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Timothy J. Richards
Lauren Chenarides
Metin Cakir

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Lauren Chenarides, Metin Çakır, and Timothy J. Richards*

Abstract

Dollar stores have become the fastest growing retail format in the United States. However, there is considerable controversy regarding their entry, particularly into underserved markets, and concerns that dollar-store entry decisions are motivated by preemptive incentives. In this paper, we aim to study the market entry of dollar stores as an equilibrium phenomenon, and to examine their impact on competing store formats, and stores from other firms, in a dynamic environment. We use census-tract level data and develop a dynamic, strategic model to estimate the impact of dollar store entry on the equilibrium entry decisions of other stores, and other formats. We find that supermarkets and other large-format owners thrive as dollar-store expansion removes their "competitive fringe" in shared markets, while other small-format stores (other dollar stores, convenience stores, and superettes) do not. Findings from this study suggest that equilibrium location decisions by retail-store owners are complex, and policies aimed at subsidizing small-format stores may be counterproductive at addressing food access concerns.

Keywords: consumer welfare, dollar stores, food deserts, food retailing, Markov-perfect equilibrium, strategic entry.

JEL Classification: D12, D83, L13, L81.

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*Chenarides is Assistant Professor and Richards is Professor and Morrison Chair of Agribusiness, Morrison School of Agribusiness, W. P. Carey School of Business, Arizona State University; Çakır is Associate Professor, Department of Applied Economics, University of Minnesota. Contact author: Richards, Address: 7231 E Sonoran Arroyo Mall, Mesa, AZ, 85212. Ph. 480-727-1488, email: trichards@asu.edu. Funding from Agriculture and Food Research Initiative (National Institute for Food and Agriculture, USDA) grant no. 2021-67024-33822 and USDA Economic Research Service Cooperative Agreement No. 58-4000-9-0033 are gratefully acknowledged.

1 Introduction

Food deserts, or areas characterized by a lack of retail grocery stores, have long been a concern to policymakers. Generally, it has been argued that without proximate access to a grocery store, consumers would not have access to reasonably priced, nutritious foods, thereby raising concerns that individuals residing in so-called "food deserts"[1] are at a greater risk for food insecurity (Gallagher, 2006; Beaulac, et al., 2009; NRC, 2009; Ver Ploeg, et al. 2009; Ver Ploeg, et al. 2015). While supermarkets, or one of the many variations that form the core of our food-retailing system, provide efficient access to high-quality, safe food for most of the population, there remain many locations that traditional food retailers do not find profitable. Whether due to socioeconomic conditions in the surrounding market area, the high cost of access, or some combination thereof, there are holes in our food retailing system (Larson, et al. 2009; Walker, et al. 2010; Cleary, et al. 2018). Lack of access to supermarkets, and the range of foods they offer, can have serious health implications (Eisenhauer 2001; Morland et al. 2002; Morland et al. 2006; Thomsen et al. 2016). These holes, moreover, are responsible for pockets of food insecurity that are simply unacceptable when food is otherwise readily available in the rest of the country. Many researchers suggest a range of policy remedies in order to attract food retailers to food deserts (Ver Ploeg et al. 2015), but the market has also responded the growth of convenience stores, bodegas, and, perhaps most importantly, dollar stores, finding profit where others could not (Cummins and Macintyre 2002, Pearson et al. 2005, Bitler and Haider 2015; Wilde et al. 2016). In this paper, we examine the market-entry of dollar stores as an equilibrium phenomenon, and to study their impact on competing store formats, and stores from other firms, in a dynamic environment in which preemption, economies of density, and competitive foreclosure are all possible motives for entry.

The food-desert concept arose largely in the nutrition and public health literatures, in response to the observation that large segments of the US population seemed to lack easy access to nutritious foods, and dietary quality suffered as a result (Larson, Story, and Nelson

[1] The US Department of Agriculture defines food deserts as low-income census tracts where a sizable proportion of households has limited access to supermarkets, super centers, and large grocery stores.

2009; Sharkey et al. 2009; Rummo et al. 2017). Particularly in the wake of the Great Recession in 2008 - 09, there were a number of policy solutions, both proposed and enacted, that aimed to reduce the incidence of food deserts. However, when subjected to rigorous economic analysis, both conceptual (Bitler and Haider 2015) and empirical (Allcott, et al. 2019), the existence of food deserts remains in question as the market appears to provide exactly what local consumers demand. Yet, there are no studies that specifically examine the role of dollar stores, and format that provide similar assortments, as market-responses to both consumer need, and local competitive forces.

The dollar store business model, defined generally as a limited-assortment format under 10,000 square feet,[2] only sometimes literally offering items for one dollar or less, began decades ago, but flourished in the "new consumerism" movement following the 2008 - 09 recession (Hitt 2011; Malanga 2020). That is, even if consumers have money to spend, they are more conscious of the fact that they do not need to waste it on consumer products from more expensive supermarkets, drug stores, or convenience stores. Dollar stores arose exactly at the right time, and filled a need for discount options on a limited assortment of goods.[3] The dollar store business model is built on locating in low-rent areas, and employing relatively few people per store, earning relatively low wages. Retailing margins are about covering overhead (Bliss 1988; Smith 2004), so if there is little overhead, retail prices can be correspondingly lower with the same level of profitability (Hitt 2011). It is perhaps not surprising, therefore, that dollar stores grew rapidly, both in store-count and total revenue, over the past decade (Wahba 2019).[4] In fact, Mende and Noble (2019) suggest that dollar stores may be either a sign, or a cause, of their "retail apocalypse."

Their popularity, however, has not been universal, and their spread not without controversy. Many communities have reacted by either banning dollar stores, or placing restrictions on what they can offer, demanding that their assortments contain a greater share of fresh foods relative to processed and non-perishable items, or providing financing for less-viable options that promise to provide more fresh foods (Anzilotti 2018). Proponents of these

[2] According to TDLinx, the average square footage of a dollar store format is 7,800 sq. ft.

[3] A similar movement is at least in part responsible for the success of Aldi in Europe, and now in the US.

[4] Deleersnyder, et al. (2007) suggest that dollar stores in the U.S. have a similar competitive effect on other retail formats as hard discounters, such as Aldi and Lidl, have had elsewhere.

efforts claim that dollar stores compete unfairly with traditional supermarkets, and cause local markets to be overwhelmed with inexpensive, poor-quality, processed food that typically comprises a dollar store's food assortment. Yet, Allcott, et al. (2019) use supermarket-entry to former food deserts to answer the question as to whether a lack of supply was the reason why diets in food-desert neighborhoods lacked fresh foods. They find that consumers in these areas simply demand a different set of products than policymakers would like them to, so sales from these newly-opened stores lean disproportionately toward the types of products that dollar stores had been criticized for selling. Their conclusion is that grocery stores sell exactly what their customers demand, and that the composition of supply changes in response to this demand. The authors, however, do not address the more important strategic question of why retailers locate where they do in the first place. Therefore, we investigate store-entry decisions, rather than the composition of their assortments.

Our approach uses a spatial-dynamic structural model of oligopolistic competition and entry among retailers that are likely to be competitors in local markets for food (Ellickson, Misra, and Nair 2012; Arcidiacono et al. 2016; Richards and Liaukonyte 2021). In this model, entry decisions are Markov perfect equilibria (MPE) conditioned on the state of consumer demand and the response from competitors in the retailer's relevant market. By estimating the cost of entry in a strategic, dynamic model, we are able to conduct counterfactual solutions of our dynamic model to determine whether entry decisions by dollar stores forced stores from other formats out of the same markets or merely replaced other small-format stores.

Structural models are necessary to test the underlying hypothesis that dollar-store entry causes other grocery stores, presumably those offering healthier assortments, to exit. In our particular setting, Allcott et al. (2019) show that accounting for the nature of consumer demand, and the assortment that stores provide in response, is critical in understanding store location. But, without accounting for the dynamic, and strategic, aspects of entry, they leave a more interesting question on the table. In fact, research on the dominance of Walmart in the US discount-retailing industry provides an instructive case study to explain how particular formats grow, and spread spatially over time as the product of strategic decision making (Jia 2008; Zhu and Singh 2009; Holmes 2011; and Zheng 2016). Using data from some combination of Walmart, Target, and K-mart, these studies demonstrate that empirical models of retail entry need to account for scale economies associated with multi-store chains (Jia 2008), that the "economies of density" in retail distribution often provide a critical cost advantage (Holmes 2011), that spatial differentiation is important when transportation costs determine store choice (Zhu and Singh 2009; Ellickson and Grieco 2013), and that motives of preemption are likely to affect the decision to enter as the market for consumer dollars is a common-pool resource that can often support only one source of supply (Zheng 2016). Our structural model accounts for each of these elements as we consider the process of dollar-store entry into local grocery markets as analogous to, yet not identical to, the process that lead to discount-store dominance in the United States.

We examine the case of dollar-store entry using a census data set that describes store performance, defined in terms of revenue, employment, and a set of attributes that are likely to be important for store success. In order to keep our analysis tractable, we focus on retail grocery stores, defined as all retail formats that sell food, in the state of Texas. Our use of data from TDLinx (Nielsen, Inc.) is not unique, as others use TDLinx store-level data to study the growth of Walmart over time (Ellickson and Grieco 2013), inter-format retail spatial competition (Ellickson, Grieco, and Khvastunov 2020) and, most importantly, questions of dynamic market equilibria and entry similar to ours (Beresteanu, Ellickson, and Misra 2010; Arcidiacono et al. 2016; Zheng 2016). We merge firm-level store-ownership and operating data with census-tract level socioeconomic and demographic data in order to measure the likely demand for groceries in each local market area in our sample. We define the concept of store-entry as the density of stores owned by a particular firm as in Zheng (2016), and consider competition among firms, and among formats, where we defined formats as either dollar stores, convenience stores, superettes, or large-format grocery stores (including both supermarkets and supercenters). Combining store operating performance and local-market socioeconomic data, we are able to identify both the patterns of demand for stores owned by different firms, and strategic decisions to enter, either through preemption or meeting competition.

Our spatial model of firm-level demand shows that the average distance to the center of a market, which we define as "market coverage," has a positive effect on revenue for both small and large-format stores, but the effect is much larger on the margin for firms that own large-format stores. In other words, supermarkets and supercenters rely on market coverage for profitability much more than small-format firms do. Second, we find that both small and large-format firms benefit from own-firm density, which we interpret as an agglomeration effect similar to that found by Holmes (2011), but this effect is much larger on the margin for larger-format firms. We interpret this finding as suggesting that agglomeration is more important for achieving the economies of scale associated with mass-merchandising bulky, and fresh foods.[5] Third, we find that "other-firm density" also has a positive effect on sales of both types of stores, and nearly equal in magnitude for both format-types. This is perhaps not surprising as the "retail center" effect is likely to be agnostic as to the type of store that attracts customers that come to the market center to shop.

In terms of our dynamic equilibrium model of firm-density, we find that the largest supermarket firms enjoy a substantial entry-cost advantage over both dollar-store parent firms, and firms that own stores of other formats (e.g., convenience stores and superettes). However, their entry-cost advantage does not necessarily constrain the process of dollar store entry. In our counterfactual simulations, we examine the competitive effects of entry by the leading dollar-store firm, and show that competing dollar stores and other small-format firms are harmed, both in terms of equilibrium density and profit. At the same time, however, supermarkets and other large-format owners thrive as dollar-store expansion removes their "competitive fringe" in shared markets.

We contribute to the literatures on retail-food access, retail-store market entry, and dynamic market equilibrium. In terms of the retail-food access literature, our findings support the insights of Allcott et al. (2019) as we explain the pattern of retail-food-store location as an equilibrium phenomenon, conditioned on both the nature of consumer demand for competing formats and the equilibrium responses from other format-owners. In addition, we build upon the growing literature on dollar-store expansion. Chenarides et al. (2021) find that the rate of dollar store exits in food deserts is significantly lower than in non-food

[5] This effect could also be due to the fact that larger stores are, by definition, larger so if we interpret the effect on a per-square-foot basis they are about equal between large and small-format stores. However, we control for store size in the model, so we believe that we isolate the agglomeration effect econometrically.

desert areas, suggesting that there is enough demand for dollar stores in areas otherwise underserved by traditional retailers. Our findings are a variation on this theme as we show that when dollar stores enter a market, or rather expand in an existing market, they do not necessarily force traditional supermarkets out, but rather preempt the entry of stores from similar formats.

Second, we contribute to the broader retail-entry literature by conditioning dynamic entry decisions on an explicitly spatial model of demand, and retail competition. Others in this literature are either purely spatial (Ellickson, Grieco, and Khvastunov 2020), or purely dynamic without a spatial element (Arcidiacono et al. 2016). In the retail-food industry, in which consumers prefer local shopping options (Ellickson and Grieco 2013), but are willing to purchase from different formats in order to find preferred items in specific categories (Cleeren, et al. 2010; Vroegrijk, Gijsbrechts and Campo 2013), we show that it is necessary to account for cross-format competition in spatial markets in order to fully capture the incentives for owners of each type of format to enter, and to expand.

Finally, we contribute to the methodological literature on dynamic market equilibria (e.g., Bajari, Benkard, and Levin 2007; Ellickson et al. 2012; Pavlidis and Ellickson 2017) by showing how to incorporate firm-level spatial elements into a dynamic equilibrium model of entry, and firm density. We show how modeling firm-level decisions adds new insights to the entry problem that individual-store data cannot.

In the next section, we describe our empirical model of spatial competition among firms that own stores of different formats, beginning with a model of spatial demand, and then a model of Markov-perfect density equilibrium as retailers compete over time in the same market. In the third section, we provide more details on the nature of our data set and our identification strategy, and generate some summary evidence on the extent of dollar store entry in our sample market over the 2014 - 19 sample time frame. In section four, we present the empirical results of our demand model, our equilibrium estimates of entry cost for all store formats, and the findings from our counterfactual simulation exercise. The final section concludes, and offers some insights for both public policies regarding food deserts, and future research on retail entry in general.

2 Empirical Model

2.1 Overview of Empirical Model

Our empirical model is designed to estimate consumer store-choice primitives, based only on observations of store revenue in specific market areas. Our approach builds on the logic developed in Chenarides, et al. (2021), namely that store-choice models should use store-level performance measures, rather than traditional category-level measures of attraction (Bell, Ho, and Tang 1998; Bell and Lattin 1998; Briesch, Chintagunta and Fox 2009), in order to capture true entry-and-location incentives. Because we focus on highly granular, census-tract level geographies, we aggregate out to the level of the firm, and consider store-density the relevant measure of entry, and competition (Zhang 2016).[6] Following Ellickson, Grieco, and Khvastunov (2020), we then model store-parent, or firm-level revenue, by estimating the unconditional probability that a consumer chooses a particular store owned by a firm within his or her own market, the number of consumers in the same market, and the share of income spent on grocery stores like the store in question. This approach allows us to estimate all the usual arguments of consumer utility, without the dimensionality problem associated with nested, category-and-store models, nor the ad hoc definition of each consumer market.

We use the store-level demand model developed by Ellickson, Grieco, and Khvastunov (EGK, 2020), as they suggest, as an input to our dynamic model of firm entry. Our demand model is particularly attractive for this purpose as it relies on the finding of DellaVigna and Gentzkow (2019) that retail chains tend to have relatively uniform pricing and assortment strategies to support an assumption that store preference is captured by a simple spatial-retailer fixed effect. This realization is powerful in our setting, because it means that we can model spatial competition among firms without creating price or assortment indices for individual stores. By describing each census tract in the data by the demographic and socioeconomic attributes of a representative consumer, we capture the relative attractiveness of each store-banner and, importantly, format on the competitive structure of each market.

[6] Throughout, we refer to the terms "retailer," "banner," "firm," and "parent" interchangably to refer to a single entity owning and controlling multiple stores. The term "store" is used throughout to refer to an individual location owned by a parent-firm within a larger chain. All decisions regardling location and entry are assumed to be made by the parent firms (Zhang 2016).

By varying the definition the market size, parametrically, we are not constrained to defining markets by fixed geographic definitions, such as a census tract or region, and rather define a sphere of influence around each store as do others in the literature (Ellickson and Grieco 2013).

We use the parameters of this model to define a dynamic entry model by dollar stores, in which banner-identity and format are the arguments of consumer utility that define the competitiveness of each entity. Our dynamic model of entry is a Markov-perfect equilibrium model (Bajari, Benkard and Levin 2007; Sweeting 2013; Arcidiacono, et al. 2016; Pavlidis and Ellickson 2017; Richards and Liaukonyte 2021) that has become a workhorse for problems like this in the empirical industrial organization literature. We then use the entry-cost estimates from this model to solve for new equilibrium market structures under different counterfactual assumptions. Specifically, we use these simulations to investigate the effect of expansion by an existing dollar store firm on the equilibrium location decisions of all other firms in the market.

2.2 Model of Retailer-and-Format Demand

Modeling the demand for stores owned by a single firm through a spatial-aggregation approach entails a number of assumptions, and consequent limitations relative to the more usual approach of considering store-demand at the category-and-store level (Gijsbrechts, Campo, and Nisol 2008; Briesch, Dillon, and Fox 2013; EGK 2020). Most importantly, we do not observe prices at the store level, nor are we necessarily concerned with prices given the insights of DellaVigna and Gentzkow (2019) and Hitsch, Hortacsu, & Lin (2019). While this means that we cannot compute welfare outcomes in the usual way, it avoids the misspecification that results from attempting to model store demand from either a few representative categories, or a price index with questionable category-weight assumptions. Given the inherent dimensionality problems associated with modeling the demand for a store that sells literally thousands of products, we regard this assumption as both valuable, and necessary.

Our demand model is a nested model of retailer-and-format choice, and the unit of observation is a census tract-year. Because we are not concerned with the number of units sold, or some other traditional measure of "demand" facing each firm in a particular market area, we follow EGK and explain the number of "expenditure units," defined as the number of dollars spent at each parent-firm, s, in each tract, t, by consumer-expenditure unit, i, for each census tract-retailer combination, and aggregate over tracts and consumers to arrive at a measure of firm revenue over its entire market-draw, or "catchment," area.[7] Our model is dynamic, in the sense that demand for a firm's stores depends on locations established by rivals in the past, but we drop time notation from the exposition here, for clarity. We model the utility obtained for each census-tract, firm, and expenditure-unit combination in the current period therefore using the notation of EGK as:

$$u_{sti} = u_{st} + \varepsilon_{sti} = \tau_0 d_{st} + \tau_1 d_{st}\mathbf{z}_t + \gamma_0 \mathbf{x}_s + \gamma_1(\mathbf{x}_s \otimes \mathbf{z}_t) + \varepsilon_{sti}, \tag{1}$$

where d_{st} is the average distance from stores owned by parent-firm s to the center of tract t, $\mathbf{z}_t$ is a vector of demographic and socioeconomic attributes of tract t, including population (POP_t), household size (HH_t), and per-capita income (INC_t), $\mathbf{x}_s$ is a vector of store attributes, including store size (SS_{st}), own-firm store density (DN_{st}), and rival-firm store density (DN_{-st}), and ε_{sti} is a GEV error term, with the nesting structure defined over store-formats (dollar stores, convenience stores, superettes, other grocery, and other stores) and individual firms within each format. While we provide more detail on the specific arguments of the elements of each vector of tract and firm attributes below, it is important to highlight exactly how the dynamic, or state, variable enters our demand model.

Unlike the case with large-footprint discount stores or supercenters as in EGK, or others in this literature, the sheer number of dollar stores, and competing convenience stores in each census tract means that modeling the decision to open a particular store is empirically intractable, and not particularly interesting. Therefore, we follow Zheng (2016) by defining the decision variable chosen by each competing parent-firm as the density of stores in each local market. That is, the state variable that forms part of the $\mathbf{x}_s$ vector is defined as the density of stores, or the number of stores per square mile, in each census tract in period τ (DN_{st}), and the density of rival-firm stores in the same local market (DN_{-st}). The demand for each firm's stores, therefore, depends not only on the extent of cannibalization from its

[7] In this approach, a census tract is analogous to a household in traditional demand analysis in the sense that market-aggregate revenue is obtained by aggregating over census tracts, and not households as is usually the case. A census tract is, therefore, considered a representative "household" with this approach.

own stores, but traffic lost to rival stores in the same time period.

With the constant innovation in assortments offered by dollar stores, and their potential competitors, the extent of sales lost to non-grocery formats is an important consideration. With this model, we assume the outside option consists of all expenditure at stores within tract t that do not belong to an inside, or modeled, parent company, or:

$$u_{0ti} = \lambda_0 \mathbf{w}_t + \lambda_1 (\mathbf{w}_t \otimes \mathbf{z}_t) + \varepsilon_{0ti}, \tag{2}$$

where $\mathbf{w}_t$ are physical attributes of tract t that may lead to non-purchase, such as the physical size of the market, population density, and the average commute by market residents.

Using the utility structure defined in equations (1) and (2), we can then define the unconditional probability of choosing a store owned by each firm as a product of the conditional probability of choosing a retailer in each consideration set, and the marginal probability of observing a retailer in the consumer's consideration set. Estimating this nested model then provides the structural parameters we need to populate our Markov-perfect equilibrium model of dollar-store entry into each, endogenous, market. Formally, the EGK model logic expresses the share of spending in tract t on firm s as:

$$P_{st}(\theta) = \Pr(r_{ti} = s) = \Pr(r_{ti} \in C_{t,k(s)}) \Pr(r_{ti} = s | r_{ti} \in C_{t,k(s)}), \tag{3}$$

for parameters θ, where r_{ti} is the retailer at which a consumer of type i allocates their expenditure, and $C_{t,k(s)}$ is the choice set of tract t, and nest k to which stores from firm s belong. With the GEV error assumption, the first term, or the marginal probability of observing firm r_{ti} in consideration set $C_{t,k(s)}$ is given by:

$$\Pr(r_{ti} \in C_{t,k(s)}) = \frac{\left(\sum_{q \in C_{t,k(s)}} \exp(u_{qt}) / \mu_{k(s)} \right)^{\mu_{k(s)}}}{\sum_{v=0}^{K} \left(\sum_{q \in C_{t,v}} \exp(u_{qt}) / \mu_v \right)^{\mu_v}}, \tag{4}$$

where there are K total branches, or store formats in the data, and μ_k is the GEV nesting parameter. The conditional choice probability of choosing a store from each firm, r_{ti}, in each tract-nest then becomes:

$$\Pr(r_{ti} = s | r_{ti} \in C_{t,k(s)}) = \frac{\exp(u_{qt}) / \mu_{k(s)}}{\sum_{q \in C_{t,k(s)}} \exp(u_{qt}) / \mu_{k(s)}}, \tag{5}$$

so the unconditional probability of choosing a store from a particular firm and tract is written as the product, or:

$$P_{st}(\theta) = \frac{(\exp(u_{qt})/\mu_{k(s)}) \left(\sum_q \exp(u_{qt})/\mu_{k(s)} \right)^{\mu_{k(s)}-1}}{\sum_{v=0}^{K} \left(\sum_{q \in C_{t,v}} \exp(u_{qt})/\mu_v \right)^{\mu_v}}, \tag{6}$$

which provides an estimable expression for the market share of each firm, in each census tract in the data.

It is important to note that a market area in our analysis is not fixed by the geographic area of a census tract. Rather, a market area varies based on the "catchment" area around each store, synonymous with a market-draw area. Also, our data are in store-level revenues, and not in purchase quantities as is usually the case. Therefore, we need a way to aggregate out the probability of firm-choice to a measure of parent-firm revenue at each market area. In this regard, we follow EGK by assuming consumers in each tract, t, spend a portion of their income, α_t, on retail grocery stores in general, so the total expected revenue for firm s in tract t is given as:

$$\hat{R}_{st}(\theta, \alpha) = \alpha_t(inc_t)n_t P_{st}(\theta), \tag{7}$$

where inc_t is the average per-household income in tract t, n_t is the population (number of households), and $P_{st}(\theta)$ is the probability expression estimated above. We depart slightly from EGK in this expression by assuming that the propensity to spend income on groceries varies across census tracts, as households, and hence tracts, with lower income are likely to spend a greater share of their income on food than households in higher-income tracts. We do not observe tract-level values for α_t, so assume the spending-propensity parameter is normally distributed with mean α_0, and standard deviation σ_α.[8] Because each firm is assumed to draw from a number of census tracts, we aggregate the expression in equation (7) over tracts in an assumed market-area (m), described above, to arrive at total predicted firm-level, market-level revenue of:

$$\hat{R}_{sm}(\theta, \alpha_t) = \sum_{t \in L_s} \hat{R}_{st}(\theta, \alpha_t), \tag{8}$$

[8] We assume normality so the numerical routine solves more easily than a log-normal assumption, and check each realization of α to ensure none are below zero, which would be clearly implausible.

conditional on each α_t estimate, where L_s is defined as the set of census tracts each firm is assumed to draw from, or: $L_s = \{t : s \in C_t\} = \{t : d_st < D\}$ and D is a fixed market-demarcation distance around each firm's stores. We assume a radius of 1 mile, so we aggregate over stores within 1 mile of each focal store.[9] As in EGK, we examine the sensitivity of our model findings to the D parameter, and find that it is relatively insensitive as the amount of expenditure drawn from stores that are distant from the focal store tends to be very small.

We observe each firm's total revenue in each market, R_{sm}, by aggregating store-revenue over all stores in the same market, m. Therefore, we estimate the model by finding the set of parameters, α, θ that minimizes the squared distance between expected and observed firm revenue. Because we allow for unobserved census-tract-level heterogeneity in the propensity-to-spend parameter, α_t, we estimate the resulting minimum-distance expression using simulation methods, or:

$$(\hat{\theta}, \hat{\alpha}) = \arg\min_{\alpha,\theta} \int \sum_s (\log(\hat{R}_{sm}(\theta, \alpha_t)) - \log(R_{sm}))^2 d\alpha, \tag{9}$$

by integrating over the distribution of α by simulation (Train 2009). In the next section, we explain how we operationalize each argument of the structural model of spatial competition and store choice above.

2.3 Empirical Application

In our application, the vectors of tract and retailer attributes are denoted as in equation (1). Consistent with our empirical approach throughout, we define retailer attributes as describing features of each parent-firm's presence in the market that would help explain the relative revenue earned by the firm. Key to the spatial nature of our empirical model, the primary variable of interest is the average distance of each store owned by the parent-firm to

[9] EGK find a draw radius around Walmart stores of 2 miles, so assuming a draw radius of 1 mile around the dollar or convenience stores in a census tract is conservative. We examine the robustness of our findings to this assumption by considering values of $D = 0.5$ and $D = 2.0$, and find that our results do not change qualitatively. The 2 mile assumption is nearly identical to the distance traveled to the nearest supermarket in Ver Ploeg, et al. (2015), but our data includes not only supermarkets, but dollar stores and convenience stores. Ver Ploeg, et al. (2015) find that when consumers use anything other than a car, the distance traveled to the preferred store is closer to 0.5 miles, so our 1 mile assumption captures any potential market substitution between larger supermarkets, and small-format stores that also sell food.

the centroid of the census tract in which it resides, which is then aggregated to the market level (DS_{sm}), as measured in terms of miles of Euclidean distance. For all variables, the census tract-level measures are aggregated to the level of the market, m, consistent with the definition of the market size, D, above.

The vector $\mathbf{x}_s$, therefore, consists of the average square footage of each store in each market (SF_{sm}), the identity of each parent-firm (PA_{sm}), and the density of stores owned by the parent in the market (defined simply as the number of stores divided by the area of the market, in square miles, $DN_{sm,\tau}$), and the density of stores owned by other parent-firms ($DN_{-sm,\tau}$). The relevant parent-stores in PA_{sm} are defined to include the top stores that account for more than 20% of each format-market, which includes 2 dollar stores, top 3 convenience stores, top 4 grocery stores, and all other stores.

The vector $\mathbf{z}_m$ captures attributes of the census tracts that comprise each market, and that are likely to explain market-level variation in spending, both at the maintenance and "luxury" levels, and across different format-types. Therefore, the elements of $\mathbf{z}_m$ consist of the total population in the market (PO_m), the average household size (HH_m), and average per-capita income (PC_m). In this way, we hope to capture the total amount of purchasing power in the relevant market, and the likelihood of buying groceries at stores of each format, and owner-parent firm.

The elements of $\mathbf{w}_m$, on the other hand, capture factors that are likely to lead consumers to acquire groceries from the outside option, or in all other formats than the ones that are the focus of our demand model. Within the limits of our census-tract data, these factors are a subset of the elements of $\mathbf{z}_m$, or the area of the market (AR_m), the population density (PD_m), and the average daily commute (in minutes, CM_m). By controlling for a broad set of observable attributes of both the store, and the market in which it competes, we isolate as carefully as possible the effect of store density, our state variable, on revenue earned by each firm.

2.4 Dynamic Model of Store Entry

Our dynamic model of store entry considers the strategic equilibrium between dollar store chains, and a broad set of incumbent retailers. In this sense, entry is endogenous, and driven by features of each local market, and the competitive structure in which dollar stores find themselves, including motives for preemption and strategic foreclosure as in Beresteanu, Ellickson, and Misra (2010) and Zheng (2016). Entry, or store proliferation in our model, is a Markov-perfect equilibrium in the sense that no players have an incentive to deviate from their equilibrium paths (Bajari, Benkard, and Levin 2007; Pavlidis and Ellickson 2017).

The elements of our dynamic model of entry capture the spatial, format, and state variables that have proven to be important in this literature (Schiraldi et al. 2012; Ellickson and Grieco 2013; Zheng 2016; EGK). Namely, the state variables for our model consist of the number of stores in each format in the local area ($N_{sm}^{k}, k = 1, 2, ...K$ formats), normalized by the area of each market, so the state variable of interest is the density of stores owned by each parent s, in each market m, during each time period τ, or $DN_{sm,\tau}$. Following Schiraldi et al. (2012) and Zheng (2016), the state-space in our model includes stores owned by the parent-firm, and by all other firms, within the same market area. Conceptually, our conditional choice probability model captures the annual probabilities of store-opening of each format in the market area of each store.

Our equilibrium model assumes an entry decision is conditioned on each player's expectations of their rivals' behaviors, and the nature of consumer demand in the retail market, including the relative distance from each retailer to the market-center. Our model extends Arcidiacono, et al. (2016), who consider the impact of Walmart entry on incumbent retailers, but do not parameterize their competitive-entry model with data as comprehensive as ours. Because of the large number of dollar stores in each market, we proxy the impact of entry by measuring market density (Zheng 2016), and consider firms competing in the relative density of stores.

Our model of dynamic entry follows the approach developed in Bajari, Benkard, and Levin (BBL, 2007), as applied to similar problems in dynamic retail competition in Beresteanu, Ellickson, and Misra (2010), Arcidiacono, et al. (2016), Zheng (2016) and others. BBL describe an approach to estimating Markov-perfect equilibrium (MPE) pricing models that avoids the need to compute dynamically-optimal solutions within the estimation algorithm. In our application of this approach, rival firms compete in locating stores to increase their coverage of each local market, conditioned by the level of demand in each market, and the state of competition, which we define as the density of store-locations by rival retailers. Store-density, in turn, evolves according to a Markov transition process described in more detail in our explanation of the BBL algorithm below. Ultimately, the model produces estimates of the structural parameters governing both stores' location strategies, which are the fixed costs of locating a store in a local market in this application. By simulating the equilibrium model over a range of rival-entry strategies, we are able to reveal the impact of dollar-store entry on the entry decisions, and profitability-performance, of rival retailers. Because entry sometimes causes rival profit to go below zero, our simulations reveal likely exit decisions, although we do not explicitly consider exit in our empirical model.

Estimating complete equilibrium models of dynamic entry decisions similar to those described here is complicated by two, related problems (BBL, 2007). First, to ensure that the decisions of each agent are fully optimal, complete solutions to the firms' dynamic programming problems must be embedded within the estimation routine (Rust 1987; Ericson and Pakes 1995; Pakes and McGuire 2001). While there are many examples of successful implementation of these models, their inherent complexity limits researchers to somewhat simplified versions of the underlying economic problem. Second, there is the possibility of multiple equilibria, so we can never be absolutely confident that the estimated parameters describe behavior that is fully optimal. The BBL method circumvents these two problems in an elegant way – by assuming the data reflects optimal behavior on the part of the agents, and accurate beliefs about not only the decisions of other agents, but about the state of the economic environment. With this assumption, the approach "...effectively recover[s] the agents' equilibrium beliefs" (p. 1332, BBL). Our solution concept is MPE as the equilibrium decisions are Markov reactions by each player, meaning reactions that are only conditioned on the state of the game. While there are many examples in the literature of dynamic discrete games that use the logic of BBL (Aguirregabiria and Mira 2007; Aguirregabiria, Mira, and Roman 2007; Pakes, Ostrovsky, and Berry 2007; Ellickson, Misra, and Nair 2012; Ryan 2012; Arcidiacono, et al. 2016), the paper that is closest to ours methodologically, and one that we follow closely, is Pavlidis and Ellickson (2017).

The BBL method is, conceptually, a two-stage estimation approach. In the first stage, we estimate policy functions that describe how each agent chooses values of the control variable in response to different states of the market. In our application, we estimate flexible regression functions that show how each parent-firm's decision to increase the density of stores in each local market (the entry decision) responds to entry decisions on the part of rival firms. Entry by rivals is defined in a similar way to our measure of market coverage, namely the density of stores by a rival firm in the same market area in the previous period. Because store-location decisions cannot be implemented instantaneously, our approach captures the essential dynamic nature of retail competition among the stores in our sample. Rivals may either foreclose potential competition, or enter stores as a means of preempting future competition. In the second stage, we use these policy functions to forward-simulate continuation values for each firm. By considering a range of "perturbations" from these optimal, or observed, continuation values, we use the equilibrium conditions for a MPE to formulate a minimum-distance estimator that recovers the unobserved structural parameters of the model. That is, the equilibrium requires that the observed data reflect fully optimal decisions by the agent, so the parameters can be recovered by comparing the observed and simulated, non-optimal, decisions. The structural parameters are the ones that fully reconcile the observed data with the simulated data that does not capture the same optimal decisions. We then use the structural model estimated in this second stage to conduct a series of counterfactual simulations that allow us to compare equilibrium store-densities under observed market conditions, and conditions that reflect different densities among dollar-store competitors, and densities from parent-firms in other formats.

In our model, assume the industry consists of $s = 1, 2, ..., S$ firms, each with state DN_{sm} and entry-decision cycle τ (year) such that the state of the system is described as the vector $\mathbf{DN}_s = (DN_{1\tau}, DN_{2\tau}, ..., DN_{N\tau})$. Each year, firms adopt actions in the current period by choosing the number of stores in each market: $N_{s\tau}$. Further, define private shocks to the profitability of each firm as υ_r and a set of Markov strategies as $\sigma = (\sigma_1, \sigma_2, ..., \sigma_N)$ that map states into actions such that: $N_{s\tau} = \sigma_s(\mathbf{DN}_\tau, \mathbf{v})$. With this structure, define the expected value of firm r as the Bellman equation (BBL, 2007):

$$A_s(\mathbf{DN}_\tau; \sigma) = E_\upsilon[\pi_s(\sigma(\mathbf{DN}_\tau, \upsilon), \mathbf{DN}_\tau, \upsilon_r) + \beta \int A_s(\mathbf{DN}'_\tau; \sigma) dP(\mathbf{DN}'_\tau | \sigma(\mathbf{DN}_\tau, \upsilon), \mathbf{DN}_\tau | \mathbf{DN}_\tau], \tag{10}$$

where $dP(\mathbf{DN}'_\tau|\sigma(\mathbf{DN}_\tau, \upsilon), \mathbf{DN}_\tau)$ defines the Markov transition process underlying the set of state variables. With each firm value given by (10), a MPE is defined as the set of strategies that are preferred to all others for the given states, or:

$$\begin{aligned} A_s(\mathbf{DN}_\tau;\sigma) \geqslant & A_s(\mathbf{DN}_\tau;\sigma'_s,\sigma_{-s}) \\ &= E_v[\pi_s(\sigma'_s(\mathbf{DN}_\tau,\upsilon_s),\sigma_{-s}(\mathbf{DN}_\tau,\upsilon_{-s}),\mathbf{DN}_\tau,\upsilon_s) \\ &+ \beta \int A_s(\mathbf{DN}'_\tau;\sigma'_s;\sigma_{-s})dP(\mathbf{DN}'_\tau|\sigma'_s(\mathbf{DN}_\tau,\upsilon_s),\sigma_{-s}(\mathbf{DN}_\tau,\upsilon_{-s}),\mathbf{DN}_\tau)|\mathbf{DN}_\tau], \end{aligned} \tag{11}$$

for each firm s. In our empirical application, therefore, we seek to estimate the parameters of the profit function, π_s, the transition probabilities $P(.)$, and the distribution of private shocks facing each firm. We assume the discount factor, β, is fixed and known to all firms.

Despite the two-stage nature of the of the BBL approach, we estimate the unknown parameters in (11) following five steps (Pavlidis and Ellickson 2017). For clarity, we describe each step of this approach in detail here. In the first step, we estimate flexible policy functions in order to recover the entry-response of each firm with respect to the existing density of rival firms. Because there is an inherent "time to build" associated with market entry, and rival firms are not likely to be completely clairvoyant as to others' entry decisions, the current density of each firm is regressed on the lagged density of rivals firms. This investment lag, therefore, represents the fundamental dynamic element of our model. Using a simple two-firm example for simplicity sake, we follow BBL in estimating a local non-linear regressions of each firm's market-density on the lagged density of the other firm, and the lagged density squared, such that:[10]

$$DN_{s\tau} = \gamma_0 + \gamma_1 DN_{-s,\tau-1} + \gamma_2 DN^2_{-s,\tau-1} + \varepsilon_{rw}, \tag{12}$$

where ε_{rw} is an iid normal error term. In this way, we allow the data to determine how each firm is likely to respond to the number of stores in the market from the other firm, assuming equilibrium responses.

In the second step, we estimate the Markov-transition probabilities for each state variable (separately) as a function of each firm's policy variable. In this regard, we follow the logic of

[10] We include the lagged density squared to allow our firm-level response functions to be as flexible as possible. We expect that market density decreases with lagged rival density, but rival density starts to decrease at decreasing rate at some point.

BBL and estimate binary logit models in which the probability of an increase in the density of each firm is a logit-function of a constant term and the firm's own store-density. For each firm, we estimate:

$$\Pr(\Delta DN_{s\tau} > 0) = \exp(\beta_0 + \beta_1 DN_{s\tau})/(1 + \exp(\beta_0 + \beta_1 DN_{s\tau})), \tag{13}$$

and use the resulting parameter estimates to calculate each element of the Markov-transition matrix, $\mathbf{Q}(\mathbf{\Delta DN}_{\tau}, \mathbf{DN}_{\tau})$. That is, each element Q_{ij} represents the marginal probability calculated from the logit regression, or its complement, so that $Q_{ii} = \partial \Pr(\Delta DN_{s\tau} > 0)/\partial DN_{s\tau}$ for the diagonal terms, and $1 - \partial \Pr(\Delta DN_{s\tau} > 0)/\partial DN_{s\tau}$ for the off-diagonal terms.[11] We then calculate new values for the state variable using the Markov transition matrix according to:

$$DN_{s,\tau+1} = DN_{s\tau} * \mathbf{Q}(\mathbf{\Delta DN}_{\tau}, \mathbf{DN}_{\tau}), \tag{14}$$

for each firm, s. Based on the estimates from the TDLinx data, we find that the Markov process reaches a steady-state after approximately 5 years, and remains constant thereafter.

In the third step, we define the initial state values, and forward-simulate profit using the state-transitions defined in the second step above. For this purpose, we follow Pavlidis and Ellickson (2017) and allow the state vectors to include the random shock from the step 1 policy-function regressions, which is the idiosyncratic shock, υ_r. After defining the initial state-variable values, we calculate optimal policies for the estimated policy functions for the initial states, calculate the associated profits with those initial states, calculate the forward-simulated states based on the Markov-transition matrix ($\mathbf{Q}$) from the second step, and calculate the profit associated with each of those forward-simulated states. Each increment of the forward-simulated profit depends on the updated state in a Markov-perfect equilibrium (MPE), and prices are consistent with each state by the policy functions estimated in step 1. Therefore, profit in each forward-simulated week depends not only upon the state, but each firm's optimal response to the state based on observed rival behavior. Profit in each week is discounted to the current period using a cost of capital ($r = 0.05$) that implies a negligible

[11] Recall that the elements of a Markov transition matrix are interpreted as representing the probability that the agent who is currently in the row-state will be the column-state in the next period. Each row must sum to one for logical consistency.

increment to the current value of the firm beyond week 2,000. We conduct the exercise with a range of discount values, and our findings are not sensitive to our choice.

In step 4, we conduct the forward-simulation process for a large number of "perturbed" or hypothetical responses in which the policy functions for each firm are defined as deviates from the optimal responses defined in Steps 1 - 3 by small amounts. For this purpose, we follow Ryan (2012) and define each perturbed value as a random, standard normal variate from the optimal policy functions. We define the number of perturbed states, H, as 500 in order to obtain a sufficient number of observations to identify the unobserved costs in the estimated value functions. Therefore, we forward-simulate 500 alternative scenarios in which the value functions are calculated with policy functions that are slight deviations from the observed, and assumed optimal, policy functions. These 500 observations then form the data for the structural estimation process described next.

Estimates of the structural parameters of the profit function, which are defined as the cost of entry, θ_s, in our case, are obtained in step 5. BBL note that estimating the cost-parameters of the problem is simplified considerably by exploiting the inherent linearity of the problem. With linear value functions, the forward-simulation process need only be carried out once, and not for every possible value of the unobserved cost vector. For example, the value function in our example is given by (Pavlidis and Ellickson 2017):

$$A_s(DN_s;\sigma_s;\theta_s) = \sum_{\tau=0}^{\infty} \beta^{\tau} \left(DN_s * R_{s\tau} * M\right) - \left(\sum_{\tau=0}^{\infty} \beta^{\tau} (R_{s\tau} * M)\right) * \theta_s, \tag{15}$$

where DN_s is the number of stores in a particular market that generate the simulated revenue, $R_{s\tau}$ is the simulated, per-store revenue-share of firm s in year τ, and M is the size of the market. Step 5 embodies the core of the BBL estimation logic as the intent is to find the value of θ_s that reconciles the optimal with the "perturbed" value-functions. That is, there is a cost parameter (θ_s) that ensures the optimal value function does indeed represent a MPE, or the optimal policy-path for the number of stores to open in a given market, conditional on the choices of the rival firm over time. Although BBL (2007) use a minimum-distance estimator to find the value of θ_s that rationalizes the observed data, we follow Pesendorfer and Schmidt-Dengler (2008) and interpret the second-stage estimates in the BBL algorithm as least-squares estimates, minimizing the squared deviations between the value functions, subject to the observations where the perturbed value exceeds the observed value.

2.5 Counterfactual Simulations

We test our core hypotheses regarding dollar-store entry and competitive response using a set of counterfactual simulations with our structural equilibrium model. Our primary interest is the impact of dollar-store entry on the economic performance, and entry-decisions, of all other formats. Therefore, we simulate an increase in density from one dollar store (Store 1, the dominant dollar store by market share), and use equation (15) to solve for equilibrium firm-level store-densities for all other firms, and the other-store aggregates. We compute our simulated equilibria using the 2,500 simulated observations from the estimation model in order to ensure that the event horizon is the same between both estimation and simulation. In addition to other-store densities, we calculate the change in store profit that results from dollar-store entry.

3 Data and Model-Free Evidence

In this section, we describe our data sources, and provide some model-free evidence as to the drivers and effects of dollar-store entry.

3.1 Data Sources

Our primary data consists of a census of store-level revenue, input, and attribute data for every tract-level market in the state of Texas. Specifically, our store-level retail-attribute data are from Nielsen's TDLinx Store Characteristics Dataset, which provides detailed estimates of annual store-level store volume (measured in terms of dollar sales), number of employees, and a variety of proxy measures for the amount of capital employed at the store level: Size of the store (in square feet), the number of checkouts, and whether the store offers services besides just grocery sales. Most importantly, we know the exact location of each store, and its format classification. Our sample period, consistent with the rise of dollar stores in our sample state, is from 2014 through 2019.

Consistent with the empirical model described in the previous section, our unit of observation is the census-tract (t) / parent-firm (s) / year (τ). That is, we are interested in the expenditure-share, or revenue share from the firm's perspective, associated with each parent-firm, in each census tract, each year. The relevant parent-firms are defined to include 2 dollar stores, top 3 convenience stores, top 4 grocery stores, and all other stores. Combined, the within-format stores account for more than 20% of each format-market. Our focus on firm-level outcomes is both necessary, due to the proliferation of dollar stores and competitive formats (i.e., convenience stores), and relevant, as firms make location decisions on a centralized basis in order to maximize profit from the perspective of the parent-firm, and not from the perspective of the individual store (Zheng 2016). We consider each parent-firm as drawing from all of the surrounding census tracts up to a specific definition of the market, which we initially assume to be 1 mile ($D = 1$).[12] While Ellickson and Grieco (2013) find that 2 miles is the practical market radius for larger grocery stores like Walmart, we suspect that the market area associated with any density of dollar stores in a particular census tract is likely to be no more than one mile in radius. Therefore, we include all own- and competing-stores within 1 mile as being in the same "market" as each focal census tract. Although this definition may seem restrictive for a single state, our market definition still leaves over $5,020$ distinct market areas in the state of Texas.

We supplement the TDLinx data with census-tract-level attributes from the American Community Survey (ACS) of the US Census Bureau (USCB 2021) and the Quarterly Census of Employment and Wages (QCEW) from the Bureau of Labor Statistics (USBLS 2021). We use the ACS data to describe the purchasing power of consumers in each census tract, including per-capita income, the total population in the census tract, average rental payment, and average household size, as well as the likelihood that they are able to travel to larger-format stores to shop through the average commute time, the geographic size of the tract, and average population density. We use the QCEW data to provide instruments for firm's decisions to locate within a given geographic area. QCEW data are not available at the census-tract level, but we merge data at the FIPS code (Federal Information Processing System, county) level on average weekly wages, employment, and total earnings.

[12] We test the sensitivity of our findings under a range of market definitions from $D = 0.5$ miles to $D = 2.0$ miles, and find no qualitative difference in our results.

We summarize our estimation data in Table 1. Because we rely on both temporal and cross-sectional variation in the TDLinx data to identify the primary determinants of entry, and spatial competition, we disaggregate the key variables in our data by year. There are a few observations from this summary information that are important to note. First, within each year, the values of standard deviation relative to their mean indicate there is ample cross-sectional variation in our key measures – revenue share, own- and market-density, and distance – to identify how store entry is likely to affect demand, and subsequent decisions to enter, for the different firms in our data. Second, the share of each major dollar store in total number of stores is small, at approximately 1.0%. Starting from a small base, however, the number of dollar stores has grown rapidly, from 1.87% to 2.02%, or about 8%, over our sample period. While dollar-store growth is still of fundamental importance due both to their locational choices and the departure of the dollar-store concept from the usual way of doing business in retail food, competing formats are also growing in number, particularly convenience stores and other small-footprint formats. Third, the small decline in both measures of density over our sample period suggest that concentration among food retailers, in general, is likely to be an important driver of profitability, and store location.

[Table 1 in here]

With our focus on store density, the existing density of each parent-store is critical information. We show this data in Table 2. In this table, note that the average density values are calculated for markets that only contain a store owned by the relevant parent firm, so the density measures are conditional on the presence of a store.[13] Therefore, density and the number of stores owned by each firm are not directly related, as some firms tend to locate stores in markets with less retail coverage than others. With this in mind, we see that, among dollar stores, Dollar Tree actually has more stores in Texas despite being the second-largest chain nationwide, and is much more densely located than Dollar General. Among the other formats, convenience stores are the most densely located, perhaps as expected, but regional supermarket chains also tend to saturate many local markets. As evidence of the difference between store numbers and density, note that Tom Thumb has relatively few stores, but

[13] Density is the number of parent stores per square mile, divided by the total number of stores per square mile in the same market, conditional on the presence of a store in that market.

tends to locate them in even fewer markets, so their density measure is the lowest of any large-format store owner.

[Table 2 in here]

Focusing specifically on dollar stores, it is instructive to examine locational choices graphically. While the summary data in Table 1 suggests that the growth in dollar stores has to be taken in the context of the entire food-retailing industry, it does not change the fact that dollar store expansion and spread is clear. In fact, we calculated the number of census tracts with a dollar store for three different years in our data: 2015, 2017, and 2019. We found that dollar stores grew in geographic reach and number in the five-year period between 2015 - 2019. In 2015, 37% of census tracts had at least one dollar store. By 2019, dollar store reach expanded, with 43% of census tracts having at least one dollar store. What is perhaps more interesting is the spread of dollar stores according to urban status. In 2015, there was already marked presence of dollar stores in rural areas (or, "non-metro census tracts, not adjacent to a metro area") according to the Rural-Urban Continuum Code of the USDA-Economic Research Service; 55% of rural tracts had at least one dollar store, compared to 34% of urban tracts and 53% of suburban tracts. However, saturation of the initial target markets meant that dollar-store operators moved into both rural and urban markets. Between 2015 and 2019, the number of dollar stores grew by 28% in suburban markets, compared to 21% in rural markets and 24% in urban markets. In the latest year of our data (2019), it was clear that dollar stores were firmly established in rural (64%), suburban (63%), and urban (40%) markets, and faced competition from the traditional retail formats in each geographic area.

3.2 Identification

Identification derives from spatial and temporal variation in consumer choice among different store formats, and chains within each format. In the store-and-format choice model above, density is the key variable of interest. While density may be correlated with the unobservable elements in the demand model, we follow EGK by assuming consumers regard the location of the stores in each chain as given, and, given that store-location decisions are made at the parent-firm level, any correlation between density-decisions and unobservable demand factors is accounted for by parent-firm fixed effects. Our assumption in this regard is analogous to

DellaVigna and Gentzkow (2019), Hitsch, Hortacsu, and Lin (2019), and Kroft, et al. (2019) who find that price and variety decisions are made on a national level, and that individual managers have little scope to change the factors that are most likely to attract customers. In our case, store density plays a similar role, as the corporate decisions that were made many years prior to the realization of demand are not likely to be correlated with the factors that consumers take into account in deciding between stores, and store-formats, in the current time period. Therefore, the variation in density that we observe in our data are, conditional on store fixed effects, exogenous to consumers' decision processes.

Our model differs from the usual nested-logit model in that we estimate the structural parameters of format-and-store choice by minimizing the squared deviation between observed and fitted store revenue, as per equation (9). Clearly, the most important parameter in this process is the marginal propensity to spend income on each store, and each format. Our marginal propensity to spend parameter (α) is identified by the substantial amount of intermarket variation in income and parent-store revenue share, variation in the data, and by allowing for a deep parameterization of the outside option. That is, we account for a broad set of factors that may influence consumers to choose where to spend their retail food dollars outside of the stores included in our data, so any variation in income is more likely to be reflected in spending on our focal stores.

There is also considerable variation, both over time and across the census-tract-based markets in our data, in the number and density of firms associated with each food-retailing format (see Table 1). Our nested model, therefore, contains sufficient variation in revenue share within and across formats to identify the extent of substitution between different types of stores. As is well understood, if consumers regard the alternatives in different nests as substitutes that are as close as the substitutes within the own-nest, then the nested logit collapses to a simple logit model. Because our data shows a substantial amount of variation in store-share within each nest, and among nests over time and across markets, then it must be the case that consumers substitute among different types of store but not perfectly. Below, we conduct formal tests on the extent of substitution within and between chains to provide a more rigorous test of this identification assumption.

On the supply side of the model, firms clearly invest in new stores at different rates over time (Table 2), and in different markets, so there is sufficient variation to identify the core cost-of-entry parameter in the equilibrium density model. In order to identify the parameters of the density model, we need the demand for each parent-firm's stores to vary among markets and over time in a way that is plausibly exogenous. By controlling for parent-firm fixed effects on the demand side of the model, the remaining variation in demand is likely due only to attributes of each market – income, population, and household size, for example – that are exogenous to each firm's decision to locate a store within the market. Conditional on controlling for parent-firm fixed effects on the demand-side, therefore, we maintain that the cost of entry for each firm is well-identified in the supply-side model.

3.3 Model-Free Evidence

We begin our data analysis by providing some model-free evidence that examines the process of dollar-store proliferation, and its effect on incumbent retailers, from all potentially-competing formats.

Consistent with the approach adopted in our empirical model above, we define "entry" in terms of a continuous measure of store density for reasons of tractability. If the objective of each firm is to maximize its share of wallet in each local market (Giesbrechts, Campo, and Nisol 2008) then the revenue share of each market area is a relevant summary measure. In the first reduced-form model, therefore, we estimate a simple regression model of parent revenue-share on a set of market and temporal fixed effects, and the revenue share of firms of each different format type. Our summary hypothesis in this first model maintains that a parent firm's revenue share is likely to decline in the share of each direct rival, whether another dollar store, convenience store, or superette, but not necessarily in formats that are intended to serve different customer markets. Our findings from estimating this model are in Table 3.

[Table 3 in here]

Our first set of reduced-form results shows that parent-density and the share of consumer-spending in any market (or its analog, firm revenue) are positively related.[14] This is to be

[14] We measure own density as the number of stores owned by the same parent in the market, per square mile, and market density is the density of stores from all other firms in the same market.

expected as density may cannibalize the sales from individual stores, but increase sales to the overall firm as more consumers have access to close and convenient stores. Also expected, firm revenue-share tends to be negatively related to market density, or the density of stores from competing firms. Using the same agglomeration-economies logic, the more densely-located are competing stores, the closer they will be to the bulk of the consumer market, and take sales away from store of the focal-parent firm. But, our reduced-form estimates show that the density of stores from formats that are not likely to be direct rivals, such as supercenters for dollar stores, or convenience stores for supermarkets, still have a negative point-estimate. However, this effect is very small relative to the effect of store-densities for formats that are likely to compete for either the same set of consumers, or the same sort of trips from a broad set of consumers. Interestingly, note that our point-estimate for Distance is positive and robust across all specifications. Recall, however, that we control for density, so this means that, all else constant, the greater the reach of a firm's stores across the market, they are likely to earn a greater share of market revenue.

In our second reduced-form model, we examine the question of entry directly, or how the density of stores owned by each parent-firm is related to the density of its own stores, the density of stores in other formats, and the density of stores from formats that are not likely to be direct rivals to the parent-firm in question. In other words, our second set of reduced-form models provides summary evidence regarding how the state variable of our MPE model described above is likely to evolve in a steady state. For this model, we expect that contemporaneous densities of stores owned by the same parent-firm are likely to be positively related, due to well-documented agglomeration effects (Holmes 2011). Because retailers tend to locate stores near to distribution centers in order to take advantage efficiencies in delivering inventory, own-store densities are likely to be positively related over time, and across markets. Further, if consumers feel that they are "always near" an outlet of a particular chain, then demand for all outlets rises – the "Starbucks Effect." This is precisely what we find in Table 4.

In addition, we find a negative effect associated with the density of stores owned by other firms. This may be due to preemption (Zheng 2016), or mere crowding out, and cannot be answered directly in this simple reduced-form model, but the statistical association is clear. Further, while we would expect to find little or no effect associated with store from nominally non-competitive chains, we instead show a strong, positive statistical association. We interpret this finding as resulting from the same dynamic as in Ellickson and Grieco (2013) and Arcidiacono, et al. (2016), namely that the entry of large supermarket competitors opens up a market niche for small stores that serve local markets, local tastes, and customers' preference for convenience in smaller shopping trips.

[Table 4 in here]

Our findings from both reduced-form models suggest that dollar-store firms tend to compete for revenue share from firms with stores in formats that are likely to be customer-rivals, but not with formats that appeal to either different customer segments, or different customer-needs. We also find evidence in support of agglomeration effects, and some form of preemption, or market saturation. However, conclusive evidence on the impact of competing for store density will require a more complete structural model of demand, and strategic rivalry, in which we control for all possible barriers to identification.

4 Results and Discussion

In this section, we present our estimation results, and discuss some of the primary implications. We begin by describing our findings from the nested model of format-and-parent choice, and then move to the MPE model of dollar-store entry, and the counterfactual-simulation findings with this model.

4.1 Nested Firm-Choice Model

We first present the results from estimating a simple model of parent-store choice, and then extend the base model to include greater depth in the complexity and richness of consumers' store-choice processes. We show that our spatial-temporal model of store competition represents the best-fitting model of store demand among all of those we consider.

We present our estimates from the demand model in Table 5. While the results shown in Table 5 consider three different model specifications, we interpret the results from the best-fitting model, where fit in the context of our revenue-deviation objective is defined as the R^2

between observed and implied observation values. In this model (Model 3), there are two sets of structural parameters – distance, store size, own-density, market-density, population, household size, and per capita income – reflecting our nesting procedure between small-format (dollar stores, c-stores, and superettes) and large-format (grocery) stores.

[Table 5 in here]

First, we test whether our GEV specification is appropriate through individual t-tests of the nesting parameters (μ_k) in the demand model above. In every specification, we reject the null hypothesis that the GEV nesting parameters are equal to zero, so conclude that a nested version of the model is appropriate. Intuitively, the fact that these parameters are non-zero, and different from 1, suggests that consumers regard sources of retail food as substitutes, but not perfect substitutes.[15]

Among the small-format parameters, we find that average store-distance to the market center has a positive, yet not-significant effect on firm revenues. This contrasts to the distance estimate for large-format stores, which are primarily supermarkets and supercenters, as distance has a large, positive, and statistically significant effect on revenues. We interpret this finding as pointing to the relatively large market-draw areas for large-format stores, and the fact that they need not be located near the center of the market if they attract customers who are willing and able to drive to the store (EGK). On the other hand, store size has a substantially larger marginal effect on revenues among small-format stores than in large-format stores. This is understandable as the proportionate difference in customer-attraction between a $35,000$ and a $40,000$-square foot store is likely far smaller than between a $2,500$ and $7,500$-square foot store. Because there is considerable heterogeneity among the dollar, convenience, and superette stores in the small-format category (as evidenced by the firm fixed-effect terms), differences in size are likely to prove critical in attracting customers.

The density estimates are clearly key to our objectives, as entry, of either a dollar store or of some other format, reflects a change in parent-density in each market. In this case, the marginal effect of own-firm density is far smaller for small-format stores than for large-format

[15] In future research on this topic, it would be of interest to examine how variation in the μ_k parameters changes as dollar stores seek to become "more like" other retail formats, such as by offering a greater variety of fresh foods (Meyersohn 2021).

retailers – roughly 1/8 the magnitude. There are likely two mechanisms at work here. First, small-format stores rely on density as a means of increasing firm-level revenue. Therefore, because average density is higher for small-format relative to large-format stores (per Table 2), the marginal effect of one more store is much smaller for firms that are already densely located. That said, the entry of a large-format store would naturally attract more customers due to its larger square footage. Considering that the small-format to large-format square footage is about 1/8 the magnitude, the marginal effects of density per square footage are very close between the two formats.

We also estimate the impact of changes in market-density, or entry by rivals, on revenue earned by each firm. Unlike in the non-nested models shown in Table 5, the estimate of market density is positive and significant for both small- and large-format firms. This result is interesting as it highlights the importance of estimating nested models of store-choice, as also noted by Richards (2007). That is, once we allow for imperfect substitution among different types of stores, the nest-conditional effect of density of like stores is positive. This is a different kind of agglomeration economies than Holmes (2011), and points to a clustering effect that is typical among restaurants, bars, and other service-retail outlets as a means of minimizing search-costs for comparison shoppers (Eaton and Lipsey 1979).[16] In contrast to the own-density estimates, the magnitude of the marginal effect is roughly similar between small-format and large-format stores. However, interpreting this effect on a per-square-footage basis, the marginal effect is larger for small formats by this measure. This finding is intuitive as consumers might have stronger preferences for clusters of smaller formats due to their higher transaction and search costs relative to those of large formats.

There are two interesting findings to note among the socioeconomic covariates in the format-demand model. Namely, the marginal effects of income and population tend to be much larger for supermarkets and (large-format firms) than for the small-format retailers in our sample. Again, large-format stores tend to draw from geographic markets with more population, at least within their spheres of influence, and higher incomes than small-format stores.

[16] In fact, Eaton and Lipsey (1979) provide a more general rationalization of the original Hotelling (1929) clustering result that had previously been considered welfare-reducing.

How these demand estimates impact equilibrium densities, however, depends on the cost of entry, and the strategic interplay of stores within formats, and among the formats themselves. We review these results in the next section.

4.2 Markov-Perfect Store Density

In this section, we present the estimation results from the policy-response function stage, which shows how each parent-firm responds to changes in other-store density in the market, and the equilibrium store-density model that is conditional on both the demand and dynamic policy-response estimates.

The policy-response estimates, which show how each firm responds to entry, or changes in density, from rivals are in Table 6.[17] In fact, the estimates in Table 6 show a remarkable similarity in density-response between the small (dollar stores, convenience stores, and superettes) and large (supermarkets and supercenters) stores, with the average marginal response to entry only 2% larger among large relative to small-format stores. In other words, conditional on the state of demand between different store formats, a one-store increase in density will increase small-store density with a probability of 85%, and large-store density by 87% (recalling that the model in Table 6 is a probability-based response model). Recall in the structure of the MPE model, however, that these parameters only condition the long-term Markov transition matrix, and do not take into account equilibrium responses, after changes in market share, profit, and entry cost are taken into account.

[Table 6 in here]

Entry costs are clearly key to profitable entry, and likely drive the decision to exploit any opportunity for apparently profitable entry in the steady-state. The entry-cost estimates are in Table 7, defined in terms of the percentage of store revenues, which we use to compare the relative magnitude of entry costs across store formats. Based on the estimates in Table 7, we see that the two largest dollar store chains, Dollar General and Dollar Tree, have some of the highest entry costs in the sample, at nearly 14% and 17% of firm revenues, respectively. On the other hand, the two largest convenience-store chains, Stripe and Circle K, have relatively

[17] Note that we exclude estimates for the aggregates, or "all other" firm categories from this table as the firm-level policy response function is not well defined without a single decision maker.

low entry costs, while the third-ranked convenience store (7-Eleven) has the highest entry costs of any store in the sample, which could explain both its third-place position, and the fact that it has merged much less aggressively than the top 2 firms in recent years. Among the supermarket and other large-format stores, the estimates in Table 7 show that Walmart and Kroger have relatively high entry costs, while HEB and Tom Thumb have the lowest entry costs among our sample stores. Interestingly the former are both large, national chains, while the latter are local and / or regional chains. Entry-cost advantage, therefore, may be able to explain some of the resilience of these local chains in the face of aggressive price competition, and likely supply-chain advantages, of the other national chains.

[Table 7 in here]

How these entry costs affect equilibrium entry, however, depends on the dynamic interplay of how entry changes store demand, firm profitability, rival entry, and own-response. Our counterfactual simulations take each of these factors into account.

4.3 Counterfactual Simulations

We test our hypotheses regarding store density and profitability by re-solving the equilibrium density model under a range of alternative assumptions regarding dollar-store entry strategies. We present these findings in Table 8.

In this table, we focus on entry by the largest dollar store chain, which is Dollar General in our sample. We model expansion of the chain by incrementing store density by 25% and then 50%, and examine the effect of potential exit by showing what happens to rival density and profit if density falls by 25%, and then 50%. It is necessary to re-solve the equilibrium entry model for each scenario, because the effect of changing density follows not only from the demand model, but how rivals respond with their own entry and exit over time, conditioned on their own profit expectations, and equilibrium entry costs.

Considering first the most extreme case of entry, or an expansion that would increase density by 50% over that shown in Table 2, we see that how that the equilibrium densities of the treated-store (Dollar General) rises, of course, but not to the full extent of the entry shock due to the feedback effects associated with rival response. Among the other "small format" stores (including both dollar stores and convenience stores, excluding "all other aggregates"), we observe substantial contraction in density as Dollar General absorbs demand from markets in which they are collocated, reducing profitability and causing exit in the long run. For the "large format" stores, however, which includes both supermarkets and supercenters, we see the opposite effect. Entry by the focal dollar store removes fringe competitors from spatial markets in which they both compete, the expected profitability of supermarket-type stores increases, and equilibrium density rises. Said differently, expansion by one dollar store deters entry of competing dollar stores, which leaves more of the primary market available for large-format entry. Our findings are approximately symmetric for both entry and exit. That is, lower levels of density from our focal dollar store are associated with higher equilibrium density levels from competing small-format stores, while the density of large-format firms falls as they lose customers to proliferating small-format locations.

[Table 8 in here]

While somewhat counterintuitive, this effect is similar to the dynamic effect of Walmart entry documented by Arcidiacono, et al. (2016), or the spatial effect shown in Ellickson and Grieco (2013), in which small-format stores thrive upon the entry of Walmart, while competing large-format stores do not. That is, Arcidiacono et al. (2016) find that Walmart entry cannibalizes revenues of incumbent large retailers, and we find that Dollar General does the same to small-format retailers. Dollar General, like Walmart, competes with retailers within its same format, and complements retailers in other formats. It is also consistent with the finding by Vroegrijk, et al. (2013) that hard-discounter entry can lead to greater profitability for traditional-format competitors. In their model, hard discounters attract traffic to the local market area as customers search for low prices in price-sensitive categories, and then purchase other high-quality, or variety-sensitive, items from traditional supermarkets. This finding also highlights the importance of accounting carefully for geographic competition, as dollar-store consumers do not necessarily only go to dollar stores for their packaged-food needs, but will optimize over product selection, pricing, and the total cost of conducting each transaction.

Our findings have important implications for the retail food industry. First, our findings are similar in nature to Allcott, et al. (2019) in that store locations are fundamentally driven by consumer-demand, and by optimal firm response. Because dollar stores tend to be opportunistic in their location decisions, it would seem to be a simple solution to the problem of food access to simply subsidize small-format stores to located in currently-underserved locations. However, our findings imply that this strategy would be likely to drive other small-format stores out of the market, and increase the profitability of large-format stores that expand on the fringes of the target food deserts. Second, our findings highlight a more general point that the retail food industry is diverse, complex, and firms compete on many different levels. While it may seem to be a simple matter to pull one lever and achieve the desired result, equilibrium responses over time are conditioned not only by consumer demand, but how competitors react, often in different ways, to take advantage of market opportunities.

5 Conclusions

In this paper, we examine the impact of dollar store entry on the profitability and location of both competing store formats, and the locational choices of large-format stores. We frame our analysis in terms of a dynamic, spatial model of store-format competition in which consumers choose among stores in their local market, and store-owners compete for traffic by locating in the most profitable areas. Firms compete in terms of a dynamic, Markov-perfect equilibrium concept of store location, among stores of similar format, and of different formats.

Our demand estimates show that density is a key variable driving firm-level revenues, but for different reasons among small- and large-format stores. While firms that manage small-format stores rely on density in order to reach as many customers as possible, large-format stores tend to "steer clear" of competitors as much as possible, yet taking advantage of agglomeration economies (Holmes 2011) by locating in close proximity to their own distribution centers, and areas that are likely to attract the most retail business. Others in this literature tend to assume store-density, or location, is exogenously determined, but we consider density as a dynamic equilibrium among stores in the same format, and of different formats.

In parameterizing our model of dynamic competition, we allow for motives for entry that are driven by either avoiding cannibalism, seeking competitive foreclosure, or preemption. While each of these are empirical possibilities, our estimates suggest that firms tend to avoid others, as the optimal competitive response is for own-density to fall in the relative density (share of total stores in the market) of other firms.

Our findings from the equilibrium model suggest that firms compete directly with others that own stores of similar formats, but tend to complement firms that own stores of differing formats. That is, by re-solving the equilibrium model after a shock to the density of a dominant dollar-store format, we show that equilibrium densities, and profits, of other dollar stores fall, while equilibrium densities of large-format stores tend to rise. From a policy perspective, this finding suggests that equilibrium location decisions by retail-store owners are much more complex than a simple demand analysis would indicate. If the goal is to encourage small-format store locations in currently under-served markets, for instance, the superficial solution of subsidizing small-format stores to locate in these areas may be counterproductive. Instead, if the complementary-location effect we find here is general, then encouraging dollar-store entry will end up benefiting the large-format stores that operate on the edges of the areas that we would like to see better served by existing grocery stores.

Future research in this area would benefit from more granular data on the prices charged, and volumes sold, of particular food categories. The data we use for this analysis (TDLinx) only describe firm-level revenues so, while ideally suited for firm-level analyses, are not able to study the types of food, and prices set, within individual stores. Our analysis is also specific to our sample state (Texas) for reasons of tractability. A more general analysis would apply a similar method to that used here to a national sample, or perhaps a different regional sample. Third, our MPE assumption considers only one dimension in which firms may compete over time. Loyalty, pricing, or variety are each clearly obvious candidates for a more general consideration of a similar problem.

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Table 1. Summary of Spatial Location Data

		2014		2015		2016		2017		2018		2019	
	Units	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Revenue Share	%	0.297	0.283	0.295	0.281	0.290	0.277	0.288	0.274	0.287	0.274	0.286	0.275
Density Share	%	0.341	0.252	0.338	0.251	0.333	0.248	0.331	0.244	0.329	0.242	0.328	0.241
Own Density	Stores / Mile^2	1.232	1.421	1.229	1.437	1.222	1.427	1.207	1.407	1.187	1.386	1.187	1.399
Market Density	Stores / Mile^2	3.201	3.690	3.189	3.719	3.207	3.714	3.132	3.579	3.072	3.507	3.069	3.511
Dollar General	% Stores	0.086	0.280	0.087	0.282	0.088	0.283	0.089	0.285	0.092	0.289	0.093	0.291
Family Dollar	% Stores	0.101	0.301	0.101	0.301	0.102	0.303	0.104	0.305	0.107	0.309	0.109	0.312
Distance	Miles	0.025	0.073	0.025	0.090	0.024	0.040	0.024	0.040	0.025	0.048	0.025	0.048
Square Feet	000 Sq Ft	0.167	0.257	0.167	0.257	0.166	0.257	0.167	0.256	0.167	0.254	0.164	0.250
Population	0,000	0.615	0.362	0.630	0.382	0.641	0.402	0.654	0.419	0.664	0.437	0.674	0.460
Population Den.	,000 / Mile^2	3.665	3.308	3.686	3.344	3.718	3.397	3.717	3.399	3.721	3.407	3.733	3.415
HH Size	#	2.835	0.527	2.840	0.520	2.841	0.518	2.843	0.514	2.851	0.513	2.848	0.513
Per Capita Inc.	$ 0,000	2.475	1.388	2.523	1.427	2.600	1.470	2.718	1.537	2.821	1.571	2.920	1.613
Area	Miles^2	39.866	196.864	39.651	186.788	40.635	195.818	33.591	115.136	34.166	116.152	34.299	115.990
Commute	Minutes	23.905	5.731	24.204	5.841	24.488	5.894	24.715	5.992	24.921	6.011	25.263	6.129

Note: Firm-level data from Nielsen / TDLInx. Demographic and socioeconomic data are from American Community Survey (U.S. Bureau of Census). SD = standard deviation. Family Dollar includes Dollar Tree data. Own Density is the number of stores owned by the same parent in the same market and Market Density is the density of all stores from all firms in the same market, other than the own-firm's stores.

Table 2. Store Densities by Parent Firm

Parent	Format	Density	Std. Dev.	Min.	Max.	N
Dollar General	Dollar Store	0.5303	0.6362	0.0003	4.7347	1,516
Dollar Tree	Dollar Store	0.9280	0.8461	0.0003	5.4274	1,766
Stripes	Convenience	0.7102	0.8932	0.0003	6.3522	518
Circle K	Convenience	0.9831	0.8928	0.0004	5.5101	905
7-Eleven	Convenience	1.1223	1.0291	0.0007	10.7426	1,039
Superettes	Superettes	1.1577	1.0645	0.0002	12.7528	740
Walmart	Supermarket	0.6990	0.8235	0.0003	4.7002	598
HEB	Supermarket	0.9494	0.9814	0.0023	7.1005	431
Kroger	Supermarket	0.9183	0.7922	0.0056	4.8150	285
Tom Thumb	Supermarket	0.3215	1.1002	0.0569	5.1860	100

Note: Dollar Tree includes Family Dollar stores. Supermarkets includes supercenters so is interpreted as all large-format grocery stores. In the estimation models, we allow for "Parent" observations that capture all-other dollar stores, all other convenience stores, and all other supermarkets, separately. Density is defined as the average of number of stores per square mile in the same market, conditional that a store belonging to the parent-firm has a presence in that market.

Table 3. Reduced Form Evidence: Revenue Share

	Model 1		Model 2		Model 3	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Distance	0.1910***	0.0125	0.1269***	0.0120	0.1370***	0.0120
Square Feet	0.2924***	0.0035	0.3017***	0.0034	0.2988***	0.0034
Own Density	0.0147***	0.0007	0.0207***	0.0007	0.0218***	0.0007
Market Density	N.A.		-0.0231***	0.0003	-0.0202***	0.0003
Market Density - Other Formats	N.A.		N.A.		-0.0031***	0.0001
Population	-0.0880***	0.0024	-0.1185***	0.0023	-0.1237***	0.0023
Pop Density	-0.0105***	0.0003	0.0024***	0.0003	0.0040***	0.0003
HH Size	0.4170***	0.0168	0.2919***	0.0162	0.2979***	0.0162
Per Capita Income	0.0078***	0.0007	0.0024***	0.0007	0.0031***	0.0007
Rent	-0.0292***	0.0033	-0.0325***	0.0032	-0.0371***	0.0032
Poverty Line	-0.0453***	0.0049	-0.0139***	0.0048	-0.0211***	0.0048
Commute	0.4755***	0.0128	0.4699***	0.0124	0.4855***	0.0123
Year Effects?	Yes		Yes		Yes	
Parent Effects?	Yes		Yes		Yes	
Format Effects?	Yes		Yes		Yes	
R^2	0.3617		0.4071		0.4099	
F	2,063.10		2,413.80		2,360.60	
N	101,901		101,901		101,901	

Note: Dependent variable is parent-firm revenue share in total market (D = 1 mile). Market radius is defined as D = 1 mile from each census tract centroid. Distance is defined as the average distance to the market center, Own Density is a leave-one-out measure of the number of own-stores per square mile in the same market, Market Density is the number of other-parent owned stores per square mile, and Market Density - Other Format is the density of stores in non-competing formats in the same market (i.e. supercenters versus dollar stores). All demographic and socioeconomic variables are from the American Community Survey (ACS), US Census Bureau. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%.

Table 4. Reduced Form Evidence: Store Density

	Model 1		Model 2		Model 3	
Variable	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
Distance	0.1522***	0.0099	0.0639***	0.0088	0.0524***	0.0088
Square Feet	0.0617***	0.0028	0.0745***	0.0025	0.0779***	0.0025
Own Density	0.0378***	0.0006	0.0460***	0.0005	0.0448***	0.0005
Market Density	N.A.		-0.0318***	0.0002	-0.0351***	0.0002
Market Density - Other Format	N.A.		N.A.		0.0035***	0.0001
Population	-0.0777***	0.0019	-0.1196***	0.0017	-0.1137***	0.0017
Pop Density	-0.0036***	0.0003	0.0142***	0.0002	0.0124***	0.0003
HH Size	0.4437***	0.0133	0.2715***	0.0119	0.2647***	0.0118
Per Capita Income	0.0181***	0.0006	0.0106***	0.0005	0.0097***	0.0005
Rent	0.0098***	0.0026	0.0053***	0.0023	0.0105***	0.0023
Poverty Line	-0.0786***	0.0039	-0.0353***	0.0035	-0.0271***	0.0035
Commute	0.2592***	0.0102	0.2516***	0.0090	0.2338***	0.0090
Year Effects?	Yes		Yes		Yes	
Parent Effects?	Yes		Yes		Yes	
Format Effects?	Yes		Yes		Yes	
R^2	0.4851		0.5982		0.6027	
F	3,484.20		5,231.50		5,154.70	
N	101,901		101,901		101,901	

Note: Dependent variable is parent-firm relative store density, or the number of parent stores per square mile, divided by the total number of stores per square mile in the same market. Market radius is defined as D= 1 mile from census tract centroid. Distance is defined as the average distance to the market center, Own Density is a leave-one-out measure of parent density per square mile, Market Density is the number of other-parent owned stores per square mile in the same market, and Market Density - Other Format is the number of stores per square mile owned by other parent firms, in non-competing formats (i.e., supercenters for dollar stores. All demographic and socioeconomic variables are from the American Community Survey (ACS), U.S. Bureau of Census. A single asterisk (*) indicates significance at a 10% level, ** at 5% and *** at 1%.

Table 5. Structural Demand Model Estimates

Variable	Model 1		Model 2		Model 3			
	Revenue-Based		Nested Revenue-Based		Nested Revenue-Based			
					Dollar / C / Superette		Grocery	
	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
Distance	0.2115***	3.1656	0.2482***	3.3842	0.0754	1.0568	0.4401***	2.5031
Store Size	0.0519***	12.4229	0.0881***	13.1638	0.1740***	7.7197	0.0849***	9.9441
Own Density	0.0834***	8.2289	0.0732***	3.9804	0.1157***	5.4521	0.9031***	14.5287
Market Density	-0.3261***	-33.3326	-0.2804***	-16.6799	0.0507***	3.1561	0.0742***	3.0679
Population	-0.2500	-0.8520	0.4408***	4.8590	0.1778	1.9165	0.4417***	3.0586
HH Size	-0.0414	-0.0804	0.7607	0.8237	0.1120	0.1288	-0.7988	-0.5840
Per Capita Income	-0.2348***	-4.2746	0.2225***	5.5973	0.1826***	5.6934	0.3512***	6.8428
Distance*Population	0.0274***	2.0659	-0.0025	-0.1836	0.0061	0.3602	-0.0862***	-3.2423
Distance*HH Size	0.5247***	2.6230	-0.0253	-0.1155	0.6199***	2.6254	-0.4788	-0.8869
Distance*Per Capita Income	-0.0483***	-7.4600	-0.0082	-1.1604	-0.0340***	-4.4210	0.0865***	5.1394
Store Size*Population	-0.0182***	-14.2808	-0.0175***	-15.8799	-0.0886***	-13.1743	-0.0118***	-11.7591
Store Size*HH Size	0.1253***	9.6742	0.1610***	6.7750	0.4314***	6.3924	0.1401***	5.1333
Store Size*Per Capita Income	-0.0011***	-3.1366	-0.0036***	-6.9296	-0.0078***	-4.8303	-0.0075***	-12.1850
Population Density	0.1906***	9.5948	0.0331***	2.6061	0.1284***	9.2063		
Commute	-1.3088	-1.2403	0.5767	1.1707	1.1165***	2.2925		
Area	-0.7769	-0.2052	-0.3517	-0.2055	-0.1881	-0.2075		
Density*Population	-0.0343***	-9.3234	0.0082***	3.2888	0.0107***	3.8368		
Commute*Popluation	0.0712	0.3339	0.6903***	7.4232	0.5336***	5.8976		
Area*Population	0.3070	0.5497	0.0822	0.1510	0.8498***	2.4637		
Density*PC Income	-0.1372***	-7.7984	-0.0127	-1.2172	0.0159	1.4204		
Commute*PC Income	2.4128***	2.8850	1.3598***	6.1651	-0.0634	-0.2372		
Area*PC Income	-0.3476	-0.1147	0.1846	0.1052	0.0199	0.0218		
μ- Dollar Stores			0.1100***	32.7740	0.1371***	333.1826		
μ- C Stores			0.4647***	26.1453	0.5919***	18.4794		
μ- Grocery Stores			0.4059***	25.4872	0.4085***	30.3268		
α	0.1654***	134.3392	0.1491***	159.5589	0.1590***	154.2097		
R^2	0.4354		0.4975		0.5579			
Revenue	31,679.95		30,588.75		30,494.75			

Note: Nesting parameter for Superettes not separately identified as there are no dominant parent-firms in the model. All stores are considered one nest for estimation purposes in Model 1, and four nests in Models 2 and 3. All estimates use a market definition of D = 1 mile. Estimates for other market definitions are similar. Parent effects not reported. A single asterisk (*) indicates significance at a 10% level, ** at 5%, and *** at 1%. N=101,901 for all models.

Table 6. Policy Function Estimates: Density Reactions

	Estimate	Std. Err.		Estimate	Std. Err.
Dollar General			Walmart		
Constant	0.8675***	0.0052	Constant	0.8740***	0.0042
Density	-0.7351***	0.0132	Density	-0.7777***	0.0109
Density^2	-0.1283***	0.0084	Density^2	-0.0948***	0.0073
Dollar Tree			HEB		
Constant	0.8131***	0.0067	Constant	0.9438***	0.0035
Density	-0.6217***	0.0160	Density	-0.9415***	0.0089
Density^2	-0.1874***	0.0097	Density^2	-0.0016	0.0058
Stripes			Kroger		
Constant	0.8352***	0.0048	Constant	0.8605***	0.0047
Density	-0.6991***	0.0132	Density	-0.7631***	0.0116
Density^2	-0.1342***	0.0090	Density^2	-0.0970***	0.0072
Circle K			Tom Thumb		
Constant	0.9049***	0.0044	Constant	0.8119***	0.0045
Density	-0.8528***	0.0117	Density	-0.6576***	0.0114
Density^2	-0.0490***	0.0079	Density^2	-0.1541***	0.0073
7-Eleven					
Constant	0.8871***	0.0037			
Density	-0.8186***	0.0102			
Density^2	-0.0655***	0.0070			

Note: Policy functions for firms in the "all other" categories are not well defined, so are excluded from the table. Parameters are estimated with local linear regression models. A single asterisk (*) indicates significance at 10%, ** at 5% and *** at 1% level of significance.

Table 7. Estimated Markov-Perfect Entry Costs

	Entry Cost	Std. Err.	Function	Chi-square
Dollar General	0.1367***	0.0001	32,564.47	65,128.95
Dollar Tree	0.1695***	0.0002	12,349.81	24,699.62
Stripes	0.1210***	0.0030	1,048.29	2,096.58
Circle K	0.1323***	0.0003	1,665.61	3,331.23
7-Eleven	0.2205***	0.0002	1,735.20	3,470.40
Walmart	0.1490***	0.0002	2,170.96	4,341.93
HEB	0.0343***	0.0005	4,253.89	8,507.79
Kroger	0.1119***	0.0002	8,267.40	16,534.80
Tom Thumb	0.0250***	0.0004	3,343.90	6,687.81

Note: Models are estimated separately. Entry Cost is defined as the cost (in $,000) to open a new store in the market, as a % of store revenue. Function is the minimized loss–function value. Aggregates of "all other" firms in each format are excluded as entry is not well-defined. A single asterisk (*) indicates significance at 10%, ** at 5%, and *** at 1%.

Table 8. Counterfactual Simulations: Dollar Store Entry

Shock	Variable	Dollar Gen.	Dollar Tree	Stripes	Circle-K	7-Eleven	Walmart	HEB	Kroger	Tom Thumb
-50%	Density	0.3258	1.0838	0.8547	1.1667	1.0544	0.5248	0.7229	0.7350	1.0713
	Std. Err.	0.0005	0.0002	0.0001	0.0002	0.0004	0.0002	0.0008	0.0002	0.0006
	Profit	2,368.7310	3,446.1270	935.0723	920.6026	1,278.2000	3,656.1980	4,343.3230	2,896.7450	2,679.6350
	Std. Err.	1,024.8220	2,344.4150	529.2890	560.9202	1,307.3840	1,246.4880	1,526.1270	817.3832	665.7387
-25%	Density	0.4379	0.9765	0.7684	1.0492	0.9589	0.5839	0.8065	0.8126	1.1826
	Std. Err.	0.0007	0.0002	0.0001	0.0002	0.0004	0.0003	0.0001	0.0003	0.0008
	Profit	3,183.0810	3,104.7720	839.7075	827.2482	1,162.7040	4,069.1090	4,844.2750	3,204.3300	2,953.9940
	Std. Err.	1,384.5510	2,133.0480	478.3513	507.6528	1,202.8200	1,546.5290	1,886.2590	1,006.5120	813.0596
Baseline	Density	0.5170	0.8699	0.6829	0.9326	0.8641	0.6440	0.8922	0.8901	1.2921
	Std. Err.	0.0008	0.0002	0.0001	0.0002	0.0004	0.0004	0.0001	0.0003	0.0009
	Profit	3,757.3740	2,765.4390	745.2496	734.7209	1,047.9510	4,490.4240	5,357.2060	3,512.1470	3,223.4960
	Std. Err.	1,651.7350	1,928.3880	428.9447	455.9282	1,109.5440	1,935.2500	2,349.8900	1,249.8600	999.4386
25%	Density	0.5657	0.7664	0.6000	0.8197	0.7720	0.7041	0.9781	0.9660	1.3976
	Std. Err.	0.0009	0.0024	0.0001	0.0001	0.0005	0.0005	0.0001	0.0004	0.0001
	Profit	4,109.8860	2,435.8330	653.8080	645.0845	936.5608	4,911.3410	5,870.3900	3,814.3000	3,482.1220
	Std. Err.	1,837.7180	1,734.8130	382.0417	406.7818	1,032.8990	2,403.8040	2,902.8420	1,545.2570	1,223.1820
50%	Density	0.5877	0.6682	0.5215	0.7127	0.6848	0.7628	1.0622	1.0390	1.4970
	Std. Err.	0.0001	0.0002	0.0001	0.0001	0.0006	0.0006	0.0002	0.0006	0.0001
	Profit	4,267.8290	2,122.9630	567.2862	560.2054	830.9209	5,322.8840	6,371.5850	4,105.5640	3,724.8840
	Std. Err.	1,955.4280	1,555.5390	338.3629	360.9988	978.5542	2,934.3560	3,522.0940	1,887.5210	1,480.9210

Note: Simulations calculated from nested-revenue demand model estimates, and equilibrium entry cost values. All values are statistically different from the Baseline estimates at a 5% level of significance, and 500 simulated observations.