine the chain's store density around the customer units they share. In that respect, in the above example, store B is related to store C through customer 3, and to both C and A through customer 2. The local store density shifts generated by the perturbations account for these dependencies (Table 2).

For example, the perturbation that readds B to the set of active stores reflects the net increase in total demand when the chain's outlet density around customer 2 is three (rather than two) and that around customer 3 is two (rather than one). Similarly, a perturbation that excludes a retained store from the network informs the model about that location's contribution to the chain's

Table 1. Summary of Inferences

Store	Status	Perturbation	Counterfactual set	Inference
A	Kept	Removal	C	Profits (AC) − Profits (C) > 0
B	Closed	Readdition	ABC	Profits (ABC) − Profits (AC) < 0
C	Kept	Removal	A	Profits (AC) − Profits (A) > 0
D	Closed	Readdition	ACD	Profits (ACD) − Profits (AC) > 0

Table 2. Store Density Changes at the Customer-Level

Perturbation	Customer 1	Customer 2	Customer 3	Customer 4
A's removal	$1 \rightarrow 0$	$2 \rightarrow 1$	1	1
B's readdition	1	$2 \rightarrow 3$	$1 \rightarrow 2$	1
C's removal	1	$2 \rightarrow 1$	$1 \rightarrow 0$	$1 \rightarrow 0$
D's readdition	1	2	1	$1 \rightarrow 2$

aggregate demand, net of the demand that would have already been captured by any neighbor outlets.

I account for supply-side interdependencies assuming a traveling salesman-type supply system. In its regular form, the traveling salesman problem involves solving for the shortest route that covers the full set of nodes on a distribution route. The model proposed in this paper builds on a less stringent assumption, requiring only that two neighbor stores are served consecutively within one route, such that the marginal cost of catering to a given store depends on the distance to the closest neighbor in the network. I use this distance metric as an inverse measure for the density economies enjoyed at the location. For a farther location, the firm has to cover a larger incremental distance and bear a larger supply cost. The model quantifies this relationship, thereby capturing a managerially relevant fundamental economic parameter, the per-mile cost of placing an outlet farther apart in the network. In this respect, it differs from the previous literature that does not measure density economies directly but provides demonstrations of their effects, such as how firms' entry patterns would have changed in their absence (Jia 2008, Ellickson et al. 2013). The closest to the current approach is that of Holmes (2011), which studies the Walmart chain. In that study, density economies are channeled through proximity to distribution centers, with each supply truck that takes off from the center serving a single location. While this assumption may be appropriate for high-volume discount retailers, in most other retail settings, where shipments involve smaller volumes, delivery trucks usually cover multiple stores per route.[8] The measure of density economies I consider conforms with this latter type of setup. It also captures potential density economies in costs that do not necessarily channel through distribution centers, such as those arising from direct deliveries by suppliers or visits related to management.

2.2.4. Separating the Demand- and Supply-Side Network Interdependencies. To separate the two types of store network effects, I differentiate between nonremote and remote locations in the network. I define a location to be remote if its trading area does not overlap with that of any other outlet. Accordingly, given a trading area radius of b miles, outlets that are at least $2b$ miles away from their closest network neighbor are denoted as remote. By construction, the cannibalization effect will be null for these stores. The model infers the impact of density economies from the extent to which such a remote outlet is more likely to close the farther away it is from its nearest neighbor, after controlling for demand.

Conversely, for a nonremote store in whose neighborhood (within a distance of $2b$) there exists at least one active outlet, I posit that the marginal supply cost factoring into the closure decision will be negligible. This is due to the fact that even with just one nearby store remaining, the firm would have to cover the area, even if the focal store were to close. As per the traveling-salesman setup, on the margin, this is independent of how many other stores there are in the vicinity.[9] The model measures the cannibalization effect from the extent to which the closure probability of such a nonremote store increases with local network density. Section 2.2.5 describes how the cannibalization effect channels through the chain-level demand model.

2.2.5. Store-Level Incremental Profit Function. In this section, I formally introduce the notation to implement the method. Let $\bar{J} \subset J$ denote the set of outlets the firm holds on to, following the store eliminations. Given that $\bar{J}$ is the profit-maximizing subset, the firm's profits must be larger when any store $j \in \bar{J}$ is in operation than when it is not; that is, for any remaining store, it must hold that $\pi(\bar{J}) > \pi(\bar{J}\backslash\{j\})$. Likewise, for any closing store $j \in J\backslash\bar{J}$, it must hold that $\pi(\bar{J} \cup \{j\}) < \pi(\bar{J})$. I define J_j and J'_j such that

$$J_j \equiv \begin{cases} \bar{J} & \textit{if } j \in \bar{J}, \\ \bar{J} \cup \{j\} & \textit{if } j \in J\backslash\bar{J}, \end{cases} \quad \text{and} \quad J'_j \equiv \begin{cases} \bar{J}\backslash\{j\} & \textit{if } j \in \bar{J}, \\ \bar{J} & \textit{if } j \in J\backslash\bar{J}. \end{cases}$$

In words, J_j denotes the set of stores in the scenario where store j is to remain. The set $\bar{J} \cup \{j\}$ is a perturbed set, which moves a closing store $j \in J\backslash\bar{J}$ to the set of remaining stores. Likewise, J'_j denotes the set of stores in the scenario that store j is to close. For any remaining store $j \in \bar{J}$, $\bar{J}\backslash\{j\}$ denotes the perturbed set involving store j's exclusion from the set of remaining stores.

Let $s_{ij} \equiv s_i(J_j)$ and $s'_{ij} \equiv s_i(J'_j)$ denote, respectively, customer i's visit probability to the chain under the store configurations J_j and J'_j. Likewise, let $FC_j \equiv FC(J_j)$ and $FC'_j \equiv FC(J'_j)$ denote, respectively, the total fixed costs the firm incurs when store j is in operation and when it is not. Total firm profits are thus written as

$$\pi_j \equiv \pi(J_j) = m \cdot \sum_{\bar{I}(J_j)} pop_i s_{ij} - FC_j \tag{5}$$

in the case that store j is to remain, and

$$\pi'_j \equiv \pi(J'_j) = m \cdot \sum_{\bar{I}(J'_j)} pop_i s'_{ij} - FC'_j \tag{6}$$

in the case that store j is to close. Accordingly, $\pi_j - \pi'_j$ gives the incremental profits from having store j active, which I rewrite in the following manner:

$$\pi_j - \pi'_j = m\left(\sum_{\bar{I}(J_j)} pop_i \cdot s_{ij} - \sum_{\bar{I}(J'_j)} pop_i \cdot s'_{ij}\right) - (FC_j - FC'_j). \tag{7}$$

Here, $\sum_{\bar{I}(J_j)} pop_i \cdot s_{ij} - \sum_{\bar{I}(J_j')} pop_i \cdot s_{ij}'$ gives the incremental customer traffic captured thanks to store j. The magnitude of this contribution will vary depending on the chain's density in j's neighborhood: At a dense region of the network, j's presence will make a smaller contribution to chain-level sales such that if it were eliminated, a large portion of the lost business could be recaptured by the nearby outlets. The differencing thus allows the model to characterize, in terms of chain-level demand, the cannibalization imposed by the network on j's location. As the model does not require a market demarcation, it accounts for spatially varying levels of cannibalization contiguously across the chain.

The second component in the incremental profits equation, $FC_j - FC_j'$, is the incremental fixed costs of keeping store j active. These fixed costs would include expenses due to utilities, lease, and labor, and also fixed cost items such as delivery and management costs, whose magnitude would vary depending on the relative position of the outlet within the network, and therefore could be subject to density economies. I assume the marginal cost associated with this latter type of expense to be null in the case where the outlet has a network neighbor within a distance of $2b$. Farther than $2b$, the supply costs increase linearly with the marginal distance the firm needs to cover to serve the outlet.

Therefore,

$$FC_j - FC_j' = \alpha_{DE} \cdot rd_j \cdot dist_j + \overline{FC}_j + \mu(j) + \vartheta_j, \quad (8)$$

with $dist_j$ denoting outlet j's distance from its nearest neighbor within the retained store set $\bar{J}$, and rd_j the *remote store* dummy variable that is equal to 1 if $dist_j$ is larger than $2b$ and 0 otherwise. Interacting the distance variable with this dummy is equivalent to truncating it such that the incremental supply cost for any nonremote store is assumed null. To control for other fixed cost items, I introduce the term

$$\overline{FC}_j = \exp(\alpha_0 + \alpha_w \cdot wage_{co} + \alpha_{\text{rent}} rent_{co}), \quad (9)$$

which includes the average wage ($wage_{co}$) and the median residential rent ($rent_{co}$) levels in j's county to proxy for the store's personnel and rent expenses. Exponentiation forces $\overline{FC}_j$ to have a negative effect on profits. Additionally, I allow two normal, independent and identically distributed (i.i.d.) error terms:[10] $\mu(j)$, denoting the city-level random effect, and ϑ_j, denoting the store-specific error term.

2.3. Identification

Following the general approach of entry models, I separate variable profits from fixed costs by the assumption that only the former is a function of market size, which in the model corresponds to the total population of customer units within the store's trade area. The model allows for full spatial differentiation such that per-capita demand can take on different values for any customer unit, its population-weighted sum across all customer units giving the chain's aggregate demand. I assume a uniform marginal profit per transaction and do not differentiate between the cost and revenue portions of the firm's variable profits. This simplification centers the model on customer traffic, a key performance indicator for the retail sector examined.

Among the demand parameters, customers' response to store density is identified from differences in the number of local stores for the customer pools of closing versus nonclosing stores: The more stores a customer has in her vicinity, the lower any one store's impact on the customer's visit probability; the larger the proportion of such customers in the store's trade area, the lower that store's contribution to the chain's total sales, and hence, because of cannibalization, the higher its probability of closure. The effects of demographic variables are identified from how these variables shift customers' store density response and generate variation in the closure outcomes across regions of similar network structure.[11] With the full range of local store densities from zero to $n_{\max}$ observed in nonremote regions (where the supply-side disadvantage is excluded), I can fully trace customers' store density response curve based on data coming from these regions. Table 3 shows that this is the case in the empirical example in this paper.

The model measures the supply-side disadvantage to remote locations, after controlling for their demand, from how their closure probability increases with the

Table 3. Summary of Perturbations

Number of local stores (retained)	Perturbations: Removing a retained store	Readding a closed store	Total
	Nonremote stores		
0	0	1,066	1,066
1	7,918	2,670	10,588
2–5	92,205	15,850	108,055
6–10	138,337	12,630	150,967
11–20	234,164	19,643	253,807
21–40	240,219	14,665	254,884
41–60	117,817	7,123	124,940
61–80	66,154	3,314	69,468
81–100	46,984	3,228	50,212
101–150	65,288	4,280	69,568
>150	163,438	10,029	173,467
	Remote stores		
0	0	852	852
1	4,102	108	4,210

distance to the closest neighbor outlet. Therefore, identification of the density economies depends on the extent to which the demand side is correctly captured by the model. Section 5 includes a further discussion of this issue.

2.4. Estimation

To estimate Equation (7), I employ simulated maximum likelihood, numerically integrating over the city-level random effect $\mu(j)$. The set of parameters to be estimated is $\theta = \{\beta, \alpha, m, \sigma\}$, with β and α, respectively, denoting the set of demand- and supply-side parameters, m denoting the marginal profit per visit, and σ denoting the standard deviation of the normally distributed city-level random effect $\mu(j) \sim N(0, \sigma^2)$. I assume the store-specific error term ϑ_j to be standard normally distributed.

The term y_j denotes the "keep or close" decision the firm has made regarding store j, with $y_j = 1$ if $j \in \bar{J}$ and $y_j = 0$ if $j \in J\backslash\bar{J}$. For any remaining store, incremental profits must be positive; that is, $\pi_j - \pi'_j > 0$ for any $j \in \bar{J}$. By contrast, for any closing store, it must be that the incremental profits would have been negative had it been retained, that is, $\pi_j - \pi'_j < 0$ for $j \in J\backslash\bar{J}$. The probability of observing the outcome y_j is therefore given by the following probit expression:

$$P(y_j) = P_j = y_j\Phi(\bar{\pi}_j) + (1 - y_j)(1 - \Phi(\bar{\pi}_j)), \tag{10}$$

where $\bar{\pi}_j$ denotes the deterministic portion of π_j, and $\Phi(\cdot)$ is the standard cumulative normal distribution.

I define $P_c = \prod_{J_c} P_j$ to be the probability of observing the set of outcomes $\{y_j^1, y_j^2, \ldots, y_j^C\}$ for the set of stores $J_c \equiv \{j^1, j^2, \ldots, j^C\}$, which is the set of all stores located in city c, with $\mu(j) = \mu_c$ for all $j \in J_c$. The likelihood function thus takes the form

$$L(y, X, \mu; \theta) = \prod_{c=1}^{C} P_c, \tag{11}$$

with y denoting the vector of firm's keep or close decisions regarding all stores j, and X denoting the set of explanatory variables in the model. The unconditional likelihood is obtained by integrating the P_c terms over the distribution of μ_c, where $\phi(\mu_c)$ is the normal density with zero mean and variance σ^2

$$L(y, X; \theta) = \prod_{c=1}^{C} \int P_c \phi(\mu_c)\, d\mu_c. \tag{12}$$

I solve the integral in Equation (12) via simulation, by averaging over a vector of R ($R = 100$) P_c^R terms obtained using a vector of R draws from the distribution of μ_c

$$\int P_c \phi(\mu_c)\, d\mu_c = \frac{1}{R} \sum_{r=1}^{R} P_c^R. \tag{13}$$

Estimation of θ therefore entails maximizing the simulated log-likelihood function

$$LL(y, X; \theta) = \sum_{c=1}^{C} \ln\left[\frac{1}{R} \sum_{r=1}^{R} P_c^R\right]. \tag{14}$$

3. Empirical Setting and Data

3.1. Background on Starbucks and the Starbucks Store Closures

Starting as a single store in 1971, Starbucks has been one of the fastest-growing retail chains of the past four decades, expanding to more than 11,000 outlets in the United States. The company holds a dominant position in the specialty coffeehouse market, with no obvious nationwide rivals. Competition is dispersed across regional coffee chains, independent coffee shops, and, to a lesser extent, food chains that sell beverages, such as Dunkin Donuts, McDonalds, etc. Two-thirds of the U.S. Starbucks stores are company operated, giving the company strict control across the chain. Store licenses are granted to external parties only when there is no other way to achieve access to a desirable retail space (e.g., universities, airports, department stores, etc.). Prices are locally uniform among the outlets serving the same neighborhood.

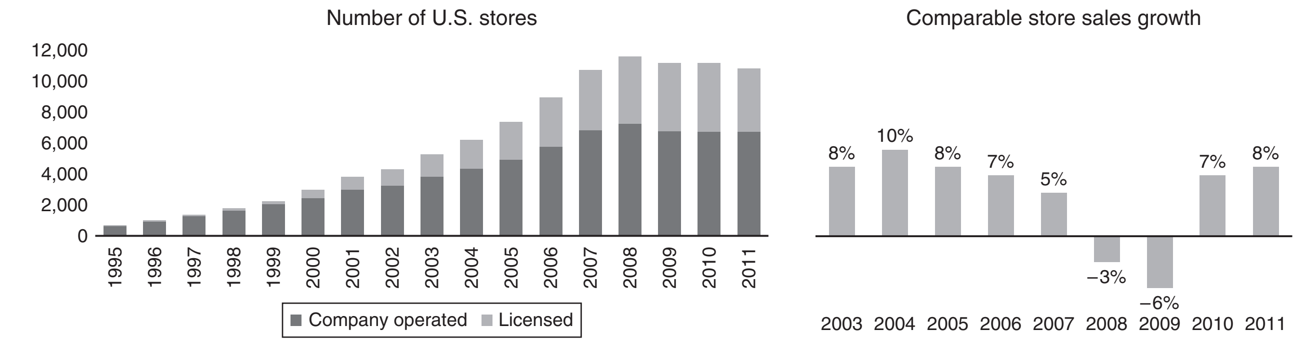
The previous chief executive officer of the company, Orin Smith, describes the economics of store density for the Starbucks chain as follows:

> Clustering stores increases total revenue and market share, even when individual stores poach on each other's sales. The strategy works because of Starbucks' size. It is large enough to absorb losses at existing stores as new ones open up, and soon overall sales grow beyond what they would have been with just one store. Meanwhile, it's cheaper to deliver to and manage stores located close together. (Bloomberg 2002)

Starbucks expanded its U.S. store portfolio from 49 stores in 1989 to more than 10,000 stores in 2007, while at the same time improving same-store sales. However, around the beginning of 2008, the company declared a drop in same-store sales for the first time and its stock price fell by 40%. Even before this period, industry experts were questioning whether the level of store density Starbucks had achieved could be sustainable. The main source of these concerns was the slowdown in comparable store sales growth that had been going on since 2005 as the company consistently opened new outlets on the order of one to two thousand per year (Figure 2). Cannibalization brought about by a too-dense store network was seen to be the main cause of this decline. Around 2008, overall economic conditions had also worsened, and consumers were obliged to cut back on nonessential purchases like premium coffee.

In July 2008, the firm announced that it would shut down 600 unprofitable stores across the United States, out of the approximately 11,000 U.S. outlets that were

Figure 2. Starbucks Expansion and Comparable Store Sales Growth



Source. Starbucks annual reports (Starbucks Corporation 1999, 2001, 2006, 2008, 2011).

in operation at the time. Company officials declared that "after these closures, there aren't a material number of stores left on their watch list, but the company would hold remaining stores to the same standards" (Chain Store Age 2008). In January 2009, a further set of 200 U.S. stores was announced for closure. Within two years, the listed locations were eventually shut down as their lease terms ended.

According to Starbucks founder Howard Schultz, the closures came about as a result of their predicating "future success on how many stores they opened during a quarter instead of taking the time to determine whether each of those stores would, in fact, be profitable" (Schultz 2011, p. 97). In fact, "70 percent of the closing stores had opened after 2006, and most were near other Starbucks stores—a sign that the company had oversaturated its markets" (Rosenwald 2008). Through the closures, the company aimed to "improve the profit potential of the U.S. store portfolio" (de la Merced 2008), taking pressure off some of the stores located in the same immediate area (Adamy 2008a).

The primary impact of the 2008 recession for Starbucks was the weakening of demand. The company's 2009 annual report mentions that "since many of the Company's operating expenses are fixed in nature, the softness in US revenues during fiscal 2008 impacted nearly all consolidated and US segment operating expense line items when viewed as a percentage of sales, and pressured operating margins" (Starbucks Corporation 2009, p. 29). To the extent that the firm was not able to predict (at a local level) and factor this effect in its store placement decisions, the recession-induced shifts in the economic variables are exogenous to the model and aid identification. Company announcements suggest this to be the case.[12]

3.2. Data Description

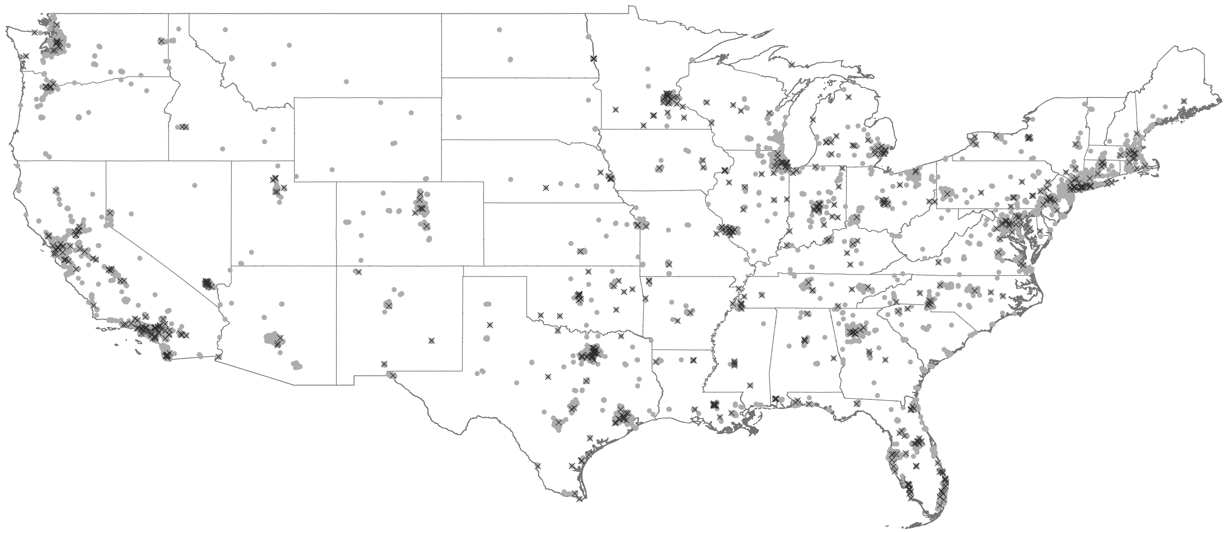
The list of closing stores was publicly announced on both of the two waves of store closure. Given that the announcements were made only six months apart and all stores were subjected to the same standards, I combine the data from the two announcements in a unified analysis. I acquired a list of all U.S. Starbucks shops that were in operation as of July 2008, through AggData LLC, a private data vendor. I complement the store location data with demographic data obtained from the 2000 and 2010 census profiles. I focus on the 11,078 Starbucks outlets located in the 48 contiguous U.S. states to obtain one contiguous space of analysis. Figure 3 presents a map of these outlets. The closing locations appear evenly dispersed across the geography.

I consider a trading area of a five-mile radius around each store.[13] In an alternative two-band specification, I allow for two concentric distance bands of three miles and three to five miles. I do not include any store whose trading area covers a population of less than 10,000 people, as their business likely does not depend on local demand.[14] Overall, there are 230 such outlets, mostly located near interstate highways or at holiday destinations.

Because the store eliminations involve only the company-operated outlets, I treat the licensed stores as exogenously given. The data set does not specify whether a particular outlet is company operated or licensed. However, the store names are informative as to whether an outlet is located in a self-contained complex such as a supermarket, department store, hotel, holiday resort, airport, business center, plaza, hospital, or university. Licenses are granted only in cases where the outlets are located within private establishments (Rubinfeld and Hemingway 2005). Leaving out these locations, I identify 7,081 company-operated stores (dispersed across 2,154 cities), which constitute the estimation sample. Of these stores, 644 were listed to be closed.

I take each census block group (CBG) as defined by the U.S. Census Bureau to represent a customer unit, covering the 129,209 CBGs whose population-weighted centroids are within the five-mile trading area of a Starbucks store. The resulting estimation sample contains 1,272,084 data points, each defined by a CBG and company-operated store pair. Based on this sample, Table 3 shows the distribution of perturbations generated by the method, separately for the nonremote and remote stores.

Figure 3. Location of Starbucks Stores in the Contiguous United States as of July 2008



Note. Dots (in grey) denote the retained stores, and crosses (in black) denote the closing stores.

To capture a snapshot of the market in the closure period, I seek to obtain the 2008 values of the relevant independent variables. The appendix contains a preliminary analysis that guides the choice of explanatory variables to include in the model. The population and age variables for the year 2008 are interpolated based on the 2000 and 2010 census counts. The age variable controls for the percentage of the CBG population between the ages of 18 to 39, which is the demographic that Starbucks mainly targets. As income data are not provided in the 2010 census, I take them directly from the 2000 census and adjust them for inflation.[15]

Prior research shows a significant effect of housing wealth on consumption (Mian et al. 2013). To measure customers' wealth levels, I use Zillow's county-level home value index from July 2008.[16] There is also evidence that consumption may respond to anticipated wealth changes (Campbell and Cocco 2007). Thus, I also control for wealth trends, using county-level percentage shifts in the Zillow home value index from July 2007 to July 2009. Summary statistics for the demand-side variables are provided in the top panel in Table 4. Overall, a total population of 198.3 million people is covered in the study. Net of the closing stores, customers have an average number of 12.65 Starbucks outlets within five miles of their location.

I use the 2008 County Business Patterns data on county-level average wage levels and the 2008 American Community Survey (ACS) data on residential rents[17] to proxy for store fixed costs related to personnel and store rental costs. The bottom panel in Table 4 presents the summary store statistics. Given a trading area of a five-mile radius, I classify the outlets that are at least 10 miles away from their closest network neighbor as remote.[18] For both the remote and nonremote store types, closing stores have smaller trading area populations and lower income and wealth levels.

In general, nonremote locations have richer and larger trading area populations, but they share customers with other outlets. I compare the strength of demand at the remote and nonremote store types through a summary measure of market potential. First,

Table 4. Summary Statistics

CBG summary statistics				
Variable	Mean	Std. dev.	Min	Max
Population (1,000s)	1.53	1.34	0.1	54.68
Population density (10,000s)	28.55	37.76	0.14	270.57
% of population aged 18–39	0.31	0.10	0	1
Per-capita income ($10,000)	2.28	1.23	0.1	31.82
Median home value ($100,000)	0.26	0.15	0.06	0.87
% change in median home value	−0.14	0.13	−0.49	0.42
No. of retained stores within 3 *miles*	5.19	11.42	0	164
No. of retained stores within 5 *miles*	12.65	21.21	0	205
No. of closing stores within 3 *miles*	0.29	0.75	0	7
No. of closing stores within 5 *miles*	0.71	1.26	0	9

Store summary statistics				
	Nonremote stores		Remote stores	
Variable	Closed	Kept	Closed	Kept
Count	599	6,274	45	163
Trading area population (1,000s)	222.1	278.2	25.91	35.82
No. of outlets within 5 *miles*	15.37	21.40	0	0
Per-capita income ($10,000)	2.41	2.56	1.82	1.84
Housing wealth ($100,000)	0.24	0.30	0.14	0.17
% change in housing wealth	−15.9	−17.4	−6.3	−6.7
Average wage ($1,000)	24.5	25.3	21.1	22.0
Median rent ($100)	9.20	9.75	6.93	7.30
Miles to closest neighbor	1.47	1.34	30.49	28.44

Table 5. Closure Ratio and Remoteness

Distance to closest neighbor outlet (miles)	Effective market size (1,000s)	Per-capita income ($10,000)	Market potential ($10 million)	Closure ratio
		Nonremote stores		
<10	25.23	2.55	59.02	0.09
		Remote stores		
>10	33.67	1.83	60.74	0.22
		Remote stores with below-median market potential		
10 to 20	19.39	1.82	34.49	0.21
20 to 30	18.92	1.82	32.25	0.35
30 to 40	22.30	1.65	35.16	0.26
40 to 50	20.62	1.65	33.37	0.33
50 to 60	21.80	1.63	35.09	0.43
>60	21.21	1.69	35.70	0.50

Note. The bottom panel summarizes data for 106 remote stores with market potential lower than the median level of $500 million.

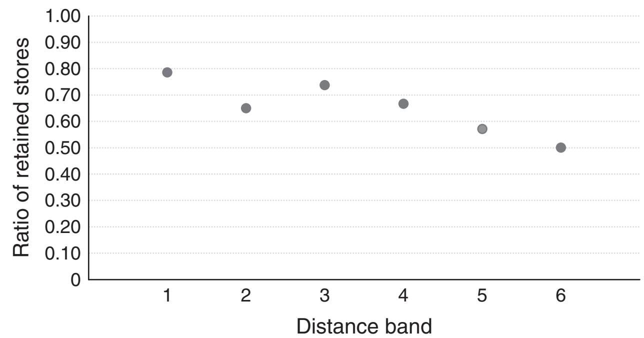
I calculate the store's effective market size by dividing its trading area population by the number of Starbucks outlets within five miles. (For the remote stores, the effective market size is equivalent to the trading area population.) Then, I multiply the effective market size by the trading area average per-capita income to obtain the market potential at a given location. Table 5 shows that, according to this measure, remote and nonremote stores have similar levels of market potential ($590.2 versus $607.4 million, respectively), but the closure rate for the remote stores is considerably higher.

To provide further evidence for density economies, I examine, within the set of remote stores, the change in closure probability as the store is located further away from its closest neighbor. I focus on remote stores with relatively low market potential (below the median level of $500 million), where the absence of density economies can have a pivotal negative effect on profitability. The closure rate for these stores goes up from 0.20 to 0.50 at increasing degrees of remoteness, while the average market potential remains steady around a mean value of $342 million (bottom panel in Table 5). This pattern, plotted in Figure 4, suggests a supply-side disadvantage to remoteness that is consistent with a weakening of density economies.

4. Results

Model estimates are presented in Table 6. Across different specifications, the utility from a Starbucks visit increases in the five-mile store density around the customer's location. Outside utility increases with population density, in line with the premise that the firm would be facing more intense competition in densely populated areas. Income and wealth both have positive effects on visit probability, a plausible finding given the premium positioning of the brand. The negative signs of the two interaction terms suggest that at higher

Figure 4. Retention Probability and Remoteness



Note. Distance band 1 corresponds to a distance of 10–20 miles, band 2 to a distance of 20–30 miles, band 3 to a distance of 30–40 miles, band 4 to a distance of 40–50 miles, band 5 to a distance of 50–60 miles, and band 6 to a distance of greater than 60 miles to the closest neighbor outlet.

levels of income and population density, demand is less responsive to changes in store density (the visit probability curve is flatter).

The specification in column (1) accounts for quadratic effects of the store and population density variables. Additionally, it controls for the age composition of the CBG as well as the recession-induced downward trends in housing wealth. While the coefficient estimates for these variables are not statistically significant, signs of the coefficients suggest that visit probability increases in the percentage of young adults in the population, and a negative trend in wealth suppresses demand. Note that the model already accounts for the customer's *level* of wealth, and this variable has a statistically significant, positive effect on visit probability. If households cut back on their discretionary spending based on their recession-impacted wealth levels as of 2008, the wealth variable captures this effect. The wealth trend variable, on the other hand, captures forward-looking behavior, the potential effect of anticipated wealth changes on customers' actual Starbucks consumption. The findings do not provide evidence for such an effect.

Column (4) provides estimates for the two-band demand model that allows the store density within three miles of the customer's location to have a differential impact on demand compared to the farther band of three to five miles.[19] Column (5) differentiates between company-operated and licensed stores. The results suggest a significantly stronger effect for more proximate locations, and for the company-operated outlets. The weaker demand at licensed stores likely reflects the fact that these are located within another destination such as a mall, supermarket, etc., and their demand is conditional on the customer visiting that particular destination. Column (6) reports results from a control that incorporates into the estimation data Starbucks' additional store openings as of January 2009, to account for the fact that the firm may have factored in the effect

Table 6. Incremental Profits from a Store

		(1)	(2)	(3)	(4)	(5)	(6)
Demand-side parameters							
Utility from the Starbucks visit							
band5mi	ln(*No. of stores within 5 miles* +1)	**1.604**	**1.595**	**1.521**			**1.594**
		(0.127)	(0.095)	(0.081)			(0.096)
band5mi_sq	*band5mi squared*	0.045					
		(0.067)					
band3mi	ln(*No. of stores within 3 miles* + 1)				**1.096**		
					(0.131)		
band3-5mi	ln(*No. of stores within 3 to 5 miles* +1)				**0.680**		
					(0.091)		
band5mi_co	ln(*No. of company-operated stores within 5 miles* +1)					**1.367**	
						(0.097)	
band5mi_lic	ln(*No. of licensed stores within 5 miles* +1)					**0.219**	
						(0.055)	
band5mi · popden	*band5mi · popden*	−0.188	**−0.120**	**−0.129**	**−0.166**	**−0.118**	**−0.119**
		(0.136)	(0.018)	(0.017)	(0.025)	(0.018)	(0.018)
band5mi · p.inc	*band5mi · p.inc*	**−0.051**	−0.043		0.054	−0.027	−0.043
		(0.025)	(0.023)		(0.042)	(0.024)	(0.023)
Utility from the outside option							
popden	ln(*Population density*) (10,000 people)	**0.645**	**0.688**	**0.679**	**0.687**	**0.665**	**0.691**
		(0.120)	(0.069)	(0.070)	(0.078)	(0.067)	(0.071)
popden_sq	*popden squared*	−0.019					
		(0.066)					
age_18to39	*% of population aged* 18 *to* 39	−0.467	−0.464		0.678	−0.375	−0.486
		(0.902)	(0.814)		(1.052)	(0.829)	(0.814)
p.inc	*Per-capita income* ($10,000)	**−0.262**	**−0.241**	**−0.110**	−0.023	**−0.193**	**−0.238**
		(0.085)	(0.080)	(0.033)	(0.117)	(0.078)	(0.0801)
wealth	*Median house value* ($100,000)	**−1.215**	**−1.341**	**−1.379**	**−1.279**	**−1.476**	**−1.340**
		(0.275)	(0.253)	(0.251)	(0.324)	(0.262)	(0.254)
wealth shift	*% Shift in wealth* (2007–2009)	−0.143	−0.179		−0.054	−0.131	−0.189
		(0.200)	(0.188)		(0.232)	(0.193)	(0.188)
dem_const	Utility constant	**4.406**	**4.721**	**4.145**	**2.527**	**4.122**	**4.744**
		(0.490)	(0.467)	(0.287)	(0.506)	(0.512)	(0.481)
Supply-side parameters							
mp	*Marginal profit* (per 1,000 customers)	**1.014**	**1.436**	**1.215**	**0.684**	**1.101**	**1.470**
		(0.415)	(0.478)	(0.343)	(0.110)	(0.379)	(0.514)
mdist_st	*Distance to closest neighbor store* (100 miles)	**0.688**	**0.668**	**0.748**	**1.361**	**0.982**	**0.641**
		(0.334)	(0.330)	(0.327)	(0.338)	(0.372)	(0.320)
avwage	*Average wage* ($1,000)	−0.655	0.073	0.073	0.044	0.004	0.071
		(5.386)	(0.108)	(0.104)	(0.131)	(0.094)	(0.107)
medrent	*Median rent* ($100)	1.458	**0.824**	**0.820**	**0.942**	**0.844**	**0.822**
		(289.267)	(0.273)	(0.266)	(0.333)	(0.236)	(0.269)
prof_const	*Intercept*	−15.345	**−15.430**	**−15.321**	**−16.640**	**−13.541**	**−15.318**
		(3338)	(5.30)	(5.092)	(6.104)	(4.314)	(5.202)
randef (S.D.)	Random effect standard deviation	**0.359**	**0.356**	**0.364**	**0.404**	**0.381**	**0.355**
		(0.049)	(0.049)	(0.049)	(0.045)	(0.049)	(0.049)
Log likelihood		−2,177.8	−2,176.4	−2,178.4	−2,215.8	−2,172.0	−2,177.7

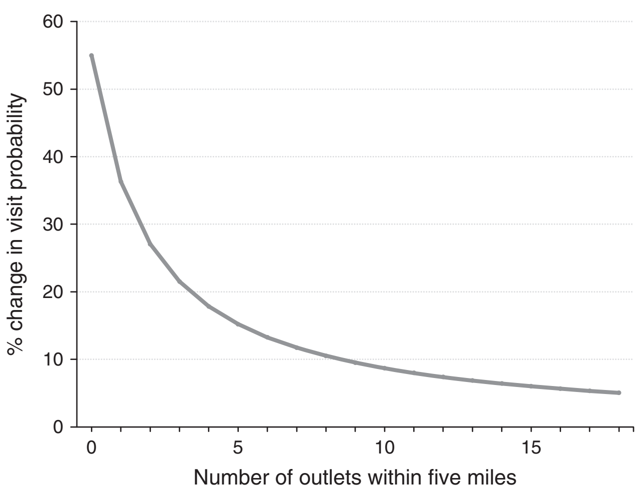
Notes. Models allow for city-level random effects for 2,154 cities in the estimation sample. Standard errors are indicated in parentheses. Estimates indicated in bold are statistically significant at the 5% level.

from these new outlets in its closure assessments.[20] The estimates obtained under this control are very close to those obtained using the original data presented in column (2).

In the rest of the analysis, interpretation relies on results from the third specification, which has a comparable fit to the richer specifications, and where all of the demand parameter estimates are statistically significant. As discussed in Section 2, it is necessary to figure out externally the frequency of the visit decision to translate the visit probability suggested by the model's estimates into the number of visits per given time interval. External data suggest that the chain's most frequent customers come to Starbucks around 16 times a month (Adamy 2008b), that is, approximately once every two days. I therefore assume the time interval of a customer's discrete choice to be, on average, two days. Net of the closing stores, the average visit probability across CBGs is 5.46%, which translates to 0.31 Starbucks visits per week. Summing over all CBGs in the chain's trading area, I estimate the total number of customer visits to be 39.54 million weekly, net of the closing stores, and 41.4 million when the firm's initial store set is considered. Specification 4, which has the best fit with the data, produces similar estimates (39.49 and 42.31 million, respectively). Given that, according to the 2008 Starbucks annual report, the firm served an average number of 50 million customers per week, and around 80% of the firm's revenues were generated in the United States; these estimates appear to be consistent with actual data.

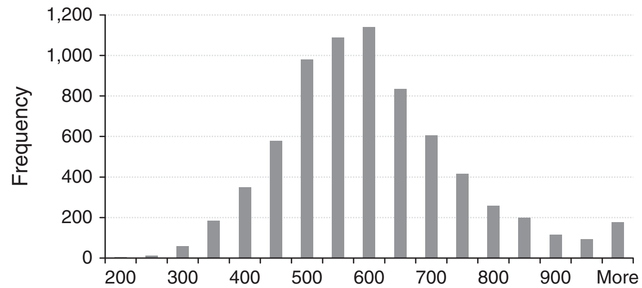
Using the demand model, I chart the percentage change in the visit frequency in response to increasing store density (Figure 5). While the initial store additions make the average customer as much as 55% more likely to visit the chain, the effect diminishes to less than 10% for more than 10 stores within five miles. At the mean five-mile store density of 12 outlets, an additional store increases the visit probability by 8.7%. There is a variation by distance from the customer; the two-band estimates suggest that an additional store within three miles has twice the impact compared to the farther band of three to five miles (16% versus 7.2%). The effect also varies by store type: on average, a stand-alone (company-operated) store increases demand by 12.8%, whereas the increase is 5.1% for a licensed store.

Figure 5. Visit Frequency and Store Density



Note. The figure charts the estimated visit frequency of the average customer with demographic characteristics set to mean levels as indicated in Table 4.

Figure 6. Distribution of Estimated Daily Incremental Visits Generated by Each Store



The model can produce estimates of the daily incremental visits generated at each outlet. To obtain these values, I calculate the difference in the chain-level visit volume when a given store is active versus when it is removed. Stores' incremental traffic levels have a bell-shaped distribution around the mean value of 581 visits per day (Figure 6). Note that the model reports these estimates in units of the average customer that generates the mean marginal profit at each visit. For example, if the average marginal profit is $2 and a store has a segment of 200 customers leaving $3 per visit, the model would represent their business as 300 standardized customers, each generating the average profit of $2 per visit. In that respect, the per-store traffic counts reported are the "average marginal profit-normalized" measures of the store's variable profits rather than the actual number of customers counted at the till. This normalization makes the model's traffic estimates comparable across stores with varying customer compositions.

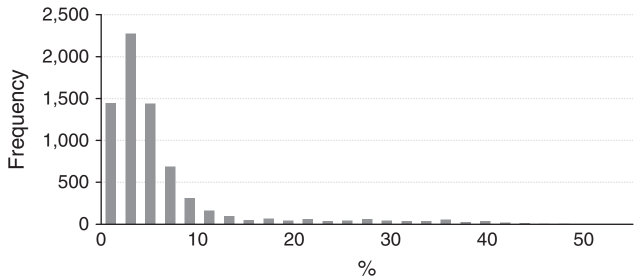
To study the determinants of customer traffic and measure the cannibalization effect at the store level, I run a simple regression of stores' incremental traffic levels against a set of trading area characteristics. This model could have practical use, as it provides a simple estimate for how much incremental business a

Table 7. Determinants of Stores' Incremental Customer Traffic

Variable	Coef.	S.E.
Population within 5 *miles* (10,000 people)	2.024	0.182
Population term squared	−0.011	0.001
Mean per-capita income within 5 *miles* ($100)	1.303	0.115
Income term squared	−0.001	0.000
Wealth ($1,000,000)	4.646	0.105
*Band*1 (No. of stores in 1 mile)	−6.895	0.425
*Band*2 (No. of stores in 1–3 miles)	−2.123	0.242
*Band*3 (No. of stores in 3–5 miles)	−0.139	0.250
Interaction term ($band1 \cdot band2$)	0.092	0.009
Interaction term ($(band1 + band2) \cdot band3$)	−0.018	0.006
Constant	200.98	15.69

Note. $n = 7{,}081$, $R^2 = 0.38$.

Figure 7. Distribution of Cannibalization Rates Incurred by Stores



candidate location would contribute to the chain given its area characteristics. The results are presented in Table 7. Average per-capita income and the population within five miles both have a positive and decreasing impact on the store's incremental business. Customer traffic decreases on average by 6.9 customers (1.2%) as a result of a neighbor outlet within one mile. The effect falls to 2.1 customers (0.4%) within one to three miles, and virtually disappears at three to five miles. The interaction terms suggest that the cannibalization due to farther neighbors is mitigated if the outlet already has other neighbors closer by.

The rate of cannibalization imposed by the network on the average store is 4.8% and ranges from zero to 50% across the locations (Figure 7). These cannibalization rate estimates are based on the counterfactual revenue the store would have generated in the absence of any nearby outlet. Given a mean ticket size of $4 per customer visit (Clark 2008), yearly incremental revenue per store turns out to be approximately $848,000, after a foregone cannibalization of $48,200. The firm's 2008 annual report indicates that their company-operated U.S. retail operations generated a total revenue of $7 billion in that year. I estimate that a total cannibalization amounting to $352 million was internalized at these stores over the period.

With regard to the density economies, the ratio of the respective coefficients in the preferred specification suggests that, for each mile of distance to its closest neighbor, the cost of operating a remote outlet increases by the marginal profit from 21.5 customer visits per week. Based on this estimate, and assuming a mean marginal profit of $2 per visit,[21] findings indicate a yearly increase of $2,250 in distribution costs, equivalent to approximately 0.30% of the average incremental store revenue, for each mile of additional distance to the closest network neighbor. At 40 miles, for instance, these costs would exceed $90,000, posing a substantial setback to the store's profitability. Table 8 provides robustness checks for this estimate. Here, for each model specification presented in Table 6, I calibrate the demand side by adjusting the visit time interval such that the chain's estimated traffic matches the 40 million weekly customers as suggested by company reports. I report estimates of density economies based on this calibration, and also the 5% range around it (i.e., with the demand-side calibrated to 38 and 42 million weekly customers respectively). Across the different specifications, the estimated per-mile supply cost as a percentage of store revenue lies in the 0.22% to 0.51% range.

4.1. Model Applications

4.1.1. Wealth Effect and the Great Recession.

While housing wealth makes up approximately one half of U.S. households' total net worth, its effect on consumption is generally difficult to identify as movements in

Table 8. Density Economies Estimates

	Total weekly visits (million)	(1)	(2)	(3)	(4)	(5)	(6)
Estimated average visit probability (%)		6.5	4.6	5.5	9.7	5.5	4.4
Implied visit choice interval (days)	38	2.5	1.8	2.1	3.7	2.1	1.7
	40	2.4	1.7	2.0	3.5	2.0	1.6
	42	2.3	1.6	1.9	3.3	1.9	1.6
Weekly incremental cost per mile	38	19.1	18.5	20.7	37.8	33.6	17.8
(customer visit equivalents)	40	20.1	19.5	21.8	39.8	35.3	18.7
	42	21.1	20.4	22.9	41.8	37.1	19.6
Yearly incremental cost per mile ($)	38	1,982	1,920	2,151	3,932	3,498	1,847
	40	2,087	2,031	2,266	4,139	3,674	1,947
	42	2,193	2,123	2,381	4,346	3,861	2,042
Per-mile cost as % of average store	38	0.23	0.23	0.25	0.46	0.41	0.22
revenue	40	0.25	0.24	0.27	0.49	0.43	0.23
	42	0.26	0.25	0.28	0.51	0.46	0.24

Notes. The numbers in the first row denote the model specification as reported in Table 6. Average visit probability is calculated using the coefficient estimates from each specification. Implied visit interval is adjusted such that the chain weekly traffic matches the 40 million (38 and 42 million for the sensitivity analysis) customers suggested by company reports.

home prices tend to be limited. Starbucks closure data are relevant in this regard, as they comes from the Great Recession period, characterized by a large drop in U.S. home prices, amounting to, on average, 30% between the years 2006 and 2009. Mian et al. (2013) document significant heterogeneity in how these wealth shocks were distributed across the United States.

Section 3.1 provides evidence that Starbucks did not foresee the recession. If the local variations in housing wealth shocks were exogenous to Starbucks' initial store placements, store closures can be informative about the causal relationship between wealth and consumption. In fact, the reduced form analysis presented in the appendix suggests that identifying a wealth effect would not have been possible by just analyzing the firm's retained store set (i.e., store entries) without closure data.

Previous research examining the wealth variations around the Great Recession period suggests that the magnitude of the wealth effect on consumption varies by industry. Mian et al. (2013) find that durables consumption has relatively higher wealth elasticity compared to groceries. Dubé et al. (2018) do not find a significant wealth effect in private label consumption. In the present context, a wealth effect can be expected, given the discretionary nature of Starbucks consumption.

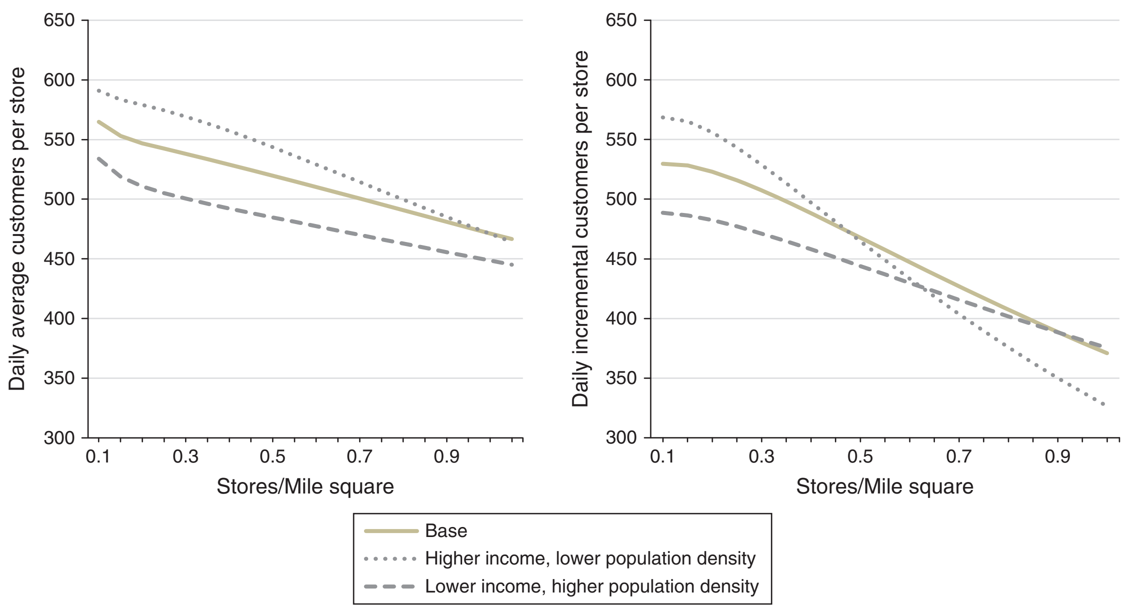
Model estimates predict that a 10% drop in home values would reduce the chain's weekly visit volume from 39.54 to 38.04 million, by 3.8%. Using census data from the recession period, Mian and Sufi (2014) estimate a 3.7% decrease in U.S. nontradable employment (retail- and restaurant-related industries) for the same percentage decline in housing net worth. Assuming a linear relationship between sales and employment levels, my estimate for Starbucks is similar to the estimate for the wider industry provided by these authors.

4.1.2. Demand Response to Store Density. Predicting how demand responds to an increase in the number of local stores under varying income and population levels is not straightforward. While population increases the size of the customer pool, competition is also expected to be stronger in densely populated areas. Model estimates suggest that demand increases with income levels, but this finding by itself does not lead to a conclusive recommendation without considering the effects of population density.

To examine the joint effects of income and population levels on demand, I run a simulation exercise that considers two variations around a model city with a five-mile radius, where the population and income levels reflect the sample means (285,000 people and $22,800, respectively). In the first variation, I increase the income level by 30% while decreasing the population count by the same percentage. The second variation characterizes the opposite case, with income lower and the population level higher by 30%.[22] For the three cases described above, I predict the average number of daily visits per store and the incremental visits additional stores generate at varying levels of store density. Figure 8 displays the results from the preferred specification. The other specifications also generate the same pattern.

This exercise produces several insights. First, for the middle ranges of the city distribution examined, income level is a more important predictor of sales than

Figure 8. (Color online) Average vs. Incremental Daily Traffic per Store at Increasing Levels of Store Density



population count. This is especially the case at low levels of store density; initial stores generate more business in high-income cities, even when the population count is significantly lower (left panel in Figure 8).

The slopes of the incremental traffic curves in the right panel of Figure 8 indicate the rate of cannibalization. These suggest that the incremental contribution from additional stores declines less steeply when population density is high; that is, population density softens the cannibalization effect. As well as the availability of a larger customer base, this finding reflects the more intense competition the chain is likely to face in densely populated regions, as an additional store can then attract relatively more business from competition than from within the chain.

In this respect, a comparison of the left and right panels in Figure 8 highlights the difference between accounting profits (number of customers counted at the till) and economic profits (incremental visits brought to the chain) generated by additional stores. In the high-income, low-population city, stores' average customer counts appear consistently higher, but actually, the incremental business generated by the marginal outlet declines faster, and eventually falls below that in the low-income, high-population city. Specifically, as of a store density of 0.6 stores per square mile, the firm is better off investing in the high-population city, even though the average sales are higher in the low-population city. As such, the exercise demonstrates that, in evaluating potential regions for additional store openings, benchmarking on the actual (accounting) rather than incremental (economic) sales levels of existing outlets could lead to suboptimal location choices.

4.1.3. Revenue Implications of a Store Expansion Policy. For a retail chain, the profitability of a store expansion policy depends on the net contribution from the new locations to firm-level sales. An advantage of the proposed model is that it focuses on the outlets' incremental contributions (factoring in cannibalization), directly predicting the net increase in total demand associated with a potential expansion move.

To demonstrate this, I consider a hypothetical example, where Starbucks opens licensed stores within Whole Foods, an upscale supermarket chain. I assume that the expansion involves the whole set of 406 Whole Foods locations listed on the company website as of October 2015. This exercise uses estimates from the fourth specification presented in Table 6, which adjusts predictions to account for licensed outlets.[23]

The assumed policy augments the chain's density for a total population of 63 million people, only 0.5% of which did not originally have a Starbucks store within five miles. A third of the firm's original trading area population observes an increase in their local Starbucks density, on average, by 13%. The demand generated from these customers goes up from 17.45 to 18.51 million (4.9%) as a result of the expansion, corresponding to an average contribution of 303 visits per day from each new store added. This is approximately half the number generated by the average company-operated store (581 customers per day). Based on the assumption of a mean ticket value of $4, the expansion implies a net increase of approximately $179 million in the firm's yearly revenues.

5. Conclusion

Store location decisions of a chain retailer are interrelated because of the opposing network effects of cannibalization and density economies. This study develops a method to quantify these effects based on firms' mass store elimination choices. The method obtains each store's contribution to the chain-level profits via one-store perturbations on the set of remaining stores and maps these onto closure data. The empirical application analyzes the Starbucks chain. The model provides estimates of how store network effects vary with distance to neighbor stores, as well as the moderating impact of demand factors such as income and wealth.

For the product category examined, results suggest demand to be highly localized and, as a result, the cannibalization effect to be weak, with the average store's revenue declining by 1.2% when a new store opens within one mile. Together with the supply-side advantage of density economies, this finding explains why most quick service chains pursue a "blanketing strategy," first increasing store penetration in existing markets rather than simultaneously moving on to new regions. The findings also demonstrate the joint effects of population and income levels on demand. Income is a more important determinant of demand at low levels of store density, whereas the firm can establish a denser network in high-population regions without incurring as much cannibalization.

The model formulation characterizes the store network effects as they would play out for a quick service firm. The empirical framework developed in this paper could therefore be useful for analyzing other firms in the industry.[24] In general, applying the method to different retail settings would call for a reconsideration of the modeling primitives. For instance, Holmes (2011) measures the density economies in the Walmart network via the store's distance to the closest warehouse, whereas the present study assumes a traveling salesman–type distribution setup. Likewise, for product categories where demand is of a more planned nature, distance to the nearest outlet would likely be a more appropriate measure of convenience than local network density.

To separate the demand- and supply-side network effects, I rely on the distinction that the cannibalization effect intensifies with local network density, whereas the supply-side disadvantage prevails at sparse regions of the network. Compared to the previous literature that makes use of revenue data (Holmes 2011, Nishida 2014) to estimate demand parameters, the method's low data requirement may be an advantage. Yet, it should be noted that separating the demand- and supply-side effects as I do may be problematic if the underlying model is not well specified. In particular, if demand is weak in remote locations because of factors that the model does not capture, their effects could be wrongly ascribed to the cost side, causing an upward bias in the estimates of density economies. In the empirical application presented in this paper, the fact that the estimates match the firm's reported customer traffic data well and also agree with the findings from the previous literature (the consumption wealth effect measured is in close agreement with Mian and Sufi 2014) gives credibility to the model. When available, calibrating the demand side of the model with actual sales data would yield more reliable estimates.

The key assumption of the proposed method is that the retained store subset is optimal under the prevailing economic conditions at the time of closures. This has two implications. First, stores are evaluated on their contribution to the firm's aggregate profits (economic profits) and not their accounting profits. Second, it justifies a static approach where the closure assessment is based on actual profitability. I thereby preclude that an unprofitable location is retained to preempt the entry of a rival, or because the firm expects the location to turn profitable in the future.[25] Future research could provide a more complete analysis of the store network entry problem by incorporating these dynamic considerations.

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Appendix

To guide the choice of variables to include in the model, I run a preliminary analysis on ACS data, which include yearly cross sections of population demographics and household economic indicators for a panel of 522 U.S. cities. The analysis focuses on the 473 cities where Starbucks was operational as of the closure announcements. Together, these cities contain 53% of the stores in the estimation data. Table A.1 reports the summary statistics for the variables considered. These include the 2007 to 2009 shifts in the economic variables that reflect the impact of the 2008 recession.

The results are reported in Table A.2, in two panels. In the left panel, the dependent variable is the retained store count in the city. In the right panel, I run the same analysis on the number of closing stores, with the number of retained stores as an additional independent variable. The proposed method includes perturbations involving both retained and closed outlets, so both panels convey information that feeds into the analysis.

I find population, age distribution, and income level to have significant effects on store density. In fact, specification (4) suggests that just the population and income variables alone explain 70% of the variation, before any state-fixed effects. The rent variable has a negative effect on store count and appears to be a good proxy for store rental costs. These variables are accounted for in the specifications presented.

The right panel indicates that closures are more likely to be observed in cities where ex post there remains a high number of outlets. This points to the cannibalization effect, a higher store count making it more likely for any given outlet to be redundant. In addition, there is a significant and negative effect of housing wealth levels on closures. Note that wealth does not have an effect on the retained store counts (the left-panel wealth estimates are not statistically significant); it is

Table A.1. Summary Statistics for City-Level ACS Data

	Mean	Std. dev.	Min	Max
Number of closing stores	0.786	1.740	0	13
Number of retained stores	11.524	19.508	0	180
2008 *population* (100,000)	2.084	4.742	0.57	83.64
2008 *income* ($1,000)	27.210	8.462	10.73	86.00
2008 *% of population aged* 20 to 44	0.367	0.043	0.24	0.55
2008 *median housing wealth* ($1,000,000)	0.279	0.176	0.064	1
2008 *median rent* ($1,000)	0.934	0.265	0.537	1.930
2008 *% of population with bachelor's degree or above*	0.306	0.131	0.045	0.746
2008 *unemployment* (%)	0.070	0.028	0.015	0.205
% difference in per-capita income 2007 to 2009	−0.048	0.068	−0.231	0.177
% difference in housing wealth 2007 to 2009	−0.098	0.160	−0.535	0.329
% difference in unemployment 2007 to 2009	0.671	0.531	−0.368	3.419

Note. $n = 473$.

Table A.2. Descriptive Regression Analysis of City-Level Closure Counts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of retained stores				*Number of closing stores*			
Population	**2.986**	**3.054**	**5.944**	**6.207**	**−0.0512**	**−0.0622**	0.0296	0.0608
	(0.125)	(0.124)	(0.229)	(0.232)	(0.0174)	(0.0187)	(0.0438)	(0.0407)
Income	**0.711**	**0.649**	**1.052**	**0.772**	−0.00960	−0.00427	−0.00783	−0.0150
	(0.175)	(0.176)	(0.302)	(0.218)	(0.0165)	(0.0170)	(0.0359)	(0.0244)
Population squared			**−0.0468**	**−0.0504**			**−0.00109**	**−0.00133**
			(0.00328)	(0.00333)			(0.000471)	(0.000448)
Income squared			**−0.00654**	−0.00589			0.0000687	−0.0000460
			(0.00326)	(0.00310)			(0.000384)	(0.000343)
% of population aged 20 to 44	**66.92**	**52.17**	**44.01**		−0.912	−1.125	−1.051	
	(16.68)	(16.80)	(13.82)		(1.569)	(1.621)	(1.638)	
Median housing wealth	6.519	−7.391	−4.358		**−1.958**	**−2.112**	**−2.134**	
	(6.941)	(9.229)	(7.506)		(0.642)	(0.881)	(0.879)	
Median rent	**−15.85**	**−13.78**	**−10.14**		0.805	0.844	0.843	
	(4.823)	(5.220)	(4.257)		(0.451)	(0.502)	(0.502)	
% of population with bachelor's	−7.589	6.160	3.221		0.134	−0.118	0.0230	
	(9.803)	(10.19)	(8.608)		(0.907)	(0.972)	(1.008)	
Unemployment (%)	21.30	49.08	35.56		2.124	2.859	2.509	
	(25.83)	(28.72)	(24.18)		(2.389)	(2.749)	(2.838)	
% difference in per-capita income 2007 to 2009	−0.195	7.747	5.756		0.359	−0.0308	0.0194	
	(9.468)	(9.716)	(7.901)		(0.875)	(0.927)	(0.925)	
% difference in housing wealth 2007 to 2009	**−15.04**	−1.447	−2.329		0.278	−0.0424	−0.126	
	(5.611)	(7.618)	(6.230)		(0.523)	(0.726)	(0.729)	
% difference in unemployment 2007 to 2009	0.854	0.0952	0.554		−0.0914	0.00495	0.0170	
	(1.206)	(1.250)	(1.015)		(0.112)	(0.119)	(0.119)	
Number of retained stores					**0.0776**	**0.0829**	**0.0752**	**0.0670**
					(0.00437)	(0.00474)	(0.00584)	(0.00509)
Constant	**−26.73**	**−21.70**	**−32.11**	**−16.29**	0.314	0.126	0.0401	0.370
	(7.908)	(8.150)	(8.166)	(3.618)	(0.740)	(0.784)	(0.974)	(0.407)
State fixed effects	No	Yes	Yes	No	No	Yes	Yes	No
N	459	459	459	473	459	459	459	473
Adjusted *R*-squared	0.591	0.637	0.761	0.711	0.560	0.584	0.587	0.560

Notes. Standard errors are in parentheses. Estimates indicated in bold are statistically significant at the 5% level.

the closure data, that is, the discrepancy between a city's initial store density and the lower demand due to the recession-impacted wealth levels (as of 2008), that help us identify the wealth effect.

There is no statistically significant effect of the 2007–2009 trends in the economic indicators on the firm's store density choices. These could affect the firm's store density choices, by shifting both actual (i.e., if customers lower their demand because of anticipated economic constraints), and (predicted) future profitability. The analysis does not provide evidence for such an effect.

Endnotes

[1] In 1948, multiple-location chain retail firms accounted for 29.6% of total retail sales in the United States. By 1997, this share went up to 61%. In parallel, the percentage of U.S. retail establishments operated by chains went up from 20.2% to 35% from 1963 to 2000 (Jarmin et al. 2009).

[2] I define the problem for a centrally owned firm maximizing its chain-level profits.

[3] Mass store closures are rather frequently observed in chain retail as part of radical restructuring initiatives. For example, in 2013, 21 U.S. chains announced such closures that involved the elimination of at least 50 outlets (Farfan 2013).

[4] For example, an ordinance enacted in San Francisco requires retail chains to notify residents of any plans to open a store in their neighborhood, which, experts say, practically "will stop retailers from coming in" (Rubinfeld and Hemingway 2005, p. 59).

[5] It is mentioned in the 2008 Starbucks annual report that the firm's business is "highly sensitive to increases and decreases in customer traffic. Increased customer visits create sales leverage, meaning that fixed expenses, such as occupancy costs, are spread across a greater revenue base, thereby improving operating margins" (Starbucks Corporation 2008, p. 22). The average spending in fast food chains is $4.34 per person (Clark 2008).

[6] Related studies on fast food chains employ this type of demand formulation (Thomadsen 2005, 2007; Pancras et al. 2012).

[7] The population density variable would also control for the negative impact on demand from potential queuing, which is more likely to occur in densely populated regions. In the quick service industry, takeaway purchases are common, and these should be less binding on store capacity. For example, 80% of Starbucks drinks in the U.S. are ordered as takeaway (Michelli 2006).

[8] The average delivery route for a U.S. retail chain includes 2.31 stops (Macklin 2002). Generally, the number of stops covered per route is a major indicator of supply chain performance (Frazelle 2001).

[9] This is consistent with store supply costs taking the form $\alpha + \alpha_{DE} dist$, which involves a fixed fee per stop (α) that is independent of the distance traveled, and a component that varies depending on the outlet's distance from its closest neighbor ($\alpha_{DE} dist$), with *dist* truncated such that it is zero for nonremote stores. The term α applies to both remote and nonremote outlets and will be subsumed in the profit intercept, and α_{DE} measures the per-mile cost of serving the remote outlets.

[10] I assume that shocks are i.i.d. across all stores, whether remaining or closing. This may be violated if closing locations are more likely to get negative shocks due to factors that the model does not account for, which may cause an upward bias in the magnitudes of the estimated network effects.

[11] Identification of the demand-side constant is based on data from customer units for whom the net value of the outside utility would otherwise sum to zero. Technically, this term shifts the denominator of the logit ratio representing the visit probability, whereas the marginal profit parameter shifts the incremental visit expression (the difference of logit ratios) as a whole, interacting with the population variable to yield the variable profits. The cost-side constant term acts as the intercept of the estimation equation.

[12] In a press report, Schultz explains that "the closures are happening in places where Starbucks built stores under the assumption that the economy would remain strong. That economic environment no longer exists" (Adamy 2009).

[13] Specifications that take into consideration the store density within 5–7 miles and 5–10 miles of the customer's location provide worse fit and unreasonable estimates.

[14] Starbucks considers a maximum penetration rate of one store for every 10,000 people (Rubinfeld and Hemingway 2005).

[15] While the decennial census provides a snapshot of the United States, American Community Survey census block–level estimates, which are available only on a five-year basis, reflect averages over the entire five-year period. Therefore, I opt for a census-based income measure.

[16] For counties where data are not available, I use the state averages. This concerns 204 counties that contain a total of 681 stores out of the total 7,081 stores in the estimation sample. For the 71 stores located in West Virginia, Kansas, Iowa, and Louisiana, state-level data are not available either, so I take as proxy the U.S. averages. Results are robust to using ZIP code–level values where available.

[17] The yearly version of the American Community Survey does not cover all counties. For counties that are not included in the 2008 survey, state averages are used. These counties represent 3.8% of the sample.

[18] I focus on the distance to the closest company-operated store, as licensed stores do not necessarily carry all products, and their operation is managed separately.

[19] An alternative specification with three distance bands (one mile, one to three miles, and three to five miles) does not yield consistent estimates for the one-mile band, likely because of the high correlation (with a correlation coefficient of 0.76) between the one-mile and one-to-three-mile store density variables.

[20] I acquired from AggData Starbucks' store list as of January 2009, where I identified 317 new outlets, and I incorporated these locations into the data as exogenously given. This affects the five-mile store density for 21% of the CBGs in the data, on average, by 2.3%.

[21] This is based on the average ticket of $4 and a conservative gross margin of 50.3% (Daily Finance n.d.).

[22] Wealth is kept constant at its mean level of $260,000. Wealth movements produce very similar demand effects as the income movements that are reported in this section.

[23] There may be heterogeneity in Starbucks' compatibility with the host chain in terms of target customers; a licensed store located within an upscale supermarket may generate more business compared to that within a discount retailer where the customer match is not as good. The estimates presented here will not be able to account for these differences. Also, the profitability of such an expansion move would also depend on how costs and revenues are shared between the host firm and Starbucks. This exercise only estimates the sales contribution.

[24] Recent examples of quick service chain mass closures include Quizno's sandwich chain closing 1,000 locations in 2010, Dunkin Donuts closing 350 locations in 2011, and Wendy's closing 150 locations in 2013.

[25] In general, the violation of these conditions could lead us to incorrectly categorize an unprofitable store as profitable and cause a downward bias in estimates of the store network effects. In the empirical example, market analyses reported that the closing Starbucks stores were in aggregate unprofitable (de la Merced 2008, Andrejczak 2008), suggesting that the above assumptions are fulfilled.

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