Retail Agglomeration and Competition Externalities: Evidence from Openings and Closings of Multiline Department Stores in the US

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Abstract

From the perspective of an existing retailer, the optimal size of a cluster of retail activity represents a trade-off between the marginal increases in consumer attraction from another store against the depletion of the customer base caused by an additional competitor. We estimate opening and closing probabilities of multi-line department stores ("anchors") as a function of pre-existing anchors by type anchor (low-priced, mid-priced or high-priced) using a bias corrected probit model with county and year fixed effects. We find strong negative competitive effects of an additional same type but no effect on openings of anchors of another type.

Key Words: Multi-line Department Stores, Shopping Centers, Openings, Closings, Bias-Corrected Probit

JEL Codes: D430, L1, L21, L81, R1, R3, R12, R33

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1. Introduction

According to the 2007 Economic Census, there were 1,122,703 retail establishments in the United States with a total of 14.2 billion square feet of retail space, and the retail sector accounts for roughly 22% of GDP.[1] Foster, Haltiwanger and Krizan (2006) document reallocation and restructuring activities in the retail sector. They find that multi-store chains are replacing independent stores, and that retail productivity has increased as a consequence.[2] Recently, large enclosed malls are being remade into open air shopping centers at great expense, while new centers open nearby. Large retail operators such as General Growth Properties (GGP) and Simon Property Group (SPG) are divesting under-performing properties. Once successful retailers such as Sears and JC Penney are now striving for survival. Against this backdrop of destruction and rebuilding, we provide empirical evidence on the decisions to open or close a new store or shopping center.

The existence of shopping centers and large clusters of retail activity are often explained based on the existence of externalities in the purchase of goods and services. Fixed costs of a shopping trip imply that multipurpose trips can account for the existence of shopping centers and districts where different types of stores concentrate (Stahl, 1982). Consumers are willing to pay for access to a diversity of products and services (Quigley, 1998; Glaeser, Kolko and Saiz, 2001), and so are likely to be willing to drive further and concentrate some of their shopping time at large concentrations of retail activity where such diversity is available.

From the perspective of an existing retailer, the optimal size of a cluster of retail activity represents a trade-off between the marginal increases in consumer attraction added by an additional retail enterprise against the depletion of existing stores' customer base caused by the addition of competing retail activity. Following the logic developed in the literature on optimal city size (Albouy and Seegert, 2010; Fenge and Meier, 2002; Arnott 1979; Tolley 1974), the incentives faced by new retail entrepreneurs do not align with the criteria for optimal shopping cluster size.[3] New commercial retail space is created and new retail establishments are opened based on the average return from a retail enterprise, while optimality in terms of total profits or rents requires balancing the marginal effect of opening a new store on total returns among all enterprises. New owners or developers ignore the external costs to current retailers or current property

[1] Consumption is about 68% of US GDP (World Bank estimate) and the BLS Consumer Expenditure Survey for 2011 indicates that the purchase of retail goods and services (not including shelter, transportation, insurance, cash contributions and similar non-retail items) accounts for about 32% of consumption.

[2] Hausman and Leibtag (2007) provide additional evidence of increased productivity from a new anchor store.

[3] The traditional view developed in this literature is that cities may be too large because potential migrants ignore the congestion externalities imposed when they move to a city (Au, Henderson, 2006; Black, Henderson, 1999; Duranton, Puga, 2001; Helsey, Strange, 1990; Henderson, 1974). Albouy and Seegart (2010) provide a simple illustration where migrants continue to move to a city until the average benefit of living in the city falls to the value of residing in the outside option, but efficiency requires that the average benefit be higher than the outside option to account for the impact of migration on the welfare of current city residents. Note that the optimal city size literature focuses on social optimality while our paper focuses on optimality from a business or developer perspective ignoring potential welfare gains on the consumer side.

owners caused by competition provided by new developments, and as a result retail clusters may be too large in equilibrium.[4] On the other hand, these external effects may be internalized by large shopping centers or large, centralized commercial developments where the corporate planner's objective is to maximize land values or commercial rents. Multiline department stores can attempt to take the trips they generate under one roof, or they can profit with an ownership interest in a shopping center, where they use rents charged to smaller stores to internalize localization economies (Konishi and Sandfort, 2003; Gould, Pashigian and Prendergast, 2005).[5]

In this study, we examine whether the likelihood of a store opening (closing) is lower (higher) when there are more existing stores in a location, which would be consistent with the current level of retail activity being above the optimal level from the perspective of existing stores. Our core intuition is that the trade-off between retail agglomeration and competition can be modeled in a discrete choice framework. The dependent variable is a decision to open or close within a county; explanatory variables focus on the number of existing stores. County fixed effects control time-invariant unobservables. Yearly fixed effects control demand-side variables that vary as a function of the US business cycle.

Clapp, Bardos and Zhou (2014) examine the probability of major expansions and contractions in the sizes of shopping centers, and find a weak positive relationship between competition and the probability that size will change, which would seem to work against the idea that retail clusters are too large.[6] However, cross-sectional studies of this type face the potential of a significant positive bias due to unobserved demand factors: places that have an unexpectedly, large numbers of competitors likely have many positive, unobserved demand attributes that contribute to the profitability associated with expanding a shopping center. In this paper, a similar concern arises in that recent increases in local demand are likely to both increase the existing number of stores and increase the likelihood of a store opening. We address this concern by estimating models of anchor store openings (and closings) controlling for location fixed effects in order to capture location demand during our time frame, and as a result the estimated models presented here will be identified by changes in the number of existing anchor stores in each location over time.

Local demand factors that vary over time but differently than the national business cycle – i.e., variation not captured by yearly fixed effects – pose a possible problem for our fixed effects approach. But omitted

[4] "Over retailing" – meaning too much retail space per capita – is associated with declining or abandoned shopping centers, loss of local tax revenue and the potential for urban blight. Deadmalls.com contains a partial list of troubled or abandoned shopping centers. When last accessed on March 20, 2014, there were over 450 such stories logged during the period covered by our data (2005 through 2011).

[5] For example, multiline department stores typically have a prominent jewelry counter, and the store is often located in a shopping center containing several stores specializing in jewelry. The decisions of these directly competitive stores to open in close proximity especially when founding anchor stores have considerable control over other tenants may be explained by the benefits associated with drawing customers to the area for comparison shopping, a benefit that also explains automobile dealers occupying "automobile row." This suggests that agglomeration benefits are powerful even in the absence of internalization.

[6] They attribute this cross-sectional result to a reduction in the value of the delay option. Here, we focus on changes over time within a local market so that we can test agglomerative *versus* competitive effects.

time varying demand factors should bias us away from finding evidence that retail clusters are too large because recent changes in demand should both increase the number of existing anchor stores based on recent openings and also increase the likelihood of openings in the current period. We estimate our core model after adding controls for observable changes in market demand, i.e. county employment and payroll, at the location level. However, we find that annual changes in these key economic indicators cannot explain. Therefore, while this analysis cannot prove or disprove are view that omitted demand factors bias us away from finding that clusters are too large, the insignificance of these major determinants of demand suggest that our time period is sufficiently short that with sample changes in observable demand factors are relatively unimportant.

The inclusion of location fixed effects and number of pre-existing stores in a model of openings implies that within location changes in the likelihood of an opening depend upon all past openings (and closings). Further, our data force us to rely on a relatively short panel for estimating location fixed effects. As a result, traditional choice analyses will suffer from an incidental parameter bias because the fixed effect contains predetermined outcomes from all years and so given the small number of years the fixed effects are correlated with the unobserved determinants of outcomes in every year. For lagged, continuous dependent variable models, this problem is addressed by first differencing the data and using earlier years as instruments (Arellano and Bond, 1991), but this approach will not work for our application because our right hand side variable, the number of anchor stores as of last year, depends upon all past openings eliminating all possible instruments. Further, our dependent variable is discrete. Therefore, we estimate a fixed effect binary choice model using recent bias correction approaches to correct for incidental parameters bias specifically under circumstances when control variables are pre-determined (Fernandez-Val, 2009). To our knowledge, the study represents the first empirical application of Fernandez-Val's (2009) bias correction estimator and one of a very small number of applications of such bias correction estimators more generally.

This study focuses on openings and closings of anchor stores: i.e., multiline department stores such as Nordstrom, Bealls, Marshalls or Target. Our focus on anchors is appropriate because it provides meaningful limits on data collection; the entire retail sector is too vast to allow assembly of data from primary sources. Moreover, a new shopping center requires a commitment from one or more anchors in order to raise debt and equity capital. Smaller, more specialized stores, the "in-line" tenants of shopping centers, will make their opening decisions after the anchors, and they pay higher rents to shopping center owners (Pashigian and Gould, 1998). Through rents charged from in-line stores, anchors internalize some of the benefits from the traffic they generate. When the anchors choose to open independently of a shopping center (i.e., a free standing department store), they sacrifice the potential to internalize. Other stores will open near the free standing anchor if they think they can feed off the traffic generated. They may try to offer complementary goods and services or they may directly compete by offering comparison shopping.[7]

Our unique data set contains a comprehensive list of multiline department stores, including both existing and new openings. We model the probability of anchor store openings and closings at the county level using discrete choice models with county and year fixed effects. The inclusion of county fixed effects in the model controls for the market demand associated with each county during our general time period, and the model is identified based on changes over time in the number of competing anchor stores. We condition our opening decisions on existing anchors in the local area at the beginning of the year prior to opening. With precise geographic location and shopping center information, we are able to distinguish anchor stores inside shopping centers from those located in a freestanding format (about 36% of our sample).

We evaluate localization effects by comparing opening decisions by type of store (defined by low-priced, mid-priced and high-priced) as conditioned on existing stores of all different types. For example, we might expect a high-priced anchor such as Macy's to find positive localization effects from being in the vicinity of a low priced anchor such as Sears; similarly, we can investigate the effect of existing anchors of the same type in the same county. In addition, we classify anchors by their typical sizes because the larger the size of the anchor, the greater the amount of externality created by the anchor (Brueckner, 1993). We might expect a small-scale anchor such as TJ Maxx to find positive localization effects from being in the same shopping center (or possibly near to) a big-scale anchor such as Wal-Mart.

We find evidence for strong negative competitive effects. Opening probability for each type of anchor is negatively and significantly influenced by the existing anchors of the same type, not by other types. In the bias corrected model, the unconditional probability of a low-priced opening, 20%, is reduced by 35% (to about 13%) by the presence of an additional pre-existing low-price anchor. The percent change for high priced-on-high is the largest (-76%), suggesting a larger competitive effect among high-price anchors. We find evidence that both the fixed effect probit estimates and the simple bias corrected estimates suffer from substantial incidental parameters bias due to the pre-determined nature of previous openings relative to the models estimated using techniques developed by Fernandez-Val (2009). Finally, these findings are robust across growing, stable and declining counties. If county retail markets are in disequilibria, we might expect positive effects of new openings in growing counties and negative effects in declining counties, and our negative estimates might arise simply because more of the counties in our sample are declining. However, we find evidence of too much retail activity in all three types of counties. We also examine a model of

[7] The Urban Land Institute (ULI, 2008) define the Wal-Mart shadow as open air strip shopping centers built in conjunction with a large Wal-Mart store. They say that "several chain stores, notably Dollar Tree, Cato and Shoe Show, make it their stated corporate objective to follow Wal-Mart's path." The ULI gives other examples of smaller stores that locate near Wal-Mart and compete directly with some of Wal-Mart's lines.

closings and find very similar results that the presence of an additional anchor store of the same type increases the likelihood of closing a same-type anchor.

Our core results are broadly consistent with the optimal city size literature which finds that many US cities are too big. Likewise, our results, which are based on an inverted U-shaped profit function, suggest that the anchors are typically beyond the point of profit maximization with respect to competition from same type stores, but near that point with respect to other types of anchors: i.e., competitive entry has driven the marginal anchor to the zero profit point. As discussed above, when we re-estimate our model including two measures of time-varying market demand within each county, total payroll and total employment. We find that these demand factors are not statistically significant and that our core finding are robust both in sign and magnitude. This suggests that most variation in demand is captured by the county fixed effects.

One striking additional finding is the absence of competitive cross-effects: an additional anchor of a given type has no negative effect on openings of anchors of another type. This finding is robust to alternative specifications. The only positive localization effect for cross-types is low priced-on-mid (15%). We find virtually no spillover effect from other price types on mid-price and high-price openings.

A third important finding is that our results are concentrated entirely among anchors stores located within shopping centers. The phenomenon of retail clusters being too large at the county level on average does not appear to affect the probability of free standing openings. We examine the probability of within shopping center openings, and again we find negative competitive effects both overall and for the subset of openings in large shopping centers. On the other hand, our results for free standing anchors, a category dominated by Wal-Mart and Target (and therefore by low-price and large scale) are remarkable for the absence of negative competitive effects. We find no statistically significant effects of existing anchors on the openings of freestanding anchors. A potential interpretation is that the freestanding anchors, Walmart and Target, adopt a strategy of "internalizing under-one-roof". This is consistent with Foster, Haltiwanger and Krizen (2006) that freestanding is a more flexible and popular format for a new entrant, such as Wal-Mart, to reap the profits from existing small anchors

The contributions of this study include:

1. A comprehensive study of all multiline department stores since the beginning of 2005 in 23 MSAs in the East and Central regions of the US. Our sample includes 49 chains in 1,515 retail properties, including 970 shopping centers and 545 freestanding properties. We have size, type (low, mid and high price) and property-level information for each store.

2. The use of county and year fixed effects to examine the marginal effect of an additional existing store of a given type on opening decisions.

3. A novel application of the bias corrected probit model to deal with the short time series of openings and closings of these anchors and the pre-determined nature of the current number of anchors of each type.

4. Establishing robust empirical regularities based on the universe of new openings and closings of these anchors from January 2005 through December 2011. We measure changes in opening and closing probabilities as a function of an additional anchor of a given type.

5. Separation of competitive and localization effects through examination of type and size effects.

This paper is structured as follows. Section 2 discusses a profit maximization model, and section 3 describes the estimation approach. Section 4 describes our data set. Sections 5, through 9 present our results. Section 10 concludes.

2. Store Profit Maximization

Our illustrative model may be motivated by considering a profitable retail market such as might be created by the completion of a new limited access highway link, or by a change in zoning, in a densely populated suburban community. The first store into this area may not draw customers very well because it is too small or specialized, but a second entrant might position itself nearby in physical space and in product space (e.g., differentiating products and services) increasing profits for both stores. As more stores enter, the marginal gains associated with increasing the attractiveness of the cluster is expected to decrease and eventually competitive externalities generated by new entrants may lead to falling profits for existing stores.

Figure 1 illustrates this idea under the assumption that there is a single type of store (e.g., a 100,000 square foot discount department store) with cluster size measured by number of stores of this type (or equivalently, aggregate square footage). The Y-axis shows the marginal profits for the aggregate of all stores and the average profit for the existing stores. The new entrant will expect and receive average profits. Marginal profits to the cluster will initially rise with entry because the cluster becomes more attractive for shoppers, and then fall as cluster sizes continues to increase because competitive effects dominate cluster attractiveness. Eventually, falling marginal profits leads to declining average profits when marginal profits fall below average.

A single retailer or developer controlling all the land would increase the number of stores until profits or rents to the whole cluster or region are maximized. This solution is represented by point B in Figure 1 where marginal profits are zero, total profits are maximized and entry is still profitable as viewed by the new store (i.e., average profits are greater than zero) even after entry of an additional competitor. Shopping centers often bid for large tracts of land near ramps to limited access roads. By controlling a large share of the local market, they may be able to achieve above normal profits or returns on land. For example, anchor stores have monopolistic power with shopping center developers and can influence tenant selection and rents because their presence is essential to obtaining financing and to induce smaller tenants to sign leases. As a result, we will treat shopping center locations separately from free standing locations by the same chain of anchors.

In a typical situation, where there are many landowners, entry is expected to drive rents past the optimal point. Shopping centers control rents within the center, but face competition from surrounding shopping centers and free standing stores. New retail commercial developers enter as long as rents exceed the value of alternative land uses in the area, and retail stores enter as long as economic profits are positive in this location. Under these circumstances, retail establishments enter until profits are zero, at point A on Figure 1, which implies that in equilibrium average retail profits are falling with cluster size. If the cluster is at point A, an additional store will discourage entry because the new entrant will expect negative profits. This can be contrasted with point B, where the effect of an additional store on entry is near zero.

A second strategy is to expand the retail cluster with different types of anchors: i.e., differentiate in product space as well as physical space. For example, shopping centers will mix discount retailers with high-end retailers in order to attract a greater number of shoppers and profit from multi-purpose shopping trips (Stahl, 1982). An optimal mix of store types provides for a larger cluster size before aggregate profits decline. We explore issues related to the mix of retailers by categorizing anchor stores by type. In terms of Figure 1, this implies that each type of retailer possibly faces a different profit function.

If markets are at equilibrium, then we will not observe the entire inverted U-shape, Figure 1. Instead, we expect to observe entry always falling with the number of existing stores consistent with equilibrium point A because ownership in local retail markets are typically dispersed. A similar assumption of competitive equilibrium is made by the optimal city size literature. In Section 9, we test for the possibility that our results are driven by markets that are out of equilibrium.

Our reduced form approach does not allow us to address causality, or to separate a space filling strategy from that of a follower or second mover in an oligopolistic framework. Instead, we use a reduced form discrete choice model and control for space with fixed effects and with our classification by anchor type.

This allows us to establish empirical regularities based on choices over time and by type, but our estimates of declining attractiveness with cluster size may be driven by other factors. The profit maximizing model illustrated by Figure 1 merely provides a point of departure for evaluating the empirical regularities we will establish.

3. Estimation of a Fixed Effects Bias Corrected Probit

A binary choice model explains choices between two discrete alternatives, such as opening or not opening in a particular county in our analyses. The model specifies the probability that a decision maker chooses one alternative, with the probability expressed as a function of observed variables that relate to the alternatives and the decision maker. An opening reveals an expectation of profitable operation at the chain level. We assume an underlying profit function as in McFadden (1974).

First, as noted by Neyman and Scott (1948), fixed effect estimates in traditional choice analyses suffer from an incidental parameter bias because the effect of unobserved individual characteristics are replaced by sample estimates, biasing estimates of model parameters.[8] Specifically, with a short panel, e.g small T with large N, an unusually high (or low) unobservable in any period will be positively correlated with the resulting sample based fixed effects biasing the fixed effect estimates upwards. When right hand side variables are not strictly exogenous, the fixed effect will be correlated with the right hand side variable since that variable is also influenced by any unusually high unobservables in an earlier period biasing the estimates of those variables downwards.

In linear models, a possible solution is to remove the fixed effect by first differencing the data. The first differenced model is still potentially biased because the differenced unobservable contains information on the lagged level unobservable, which is then correlated with any lagged dependent or pre-determined variables. The problem is solved by constructing instruments for the lagged dependent variable from the second and longer lags of the dependent or pre-determined variables (Anderson and Hsiao, 1982).[9] This solution is not feasible in our case because our right hand side variable, current number of anchor stores, is affected by the determinants of outcomes, anchor store entry or exit, in every preceding year. This occurs because an opening (a closing) in any year increases (decreases) the number of existing anchors at the beginning of next year and that anchor is then present in the count of anchors for all future years.

We follow Fernandez-Val (2009) and estimate a fixed effect binary choice model using recent bias correction approaches to correct for incidental parameters bias. This method is designed to explicitly address the small T and large N problem, where T is the number of time periods in our sample and N is the number

[8] Other studies on incidental parameters problem include Nerlove (1971), Heckman (1981), Nickell (1981), Katz (2001), Greene (2004) and Hahn and Newey (2004).

[9] See for example the dynamic panel estimators proposed by Arellano-Bond (1991), Arellano-Bover (1995) and Blundell-Bond (1998).

of cross-sectional units. The logic behind these types of corrections is based on recognizing that the estimates are consistent in large *T* and so only suffer from small sample bias. The small sample bias for the fixed effect estimates are estimated using a first order Talyor series expansion, and the bias corrected estimates are simply the fixed effect estimates minus the correction. While the fixed effect estimates are still influenced by the unobservables for individual years, the estimates have been re-centered so that their expectation is now very near zero. Since the expected value of the fixed effect estimate is now near zero, the expectation of the estimate for any variables that are correlated with the fixed effects are also re-centered on the true value of the estimate. Fernandez-Val (2009) develops this alternative to earlier bias correction approaches (Hahn and Kuersteiner, 2004) in order to improve estimation performance in cases where right hand side variables are not strictly exogenous, e.g. predetermined or lagged dependent variables. He demonstrates in his simulations that his estimator suffers from minimal bias when *T* equals eight.

Given a binary response *Y* and a *p* x 1 regressor vector *X*, Fernandez-Val assumes that the response for individual *i* at time *t* is assumed to be generated by the following process

$$Y_{it} = \mathbf{1}\{X_{it}'\theta_0 + \alpha_i - \epsilon_{it} \geq 0\} \tag{1}$$

where $\mathbf{1}\{C\}$ is an indicator function that takes on value one if condition C is satisfied and zero otherwise; θ_0 denotes a *p* x 1 vector of parameter; α_i is a scalar unobserved individual effect and ϵ_{it} is a time-individual specific random shock.

To estimate the model parameters, a sample of observable variables $\{Y_{it}, X_{it}\}$ is drawn, *t* = 1, …, *T*; *i* = 1, …, *n*, where *t* and *i* represent time and individuals, respectively. The conditional log-likelihood for observation *i* at time *t* is

$$l_{it}(\theta, \alpha_i) := Y_{it} log F_{it}(\theta, \alpha_i) + (1 - Y_{it})\log(1 - F_{it}(\theta, \alpha_i)) \tag{2}$$

where $F_{it}(\theta, \alpha_i)$ denotes $F_\epsilon(X_{it}'\theta_0 + \alpha_i | X_i^t, \alpha_i)$, assuming ϵ_{it}'s are i.i.d. conditional on X_i^t and α_i, with cdf $F_\epsilon(\cdot\, | X_i^t, \alpha_i)$.

The maximum likelihood estimator (MLE) of θ is the solution to

$$\hat{\theta} := arg \max_\theta \textstyle\sum_{i=1}^{n} \sum_{t=1}^{T} l_{it}(\theta, \hat{\alpha}_i(\theta)) \,/nT, \tag{3}$$
$$\hat{\alpha}_i(\theta) := arg \max_\alpha \textstyle\sum_{t=1}^{T} l_{it}(\theta, \alpha) \,/T$$

For $n \to \infty$ with *T* fixed,

$$\hat{\theta} \xrightarrow{p} \theta_T, \theta_T := \arg\max_{\theta} E_n\left[\sum_{t=1}^{T} l_{it}(\theta, \hat{\alpha}_i(\theta))/T\right] \tag{4}$$

where $E_n[m(Z_{it}, \alpha_i)] := \lim_{n\to\infty} \sum_{i=1}^{n} m(Z_{it}, \alpha_i)/n$, if $Z_{it} := (Y_{it}, X_{it})$ and any function $m(Z_{it}, \alpha_i)$.

The incidental parameter problem implies that $\theta_T \neq \theta_0$ since $\hat{\alpha}_i(\theta) \neq \alpha_i$. In what follows, we explain the Fernandez-Val (2009) method for using the small T sample to correct this bias. The method is based on a first order approximation to an expansion around theta-zero.

For the smooth likelihoods considered here, $\theta_T = \theta_0 + \frac{\mathcal{B}}{\mathrm{T}} + O(\frac{1}{T^3})$ for some $\mathcal{B}$. Therefore,

$$\sqrt{nT}(\hat{\theta} - \theta_0) = \sqrt{nT}(\hat{\theta} - \theta_T) + \sqrt{nT}\frac{\mathcal{B}}{\mathrm{T}} + O_p(\sqrt{\frac{n}{T^3}}) \tag{5}$$

Fernandez-Val's expression for the bias is based on Hahn and Kuersteiner (2004)'s stochastic expansion of the fixed effects estimator in orders of T. Let

$$u_{it}(\theta, \alpha) := \frac{\partial}{\partial\theta} l_{it}(\theta, \alpha), v_{it}(\theta, \alpha) := \frac{\partial}{\partial\alpha} l_{it}(\theta, \alpha) \tag{6}$$

Additional subscripts denote partial derivatives. For example, $u_{it\theta}(\theta, \alpha) := \frac{\partial}{\partial\theta'} u_{it}(\theta, \alpha)$, $v_{it\theta}(\theta, \alpha) := \frac{\partial}{\partial\theta'} v_{it}(\theta, \alpha)$

The first term of the large-T expansion of the asymptotic bias is

$$T(\hat{\theta} - \theta_0) \xrightarrow{p} T(\theta_T - \theta_0) = -\mathcal{J}^{-1} b := \mathcal{B} \tag{7}$$

where $\mathcal{J}$ is the probability limit of the Jacobian of the estimating equation for θ,

$$\mathcal{J} := E_n\left[E_T[u_{it\theta}] - E_T[u_{it\alpha}]\frac{E_T[v_{it\theta}]}{E_T[v_{it\alpha}]}\right] \tag{8}$$

where $E_T[h_{it}] := \lim_{T\to\infty} \sum_{t=1}^{T} h_{it}/T$; and b is the bias of estimating equation for θ,

$$b := E_n\left\{E_T[u_{it\alpha}]\beta_i + \bar{E}_T[u_{it\alpha}\varphi_{is}] + \frac{1}{2}\sigma_i^2 E_T[u_{it\alpha\alpha}]\right\} \tag{9}$$

where $\bar{E}_T[h_{it}k_{is}] := \sum_{j=-\infty}^{\infty} E_T[h_{it}k_{i,t-j}]$. $\bar{E}_T$ can be replaced by E_T if the regressors are exogenous.

Large-T correction methods remove an estimate of $\mathcal{B}$/T from the fixed effect estimator. This method reduces the order of the bias from O(T^{-1}) to O(T^{-2}). The probability limit θ_T can be expressed as $\theta_T =$

$\left(I_p + \frac{\mathcal{B}}{\mathrm{T}}\right)\theta_0 + O_p(T^{-2})$, where I_p is the p x p identity matrix and $\mathcal{B}$ is a positive definite matrix. In Fernandez-Val (2009) Proposition 1,

$$\mathcal{B} = \frac{1}{2}E_n[\mathcal{J}_i]^{-1}E_n[\sigma_i^2\mathcal{J}_i]\theta_0 \tag{10}$$

where

$$\mathcal{J}_i = E_T[H_{it}\emptyset_{it}X_{it}X_{it}'] - \sigma_i^2 E_T[H_{it}\emptyset_{it}X_{it}]E_T[H_{it}\emptyset_{it}X_{it}'] \tag{11}$$

$$\sigma_i^2 = E_n[H_{it}\emptyset_{it}]^{-1} \tag{12}$$

with $H_{it} = \emptyset_{it}/[\Phi_{it}(1-\Phi_{it})]$, $\emptyset_{it} = \emptyset(X_{it}'\theta_0 + \alpha_i)$ and $\Phi_{it} = \Phi(X_{it}'\theta_0 + \alpha_i)$. $\emptyset$ and Φ denote the pdf and cdf of the standard normal distribution, respectively.

Marginal Effects of the Bias Corrected Probit

Marginal effects in nonlinear models depend on the individual effects and the level of chosen for evaluating the regressors. For a model with two regressors, X_1 and X_2, with corresponding parameters θ_1 and θ_2, the marginal effect of one-unit increase in X_1 on the conditional probability of Y for individual i at time t, evaluated at $x_{it} = (x_{1it}, x_{2it})$ is given by

$$\begin{aligned} m(x_{it}, \theta, \alpha_i) := {} & F_\epsilon\big((x_{1it}+1)\theta_1 + x_{2it}\theta_2 + \alpha_i \big| x_{it}, \alpha_i\big) \\ & - F_\epsilon(x_{1it}\theta_1 + x_{2it}\theta_2 + \alpha_i | x_{it}, \alpha_i) \end{aligned} \tag{13}$$

When X_1 is continuous, the marginal effect becomes

$$\begin{aligned} \widetilde{m}(x_{it}, \theta, \alpha_i) := {} & \frac{\partial}{\partial x_{1it}} F_\epsilon(x_{1it}\theta_1 + x_{2it}\theta_2 + \alpha_i | x_{it}, \alpha_i) \\ & = \theta_1 f_\epsilon(x_{1it}\theta_1 + x_{2it}\theta_2 + \alpha_i | x_{it}, \alpha_i) \end{aligned} \tag{14}$$

A common practice is to report the average observed effect. Based on Chamberlain (1994), the average effect for an individual randomly drawn from the population is

$$\mu(\theta) = \int \widetilde{m}(X_{2it}, \theta, \alpha_i) dH_{X_{it},\alpha_i}(X_{it}, \alpha_i) \tag{15}$$

where H is the joint distribution of and (X_{it}, α_i).

Fixed effects estimators for average marginal effects can be constructed by replacing population moments by sample analogs and using fixed effects estimators of the individual effects as follows

$$\hat{\mu}(\theta) = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{m}(X_{it}, \theta, \hat{\alpha}_i(\theta)) \tag{16}$$

In Proposition 2 of Fenandez-Val (2009), the bias for marginal effects is calculated as

$$\hat{\mu}(\hat{\theta}) \xrightarrow{p} \mu + \frac{1}{T}\mathcal{B}_{\mu} + O(T^{-2}) \tag{17}$$

where

$$\mathcal{B}_{\mu} = \frac{1}{2}E_n\{E_T[\emptyset_{it}(\xi_{it}\theta_0(X_{it} - \sigma_i^2 E_T[H_{it}\emptyset_{it}X_{it}])' - I_p)](\sigma_i^2 I_p - E_n[\mathcal{J}_i]^{-1}E_n[\sigma_i^2\mathcal{J}_i])\}\theta_0 \tag{18}$$

$$\xi_{it} = X_{it}'\theta_0 + \alpha_i,\ \sigma_i^2 = E_T[H_{it}\emptyset_{it}]^{-1} \tag{19}$$

$$\mathcal{J}_i = -\{E_T[H_{it}\emptyset_{it}X_{it}X_{it}'] - \sigma_i^2 E_T[H_{it}\emptyset_{it}X_{it}]E_T[H_{it}\emptyset_{it}X_{it}']\} \tag{20}$$

with $H_{it} = \emptyset_{it}/[\Phi_{it}(1-\Phi_{it})]$, $\emptyset_{it} = \emptyset(\xi_{it})$ and $\Phi_{it} = \Phi(\xi_{it})$.$\emptyset$ and Φ denote the pdf and cdf of the standard normal distribution, respectively

4. Summary Statistics

Table 1 shows descriptive statistics for the retail clusters in 125 counties in 23 MSAs in the East and Central Regions with at least one pre-existing anchor as of the beginning of 2005.[10] We require at least one pre-existing anchor in order to focus on the effect of adding or closing a store. A typical county in our sample of MSAs spans an area with a radius of approximately 11 miles, which is considered as a reasonable trade area of small-to-medium sized centers.[11] Anchors are classified into three price categories, high-price, mid-price and low-price based on price level and quality (Vitorino, 2012 and Gould, Pashigian and Prendergast, 2005). For example, Wal-Mart is classified as a low-price anchor while Nordstrom is classified a high-price anchor. Anchors are also classified into two size categories, small-scale and big-scale based on the typical size of anchors, where small-scale is defined as GLA less than 70,000 sq. ft. and big-scale is defined as GLA greater than 70,000 sq. ft. For example, TJ Maxx is classified as a small anchor while Macy's is classified as a big anchor.

[10] These are all the MSAs in the east and central regions with population more than 750,000 and have no mass transit system. I.e., our limits on MSA size provide meaningful boundaries on data collection and allow us to focus on automobile-oriented trade areas.

[11] Clapp, Salavei and Zhou (2014) support the following trade area for different types of shopping centers: a 40 mile radius for superregional shopping centers, a 20 mile radius for regional shopping centers, and a 10 mile radius for community and power centers, implying that counties are reasonable approximations to most trade areas.

Panel A presents descriptive statistics on openings and closings for 125*7=875 county-years. The first row in Panel A says that there are 173 county-years with low-price openings. The mean is 173/875=0.198, which is the unconditional probability that a county-year has a low-price opening. In general, there are more county-years with low-price (big-scale) openings than county-years with openings of the other price types (small-scale). When we look at openings inside shopping centers and openings of new shopping centers, there are more county-years with mid-price openings than county-years with openings of the other price types. Freestanding openings are dominated by low-price and large-scale anchors such as Wal-Mart and Target. There are more freestanding openings of Wal-Mart than Target (48 county-years versus 18 county-years) because a larger proportion of Target openings are inside shopping centers, suggesting that Wal-Mart adopt a different strategy than Target, a head-to-head competitor.[12] Different from openings, there are more closings of high-price anchors than closings of the other types.

We conclude from panel A that our discrete choice models need to be disaggregated by type and by location inside or outside shopping centers. Openings are dominated by low- and mid-price types with a large footprint. High priced anchors had very low unconditional probabilities of opening – almost none in a free standing format – and their probability of closing was about 1.5 times the probability of opening (4.2% vs. 2.5% in any year).

Panel B shows the number of anchors pre-existing in 2005 by type. The first row ("all pre-existing") shows that, in 125 counties with at least one opening during our sample period, the average number of low-price pre-existing anchors is 5.712 and the total number of low-price pre-existing anchor is 714 as of the beginning of 2005. The second row ("all openings") shows the sample with further restrictions to counties with at least one opening. Compared with "all pre-existing", the means are larger for all types of existing anchors in "all openings" and in openings with any classifications. It suggests that new entrants position themselves nearby in physical space. As more stores enter, the marginal gains associated with increasing the attractiveness of the cluster is expected to decrease. "Closings" have the largest mean values of all types, suggesting that competitive externalities generated by new entrant may lead to negative profits for existing stores and eventually to store closings.

5. **Anchor Store Openings at the County Level**

Table 2 reports fixed effects probit estimates of coefficients, marginal effects and percentage changes based on a sample of county-level openings by price types (Panel A) and by operation scale or size (Panel

[12] Wal-Mart often opens a 200,000 square foot free standing supercenter whereas Target prefers 140,000 square feet in a shopping center (as classified by CoStar) with relatively few smaller retailers. Unreported results also show that some Wal-Mart and Target open inside shopping centers. However, most of those shopping centers are neighborhood centers and dominated by Wal-Mart or Target.

B). To focus on existing retail clusters, we keep counties with at least one pre-existing anchor as of the beginning of 2005. P(Open) is the unconditional probability of opening from the first row of Panel A Table 1. For dependent variables, Open Low/Mid/High equals 1 if there is any low/mid /high-price openings within the county and 0 otherwise. For the independent variable, Low/Mid/High is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening.[13] All the regressions control for county and year fixed effects. FE denotes uncorrected fixed effect estimates. Fernandez-Val (2009) develops two estimators for bias correction, BC3 and BC3p, where BC3p allows for variables that are predetermined, i.e. not strictly exogenous. In our application, an opening or closing changes the number of anchors counted as existing for the next year of openings or closings, making BC3p the preferred estimator.

The first set of rows contains the parameter estimates, the second set contains the marginal effects, and the third set contains the percentage change in the probability of an opening relative to the unconditional probability for that store type. To indicate statistical significance, we mark coefficient estimates and marginal effects with *t*-statistics greater than 2.58 with ***, *t*-statistics greater than 1.96 with *** and *t*-statistics greater than 1.65 with *. Comparing across columns, our results show that BC3p consistently yields substantially smaller estimates suggesting significant bias from incidental parameters in the other models.[14] Standard errors are presented in parentheses.

Qualitatively, we find evidence for strong negative competitive effects with the BC3p estimates indicating that an opening of any type lowers the likelihood of a future opening of that type. In the BC3p model, an additional low-price pre-existing anchor reduces the probability of a low-price opening from 0.198 by 0.069, a 35% reduction. The percent change for high-on-high is the highest (-76%), suggesting a larger competitive effect among high-price anchors. Mid-priced anchors are in the middle with a -54% competitive effect. Consistent with unconditional probabilities, low-price (high-price) openings have the least (most) negative competition effect. We find virtually no spillover effect from other price types on mid-price and high-price openings. The only significant localization effect for cross-type is low-on-mid (15%). Near zero localization effects suggest that retail clusters are near an optimal mix of anchors by type, on average over our sample.

In Panel B, when we classify anchors based on their sizes, we find similar results. The opening probability for a small (large) anchor is strongly and negatively influenced by the existing number of small

[13] It is noted that we do not estimate the whole pattern (i.e. the inverted U-shape) illustrated in Figure 1. We focus only whether anchors are near or beyond the profit maximization. As a result, we do not add non-linear terms in our model. Unreported results show that squared terms of independent variable have opposite signs of the linear terms. Squared terms of independent variables are statistically significant only if their linear terms are statistically significant. The marginal effects of the squared terms are less than one tenth of the linear terms.

[14] The female labor participation application in Fernandez-Val (2009) does not find a large difference between the BC3 and BC3p estimates on the right-hand-side variables, such as household income and number of kids, which are relatively exogenous. The differences between BC3 and BC3p estimates are substantial in our study, and the BC3p estimates are consistently smaller than BC3 estimates.

(large) anchors, (i.e., of the same type), not by the other type. The estimated coefficient of small-on-small is larger than the coefficient of big-on-big (-48% versus -18%). This suggests that smaller anchors may be more sensitive to competition. This is consistent with evidence in Foster, Haltiwanger and Krizen (2006): small retail establishments are more sensitive to competition than big retailers.[15] Appendix 1 shows that fixed effect logit regressions results are consistent with probit regressions, except that sample sizes are too small to estimate high-price openings.

These results should be interpreted as the effect of one extra existing anchor of a given type on the decision to open a new anchor in the next year, holding all county time-invariant characteristics constant. The inverted U-shaped profit function in Figure 1 suggests that the anchors are beyond the point of aggregate profit maximization with respect to competition, but near that point with respect to other types of anchors.

Interpretation and Robustness of Core Results

Zoning and accessibility to the most desirable markets are unlikely to vary systematically over the short time period examined, so they should be captured by the county fixed effects. Changes in the attractiveness of existing markets cannot be captured by the county fixed effects, but these factors should operate against our findings. If openings happen in places where the market has grown the most, then those openings should correlate with existence of unmet demand creating a positive correlation between openings and future openings. Therefore, time varying changes in market demand likely bias our analysis away from our findings of reduced attractiveness of a retail location as new establishments are opened.

The results suggest segmentation by type, as might be expected if costs of goods sold are lower for low priced retailers: see evidence provided by Hausman and Liebtag (2007).[16] Segmented strategies, whether based on cost differences or different expectations about competitive reactions, allow for the different magnitudes of competitive coefficients. For example, we find that Wal-Mart and Target, the dominant retailers in the low-priced market, follow strategies of locating independently and separating themselves spatially from their competitors, whereas high priced retailers are more likely to open in shopping centers, especially the larger regional and super regional centers.

Our results might be sensitive to alternative parametric panel binary choice models. Appendix 1 presents our results using fixed effect logit regressions. Although logit regressions generate somewhat larger (in absolute value) coefficient estimates and marginal effects, we find patterns that are very similar to the

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[15] It is noted that small retailers in Foster, Haltiwanger and Krizen (2006) refer to retailers with few establishments, not multi-line department (anchor) stores. As a result, our anchors stores are all "big" from the perspective of Foster, Haltiwanger and Krizen (2006).

[16] Additional evidence is provided by the Urban Land Institute (ULI) (2008). They say that Wal-Mart introduced new methods for supply-chain management and cost control that allow it to profitably follow a discount strategy.

more conservative probit results. The competition effects dominate the localization effects: the strongly negative competition effects exist by the pre-existing same type, not by other types.

Omitted time-varying demand-side factors might bias our results since a positive shock to demand (e.g., from substantial hiring by large employers within the county) should attract more openings and deter closings. In this case, we would expect positive bias in coefficients on our core variables: i.e. the inclusion of demand-side variables should result in larger negative coefficients.

We re-estimated the models in Table 2 with the addition of log of total annual payroll and employment from County Business Patterns. We test a one-year lag, a three-year lag and a three-year moving average based on t-1, t-2 and t-3 (results not shown). Total payroll is our preferred demand-side variable since it should reflect income changes within a county. Coefficient estimates on both demand proxies are not significant and coefficients reported in Table 2 are substantially unchanged. We interpret this as confirming that most variation in demand-side variables is captured by the county and the annual time dummies, and that systematic changes in local demand are relatively uncommon during our sample period.

6. Anchor Store Closings

Table 3 includes results for anchor storing closings. An additional low-price pre-existing anchor increases the likelihood of low-price closings by 31%. We find a similar pattern for high-price openings. An additional high-price pre-existing anchor increases the high-price closing probability by 90%. The larger effect for high-price closings is consistent with larger numbers of existing anchor closings in this market segment: see summary statistics in Table 1, Panel A. The results for mid-priced anchor closings are similar at 60%, but the estimate was statistically insignificant. These results are complementary to county-level openings in Table 2: strong competitive effects imply that an additional anchor increases the probability of closing of a same-type anchor.

Table 3 suggests stronger cross-type effects than we observed in Table 2. As in Table 2, cross effects exist for the low-price market segment, but the effects are both larger in magnitude and broader in scope. An additional mid-price (high-price) pre-existing anchor decreases the likelihood of low-price closings by 65% (58%). In addition, the probability of a high-priced closing is somewhat diminished by the presence of an additional low-priced anchor. We do not have sufficient closings by small-anchors in order to estimate the bias corrected probit (Panel B), and the results for closing of big anchors are not significant. Appendix 2 reports that fixed effect logit regressions results are consistent with probit regressions.

7. Comparisons among Growth, Stable and Decline Markets

It is possible that our results are driven by markets that are in disequilibrium, i.e. some market might be below the peak of the inverted U-shaped profit curve and some might be far beyond the peak because the market has not yet adjusted to some shock. For example, an increase in the size of the market might increase the optimal number of stores. If this were the case, we would expect to observe less (or no) competitive effect in growth markets and more negative effect in declining markets, i.e., we would be observing the entire inverted U in Figure 1, not just the equilibrium points A or B. Most significantly, if more counties are declining than growing in our sample of Northeast and Midwest counties, the estimated negative effects of the number of stores in our entire sample may be associated with disequilibrium, rather than a phenomenon where all retail clusters are too large in equilibrium.

To test this concern, we classify counties into "Growth", "Stable" and "Decline" based on average growth rate of employment in retail trades from 1995Q1 to 2005Q1. Data are collected from Census of County Business Patterns. "Growth" counties have growth rates greater than 67th percentile. "Decline" counties have growth rates less than 33rd percentile. There are 125 counties, among which 42 counties are classified as "Growth", 42 counties are classified as "Decline" and the remaining 41 are classified as "Stable". The unconditional opening probabilities in the first row of Table 4 reflect this classification.

In Table 4, the strong negative competition effects still hold for all the three markets and there is virtually no positive spillover effect among different types of anchor stores. The competition results for openings in shrinking markets are unlikely to be explained by the disequilibrium story because in those markets disequilibrium is likely associated with the need to close, not open, anchor stores. Results are similar in Appendix 3 using logit model.

An interesting finding is a greater deterrence of competition in growth markets than in declining markets. As discussed earlier, our "over-retailing" story could be driven by disequilibrium markets. If we had found a larger competitive effect in declining markets, the disequilibrium story would have been supported. However, the absolute value of our point estimates are smaller in declining markets and the differences with stable and growth markets are not statistically significant. The significant negative competitive effects in all three types of markets support our conclusion that the existing retail clusters are too big.

In addition, observing an opening or a closing might correlate with unobservable information on changes in the attractiveness of this location, time-varying changes which would not be captured by county fixed effects. This correlation would imply a positive correlation between increases in the number of stores and the likelihood of new openings, and so such a correlation cannot explain the strong deterrence effects in our estimates. Similarly, in this case, one might expect growing locations to have a smaller deterrence effect because the growing market both caused the higher levels of existing anchor stores from past openings and the new openings that are captured by the dependent variable. However, the deterrence effect is largest in growing areas so this result cannot be explained by changes in market demand.

In unreported results we further tested the possibility of omitted time-varying factors. First, we classified counties into four quartiles based on number of households. The lowest quartile had none or few anchors of each type and the highest had many. The mean number of big anchors was 1.2 for the lowest quartile, followed by 2.6, 6.7 and 27.5. It would appear that our fixed effects capture a dominant feature of the data, and that our explanatory variables do not represent movement along the X-axis of Figure 1. Secondly, to further tested the disequilibrium story the BC3p estimators in Table 2 were modified to include an additional variable, the number of same type squared. Results showed very little economic effect of the squared terms and the sign pattern was opposite to the one predicted by the inverted U.

8. **Openings Inside Shopping Centers versus All Openings**

In this section, we redefine our left-hand-side variables so that they only take the value of one based openings inside shopping centers (Table 5) and compare findings to a model of all openings (Table 2). Explanatory variables, including county and year fixed effects are the same in the two tables. Our definition of shopping centers is based on CoStar and includes a few small-scale neighborhood centers. Therefore, we also estimate a second set of models where openings are based only on openings in large shopping centers. We define large shopping centers as those greater than 400,000 sq.ft., which is considered as a reasonable cut between small and large scale shopping centers.[17] For each model specification, we compare all counties with pre-existing centers ("All") and counties with large pre-existing centers ("Large SC").[18]

Open_Low/Mid/High equals 1 if there is any low/mid /high-price openings in a shopping center and 0 otherwise. Similarly, in Panel B, Open_Small/Big equals 1 if there is any small/big-scale openings in a shopping center and 0 otherwise. Independent variables are defined in the same way as in Table 2. Low/Mid/High is the number of low/mid/high-price anchors pre-existing within the county as of the beginning of the year preceding opening; Small/Big is defined similarly.

[17] Based on the classification by International Council of Shopping Centers (ICSC), a typical regional center ranges from 400,000 sq.ft. to 800,000 sq.ft.

[18] One might think that shopping centers should have smaller negative effects of the number of anchor stores because they can internalize the negative effects of new opening, but any internalization by shopping centers decreases the equilibrium number of anchors in a county. As a results, the entire county moves back along the upside down U, and so such internalization should result in smaller negative effects for all types of anchors in the county, not just anchors in shopping centers,

Results in Table 5 are similar to Table 2. For the entire subsample, we find strong negative effects of an opening on future openings of the same type in shopping centers. When we restrict our left-hand-side variables to be based on openings inside shopping centers, there are still sizable, but somewhat smaller negative competition effects from same-type pre-existing anchors in the county. In fact, the percentage changes of 35%, 50% and 76% for low, mid and high, respectively, are nearly identical to the effects in Table 2. The negative effects for the largest shopping malls are noticeably smaller for low and mid anchors at 26% and 22% and larger for high anchors at 104%. Appendix 4 presents our results using fixed effect logit regressions. We find similar results to the probit regressions.

In Panel B, we find a similar pattern for big-on-big as was observed for low and high-priced openings. All results are robust to restricting the estimates to openings in shopping centers with an extra small (big) store reducing the likelihood of a small (big) opening by 50% (18%), as compared to 48% (18%) in Table 2. For openings in large shopping centers, however, only the negative effects for small stores are robust at 47%, and for large stores the estimate effect falls to 8% and is statistically insignificant.

9. Openings by Freestanding Anchors, Wal-Mart and Target

Table 6 includes results where the dependent variable is based only on freestanding openings. Most of the freestanding anchors are Wal-Mart and Target (61%), which are classified as low-price and big-scale anchors. Due to limited observations, we include only those two types.[19] We then examine each of these two head-to-head competitors separately in the last two columns of Table 6.[20] In contrast to earlier tables, there are no significant results in Table 6 Panels A (price) or B (size). The findings are very similar for all low-priced, big anchors and for models that analyze Target and Wal-Mart separately. Unlike for openings in shopping centers, likelihood of opening of low-priced, big standalone stores is unaffected by the number of existing low-priced or big anchor stores in the county.[21] Using the model framework summarized by Figure 1 to interpret these results, we conclude that the number of free standing anchors in counties tends to be near an optimum from the point of view of the two big, low-priced free standing anchors, Target and Wal-mart. Entry has not driven the retail cluster size beyond the maximization of average profits, so we find no negative competitive effects.[22]

[19] In fact, there are a few Target and some Wal-Mart opened inside shopping centers. In order to make a consistent comparison, we include only freestanding openings by Wal-Mart and Target in Table 5.

[20] While they are direct competitors, they differentiate themselves in product space as suggested by their different footprints and different choices with respect to inside a shopping center *vs* free standing.

[21] Unreported results show no significant association between number of anchors and openings for subsamples of growing, stable and declining counties, as well.

[22] Appendix 5 provides complementary results using fixed effect logit regressions. The results are consistent with probit regressions.

Why would freestanding anchors have such a different reaction to competitive conditions than all anchors (Table 2) or those entering inside shopping centers (Table 5)? According to the Urban Land Institute (ULI), freestanding anchors adopt a strategy of "internalizing under-one-roof" in that the attractiveness of one broad area of merchandise creates external shopping benefits for other lines of merchandise, which are captured in a very large anchor with a broad array of retail goods. This strategy is consistent with Foster, Haltiwanger and Krizen (2006) that freestanding is a more flexible and popular format for a new entrant, such as Wal-Mart, to reap the profits from existing small anchors. Likewise, Hausman and Liebtag (2007) present evidence that Wal-Mart has developed a new low cost technology allowing it to be profitable relative to its competitors, and Target has followed a similar strategy. These differences between Wal-mart and Target and the other anchor stores in our sample may provide a second more plausible explanation for our findings. The cost and structural advantages that distinguish Wal-Mart and Target from other competitors may create a situation where each views the other as its primary competitor. The resulting concentrated market power enables Wal-Mart and Target to behave in a non-competitive manner, which allows for a within county concentration of those two stores that is near the profit maximizing scale.

10. Conclusion

This paper examines whether changes in the number of retail competitors changes the likelihood of anchor stores opening or closing and investigates the trade-off between localization economies and competition associated with an additional pre-existing anchor selling close substitutes. We utilize fixed-effect nonlinear regressions with bias correction proposed by Fernandez-Val (2009). The substantially smaller corrected estimates and marginal effects (in absolute value) in the columns labelled BC3p compared to the FE and the BC columns suggest that the Fernandez-Val method eliminates a large amount of incidental parameters bias in our application.

Our core results show strong negative competitive effects for localization economies in openings of all anchors and openings inside pre-existing shopping centers. The strongly negative competitive effects come from same-type pre-existing anchors. These results are consistent with the notion that free entry leads to retail clusters that are larger than the rent or profit maximizing level of activity for the cluster as a whole. There is some evidence that entrants are encouraged by the presence of anchor stores of different-types potentially due to complementarity in shopping activities, but the magnitudes of changes in the probability of an opening are small. Our results also suggest that the competition effect is more intensive among high-priced anchors, compared with low- and mid-priced anchors. The unconditional odds of opening (closing) are much lower (higher) in high-price anchors. In addition, an additional same-type existing anchor has much larger impact on the probability of high-price openings.

Results of anchor closings are complimentary to results of anchor openings. An additional pre-existing same-type anchor increases the likelihood of closings while an additional pre-existing different-type anchor has no significant effect, or is associated with a small decrease in the likelihood of a closing. Our results are also robust when we test for disequilibrium markets by disaggregating into rapidly growing, stable and declining counties.[23] Disaggregation supports our hypothesis that we generally observe markets near zero profit equilibrium.

In freestanding openings, we find no significant effects for either competition (same type pre-existing anchors) or localization (pre-existing anchors of a different type). This finding may in part be attributable to the structure of the market. The large, free standing anchor store market segment is dominated by two major players, Wal-Mart and Target which have developed low cost logistical and supply-chain management systems. Both favor a large footprint (between 140,000 and 200,000 square feet) freestanding format. As a result, these large companies may be able to internalize the competitive effects of opening additional stores in the same county, and so limit the extent to which other anchors influence their decisions. This is consistent with a retail market dominated by low cost, free-standing anchor stores (Foster, Haltiwanger and Krizen 2006, Hausman and Liebtag 2007).

Our results are robust to models designed to correct any bias from unobserved demand factors based on the notion that the time frame considered is relatively short from the perspective of long-term retail planning. When we include the log of annual county payroll in all industries (alternatively, total employment) in our models it is not significant and coefficients on pre-existing anchors are substantially unchanged. This suggests that unobserved demand variables are relatively slow moving and the factors that are not captured by the county fixed effects are dominated by the US business cycle which is captured by annual time dummies.

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Table 1 County-level Multiline Department Stores (Anchors)

The summary statistics is based on a sample of pre-existing and new anchor stores from 2005 to 2011 in 23 MSAs in East and Central regions in the US. Anchors are classified into high-price, mid-price and low-price types based on price level and quality (based on Vitorino, 2012 and Gould, Pashigian and Prendergast, 2005). Anchors are classified into small-scale and big-scale based on typical size of anchors. Small-scale is defined as GLA less than 70,000 sq. ft and big-scale is defined as GLA greater than 70,000 sq. ft. Panel A presents descriptive statistics of county-year openings and closings. We restrict our sample to 125 counties with at least one pre-existing anchor as of the beginning of 2005. There are 125*7=875 county-years. Examples for interpretation: the first row in Panel A suggests that there are 173 county-years with low-price openings. The mean is 173/875=0.198, which is unconditional probability that a county-year has a low-price opening. Panel B presents descriptive statistics of initial market conditions. Examples for interpretation: the first row in Panel B suggests that, for counties with at least one opening from 2005 to 2011, the average number of low-price preexisted anchor is 7.739 and the total number of low-price preexisted anchor is 681.

Panel A. Unconditional Probability of Annual Anchor Openings and Closings in any County with at Least One Anchor Pre-existing in 2005 by type

County-Year	Mean	Std Dev	# county years with openings/closings
All openings			
- Low	0.198	0.399	173
- Mid	0.173	0.378	151
- High	0.025	0.157	22
- Small	0.101	0.301	88
- Big	0.257	0.437	225
Openings inside shopping centers			
- Low	0.137	0.344	120
- Mid	0.159	0.366	139
- High	0.025	0.157	22
- Small	0.094	0.292	82
- Big	0.195	0.397	171
Openings as freestanding anchors			
- Low	0.094	0.292	82
- Mid	0.021	0.142	18
- High	0.001	0.034	1
- Small	0.008	0.089	7
- Big	0.106	0.308	93
- Wal-Mart	0.055	0.228	48
- Target	0.021	0.142	18
Closings			
- Low	0.026	0.160	23
- Mid	0.026	0.160	23
- High	0.042	0.201	37
- Small	0.027	0.163	24
- Big	0.066	0.249	58

Panel B Market Condition: Number of Anchors Pre-existing in 2005 by Type

	Mean #	Std Dev	# pre-existing
125 counties with pre-existing stores			
- Low	5.712	7.470	714
- Mid	4.592	6.336	574
- High	2.464	3.231	308
- Small	3.136	4.067	392
- Big	9.632	12.626	1204
88 counties with any openings			
- Low	7.739	8.068	681
- Mid	6.250	6.872	550
- High	3.170	3.601	279
- Small	4.011	4.537	353
- Big	13.148	13.571	1157
77 Counties with Openings inside Shopping Centers			
- Low	8.610	8.230	663
- Mid	7.039	6.988	542
- High	3.481	3.740	268
- Small	4.481	4.661	345
- Big	14.649	13.825	1128
55 Counties with Freestanding Openings			
- Low	9.182	8.895	505
- Mid	7.200	6.969	396
- High	3.691	4.004	203
- Small	4.636	4.786	255
- Big	15.436	14.757	849
45 Counties with Any Closings			
- Low	11.822	9.066	532
- Mid	10.200	7.251	459
- High	4.978	4.054	224
- Small	6.422	4.993	289
- Big	20.578	14.747	926

Table 2 County-Level Openings

Probit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Open_Low/Mid/High equals 1 if there is any low/mid /high-price openings within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Small/Big equals 1 if there is any small/big-scale openings within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. FE denotes uncorrected fixed effects estimator. BC3 denotes the bias-corrected estimator proposed by Fernandez-Val (2009). BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. For example, P(Open) in Model "Low" of Panel A is 0.198. It is calculated as the number of county-years with low openings (173 in Panel A of Table 1) divided by the total number of county-years (875 in Panel A of Table 1). % change is calculated as the marginal effect divided by unconditional probability. For example, % change of Low in Model "Low-FE" of Panel A is -49%. It is calculated as the marginal effects of Low-on-Low (-0.097) divided by the unconditional probability (0.198). With an additional low-price existing anchor, the probability of low-price opening reduces from 0.198 by 0.097, which is 49% reduction. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low			Open_Mid			Open_High		
P(Open)	0.198			0.173			0.025		
	FE	BC3	BC3p	FE	BC3	BC3p	FE	BC3	BC3p
Coefficients									
Low	-0.679***	-0.549***	-0.395***	0.087	0.070	0.064	-0.019	-0.030	-0.015
	(0.097)	(0.091)	(0.095)	(0.072)	(0.071)	(0.089)	(0.280)	(0.190)	(0.120)
Mid	0.241***	0.198**	0.164**	-0.978***	-0.791***	-0.610***	-0.720*	-0.125	-0.134
	(0.090)	(0.086)	(0.074)	(0.119)	(0.111)	(0.115)	(0.408)	(0.213)	(0.136)
High	-0.214	-0.178	-0.122	0.044	0.030	0.066	-2.288***	-1.044***	-0.602***
	(0.162)	(0.152)	(0.135)	(0.162)	(0.154)	(0.152)	(0.653)	(0.338)	(0.193)
Marginal Effects									
Low	-0.097***	-0.094***	-0.069***	0.011	0.010	0.010	0.000	-0.001	0.000
	(0.013)	(0.013)	(0.014)	(0.009)	(0.009)	(0.012)	(0.005)	(0.005)	(0.003)
Mid	0.035***	0.034***	0.029**	-0.123***	-0.118***	-0.094***	-0.013*	-0.004	-0.004
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.015)	(0.007)	(0.005)	(0.004)
High	-0.031	-0.031	-0.021	0.006	0.005	0.010	-0.042***	-0.031***	-0.019***
	(0.023)	(0.023)	(0.021)	(0.020)	(0.021)	(0.021)	(0.010)	(0.008)	(0.006)
% Change									
Low	-49%	-47%	-35%	6%	6%	6%	0%	-4%	0%
Mid	18%	17%	15%	-71%	-68%	-54%	-52%	-16%	-16%
High	-12%	-12%	-11%	3%	3%	6%	-168%	-124%	-76%
Observations	875	875	875	875	875	875	875	875	875
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: By Scale

	Open_Small			Open_Big		
P(Open)	0.101			0.257		
	FE	BC3	BC3p	FE	BC3	BC3p
Coefficients						
Small	-0.759***	-0.633***	-0.449***	-0.132	-0.107	-0.140
	(0.136)	(0.131)	(0.156)	(0.130)	(0.124)	(0.105)
Big	0.101	0.085	0.083	-0.458***	-0.371***	-0.223***
	(0.061)	(0.060)	(0.061)	(0.077)	(0.072)	(0.059)
Marginal Effects						
Small	-0.068***	-0.067***	-0.048***	-0.022	-0.021	-0.029
	(0.011)	(0.011)	(0.015)	(0.022)	(0.022)	(0.019)
Big	0.009*	0.009*	0.009	-0.077***	-0.074***	-0.046***
	(0.005)	(0.005)	(0.006)	(0.012)	(0.012)	(0.011)
% Change						
Small	-67%	-66%	-48%	-9%	-8%	-11%
Big	9%	9%	9%	-30%	-29%	-18%
Observations	875	875	875	875	875	875
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 3 County-Level Closings

Probit regressions are based on a panel sample of anchor store closings from 2005 to 2011. Counties are units of observations. In Panel A, Close_Low/Mid/High equals 1 if there is any low/mid /high-price closings within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Close_Small/Big equals 1 if there is any small/big-scale closings within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Close) is unconditional probability of closings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Close_Low	Close_Mid	Close_High
P(Close)	0.026	0.026	0.042
	BC3p	BC3p	BC3p
Coefficients			
Low	0.235	0.035	-0.209*
	(0.149)	(0.171)	(0.112)
Mid	-0.486***	-0.466	0.185
	(0.157)	(0.335)	(0.113)
High	-0.437*	-0.300	0.842***
	(0.251)	(0.377)	(0.246)
Marginal Effects			
Low	0.008*	0.001	-0.009*
	(0.004)	(0.005)	(0.005)
Mid	-0.017***	-0.015	0.008
	(0.005)	(0.009)	(0.005)
High	-0.015**	-0.010	0.037***
	(0.007)	(0.011)	(0.010)
% Change			
Low	31%	4%	-21%
Mid	-65%	-62%	19%
High	-58%	-38%	90%
Observations	875	875	875
County FE	Y	Y	Y
Year FE	Y	Y	Y

Panel B: By Scale

	Close_Small	Close_Big
P(Close)	0.027	0.066
	BC3p	BC3p
Coefficients		
Small	N.A.	-0.037
		(0.097)
Big	N.A.	0.032
		(0.058)
Marginal Effects		
Small	N.A.	-0.003
		(0.007)
Big	N.A.	0.003
		(0.004)
% Change		
Small	N.A.	-5%
Big	N.A.	5%
Observations	875	875
County FE	Y	Y
Year FE	Y	Y

Table 4 Openings in Growth, Stable and Decline Markets

Probit regressions are based on a panel sample of anchor store closings from 2005 to 2011. Counties are units of observations. Counties are classified into "Growth", "Stable" and "Decline" based on average growth rate of employment in retail trades from 1995Q1 to 2005Q1. For example "Growth" counties have growth rates greater than 67^{th} percentile. "Decline" counties have growth rates less than 33^{rd} percentile. There are 125 counties, among which 42 counties are classified as "Growth", 42 counties are classified as "Decline" and the remaining 41 are classified as "Stable". In Panel A, Open_Low/Mid/High equals 1 if there is any low/mid /high-price closings within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Small/Big equals 1 if there is any small/big-scale closings within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low			Open_Mid			Open_High		
	Growth	Stable	Decline	Growth	Stable	Decline	Growth	Stable	Decline
P(Open)	0.241	0.213	0.139	0.235	0.202	0.082	0.031	0.017	0.027
	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p
Coefficients									
Low	-0.733***	-0.344***	-0.329***	0.158	-0.059	0.283*	0.464*	N.A.	-0.032
	(0.140)	(0.156)	(0.134)	(0.140)	(0.162)	(0.148)	(0.252)		(0.302)
Mid	0.165	0.093	0.350*	-0.982***	-0.563***	-0.544***	-0.185	N.A.	-0.771***
	(0.156)	(0.113)	(0.157)	(0.183)	(0.167)	(0.188)	(0.198)		(0.306)
High	-0.430	-0.221	0.204	0.311	0.205	-0.232	-1.150	N.A.	-1.169***
	(0.298)	(0.151)	(0.302)	(0.292)	(0.230)	(0.292)	(0.790)		(0.432)
Marginal Effects									
Low	-0.138***	-0.061***	-0.047***	0.029	-0.010	0.023*	0.020*	N.A.	-0.001
	(0.024)	(0.024)	(0.017)	(0.024)	(0.024)	(0.011)	(0.009)		(0.008)
Mid	0.031	0.016	0.050**	-0.183***	-0.094***	-0.043***	-0.008	N.A.	-0.022***
	(0.027)	(0.018)	(0.020)	(0.029)	(0.025)	(0.014)	(0.007)		(0.008)
High	-0.081	-0.039	0.029	0.058	0.034	-0.019	-0.049	N.A.	-0.034***
	(0.051)	(0.024)	(0.039)	(0.049)	(0.035)	(0.021)	(0.034)		(0.012)
% Change									
Low	-57%	-29%	-34%	12%	-5%	28%	64%	N.A.	-3%
Mid	13%	8%	36%	-78%	-46%	-53%	-26%	N.A.	-82%
High	-34%	-18%	21%	25%	17%	-23%	-159%	N.A.	-124%
Observations	294	287	294	294	287	294	294	287	294
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: By Scale

	Open_Small			Open_Big		
	Growth	Stable	Decline	Growth	Stable	Decline
P(Open)	0.143	0.111	0.048	0.313	0.282	0.177
	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p
Coefficients						
Small	-1.053***	-0.231	-0.573*	-0.228	-0.113	-0.074
	(0.311)	(0.186)	(0.298)	(0.171)	(0.231)	(0.236)
Big	0.120	0.041	0.055	-0.368***	-0.406***	-0.054
	(0.111)	(0.090)	(0.122)	(0.084)	(0.107)	(0.105)
Marginal Effects						
Small	-0.132***	-0.029	-0.031**	-0.054	-0.022	-0.012
	(0.034)	(0.020)	(0.014)	(0.037)	(0.040)	(0.035)
Big	0.015	0.005	0.003	-0.087***	-0.078***	-0.009
	(0.013)	(0.010)	(0.006)	(0.017)	(0.018)	(0.016)
% Change						
Small	-92%	-26%	-65%	-17%	-8%	-7%
Big	10%	5%	6%	-28%	-28%	-5%
Observations	294	287	294	294	287	294
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Table 5 Openings inside Shopping Centers

Probit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Open_Low/Mid/High equals 1 if there is any low/mid /high-price openings in shopping centers within the county and 0 otherwise. Each specification contains "All" based on all pre-existing shopping centers and "Large SC" based on pre-existing shopping centers with GLA>400,000 sq.ft. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Small/Big equals 1 if there is any small/big-scale openings in shopping centers within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low		Open_Mid		Open_High	
	All	Large SC	All	Large SC	All	Large SC
P(Open)	0.137	0.061	0.159	0.067	0.025	0.017
	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p
Coefficients						
Low	-0.353***	-0.203**	0.055	0.028	-0.015	-0.043
	(0.091)	(0.085)	(0.083)	(0.072)	(0.120)	(0.160)
Mid	0.202**	0.036	-0.532***	-0.161	-0.134	-0.105
	(0.080)	(0.109)	(0.117)	(0.124)	(0.136)	(0.173)
High	-0.099	0.018	0.158	0.273	-0.602***	-0.811***
	(0.127)	(0.155)	(0.167)	(0.142)	(0.193)	(0.237)
Marginal Effects						
Low	-0.048***	-0.016**	0.008	0.003	0.000	-0.001
	(0.011)	(0.006)	(0.011)	(0.006)	(0.003)	(0.003)
Mid	0.027***	0.003	-0.080***	-0.015	-0.004	-0.002
	(0.010)	(0.008)	(0.015)	(0.010)	(0.004)	(0.003)
High	-0.013	0.001	0.024	0.025*	-0.019***	-0.018***
	(0.015)	(0.011)	(0.022)	(0.011)	(0.006)	(0.005)
% Change						
Low	-35%	-26%	5%	4%	-2%	-6%
Mid	20%	5%	-50%	-22%	-17%	-14%
High	-10%	2%	15%	37%	-76%	-104%
Observations	875	875	875	875	875	875
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Panel B: By Scale

	Open_Small		Open_Big	
	All	Large SC	All	Large SC
P(Open)	0.094	0.04	0.195	0.098
	BC3p	BC3p	BC3p	BC3p
Coefficients				
Small	-0.469***	-0.319**	-0.165	-0.143
	(0.153)	(0.142)	(0.105)	(0.105)
Big	0.081	0.122*	-0.199***	-0.070
	(0.062)	(0.072)	(0.060)	(0.061)
Marginal Effects				
Small	-0.047***	-0.019**	-0.029*	-0.016*
	(0.013)	(0.007)	(0.016)	(0.010)
Big	0.008	0.007*	-0.035***	-0.008
	(0.006)	(0.004)	(0.009)	(0.006)
% Change				
Small	-50%	-47%	-15%	-17%
Big	9%	18%	-18%	-8%
Observations	875	875	875	875
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 6 Openings of Freestanding Anchors

Probit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Open_Low/Wal-Mart/Target equals 1 if there is any openings of low-price/Wal-Mart/Target within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Big/Wal-Mart/Target equals 1 if there is any openings of big-scale/Wal-Mart/Target within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

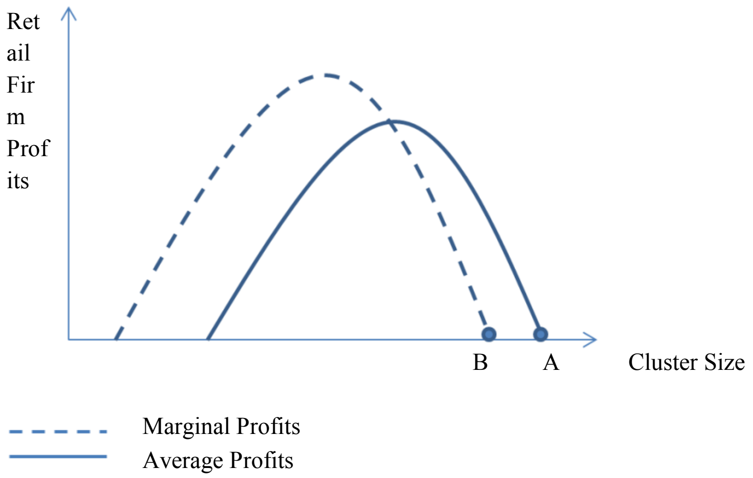
	Open_Low	Wal-Mart	Target
P(Open)	0.093	0.055	0.021
	BC3p	BC3p	BC3p
Coefficients			
Low	-0.053	-0.065	-0.045
	(0.081)	(0.109)	(0.151)
Mid	0.059	0.109	-0.014
	(0.101)	(0.114)	(0.161)
High	-0.156	-0.277	-0.089
	(0.137)	(0.177)	(0.373)
Marginal Effects			
Low	-0.006	-0.005	-0.001
	(0.009)	(0.007)	(0.004)
Mid	0.007	0.008	0.000
	(0.011)	(0.008)	(0.004)
High	-0.019	-0.021*	-0.003
	(0.014)	(0.012)	(0.010)
% Change			
Low	-6%	-9%	-7%
Mid	8%	15%	-2%
High	-20%	-39%	-14%
Observations	875	875	875
County FE	Y	Y	Y
Year FE	Y	Y	Y

Panel B: By Scale

	Open_Big	Wal-Mart	Target
P(Open)	0.106	0.055	0.021
	BC3p	BC3p	BC3p
Coefficients			
Small	-0.138	-0.121	0.023
	(0.113)	(0.135)	(0.287)
Big	0.031	0.064	-0.049
	(0.054)	(0.068)	(0.107)
Marginal Effects			
Small	-0.019	-0.009	0.001
	(0.014)	(0.009)	(0.008)
Big	0.004	0.005	-0.002
	(0.007)	(0.005)	(0.003)
% Change			
Small	-18%	-17%	4%
Big	4%	9%	-8%
Observations	875	875	875
County FE	Y	Y	Y
Year FE	Y	Y	Y

Figure 1 Average Aggregate Profit and Marginal Aggregate Profit in Retail Clusters

This table shows an inverted U shape for the profitability of a new retail entrant. Retail establishments enter until profits are zero, at point A, which implies that in equilibrium average retail profits are falling with cluster size. Marginal aggregate profits (dashed line) intersect average aggregate profits (solid line) at the maximum of average profits and lies well below average retail profits in equilibrium. Equilibrium cluster size is greater than optimal cluster size, point B, where marginal retail profits are zero.



Appendix 1 County-Level Openings - Fixed Effect Logit Regressions with Bias Correction

This table is supplementary to Table 2 of county-level openings. Logit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Open_Low/Mid/High equals 1 if there is any low/mid /high-price openings within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Small/Big equals 1 if there is any small/big-scale openings within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. FE denotes uncorrected fixed effects estimator. BC3 denotes the bias-corrected estimator proposed by Fernandez-Val (2009). BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low			Open_Mid			Open_High		
P(Open)	0.198			0.173			0.025		
	FE	BC3	BC3p	FE	BC3	BC3p	FE	BC3	BC3p
Coefficients									
Low	-0.854***	-0.667***	-0.481***	0.117	0.091	0.084	-0.087	N.A.	N.A.
	(0.127)	(0.109)	(0.115)	(0.076)	(0.072)	(0.084)	(0.303)		
Mid	0.267***	0.210**	0.181**	-1.066***	-0.839***	-0.643***	-0.668*	N.A.	N.A.
	(0.094)	(0.087)	(0.079)	(0.144)	(0.124)	(0.128)	(0.390)		
High	-0.271	-0.216	-0.153	0.158	0.123	0.141	-2.267***	N.A.	N.A.
	(0.176)	(0.161)	(0.148)	(0.175)	(0.161)	(0.164)	(0.673)		
Marginal Effects									
Low	-0.122***	-0.115***	-0.085***	0.015	0.014	0.013	-0.002	N.A.	N.A.
	(0.016)	(0.015)	(0.017)	(0.010)	(0.010)	(0.012)	(0.006)		
Mid	0.038***	0.036***	0.032**	-0.137***	-0.131***	-0.103***	-0.013	N.A.	N.A.
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.017)	(0.008)		
High	-0.039	-0.037	-0.027	0.020	0.019	0.023	-0.045***	N.A.	N.A.
	(0.025)	(0.025)	(0.024)	(0.023)	(0.022)	(0.024)	(0.011)		
% Change									
Low	-62%	-58%	-43%	9%	8%	8%	-8%	N.A.	N.A.
Mid	19%	18%	16%	-79%	-76%	-60%	-52%	N.A.	N.A.
High	-20%	-19%	-14%	12%	11%	13%	-180%	N.A.	N.A.
Observations	875	875	875	875	875	875	875	875	875
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: By Scale

	Open_Small			Open_Big		
P(Open)	0.101			0.257		
	FE	BC3	BC3p	FE	BC3	BC3p
Coefficients						
Small	-0.884***	-0.726***	-0.522***	-0.120	-0.098	-0.132
	(0.173)	(0.155)	(0.188)	(0.132)	(0.120)	(0.105)
Big	0.079	0.066	0.065	-0.541***	-0.417***	-0.250***
	(0.062)	(0.060)	(0.061)	(0.087)	(0.076)	(0.063)
Marginal Effects						
Small	-0.080***	-0.078***	-0.057***	-0.021	-0.020	-0.028
	(0.014)	(0.013)	(0.017)	(0.023)	(0.022)	(0.021)
Big	0.007	0.007	0.007	-0.093***	-0.086***	-0.054***
	(0.006)	(0.006)	(0.006)	(0.014)	(0.013)	(0.012)
% Change						
Small	-79%	-77%	-56%	-8%	-8%	-11%
Big	7%	7%	7%	-36%	-33%	-21%
Observations	875	875	875	875	875	875
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Appendix 2 County-Level Closings - Fixed Effect Logit Regressions with Bias Correction

This table is supplementary to Table 6. Logit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Close_Low/Mid/High equals 1 if there is any low/mid /high-price closings within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Close_Small/Big equals 1 if there is any small/big-scale closings within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.6; ** for *t*-statistics > 2.3; and * for *t*-statistics > 1.96.

Panel A: By Price

	Close_Low	Close_Mid	Close_High
P(Open)	0.026	0.026	0.042
	BC3p	BC3p	BC3p
Coefficients			
Low	N.A.	N.A.	-0.229*
			(0.120)
Mid	N.A.	N.A.	0.195
			(0.124)
High	N.A.	N.A.	0.913***
			(0.292)
Marginal Effects			
Low	N.A.	N.A.	-0.011**
			(0.005)
Mid	N.A.	N.A.	0.009*
			(0.005)
High	N.A.	N.A.	0.043***
			(0.012)
% Change			
Low	N.A.	N.A.	-26%
Mid	N.A.	N.A.	21%
High	N.A.	N.A.	102%
Observations	875	875	875
County FE	Y	Y	Y
Year FE	Y	Y	Y

Panel B: By Scale

	Open_Big	Wal-Mart
P(Open)	0.027	0.066
	BC3p	BC3p
Coefficients		
Small	N.A.	-0.036
		(0.094)
Big	N.A.	0.029
		(0.055)
Marginal Effects		
Small	N.A.	-0.003
		(0.007)
Big	N.A.	0.002
		(0.004)
% Change		
Small	N.A.	-5%
Big	N.A.	3%
Observations	875	875
County FE	Y	Y
Year FE	Y	Y

Appendix 3 Openings in Growth, Stable and Decline Markets - Fixed Effect Logit Regressions with Bias Correction

This table is supplementary to Table 7. Logit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. Counties are classified into "Growth", "Stable" and "Decline" based on average growth rate of employment in retail trades from 1995Q1 to 2005Q1. For example "Growth" counties have growth rates greater than 67th percentile. "Decline" counties have growth rates less than 33rd percentile. There are 125 counties, among which 42 counties are classified as "Growth", 42 counties are classified as "Decline" and the remaining 41 are classified as "Stable". In Panel A, Open_Low/Mid/High equals 1 if there is any low/mid /high-price closings within the county and 0 otherwise. Each specification contains three subsamples, "Growth", "Stable" and "Decline". Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Small/Big equals 1 if there is any small/big-scale closings within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low			Open_Mid			Open_High		
	Growth	Stable	Decline	Growth	Stable	Decline	Growth	Stable	Decline
P(Open)	0.241	0.213	0.139	0.235	0.202	0.082	0.031	0.017	0.027
	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p
Coefficients									
Low	-0.795***	-0.410***	-0.366***	0.164	-0.065	0.262*	N.A.	N.A.	N.A.
	(0.159)	(0.188)	(0.165)	(0.139)	(0.159)	(0.145)			
Mid	0.166	0.092	0.360*	-1.022***	-0.580***	-0.483***	N.A.	N.A.	N.A.
	(0.159)	(0.124)	(0.161)	(0.191)	(0.188)	(0.180)			
High	-0.429	-0.147	0.122	0.332	0.173	-0.212	N.A.	N.A.	N.A.
	(0.306)	(0.219)	(0.321)	(0.291)	(0.238)	(0.286)			
Marginal Effects									
Low	-0.150***	-0.074***	-0.053***	0.032	-0.011	0.022*	N.A.	N.A.	N.A.
	(0.027)	(0.028)	(0.020)	(0.025)	(0.025)	(0.012)			
Mid	0.031	0.017	0.052**	-0.197***	-0.101***	-0.041***	N.A.	N.A.	N.A.
	(0.028)	(0.020)	(0.021)	(0.029)	(0.028)	(0.014)			
High	-0.081	-0.026	0.018	0.064	0.030	-0.018	N.A.	N.A.	N.A.
	(0.053)	(0.036)	(0.043)	(0.051)	(0.038)	(0.023)			
% Change									
Low	-62%	-35%	-38%	14%	-5%	27%	N.A.	N.A.	N.A.
Mid	13%	8%	37%	-84%	-50%	-50%	N.A.	N.A.	N.A.
High	-34%	-12%	13%	27%	15%	-22%	N.A.	N.A.	N.A.
Observations	294	287	294	294	287	294	294	287	294
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: By Scale

	Open_Small			Open_Big		
	Growth	Stable	Decline	Growth	Stable	Decline
P(Open)	0.143	0.111	0.048	0.313	0.282	0.177
	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p
Coefficients						
Small	-1.0232***	-0.274	-0.526*	-0.231	-0.160	-0.029
	(0.474)	(0.248)	(0.287)	(0.167)	(0.251)	(0.218)
Big	0.092	0.037	0.035	-0.338***	-0.379***	-0.049
	(0.114)	(0.099)	(0.114)	(0.084)	(0.104)	(0.101)
Marginal Effects						
Small	-0.154***	-0.034	-0.030*	-0.058	-0.033	-0.005
	(0.048)	(0.026)	(0.014)	(0.038)	(0.046)	(0.034)
Big	0.011	0.005	0.002	-0.085***	-0.078***	-0.009
	(0.015)	(0.011)	(0.006)	(0.018)	(0.018)	(0.016)
% Change						
Small	-108%	-31%	-63%	-19%	-12%	-3%
Big	8%	5%	4%	-27%	-28%	-5%
Observations	294	287	294	294	287	294
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Appendix 4 Openings inside Pre-existing Shopping Centers - Fixed Effect Logit Regressions with Bias Correction

This table is supplementary to Table 3. Logit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Open_Low/Mid/High equals 1 if there is any low/mid /high-price openings inside pre-existing shopping centers within the county and 0 otherwise. Each specification contains "All" based on all pre-existing shopping centers and "Large SC" based on pre-existing shopping centers with GLA>400,000 sq.ft. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Small/Big equals 1 if there is any small/big-scale openings inside pre-existing shopping centers within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low		Open_Mid		Open_High	
	All	Large SC	All	Large SC	All	Large SC
P(Open)	0.137	0.061	0.159	0.067	0.025	0.017
	BC3p	BC3p	BC3p	BC3p	BC3p	BC3p
Coefficients						
Low	-0.424***	-0.207***	0.085	0.040	-0.050	N.A.
	(0.117)	(0.090)	(0.079)	(0.074)	N.A.	
Mid	0.222**	0.047	-0.571***	-0.188	-0.182	N.A.
	(0.087)	(0.109)	(0.128)	(0.136)	N.A.	
High	-0.132	0.001	0.230	0.249*	-0.663	N.A.
	(0.139)	(0.153)	(0.177)	(0.137)	N.A.	
Marginal Effects						
Low	-0.059***	-0.017***	0.013	0.004	N.A.	N.A.
	(0.013)	(0.006)	(0.011)	(0.006)		
Mid	0.031***	0.004	-0.089***	-0.018	N.A.	N.A.
	(0.011)	(0.008)	(0.017)	(0.011)		
High	-0.018	0.000	0.036	0.023*	N.A.	N.A.
	(0.017)	(0.011)	(0.025)	(0.011)		
% Change						
Low	-43%	-28%	8%	6%	N.A.	N.A.
Mid	22%	6%	-56%	-26%	N.A.	N.A.
High	-13%	0%	23%	35%	N.A.	N.A.
Observations	875	875	875	875	875	875
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y

Panel B: By Scale

	Open_Small		Open_Big	
	All	Large SC	All	Large SC
P(Open)	0.094	0.040	0.195	0.098
	BC3p	BC3p	BC3p	BC3p
Coefficients				
Small	-0.522***	-0.310**	-0.147	-0.143
	(0.182)	(0.142)	(0.106)	(0.107)
Big	0.066	0.129*	-0.210***	-0.078
	(0.062)	(0.075)	(0.065)	(0.064)
Marginal Effects				
Small	-0.053***	-0.018**	-0.027	-0.017
	(0.016)	(0.007)	(0.017)	(0.011)
Big	0.007	0.008*	-0.038***	-0.009
	(0.006)	(0.004)	(0.010)	(0.007)
% Change				
Small	-56%	-46%	-14%	-17%
Big	7%	19%	-20%	-9%
Observations	875	875	875	875
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Appendix 5 Openings of Freestanding Anchors - Fixed Effect Logit Regressions with Bias Correction

This table is supplementary to Table 5. Logit regressions are based on a panel sample of anchor store openings from 2005 to 2011. Counties are units of observations. In Panel A, Open_Low/Wal-Mart/Target equals 1 if there is any openings of low-price/Wal-Mart/Target within the county and 0 otherwise. Low/mid/high is the number of low/mid/high-price anchors pre-existing within the county at the beginning of the year of the opening. In Panel B, Open_Big/Wal-Mart/Target equals 1 if there is any openings of big-scale/Wal-Mart/Target within the county and 0 otherwise. Small/big is the number of small/big-scale anchors pre-existing within the county at the beginning of the year of the opening. All the regressions are controlled for county and year fixed effect. BC3p denotes the bias-corrected estimator proposed by Fernandez-Val (2009) when the regressors are treated as predetermined. P(Open) is unconditional probability of openings. % change is calculated as the marginal effect divided by unconditional probability. *** for *t*-statistics > 2.58; ** for *t*-statistics > 1.96; and * for *t*-statistics > 1.65.

Panel A: By Price

	Open_Low	Wal-Mart	Target
P(Open)	0.093	0.055	0.021
	BC3p	BC3p	BC3p
Coefficients			
Low	-0.037	-0.078	-0.036
	(0.077)	(0.113)	N.A.
Mid	0.053	0.127	-0.021
	(0.095)	(0.113)	N.A.
High	-0.148	-0.345*	-0.102
	(0.128)	(0.209)	N.A.
Marginal Effects			
Low	-0.005	-0.006	N.A.
	(0.009)	(0.008)	
Mid	0.007	0.010	N.A.
	(0.011)	(0.008)	
High	-0.019	-0.027*	N.A.
	(0.014)	(0.014)	
% Change			
Low	-5%	-11%	N.A.
Mid	8%	18%	N.A.
High	-20%	-50%	N.A.
Observations	875	875	875
County FE	Y	Y	Y
Year FE	Y	Y	Y

Panel B: By Scale

	Open_Big	Wal-Mart	Target
P(Open)	0.106	0.055	0.021
	BC3p	BC3p	BC3p
Coefficients			
Small	-0.142	-0.120	N.A.
	(0.110)	(0.131)	
Big	0.032	0.063	N.A.
	(0.051)	(0.065)	
Marginal Effects			
Small	-0.021	-0.010	N.A.
	(0.014)	(0.009)	
Big	0.005	0.005	N.A.
	(0.007)	(0.005)	
% Change			
Small	-20%	-18%	N.A.
Big	5%	9%	N.A.
Observations	875	875	875
County FE	Y	Y	Y
Year FE	Y	Y	Y