The Impact of Retail Location on Retailer Revenues: An Empirical Investigation

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This paper investigates the impact of store location, a retailer's most costly and long-term marketing mix decision, on retailer revenues. We estimate models of consumer spending at the leading packaged goods retailers in a metropolitan market based on two dimensions of retail location: (i) proximity to consumers, i.e., travel times, and (ii) proximity to other stores, i.e., agglomeration. Both are important predictors of consumer spending and hence retailer revenues. Moreover, location effects are heterogeneous and often asymmetric across retail formats.

Key findings pertain to discount stores and supercenters, which are simply discount stores with a full-service grocery. We find that travel times to a retailer's own stores have a much greater impact on Wal-Mart Discount store revenues than on Wal-Mart Supercenter revenues. We also find that grocery retailers generally benefit from agglomerating with discount stores while Wal-Mart Discount stores suffer from agglomerating with grocery stores. Substituting supercenters for discount stores causes these agglomeration effects to disappear, suggesting that demand for packaged goods is higher at supercenters than at discount stores because cross-shopping with grocery stores is reduced.

INTRODUCTION

"Location, location, location" is a mantra for retail success. Store location is a retailer's most costly and long-term marketing-mix decision. Unlike a bad pricing or promotional decision, a poor store location adversely affects retailer performance for several years. We know that retailers prefer to locate close to consumers, but doing so exposes them to competition from other retailers that also want to be close to consumers. From the retailer's point-of-view, proximity to consumers means proximity to other stores.

The phenomenon of stores locating near one another is called *agglomeration*. Stores of different types commonly co-locate in shopping centers and malls (inter-type agglomeration). Stores of the same type, such as restaurants, hotels, jewelers, furniture stores, and automobile dealerships, also often locate close together (intra-type agglomeration). Though agglomeration may be driven by retailers' need to be near consumers, it can also be intrinsically beneficial for retailers. Miller, Reardon and McCorkle (1999) suggested that net gains/losses from agglomeration depend on the balance of two countervailing forces. The first force captures the incremental attractiveness of stores located close together compared to the attractiveness of those same stores individually. This incremental attractiveness reflects a reduction in consumers' costs of searching among stores and multi-purpose shopping. In effect, an agglomeration of stores becomes a shopping destination. Miller, et al. termed this positive force *symbiosis*. The second force reflects competition for consumer purchases among stores that sell similar products (even if they sell different products, stores compete for consumers' disposable income). Miller, et al. called this negative force *Darwinism*, evoking the process of natural selection. The balance of these two forces can result in either a positive, neutral or negative effect of agglomeration on retailer performance.

In recent decades, the US retail environment has become increasingly fragmented. Product offerings of newer retail formats such as supercenters, warehouse clubs, and dollar stores all overlap to varying degrees with those of established formats like grocery, drug, and discount stores. This overlap blurs inter-type distinctions, necessitating a more in-depth understanding of retail location.

The objective of this paper is to estimate travel time and agglomeration effects for different packaged goods retailers. Our approach is to estimate household-level models of consumer spending at leading retailers in a major metropolitan market using multi-outlet panel data. In this market, the leading retailers include Wal-Mart (hereafter WMT) discount stores and supercenters along with four grocery store chains (we will use the terms "retailer" and "store chain" interchangeably), which together account for 77.2% of total packaged goods purchases. Because most households don't shop at all retailers, we use censored regressions to model household spending. We specify spending as a function of two types of retail location factors: (i) proximity of stores to consumers and (ii) proximity of stores to other stores; i.e., agglomeration. Proximity of stores to consumers is defined as the time it takes to travel from the consumer's home to the retailer's closest store. Agglomeration is defined as the retail density around that closest store.[1]

Retail density is measured separately for several formats—warehouse club, dollar, drug, grocery and discount stores, as well as supercenters. We are therefore able to determine how agglomerating with stores of different formats affects consumer spending, and hence revenues, at each of the leading retailers. Spending models for the leading retailers are linked in a multivariate system of equations because spending at one retailer may affect spending at others. Retail location factors, along with demographic covariates, enter the spending model through a

[1] Agglomeration has previously been measured only for retail centers and in geographic areas. To determine the effect of agglomeration on individual consumers, we make the common assumption that they visit the retailer's closest store to their home.

hierarchical equation which we specify in a Bayesian framework. Thus, our empirical analysis uses a multivariate system of hierarchical Bayesian censored regressions.

This research extends the literatures on retail location and spatial competition in three ways. First, it decomposes retail location into proximity to consumers and proximity to other stores. Second, it uses household-level purchase data that includes retailers of different formats, enabling a broad-based descriptive investigation of location effects on retailer revenues. Third, it allows for asymmetric location effects both within and across formats: for example, Retailer A may prefer to locate near Retailer B but Retailer B would want to avoid Retailer A.

We find that consumers' travel times to retailers' stores have negative own-effects and positive cross-effects, as one would expect. Own-effects are greatest for WMT Discount stores but least for WMT Supercenters, which are simply WMT Discount stores with a full-service grocery. In fact, WMT Supercenter revenues are more sensitive to consumers' travel times to WMT Discount stores than to the supercenters themselves. We also find that agglomeration effects between grocery and discount stores are asymmetric; the leading grocery retailers generally gain from agglomerating with discount stores while WMT Discount stores lose from agglomerating with grocery stores. Adding a full-service grocery to the WMT Discount store, thereby creating a WMT Supercenter, causes both agglomeration effects to disappear. These findings suggest that demand for packaged goods is higher at supercenters than at discount stores because cross-shopping with grocery stores is reduced. Further, we find that intra-type agglomeration is not harmful for the leading grocery retailers, but inter-type agglomeration can be. This contradicts Miller et al.'s contention that retailers benefit more from inter-type than intra-type agglomeration.

The remainder of the paper unfolds as follows. The next section discusses the relevant literature. The following sections describe the data and the model used in our analysis. The results are presented next, followed by a discussion of the results and their implications. The final section offers limitations and ideas for future research.

LITERATURE REVIEW

Since Hotelling (1929) developed his landmark retail location model (which assumed no symbiosis between stores and symmetrical agglomeration effects), research on store location has focused primarily on either the proximity of stores to consumers or the proximity of stores to other stores. All such research has made either implicit or explicit simplifying assumptions about how retail location affects consumer shopping behavior, assumptions this paper subjects to joint empirical examination.

Retail Location and Consumers

"Retail gravitation" (Reilly 1931, Huff 1964) implies that consumer choice among retail centers (groups of stores) is governed by the centers' attraction, which increases with a center's size but decreases with its distance from the consumer's home. "Central place theory," an extension of retail gravitation, holds that shoppers will choose the closest retail center conditional on the availability of the types of products sought (Christaller 1966). These theories implicitly assume that shoppers minimize their travel costs to obtain the goods that they want (Hubbard 1978). Empirical evidence has been mixed, however, with studies showing that shoppers actually purchase groceries at the closest store less than half of the time (Gollege, et al. 1966, Rushton, et al. 1967).

Consumers' choice of individual stores (as opposed to retail centers) and the effect of retail location on that choice have been studied extensively. Consumers usually report that spatial convenience is their most important criterion when choosing a store (Arnold, Ma and Tigert 1978; Arnold and Tigert 1981; Arnold, Roth and Tigert 1981; Arnold, Oum and Tigert 1983). Bell Ho and Tang (1998) modeled store choice as dependent on the fixed and variable costs of shopping. Travel distance from the consumer's home to the store was the primary fixed cost of shopping in their panel-data study and was found to be an important predictor of store choice. Fox, Montgomery, Lodish (2004) used travel time from the consumer's home to the store to predict their patronage and spending at stores of different retail formats. Shopping and spending at grocery, drug, and discount retailers were found to be highly sensitive to travel time.

Retail Location and Other Stores

Retail agglomeration has been studied extensively by researchers in urban planning, geography, and marketing. The behavioral justification for agglomeration is that it facilitates consumer search (primarily intra-type agglomeration) and multipurpose shopping (primarily inter-type agglomeration).

Models of sequential search among grocery stores were introduced by Burdett and Malueg (1981) and Carlson and McAfee (1984). They determined the conditions under which it is normative for a consumer to search for low prices at multiple stores on a single shopping trip. Subsequent studies found empirical evidence of consumer price search among grocery stores (e.g., Carlson and Gieseke 1983; Urbany, Dickson, Kalapurakal 1996; Petrevu and Ratchford 1997). A more recent study used scanner panel data to show that consumers frequently visit multiple grocery stores on the same trip, a practice known as cherry-picking (Fox and Hoch

2005). Because it facilitates search, retailers of the same type may increase their profits by agglomerating (Brown 1989).

Ghosh (1986) proposed that stores of different types should also agglomerate in order to facilitate purchases of different types of products on a single shopping trip, reducing a consumer's travel costs compared to separate trips to each store. Models of "trip-chaining" (see Thill and Thomas 1991 for a review), as this phenomenon is known, have been developed to address shopping for: (i) a single type of product at multiple stores (Kitamura 1984), (ii) multiple types of products at shopping centers (Arentze, Borgers and Timmermans 1993) and (iii) multiple types of products at multiple stores (Dellaert, et al. 1998). Arentze, Opewal and Timmermans (2005) studied the effects of agglomeration on shopping trip purpose and destination. They found that agglomeration adds to the attraction of a retail location and draws both multi-purpose and single-purpose shopping trips.

Miller, et al. (1999) tested the effect of agglomeration on variables such as market saturation and average store size, though they did not examine its effect on retailer performance.[2] They determined that agglomeration of different types of stores is mutually beneficial, while intra-type agglomeration is not. Interestingly, they found these benefits to be asymmetric; specialty stores benefit more from locating near stores offering broad lines than vice versa.

Spatial competition between grocery stores has also been observed in scanner data, though only at the category level. Walters (1990) and Kumar and Leone (1988) found cross-promotional effects among nearby grocery stores, and showed that promotions at one store can affect sales in that category at nearby stores. A more recent paper examined spatial competition between a grocery store and supercenter. Singh, Hansen and Blattberg (2006) used a natural experiment, the

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[2]. Miller, et.al. considered specialty stores (e.g., ACE Hardware), broader line retailers (e.g., Home Depot), and mass retailers (e.g., Sears).

opening of a WMT Supercenter across the street from a grocery store, to study changes in the shopping behavior of the grocery store's card members. The authors found that card members continued to visit the grocery store, but spent less; 17% of their expenditures were lost after the supercenter opening. Their research is among the first disaggregated studies to use revenues in assessing retailer performance.

DATA

Our dataset is a multi-outlet panel from a major metropolitan market in the southeastern US during the period September 2002 through September 2004, which we augment with precise location information for panelists and stores (supplied by Information Resources, Inc.). Unlike panels commonly used in marketing research, participants in multi-outlet panels record all purchases of products with Uniform Product Codes (UPCs) using in-home scanning equipment. Purchases in all outlets—including supercenters, warehouse clubs, drug, discount and dollar stores—are captured, providing much more information about retail competition.

The primary drawback of multi-outlet panel data is that purchases are identified only by retailer (i.e., store chain), not by individual store. We therefore analyze purchases by retailer, which fortunately matches retail managers' focus on chain-level revenues and profits in matters of location (e.g., avoiding cannibalization). Our analysis focuses on the six highest-share retailers in the market, which together account for over 77.2% of all consumer spending on UPCs at known retailers. We model consumer spending at (and hence revenues of) grocery, supercenter and discount retailers, but we also capture the impact of agglomerating with drug, dollar, and club stores on the highest-share retailers.

Because we were concerned that panelists might not have recorded all of their purchases in various outlets over the entire 104-week period, we eliminated households that did not meet the following criteria: (i) purchases were recorded in each of the 24 consecutive months during which data were gathered, and (ii) recorded purchases averaged at least $25 per week. Although we may have eliminated a few households that did faithfully record their purchases, this is less problematic than including households that significantly under-reported their spending. We also eliminated households for which we did not have precise locations, and those that made most of their purchases at retailers not included in our analysis.

The resulting dataset includes 348 households that made an average of 180 shopping trips and spent an average of $5,108 on packaged goods at the top six retailers during the 24-month duration of the data. Table 1 shows demographic information about these households.

< Insert Table 1 about here >

Table 2 presents descriptive information about the six leading retailers in the market, including annual household spending and number of store visits, percent of households that shop there (penetration), and average travel time from panelists' homes to the closest store of that chain. As the table shows, the retailers include four grocery store chains (Grocery 1 – Grocery 4), WMT Supercenter and "Division One" WMT Discount stores.[3] A larger percentage of households visit Grocery 2 annually than visit any other chain (89%), followed by WMT Supercenter (77%) and Grocery 3 (73%). WMT Discount (51%) has the lowest household penetration. The average number of store visits follows a similar pattern, with the more visits made to Grocery 2 (30.0/year) than to any other retailer, followed by WMT Supercenter (15.8/year) and Grocery 3 (15.5/year). Consumers spend more money on packaged goods at

[3] Though both formats carry the Wal-Mart brand name, we separate them because they offer a substantially different mix of products

Grocery 2 ($770/year), followed in order by Grocery 3 ($595/year) and WMT Supercenter ($484/year). Consumers spend less at WMT Discount ($128/year) and Grocery 4 ($248/year) than at other retailers.

< Insert Table 2 about here >

MODEL

The objective of this paper is to determine how retail location affects consumer shopping behavior and, as a result, retailer revenues. To address this objective, we estimate models of consumer spending over time for each retailer. We aggregate spending over time for three reasons: (i) retailer revenues are by definition consumer expenditures aggregated over time, so specifying a temporally aggregated model will improve our revenue predictions (Man 2004);[4] (ii) temporal aggregation facilitates estimation of spending relationships among retailers, both within and across formats (Fox, Montgomery and Lodish 2004); (iii) because of the absence of temporal variation in locations of stores and households, a disaggregated analysis could yield no information about location effects despite adding complexity to the model.

We estimate separate Tobit censored regressions of household-level spending for each retailer. In contrast to more commonly use non-censored regression models, Tobit censored regressions account for informative zero observations—in our case, observations of zero spending by a household at a retailer during a given period. The time period over which we aggregate household expenditures is a quarter year, long enough that most observations are non-zero but short enough that there are plenty of observations from which to estimate household-level parameters. Relationships in spending across retailers are captured by estimating the Tobit

[4] This is due in part to the fact that the true data generating process underlying consumer purchases is undoubtedly complex, heterogeneous, and highly non-linear. In such situations, temporal aggregation reduces misspecification bias.

censored regressions within a multivariate framework (covarying error terms), which improves the efficiency of estimation.

Tobit Specification

Our specification begins by defining the dependent variable of the Tobit censored regression, y^*_{ijk}. If spending is observed (i.e., greater than zero), then the dependent variable is equal to that observed spending value, y_{ijk}. If no spending is observed, the dependent variable is latent and takes on a value less than or equal to zero. This indicates utility below the threshold necessary for the household to shop at that retailer. Formally, the latent dependent variable is defined by

(1) $$y_{ijk} = \begin{cases} y^*_{ijk} & if \quad y_{ijk} > 0 \\ 0 & otherwise \end{cases}$$

where i indexes households (i=1, …, I), j indexes retailers (j=1, …, J), and k indexes quarterly observations (k=1, …, K).

We model the dependent variable with a linear regression

(2) $$y^*_{ijk} = \theta_{ij} + \boldsymbol{\beta}'_j \mathbf{x}_k + \varepsilon_{ijk}$$

where θ_{ij} is a household-specific intercept, $\mathbf{x}_k$ is a vector of time-varying factors and $\boldsymbol{\beta}_j$ is the associated parameter vector. The time-varying factors are (i) *dummy variables for the different quarters of the year* and (ii) a *linear trend variable*. Though these time-varying factors are not central to our investigation, we include them to capture spending dynamics and avoid model misspecification.

We assume that the Tobit spending models for the J retailers are linked via the error distribution

(3) $$\varepsilon_{ijk}\varepsilon_{ij'k} \sim N(0, \Sigma)$$

where $\Sigma = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1J} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{J1} & \sigma_{J2} & \cdots & \sigma_J^2 \end{bmatrix}$

This covariance structure captures relationships in consumer spending across retailers. For example, if a consumer spends more than expected at WMT Supercenter, one might predict that s/he spends less than expected at traditional grocery retailers. To estimate Σ, we structure the design matrix as in seemingly unrelated regression (Zellner 1962).

Hierarchical Equation

The retail location variables enter our analysis in a hierarchical equation for the household-specific intercept

(4) $$\theta_{ij} = \mu_j + \boldsymbol{\delta}'_j \mathbf{d}_i + \boldsymbol{\chi}_j \mathbf{c}_i + \boldsymbol{\alpha}'_j \mathbf{a}_{ij} + \boldsymbol{\gamma}'_j \left(\mathbf{a}_{ij} c_{ij}\right) + \xi_{ij}$$

where: μ_j is a retailer-specific intercept; $\mathbf{d}_i$ is a vector of demographic covariates; $\mathbf{c}_i$ is a vector of travel times between the consumer's home and the closest store of each retailer; $\mathbf{a}_{ij}$ is a vector that captures the retail agglomeration affecting the closest store of retailer *j* to the consumer's home; and $\mathbf{a}_{ij}c_{ij}$ is the interaction of that agglomeration with travel time to the closest store of retailer *j*.[5] The parameters associated with the four vectors are $\boldsymbol{\delta}_j$, $\boldsymbol{\chi}_j$, $\boldsymbol{\alpha}_j$ and $\boldsymbol{\gamma}_j$, respectively. Note that these parameters are retailer-specific, allowing differences in response across store chains and retail formats.

Demographic variables are included to capture systematic variation in household spending not related to retail location. These variables are: (i) *family size* (# members), (ii) *household*

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[5] Only interactions between format-level agglomeration and consumer travel times to the store are specified; more complicated interactions (e.g., three- and four-way) are not considered.

income (×\$10,000), (iii) *head-of-household age* (×10), (iv) *head-of-household education* (college degree=1, no college degree=0), and (v) *working woman* in the household (yes=1, no=0).[6] ξ_{ij} are random components that capture unobserved heterogeneity in spending preferences at retailer *j*. They are distributed

$$\xi_{ij}\xi_{ij'} \sim N(0,\Omega) \tag{5}$$

where $\Omega = diag\left[\omega_1^2 \quad \omega_2^2 \quad \cdots \quad \omega_J^2\right]$. Thus, unobserved heterogeneity in spending preferences is retailer-specific, reflecting differences in baseline spending and patronage across retailers. Off-diagonal elements of Ω are restricted to be zero. Though spending preferences may actually covary between retailers, this would be captured in the error covariance matrix Σ (see equation (3)).

Our empirical analysis focuses on the variables $\mathbf{c}_i$, $\mathbf{a}_{ij}$, $\mathbf{a}_{ij}c_{ij}$ and their parameters, which together characterize the effect of retail location on household spending. We now discuss these variables in more detail.

Location of stores vis-à-vis consumers. The travel time from shopper *i*'s home to the closest store of retailer *j* reflects *i*'s cost of visiting *j*. Observe that we specify travel times rather than distances because they more closely approximate travel costs. Unlike distances, travel times incorporate geographic factors that facilitate travel (e.g., road networks) or hamper travel (e.g., rivers, mountains). Averaging travel times across consumers tells us how close a retailer's stores are to consumers.

We expect spending at retailer *j* to be negatively affected by travel time to its closest store (i.e., own-effect) but positively affected by travel time to the closest stores of the other *J*-1 retailers (i.e., cross-effects). We estimate different parameters for each retailer because spending

[6] We also estimated a model specification that included home ownership among the demographic variables, but it offered little additional explanation of household spending.

at retailer *j* can be affected differently by the household's proximity to various other retailers. This allows substantial flexibility in patterns of spatial competition.

We expect travel time to the store to have a diminishing marginal effect on consumer spending. Consider a ten-minute increase in travel time. This additional time would have a larger impact on spending if a five-minute trip were increased to fifteen minutes than if a half-hour trip were increased to 40 minutes, implying a concave relationship between travel time and spending. We therefore test concave transformations of travel time (ln(*TT*), sqrt(*TT*) and -1/(*TT*)), along with untransformed *TT*, to determine which offers the best fit (see the "Specification Search" in the following section).

Location of stores vis-à-vis other stores: agglomeration. We measure retail density around a store as the number of stores of format m (m=1, …, M), not including the focal store itself, that are close enough to facilitate cross-shopping, $\#stores_m$. We consider M=6 different formats, each of which offers a variety of packaged goods: (i) *dollar stores*, (ii) *drug stores*, (iii) *grocery stores*, (iv) *discount stores*, (v) *supercenters*, and (vi) *warehouse clubs*. The density of format m around the closest store of retailer j to household i is determined in two steps: (i) for each of retailer j's stores, count the stores of format m that are close enough to facilitate cross-shopping, then (ii) determine which of retailer j's stores is closest to household i.

But how do we determine which stores are close enough to facilitate cross-shopping? Stores that are within the same shopping center certainly qualify, but stores not in the same center may also be close enough. Cross-shopping is most likely when travel between stores takes little time. We make the simplifying assumption that consumers are uniformly willing to travel no more than a certain amount to cross-shop stores, so "close enough" is defined by a threshold time between stores. We determine this threshold empirically using a grid search procedure (see the "Specification Search" in the next section).

The functional form of the relationship between retail density and spending is also uncertain. One might hypothesize that density will have a decreasing marginal effect on consumer spending at the retailer. Consider, for example, the effect of dollar store agglomeration on consumer spending at a discount store. We would expect that increasing by one the number of dollar stores near the focal discount store would have a bigger impact on discount store spending if the increase were from zero to one dollar store than if the increase were from ten to eleven dollar stores. We determine whether there is a diminishing marginal effect empirically by testing concave transformations of the number of stores of format m ($\ln(1 + \#stores_m)$, $\text{sqrt}(\#stores_m)$ and $-1/(1 + \#stores_m)$), along with the untransformed number of stores, as the agglomeration variable a_{ijm} (see the "Specification Search" in the next section).

Interaction between travel time and agglomeration. Because an agglomeration of stores is more attractive for shoppers than a single store, shoppers should be willing to travel farther to reach such an agglomeration. This implies that shopper's disutility for travel to a store should be lower for stores with higher retail density levels. We therefore posit an interaction between travel time to the closest store of retailer j, c_{ij}, and the vector of agglomeration variables for that store, $\mathbf{a}_{ij}$. The interaction parameter should have a positive effect on spending, ameliorating the negative effect of own-travel time, c_{ij}.

Estimation

Inter-type agglomeration (Miller, et al. 1999) implies that stores of different retail formats locate near one another. This creates collinearity in agglomeration levels across formats, which could inflate standard errors of the parameter estimates. To avoid this problem, we decompose the format-level agglomeration variables into their principal components and estimate parameters for these principal components. Thus, the parameters do not map to the agglomeration variables and interactions themselves. This makes interpreting the parameters difficult but permits statistical inference. We will circumvent the interpretation problem by computing the elasticity of retailer revenues to changes in agglomeration and travel times.

Data augmentation (Tanner and Wong 1987) is used to estimate the dependent variable of the Tobit censored regression models in our Bayesian framework (see Wei and Tanner 1990 and Chib 1993 for applications of data augmentation to Tobit models). If no spending is observed, the dependent variable is augmented so that $y^{*}_{ijk} \leq 0$. Details of data augmentation and all full conditional distributions are reported in Web Appendix 1. Prior distributions were selected so that the posterior distributions are driven almost entirely by the data. Detailed specifications of prior distributions are in Web Appendix 2.

Equations (1) – (5) were estimated using the Gibbs Sampler, which samples sequentially from the full conditional distributions over a large number of iterations. We made 50,000 draws from a single continuous Gibbs chain. The first 25,000 draws were used as a "burn in" period and subsequently discarded. Convergence of the Gibbs Sampler was confirmed by applying Geweke's test (1992). To reduce autocorrelation in the Gibbs draws, only every 10th draw was used for inference.

RESULTS

Specification Search

We address the three key specification issues by conducting a search over: (i) times between stores that facilitate cross-shopping, (ii) transformations of $\#stores_m$, the retail density measure for the m^{th} retail format around a focal store, and (iii) transformations of *TT*, consumers' travel times to retailers' stores.[7] Because all specifications have the same number of parameters, log-likelihoods are used for comparison.

<Insert Table 3 here>

The specification search in Table 3 shows that the best fitting model (in bold) uses a square-root transformation of travel time, *TT*, and a log transformation of the retail density measure, $\#stores_m$. The density measure in the best-fitting specification counts stores within seven minutes of the focal store. This suggests that, across retail formats, stores within seven minutes of one another are close enough to facilitate cross-shopping.

For each specification, we performed an eigen decomposition of the agglomeration variables α_{ijm} for the M=6 retail formats and used the resulting principal components for estimation. Eigenvalues and eigenvectors for our best-fitting specification (i.e., using log-transformed retail densities and a seven-minute threshold between stores) are reported in Table 4.

<Insert Table 4 here>

After determining the best-fitting specification, we used forward and backward stepwise procedures—incrementally adding or removing principal components, respectively—to determine which principal components should be retained. Both stepwise procedures indicated

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[7] We use the following procedure. First, we determine retail density by selecting a time threshold (i.e., the longest time between stores that still facilitates cross-shopping) anywhere between three and fifteen minutes. The density is computed by counting the stores of each of the *m* formats within that threshold time of the focal store (i.e., the closest store of retailer *j* to the consumer's home). Second, we create the agglomeration variables using either the density measure or a concave transformation thereof; either $\ln(1 + \#stores_m)$, $\mathrm{sqrt}(1 + \#stores_m)$ or $-1/(1 + \#stores_m)$. Third, we determine the consumer's proximity to retailer's stores using either *TT* or a concave transformation; either ln(*TT*), sqrt(*TT*) or -1/(*TT*). Overall, we test a total of 13×4×4=208 alternative specifications.

that all principal components contributed to model fit, so all were retained for subsequent analysis.

Nested Models

To demonstrate the contribution to fit of retail location variables, we estimate a series of nested models. Fit statistics for these nested models are shown in Table 5. We compute log-marginal density, a common measure of fit for Bayesian models, using the modified LaPlace method (Kass and Raftery 1995). We also compute the Deviance Information Criteria, or DIC, a relatively new measure of fit that is analogous to information criteria used in classical statistics (Speigelhalter, et al. 2002). To capture the proportion of variance in consumer spending explained by the model, we compute a pseudo-R^2 measure. The pseudo-R^2 measure requires that we compute expected consumer spending, so we adapt the univariate calculation for censored regressions to our multivariate system of censored regressions:

(6)
$$E(y_{ijk}) = \Phi\left(\frac{\theta_{ij} + \boldsymbol{\beta}'_j \mathbf{x}_k}{c_j}\right)\left(\theta_{ij} + \boldsymbol{\beta}'_j \mathbf{x}_k + \lambda_{ijk} c_j\right),$$

where $\Sigma = CC'$, c_j is the j^{th} diagonal element of the Cholesky root C, and

$$\lambda_{ijk} = \varphi\left(\frac{\theta_{ij} + \boldsymbol{\beta}'_j \mathbf{x}_k}{c_j}\right) \Big/ \Phi\left(\frac{\theta_{ij} + \boldsymbol{\beta}'_j \mathbf{x}_k}{c_j}\right).$$

$\Phi(\cdot)$ and $\varphi(\cdot)$ denote the CDF and PDF of the standard normal distribution, respectively. We use diagonal elements of the Cholesky root of Σ rather than the square root of the diagonal elements of Σ in order to exploit the error covariances between retailers. Using expected and observed consumer spending, we calculate pseudo-R^2 as follows:

(7) $$Psuedo\ R^2 = \left(\sum_I \sum_J \sum_K \left(y_{ijk} - \bar{y}\right)^2 - \sum_I \sum_J \sum_K \left(y_{ijk} - E\left(y_{ijk}\right)\right)^2 \right) \Big/ \sum_I \sum_J \sum_K \left(y_{ijk} - \bar{y}\right)^2 .$$

<Insert Table 5 here>

Finally, we assess our model's out-of-sample prediction by partitioning the dataset randomly into two sub-samples, re-estimating the model on one then applying the parameter estimates to the other. We re-estimate the model on roughly two-thirds (230) of the households, then compute the likelihood of the spending observations for the remaining 118 households, conditional on the parameter estimates.[8]

Log-marginal density, DIC, and out-of-sample likelihood criteria all favor the model that includes all location-related factors: travel times to the retailer's own stores (own-TT), travel times to other retailers' stores (cross-TT), agglomeration variables, and own-TT × agglomeration interactions. The contribution to fit of these variables is of particular interest. Recall that the model without retail location effects includes time-varying factors, unobserved heterogeneity and observed heterogeneity due to demographics. Together, they explain only 7.4% of the variance in quarterly consumer spending. Adding own-TT more than doubles the explanatory power of the model, to 14.9% of variance explained. Adding the cross-TT variables explains an additional 5.6% of the variance for a total of 20.5%. Overall then, locations of stores vis-à-vis consumers explain 13.1%=20.5%-7.4% of the variance in quarterly spending observations at the six retailers. Adding agglomeration variables explains an additional 1.9% of variance. The addition of interactions between own-TT and agglomeration variables explains another 2.8% of variance. Overall then, the variables that reflect locations of stores vis-à-vis other stores explain 4.7% of

[8] The parameter estimates from the sample are very close to those estimated using the full dataset.

the variance in spending independent of the explanation offered by own- and cross-TT. Together, all retail location variables explain 17.8%=25.2%-7.4% of the variance.

Parameter Estimates

Because our analysis focuses on retail location, which is captured in the hierarchical equation (4), parameter estimates from the hierarchical equations of all six retailer models are presented in Table 6. Only three of 30 demographic parameters are statistically significant—*Famsize* for WMT Discount, *Income* for Grocery 3 and *College* for Grocery 4—indicating that household characteristics explain little systematic variation in consumer spending.

<Insert Table 6 here>

Travel times to stores appear to have more explanatory power, with 15 of 36 parameter estimates statistically significant. All own-TT effects are negative (e.g., the parameter estimate of *TT-Grocery 3* is -139.4 in Grocery 3's spending model) and significant, implying that consumers who live farther from a retailer's store spend less there. Eight of the nine significant cross-TT effects are positive, suggesting that the consumers spend more at a retailer if they live farther from its competitors' stores. Thus, almost all significant travel time parameters have the expected sign.

Interpreting the agglomeration parameters and their interactions with own-TT is problematic because the variables are principal components of log-transformed retail density measures. However, we do find that six out of 36 parameter estimates for the agglomeration principal components are statistically significant. Six interaction parameters are also significant.

Revenue Elasticities

Our primary objective is to investigate the impact of travel times and agglomeration on retailer revenues. We therefore compute revenue elasticities for these retail location variables. Not only does this address a key criterion in store location decisions, but it overcomes the problem of interpreting parameter estimates.

Revenue elasticity is defined as the percentage change in the retailer's expected revenues in response to a one-percent change in the predictor variable *v*. For example, the own-TT elasticity for WMT Supercenter measures the percentage change in revenues that would result if every consumer's home was one percent farther from the closest WMT Supercenter.[9] We compute the revenue elasticity of retailer *j* to variable *v* by first computing expected revenues (summing expected spending from equation (6) over households and time in our sample):

(8) $$E(y_j) = \sum_I \sum_K E(y_{ijk}),$$

then computing the revenue elasticity:

(9) $$\eta_{jv} = \frac{\partial E(y_j)}{\partial v} \frac{v}{E(y_j)}.$$

<Insert Table 7 here>

Table 7 shows the revenue elasticities of travel times to the retailer's closest store. For an "across the board" change in consumers' proximity to stores of a retailer (by row), we report the resulting changes in revenues of all retailers (by column). As is common in Bayesian applications, we report a 95% confidence interval for the elasticity (in parentheses below the estimate). Consistent with the parameter estimates reported previously, all own-TT elasticities are negative and significant. They range from -1.005 for WMT Discount to -0.400 for Grocery 2. Note that Grocery 2 and WMT Supercenter have the smallest own-TT elasticities; both are

[9] While such a proportionately uniform movement away from all consumers may not be operationally possible on a given road network, it captures the overall strength of travel-time effects.

EDLP stores with a full line of grocery items.[10] Also consistent with the parameter estimates, nearly all (eight of nine) significant cross-TT elasticities are positive. Cross-TT elasticities are generally symmetric among the four grocery chains. Grocery 2 and Grocery 3 appear to compete with one another more directly, as do Grocery 1 and Grocery 4. Interestingly, cross-TT elasticities between the Wal-Mart formats are highly asymmetric, with WMT Supercenter revenues far more sensitive to consumers' travel times to WMT Discount than WMT Discount revenues are to travel times to WMT Supercenter. In fact, WMT Supercenter revenues are over twice as sensitive to consumers' proximity to WMT Discount stores as to its own stores.

<Insert Table 8 here>

Agglomeration elasticities are shown in Table 8. For a one-percent change "across the board" in the number of stores of a given retail format (by row) near the retailer's own stores, we report the resulting percentage change in retailer (by column) revenues. Seven of the 36 agglomeration elasticities (6 leading retailers × 6 format agglomeration variables) are significant. WMT Discount is more sensitive than other retailers to changes in agglomeration, with three significant elasticities. WMT Discount benefits significantly from locating near dollar stores (η=0.588) and drug stores (η=0.619), but suffers from locating near grocery stores (η=-1.191). Interestingly, all four grocery retailers in our sample benefit from locating near discount stores, though only Grocery 3 has a significant elasticity of discount store agglomeration. The asymmetric response between discount and grocery stores implies that WMT Discount should avoid grocery stores, while grocery stores should seek to locate near discount stores. In contrast, WMT Supercenter (essentially a Wal-Mart Discount store and full-service grocery under one roof) is not affected by agglomeration with any retail format, but supercenter agglomeration has a generally negative

[10] This seems to imply that consumers will travel farther to shop at EDLP stores, confirming the findings of Bell and Lattin (1998).

effect on grocery retailers though the elasticity is significant only for Grocery 1. Thus, by adding a full-service grocery to the discount store (i) the negative effect of grocery store agglomeration is diminished, while (ii) the net positive effect of discount store agglomeration on grocery store revenues changes to a net negative effect for supercenter agglomeration. Other significant agglomeration elasticities appear to be idiosyncratic, without clear patterns.

Travel Time/Agglomeration Tradeoffs

Given our premise that retailers should consider proximity to both consumers and other stores when evaluating retail locations, we now focus on the tradeoffs between these two factors. Specifically, we quantify how consumer travel time can compensate for an increase in retail agglomeration. Each cell in Table 9 presumes that the number of stores of format *m* (by row) near retailer *j*'s (by column) stores is uniformly increased by one. We report the amount that every consumer's travel time to retailer *j*'s stores would have to increase/decrease to offset the revenues gained/lost due to this change in agglomeration. Though a one-store increase in agglomeration may be large relative to current levels (e.g., for club stores and supercenters), a discrete change is consistent with our definition of retail density.

<Insert Table 9 here>

In general, increasing supercenter agglomeration would require the largest travel time tradeoffs. For example, travel times to Grocery 1's stores would have to be reduced by 4.04 minutes (-39%) to offset an increase in Grocery 1's supercenter agglomeration (+163%). The largest tradeoff would be required of WMT Supercenter, where consumers would have to be 7.38 minutes closer to its stores (-35%) to offset an increase in supercenter agglomeration (+458%). Increasing warehouse club store agglomeration would also require substantial, though somewhat smaller, travel time tradeoffs. In particular, consumers would have to be 1.89 minutes closer to WMT Discount stores (-11%) and 1.09 minutes closer to WMT Supercenters (-5%) to offset increases in club store agglomeration (+245% and +316% for the two retailers, respectively). In general, supercenter and club store agglomeration negatively impact the revenues of our six retailers, as does dollar store agglomeration. Only WMT Discount is positively affected by dollar store agglomeration; an additional 1.02 minutes of travel time (+6%) would be required to offset an increase in dollar store agglomeration (+18%). Both Wal-Mart formats would be willing to locate substantially farther from consumers to increase drug store agglomeration. WMT Discount would trade off an additional 1.40 minutes of travel time (+8%) while WMT Supercenter would trade off an additional 1.21 minutes (+6%) to increase drug store agglomeration (+18% and +22% for the two retailers, respectively). Finally, WMT Discount would have to be 0.87 minutes closer to consumers (-5%) to compensate for an increase in grocery store agglomeration (+13%). The other retailers, even grocery retailers, are positively affected by grocery store agglomeration and so should be willing to trade off proximity to consumers for an increase grocery store agglomeration.

DISCUSSION AND IMPLICATIONS

Our findings have important general implications and also suggest format-specific hypotheses about the nature of spatial interaction among retailers. There are five general implications: First, consumer travel times to stores are strong predictors of consumer spending (and hence of retailer revenue), significantly outperforming household demographics. Second, own-TT reduces a retailer's revenues while cross-TT (to other stores) generally increases a retailer's revenues, with magnitudes varying across retailers and formats in discernible patterns. Third, even after accounting for travel time effects, agglomeration has a noticeable effect on a retailer's revenue. Fourth, this effect of agglomeration varies in sign and magnitude depending on the focal retailer and the formats of nearby stores. Fifth, agglomeration effects are often asymmetric in sign or magnitude, with retailer A benefiting from the proximity of format B while a retailer of format B either suffers or benefits much less from proximity to A.

These results suggest that differentiated levels of attraction between retailers and consumers create complex interactions. The value of a retail location is affected by both its proximity to consumers and to other retailers; the latter influence varies across formats and may be positive or negative, symmetric or asymmetric.

No matter what dynamic one imagines for the store location process—simultaneous moves, deterministic entry sequences, discretionary move timing with or without information lags, etc.—it seems unlikely that formal models capturing this complexity would be analytically tractable. It is possible, however, to inquire about the causal forces that underlie our general findings. Symmetric Darwinism between retailers with category overlap, for example, could follow in a Nash equilibrium simply from an increasing marginal incentive to try to steal rivals' customers with price cuts as proximity increases. The marginal incentive for business stealing increases with proximity because, as stores grow closer, their customer pools have increasingly similar travel times to each and so are easier to lure away. When stores are far apart, each one's customer pool is dominated by consumers who are closer than their rival, which means that (i) it takes bigger price cuts to get consumers to switch, and (ii) more of the price cuts will go to consumers who would have shopped at the store anyway (and so will be "wasted").

Unfortunately, as is often the case with game-theoretic arguments, different but equally plausible equilibrium concepts or assumptions can reverse the results. For example, imagine stores playing a repeated pricing game (i.e., a supergame) and being able to condition their strategies at each moment on the whole history of the game to that point. According to the "topsy-turvy principle" (Shapiro 1989, p. 365), *higher* prices can be sustained in a supergame Nash equilibrium when the stores are closer together. This reversal occurs because increasing proximity makes the one-shot equilibrium worse for both stores, as described in the previous paragraph, and the one-shot payoff is the threat used to punish defectors from the tacitly collusive supergame equilibrium. The higher the supergame payoff, the greater the temptation to defect by undercutting on price, and so the stronger the deterrent needed to forestall such behavior. The worse one-shot payoff with greater proximity is therefore able to support a higher supergame payoff.[11] Hence, the effect of agglomeration on price competition is ambiguous.

One could interpret our findings about travel-time and agglomeration elasticities as empirically selecting between these competing models. For within-format competition, the own-TT and cross-TT elasticities are consistent with the one-shot model and not the supergame, in that we see fairly symmetrical benefits to each retailer from other stores moving farther from each household. The revenue elasticity results for intra-format agglomeration are not as informative, but it should be remembered that they occur only after taking travel times into account, which almost certainly attenuates the agglomeration effects.

In addition to these general implications, a few format-specific findings suggest possible interpretations. In particular, the asymmetry in agglomeration response between discount and grocery stores and how that differs from the supercenter-grocery store relationship calls for comment. We find that nearby discount stores are good for grocery store revenues, but nearby grocery stores are bad for discount store revenues. The natural interpretation of the former

[11] Besides supergames, other standard mechanisms such as multimarket contact, quick-response equilibria, or incomplete information could affect the comparative statics of price competition with varying proximity.

finding is that the presence of discount stores generates extra consumer trips to the vicinity, and that some of the purchases on those trips "leak" from the discount store to the grocery store through trip chaining or consumer search. The latter finding suggests that grocery stores do not generate extra visits to the discount store and/or that consumers spend a lot less at the discount store when visiting a grocery store on the same trip. Given that non-overlapping product categories of discount stores and grocery stores are primarily durables/soft goods and perishables, respectively (the overlap is mostly packaged goods), this suggests that marginal trips to retail centers with both formats are motivated more by durables and soft goods than by high-frequency perishables.

This interpretation is further supported by the impact of grocery stores on supercenter revenues and vice versa. Recall that a supercenter is the union of a grocery store and a discount store. Our results show that supercenters, which include perishables, are immune to the negative effect of grocery-store proximity and that grocery stores do not benefit from supercenter proximity. These findings strongly suggest that supercenters generate visits in a manner similar to discount stores, but do not suffer the revenue "leak" that discount stores experience. Thus, the usual rationale for the supercenter format—that groceries generate traffic to the store, resulting in extra hard-goods sales—appears to be backward; extra visits seem to be driven by durables and soft goods, with the grocery component of the supercenter capturing the excess revenue from these trips that would otherwise go to grocery stores.

A final piece of evidence for the proposition that durables/soft goods are stronger traffic generators than perishables comes from the asymmetry in the cross-TT elasticities of the two Wal-Mart formats, discount stores and supercenters. Recall that supercenters suffer when consumers live near discount stores, while the reverse is not true (agglomeration elasticities, though not statistically significant, point in the same qualitative direction). If perishables were the main drivers of supercenter visits, then we would expect the asymmetry to go in the other direction, with discount stores suffering when consumers live closer to supercenters. Instead, it appears that discount stores siphon off some of the visits motivated by durables and soft goods that supercenters would otherwise get, causing them to lose accompanying packaged goods sales.

Finally, our results have implications for the timing of retail location decisions. For example, supercenters are relatively unaffected by the proximity of grocery stores, but grocery stores may be harmed by nearby supercenters (Singh, Blattberg, and Hansen 2006). Our analysis of the agglomeration-travel time tradeoff shows that Groceries 1, 3, and 4 should be willing to suffer substantial travel time penalties to avoid proximity to a supercenter, while WMT supercenters are insensitive to their presence. It follows that, in an undeveloped market, the supercenter ought to locate first; then the three high-low grocers should react to its location. Of course, most markets have had grocery stores long before the supercenter format arrived, so this argument would not apply unless the grocers planned to relocate. Grocery 2, by contrast, does not suffer from proximity to a supercenter and so would not be better off waiting for the supercenter to locate first.

LIMITATIONS AND FUTURE RESEARCH

Our analysis of retail location, while capturing format heterogeneity and effect asymmetries, does not account for all possible interaction patterns. For example, we define agglomeration as the number of stores around a focal retailer's nearest store to a household. In some cases, that could be a source of error because a more-distant retail center with positive agglomeration effects may draw the consumer to drive past a nearer store. Also, shopping trips may originate from workplaces or other non-household locations, introducing noise into our travel-time variables.

It would be interesting to look at the revenue impact of travel time and agglomeration on smaller-share formats. Warehouse club dollar, drug, , and convenience stores, for example, also face important location decisions and are probably affected by both within- and across-format spatial factors. It could also be useful to combine trip-chaining and category-purchase data with the spatial model to see more directly which categories drive traffic to which stores. In addition, models of this type might play a role in treating store locations as endogenous decisions in retail strategy.

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Table 1
Descriptive Statistics – Panelists

	N	Mean	Std Dev
Income (x $1,000)	348	55.2	30.5
Family Size	348	2.65	1.16
Head of Household Age	348	51.3	11.4
College Education	348	0.39	0.49
Working Woman	348	0.50	0.46

Table 2
Descriptive Statistics – Retailers

Retailer	N	Spending per Year	Store Visits per Year	Penetration per Year	Consumer Travel Time (min)[a]
Grocery 1	696	$329	11.2	0.636	10.4
Grocery 2	696	$770	30.0	0.885	4.8
Grocery 3	696	$595	15.5	0.731	8.5
Grocery 4	696	$248	10.4	0.634	8.8
WMT Supercenter	696	$484	15.8	0.764	21.2
WMT Discount	696	$128	7.0	0.509	16.6

[a] N = 348

Table 3

Specification Search

Variable specifications		Maximum time(min) between stores when computing *#stores* $_m$												
c_{ij}	a_{ijm}	3	4	5	6	7	8	9	10	11	12	13	14	15
TT	*#stores* $_m$	-37249	-37134	-37069	-36906	-36740	-36696	-36940	-36947	-37036	-36811	-36882	-36734	-36929
TT	ln(1+*#stores* $_m$)	-37223	-37193	-37086	-36784	-36533	-36527	-36782	-36832	-36907	-36837	-36849	-36714	-36816
TT	sqrt(*#stores* $_m$)	-37217	-37142	-37135	-36781	-36651	-36622	-36880	-36917	-36972	-36917	-36951	-36819	-36923
TT	-1/(1+*#stores* $_m$)	-37227	-37184	-37176	-36818	-36568	-36686	-36749	-36768	-37050	-37164	-37157	-36986	-36999
ln(*TT*)	*#stores* $_m$	-37270	-37126	-36973	-36880	-36657	-36775	-37034	-36971	-36981	-36785	-36822	-36572	-36930
ln(*TT*)	ln(1+*#stores* $_m$)	-37270	-37121	-37004	-36666	-36442	-36681	-37018	-36961	-36926	-36827	-36722	-36508	-36792
ln(*TT*)	sqrt(*#stores* $_m$)	-37275	-37129	-37030	-36707	-36553	-36777	-37113	-37067	-36992	-36855	-36786	-36567	-36865
ln(*TT*)	-1/(1+*#stores* $_m$)	-37263	-37138	-36967	-36696	-36609	-36831	-37019	-37048	-37204	-37248	-37272	-37160	-37245
sqrt(*TT*)	*#stores* $_m$	-37047	-36953	-36855	-36730	-36556	-36570	-36821	-36772	-36815	-36648	-36667	-36489	-36757
sqrt(*TT*)	ln(1+*#stores* $_m$)	-37025	-36984	-36921	-36556	**-36313**	-36424	-36713	-36720	-36748	-36687	-36631	-36457	-36671
sqrt(*TT*)	sqrt(*#stores* $_m$)	-37024	-36975	-36955	-36603	-36447	-36516	-36830	-36801	-36824	-36723	-36708	-36552	-36727
sqrt(*TT*)	-1/(1+*#stores* $_m$)	-37029	-36997	-36959	-36621	-36476	-36611	-36764	-36777	-36996	-37084	-37091	-36909	-36994
-1/(*TT*)	*#stores* $_m$	-38688	-38339	-37994	-37804	-37748	-38098	-38154	-38095	-38069	-37827	-37857	-37610	-38026
-1/(*TT*)	ln(1+*#stores* $_m$)	-38823	-38409	-38003	-37787	-37769	-38028	-38292	-38338	-38290	-38072	-37923	-37759	-38136
-1/(*TT*)	sqrt(*#stores* $_m$)	-38774	-38342	-37988	-37755	-37805	-38082	-38345	-38362	-38207	-37966	-37811	-37675	-38019
-1/(*TT*)	-1/(1+*#stores* $_m$)	-38894	-38490	-38163	-37981	-38008	-38292	-38585	-38652	-38631	-38571	-38703	-38558	-38673

Table 4
Agglomeration Principal Components

	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6
Eigenvalues	0.670	0.362	0.189	0.122	0.090	0.047
Eigenvectors						
ln(# Club Stores)	0.183	0.131	0.360	0.395	0.791	0.196
ln(# Dollar Stores)	0.675	-0.574	-0.331	-0.146	0.211	-0.198
ln(# Drug Stores)	0.408	0.704	-0.141	0.099	-0.060	-0.552
ln(# Grocery Stores)	0.479	0.323	0.002	-0.318	-0.187	0.728
ln(# Discount Stores)	0.327	-0.220	0.764	0.196	-0.448	-0.149
ln(# Supercenters)	0.090	-0.073	-0.397	0.821	-0.301	0.255

Table 5
Nested Models

Model	Parameters	Log-Likelihood [a]	Log-Marginal Density [a]	DIC [a]	Psuedo-R^2 [a]	Out-of-Sample Log-Likelihood
No Location Variables	75	-45339	-46039	89022	0.074	-15175
Add Own-Travel Time	81	-40468	-41093	79437	0.149	-13991
Add Cross-Travel Times	111	-38037	-38966	73882	0.205	-13471
Add Format-Level Agglomeration	147	-37271	-38600	71448	0.224	-13451
Add Agglomeration x Own-TT Interactions	183	-36313	-37996	68759	0.252	-13439

[a] In-sample

Table 6
Parameter Estimates

Variable	Grocery 1	Grocery 2	Grocery 3	Grocery 4	WMT Supercenter	WMT Discount
Intercept	437 *	19	-89	126	15	220 *
	(186)	(193)	(190)	(148)	(199)	(97)
Famsize	6.8	14.1	4.9	4.9	15.3	12.3 *
	(12.7)	(13.2)	(15.8)	(10.3)	(12.6)	(5.5)
Income	2.2	-7.03	28.15 **	-1.97	2.71	1.94
	(4.9)	(5.29)	(6.16)	(3.90)	(4.90)	(2.12)
Age	-0.3	-8.4	9.1	-4.9	-16.7	3.2
	(13.2)	(14.0)	(16.8)	(10.6)	(13.0)	(5.8)
Femwork	-19.9	37.1	-61.1	-41.4	-38.0	-10.7
	(31.5)	(33.6)	(39.5)	(24.3)	(31.0)	(13.9)
College	-28.9	-16.6	66.2	-56.3 *	-0.3	-10.3
	(29.3)	(30.7)	(34.9)	(23.2)	(27.7)	(13.0)
TT to Grocery 1	-113.2 **	22.3	35.6	26.5 *	-12.2	13.2
	(18.1)	(17.0)	(18.5)	(13.0)	(17.1)	(7.4)
TT to Grocery 2	22.8	-87.8 **	79.8 **	13.6	-25.6	10.9
	(24.9)	(25.4)	(28.4)	(17.4)	(21.4)	(9.0)
TT to Grocery 3	30.3	57.3 **	-139.4 **	19.9	-1.2	20.1 *
	(19.5)	(21.4)	(24.4)	(15.9)	(18.4)	(7.8)
TT to Grocery 4	40.5 *	33.5 *	20.8	-108.2 **	38.9 *	-26.0 **
	(19.5)	(15.7)	(19.2)	(15.4)	(18.1)	(6.8)
TT to WMT Supercenter	-25.5	10.4	-29.5	10.3	-56.0 **	13.5
	(18.9)	(21.0)	(20.8)	(16.6)	(18.7)	(9.0)
TT to WMT Discount	2.0	7.7	3.6	10.2	73.0 **	-53.8 **
	(14.2)	(15.9)	(19.6)	(13.5)	(15.1)	(7.8)
Agglomeration PC 1	-81.3 **	-22.6	-11.4	-13.2	-34.8	-24.0
	(20.8)	(21.7)	(18.5)	(16.9)	(66.1)	(34.9)
Agglomeration PC 2	-37.4	-73.9 *	-39.0	7.0	-10.8	-25.8
	(24.4)	(30.6)	(21.6)	(16.5)	(45.6)	(31.7)
Agglomeration PC 3	-62.2	-5.5	136.3 **	-17.7	50.5	-31.9
	(38.5)	(38.5)	(41.5)	(28.9)	(128.4)	(26.6)
Agglomeration PC 4	-1.0	78.2	7.9	-58.9 *	-37.8	0.6
	(31.2)	(50.9)	(38.5)	(27.5)	(99.5)	(24.1)
Agglomeration PC 5	56.9	1.3	108.0 *	57.4	13.4	-36.1
	(36.2)	(39.8)	(56.5)	(39.1)	(52.9)	(124.1)
Agglomeration PC 6	-26.2	133.1 *	-77.7	34.8	9.1	-4.5
	(26.4)	(66.3)	(50.9)	(49.1)	(45.2)	(125.9)
Own-TT x Agglom PC 1	-110.2 *	37.9	-30.5	-134.7 *	-83.4	77.2
	(49.2)	(67.4)	(47.1)	(52.7)	(136.7)	(254.3)
Own-TT x Agglom PC 2	27.3	42.8	-47.2	-101.5 *	-0.2	43.6
	(47.3)	(74.1)	(50.7)	(46.6)	(112.1)	(259.1)
Own-TT x Agglom PC 3	41.5	-105.4	-65.7	10.1	-58.6	59.2
	(55.8)	(61.9)	(74.2)	(47.0)	(67.4)	(116.0)
Own-TT x Agglom PC 4	44.4	-181.0	-41.0	36.2	-76.7	42.2
	(48.2)	(96.2)	(70.0)	(41.0)	(54.7)	(103.3)
Own-TT x Agglom PC 5	52.6	36.1	87.0	-38.5	-42.1	-215.6 *
	(83.6)	(65.6)	(85.4)	(74.4)	(73.3)	(104.7)
Own-TT x Agglom PC 6	34.0	-249.6 **	355.0 **	-22.8	13.3	-49.4
	(103.2)	(82.8)	(99.1)	(86.0)	(56.4)	(90.0)

* Significant at α=0.05
** Significant at α=0.01

Table 7

Travel Time (TT) Elasticities

Δ Travel Time to	Resulting Revenues at Grocery 1	Grocery 2	Grocery 3	Grocery 4	WMT Supercenter	WMT Discount
Grocery 1	-0.921 *	0.162	0.246	0.373 *	-0.095	0.250
	(-1.289 , -0.509)	(-0.075 , 0.405)	(-0.015 , 0.502)	(0.009 , 0.737)	(-0.360 , 0.171)	(-0.025 , 0.521)
Grocery 2	0.184	-0.400 *	0.377 *	0.135	-0.139	0.133
	(-0.184 , 0.568)	(-0.613 , -0.182)	(0.116 , 0.645)	(-0.204 , 0.484)	(-0.370 , 0.094)	(-0.074 , 0.360)
Grocery 3	0.323	0.390 *	-0.733 *	0.280	-0.008	0.333 *
	(-0.106 , 0.745)	(0.099 , 0.678)	(-0.960 , -0.501)	(-0.146 , 0.751)	(-0.282 , 0.266)	(0.076 , 0.591)
Grocery 4	0.393 *	0.223 *	0.134	-0.934 *	0.291 *	-0.416 *
	(0.012 , 0.806)	(0.019 , 0.429)	(-0.101 , 0.385)	(-1.222 , -0.607)	(0.025 , 0.556)	(-0.618 , -0.218)
WMT Supercenter	-0.340	0.096	-0.252	0.200	-0.460 *	0.396
	(-0.818 , 0.143)	(-0.280 , 0.467)	(-0.584 , 0.105)	(-0.435 , 0.827)	(-0.778 , -0.139)	(-0.112 , 0.920)
WMT Discount	0.037	0.081	0.036	0.216	1.015 *	-1.005 *
	(-0.416 , 0.504)	(-0.246 , 0.411)	(-0.334 , 0.410)	(-0.329 , 0.789)	(0.604 , 1.432)	(-1.304 , -0.703)

* Significant at α=0.05

Table 8
Agglomeration Elasticities

Δ #Stores	Resulting Revenues at Grocery 1	Grocery 2	Grocery 3	Grocery 4	WMT Supercenter	WMT Discount
Club	-0.021	-0.019	0.016	-0.018	-0.027	-0.062
	(-0.091 , 0.067)	(-0.045 , 0.013)	(-0.074 , 0.112)	(-0.092 , 0.078)	(-0.097 , 0.053)	(-0.190 , 0.092)
Dollar	-0.070	-0.154	-0.405 *	-0.139	-0.197	0.588 *
	(-0.407 , 0.257)	(-0.438 , 0.129)	(-0.616 , -0.182)	(-0.532 , 0.272)	(-1.246 , 0.846)	(0.214 , 0.963)
Drug	-0.629 *	-0.114	0.349	0.056	0.255	0.619 *
	(-1.226 , -0.008)	(-0.480 , 0.240)	(-0.159 , 0.866)	(-0.789 , 0.938)	(-0.170 , 0.675)	(0.030 , 1.241)
Grocery	0.086	0.117	0.156	0.038	0.012	-1.191 *
	(-0.783 , 0.995)	(-0.281 , 0.495)	(-0.326 , 0.621)	(-0.703 , 0.804)	(-0.775 , 0.807)	(-2.210 , -0.173)
Discount	0.057	0.075	0.179 *	0.053	-0.056	0.044
	(-0.177 , 0.306)	(-0.086 , 0.241)	(0.017 , 0.352)	(-0.139 , 0.275)	(-0.376 , 0.273)	(-0.086 , 0.185)
Supercenter	-0.201 *	0.068	-0.016	-0.096	-0.053	.
	(-0.327 , -0.053)	(-0.051 , 0.193)	(-0.080 , 0.057)	(-0.277 , 0.105)	(-0.221 , 0.113)	(. , .)

* Significant at $\alpha=0.05$

Table 9

Agglomeration/Travel Time Tradeoffs

Δ	Grocery 1		Grocery 2		Grocery 3		Grocery 4		WMT Supercenter		WMT Discount	
Format Agglomeration	TT Tradeoff[a]	#Stores[b]	TT Tradeoff[a]	#Stores[b]	TT Tradeoff[a]	#Stores[b]	TT Tradeoff[a]	#Stores[b]	TT Tradeoff[a]	#Stores[b]	TT Tradeoff[a]	#Stores[b]
Club	-0.78	0.49 +1	-0.84	0.23 +1	0.21	0.35 +1	-0.91	0.33 +1	-1.09	0.32 +1	-1.89	0.41 +1
	(-8%)	(+204%)	(-18%)	(+430%)	(+2%)	(+288%)	(-10%)	(+303%)	(-5%)	(+316%)	(-11%)	(+245%)
Dollar	-0.09	6.40 +1	-0.30	5.02 +1	-0.74	5.74 +1	-0.16	5.34 +1	-0.57	6.15 +1	1.02	5.42 +1
	(-1%)	(+16%)	(-6%)	(+20%)	(-9%)	(+17%)	(-2%)	(+19%)	(-3%)	(+16%)	(+6%)	(+18%)
Drug	-0.88	5.34 +1	-0.27	4.34 +1	0.37	5.53 +1	0.01	4.64 +1	1.21	4.64 +1	1.40	5.47 +1
	(-8%)	(+19%)	(-6%)	(+23%)	(+4%)	(+18%)	(0%)	(+22%)	(+6%)	(+22%)	(+8%)	(+18%)
Grocery	0.06	7.74 +1	0.10	6.42 +1	0.55	8.15 +1	0.03	6.76 +1	0.02	7.16 +1	-0.87	7.88 +1
	(+1%)	(+13%)	(+2%)	(+16%)	(+6%)	(+12%)	(0%)	(+15%)	(0%)	(+14%)	(-5%)	(+13%)
Discount	0.20	1.07 +1	-0.77	0.92 +1	1.14	1.07 +1	0.27	0.95 +1	-1.56	1.07 +1	0.54	0.69 +1
	(+2%)	(+94%)	(-16%)	(+109%)	(+13%)	(+94%)	(+3%)	(+105%)	(-7%)	(+94%)	(+3%)	(+146%)
Supercenter	-4.04	0.61 +1	1.55	0.41 +1	-2.06	0.46 +1	-1.21	0.39 +1	-7.38	0.22 +1	.	0.00 +1
	(-39%)	(+163%)	(+33%)	(+245%)	(-24%)	(+219%)	(-14%)	(+258%)	(-35%)	(+458%)	.	N/A

[a] TT Tradeoff is in minutes; percentage changes are reported in parentheses below.

[b] #Stores of the retail format in the left column; percentage changes are reported in parentheses below.

Web Appendix 1 – Full Conditional Distributions

We rewrite equation (2) in a modified SUR form:

(W1.1)
$$\begin{bmatrix} \mathbf{y}_1^* \\ \mathbf{y}_2^* \\ \vdots \\ \mathbf{y}_J^* \end{bmatrix} = \begin{bmatrix} \boldsymbol{\theta}_1 \\ \boldsymbol{\theta}_2 \\ \\ \boldsymbol{\theta}_J \end{bmatrix} \otimes [\mathbf{1}_K] + \begin{bmatrix} X & & & \\ & X & & \\ & & \ddots & \\ & & & X \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_1 \\ \boldsymbol{\beta}_2 \\ \vdots \\ \boldsymbol{\beta}_J \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \vdots \\ \boldsymbol{\varepsilon}_J \end{bmatrix}$$

where $\mathbf{y}_j^* = \begin{bmatrix} y_{1j1}^* & y_{1j2}^* & \cdots & y_{IjK}^* \end{bmatrix}'$, $\boldsymbol{\theta}_j = \begin{bmatrix} \theta_{1j} & \theta_{2j} & \cdots & \theta_{Ij} \end{bmatrix}'$, $X = [\mathbf{1}_I] \otimes \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_K \end{bmatrix}'$, and $\boldsymbol{\varepsilon}_j = \begin{bmatrix} \varepsilon_{1j1} & \varepsilon_{1j2} & \cdots & \varepsilon_{IjK} \end{bmatrix}'$. For compactness, we rewrite equation (W1.1) above:

(W1.2)
$$y^* = \boldsymbol{\theta} + X\boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

We rewrite equation (4) as:

(W1.3)
$$\theta_{ij} = \boldsymbol{\psi}'_j \mathbf{z}_{ij} + \zeta_{ij},$$

where $\boldsymbol{\psi}_j = \begin{bmatrix} \mu_j & \boldsymbol{\delta}'_j & \chi'_j & \alpha'_j & \boldsymbol{\gamma}'_j \end{bmatrix}'$ and $\mathbf{z}_{ij} = \begin{bmatrix} 1 & \mathbf{d}'_j & \mathbf{c}'_{ij} & \mathbf{a}'_{ij} & (\mathbf{a}_{ij} c_{ij})' \end{bmatrix}'$; then in SUR form:

(W1.4)
$$\begin{bmatrix} \boldsymbol{\theta}_1 \\ \boldsymbol{\theta}_2 \\ \\ \boldsymbol{\theta}_J \end{bmatrix} = \begin{bmatrix} Z_1 & & & \\ & Z_2 & & \\ & & \ddots & \\ & & & Z_J \end{bmatrix} \begin{bmatrix} \boldsymbol{\psi}_1 \\ \boldsymbol{\psi}_2 \\ \vdots \\ \boldsymbol{\psi}_J \end{bmatrix} + \begin{bmatrix} \boldsymbol{\varsigma}_1 \\ \boldsymbol{\varsigma}_2 \\ \vdots \\ \boldsymbol{\varsigma}_J \end{bmatrix}$$

where $\boldsymbol{\theta}_j = \begin{bmatrix} \theta_{1j} & \theta_{2j} & \cdots & \theta_{Ij} \end{bmatrix}'$, $Z_j = \begin{bmatrix} \mathbf{z}_{1j} & \mathbf{z}_{2j} & \cdots & \mathbf{z}_{Ij} \end{bmatrix}'$, and $\boldsymbol{\varsigma}_j = \begin{bmatrix} \varsigma_{1j} & \varsigma_{2j} & \cdots & \varsigma_{Ij} \end{bmatrix}'$. Finally, we rewrite equation (W1.4) for compactness:

(W1.5)
$$\boldsymbol{\alpha} = Z\boldsymbol{\psi} + \boldsymbol{\varsigma}$$

The full conditional distributions for our model follow. The term "rest" is used to denote the dataset and all model parameters other than those whose conditional distributions are being specified.

(W1.6) $y^*_{ijk} \mid \text{rest} \sim \begin{cases} y_{ijk} & \text{if } y_{ijk} > 0 \\ N_{truncated}\left(\theta_{ij} + \boldsymbol{\beta}'_{jk} x_k - \boldsymbol{\sigma}_{jr}\Sigma_r^{-1}\left(\mathbf{y}^*_{i,r\neq j,k} - E\left(\mathbf{y}^*_{i,r\neq j,k}\right)\right), \sigma_{jj} - \boldsymbol{\sigma}_{jr}\Sigma^{-1}_{r\neq j}\boldsymbol{\sigma}_{rj}\right) & \text{otherwise} \end{cases}$

where $\Sigma = \begin{bmatrix} \sigma_j^2 & | & \boldsymbol{\sigma}_{jr} \\ -- & + & -- \\ \boldsymbol{\sigma}_{rj} & | & \Sigma_{r\neq j} \end{bmatrix}$, $\mathbf{y}^*_{ik} = \begin{bmatrix} y^*_{ijk} \\ -- \\ \mathbf{y}^*_{i,r\neq j,k} \end{bmatrix}$, and $E\left(\mathbf{y}^*_{i,r\neq j,k}\right) = \left[\theta_{i2} - \boldsymbol{\beta}'_2\mathbf{x}_k \quad \cdots \quad \theta_{iJ} - \boldsymbol{\beta}'_J\mathbf{x}_k\right]'$.

As the notation suggests, the $\mathbf{y}^*_{jl}$ vector and Σ matrix are partitioned between the retailer of interest, *j*, and all other retailers, $r \neq j$. Without loss of generality, we have shown the retailer of interest first.

(W1.7) $$\boldsymbol{\beta} \mid \text{rest} \sim N\left(O\left(X'\left(\Sigma^{-1} \otimes I_{IK}\right)\left(\mathbf{y}^* - \boldsymbol{\theta}\right) + \nu_\beta V_\beta^{-1}\overline{\boldsymbol{\beta}}\right), O\right)$$

where $O = \left(X'\left(\Sigma^{-1} \otimes I_{IK}\right)X + \nu_\beta V_\beta^{-1}\right)^{-1}$

(W1.8) $$\boldsymbol{\theta}_i \mid \text{rest} = N\left(P\left(U'\left(\Sigma^{-1} \otimes I_K\right)\left(\mathbf{y}^*_i - X_i\boldsymbol{\beta}\right) + \Omega^{-1}Z_i\boldsymbol{\psi}\right)\right)$$

where U = block diag [$\mathbf{1}_K$, $\mathbf{1}_K$, … $\mathbf{1}_K$] and $P = \left(U'\left(\Sigma^{-1} \otimes I_K\right)U + \Omega^{-1}\right)^{-1}$

(W1.9) $$\boldsymbol{\psi} \mid \text{rest} \sim N\left(Q\left(Z'\left(\Omega^{-1} \otimes I_I\right)\boldsymbol{\theta} + \nu_\psi V_\psi^{-1}\overline{\boldsymbol{\psi}}\right), Q\right)$$

where $Q = \left(Z'\left(\Omega^{-1} \otimes I_I\right)Z + \nu_\psi V_\psi^{-1}\right)^{-1}$

(W1.10) $$\Sigma^{-1} \mid \text{rest} \sim \text{Wish}\left(HQ + \nu_\Sigma, \left(\nu_\Sigma V_\Sigma + \boldsymbol{\varepsilon}\boldsymbol{\varepsilon}'\right)^{-1}\right)$$

(W1.11) $$\omega_j^{-2} \mid \text{rest} \sim \chi^2\left(H + \nu_\omega, \left(\nu_\omega \overline{\omega}_j^2 + \varsigma_j\varsigma'_j\right)^{-2}\right)$$

Web Appendix 2– Prior Distributions

For the first stage of the model, given by equations (2) and (3), we specify the prior for the parameters as

(W2.1) $$\boldsymbol{\beta} \sim N\left(\bar{\boldsymbol{\beta}}, \nu_\beta V_\beta\right),$$

where $\boldsymbol{\beta} = \begin{bmatrix}\boldsymbol{\beta}_1' & \boldsymbol{\beta}_2' & \cdots & \boldsymbol{\beta}_J'\end{bmatrix}'$, and a natural conjugate prior for the error covariance matrix as

(W2.2) $$\Sigma^{-1} \sim \text{Wish}\left(\nu_\Sigma, V_\Sigma^{-1}\right).$$

For the second stage of the model, given by equations (4) and (5), we specify the prior for elements of the diagonal covariance matrix, Ω, as

(W2.3) $$\omega_j^{-2} \sim \chi^2\left(\nu_\omega, \overline{\varpi}_j^{-2}\right).$$

The prior for $\boldsymbol{\psi}$ is specified as

(W2.4) $$\boldsymbol{\psi} \sim N\left(\bar{\boldsymbol{\psi}}, \nu_\psi V_\psi\right),$$

where $\boldsymbol{\psi} = \begin{bmatrix}\boldsymbol{\psi}_1' & \boldsymbol{\psi}_2' & \cdots & \boldsymbol{\psi}_J'\end{bmatrix}'$.

We select relatively diffuse values for the priors in equation (10) so that posterior distributions will be determined almost entirely by the data: $\bar{\boldsymbol{\psi}} = [\mathbf{0}]$, $\nu_\psi = 1$, and $V_\psi = 10^5 I$. Values for $\bar{\boldsymbol{\beta}}$, V_β, V_Σ and $\overline{\varpi}_j^2$ will be determined empirically using pooled models in which the intercept is restricted to be the same for all households ($\theta_{ij} = \theta_j$) and errors are assumed to be IID normal. Our strategy is to shrink the parameters and variances of time-varying factors as well as other relevant variances toward estimates from these pooled models.

Priors for the variances V_β, V_Σ, and $\overline{\varpi}_j^2$ are set in a way that incorporates the expected reduction in variance relative to the pooled model (Montgomery 1997). For example, the prior on the variance term in the hierarchical equation, $\overline{\varpi}_j^2$, should reflect our belief that that ω_j^2 will be much smaller than the estimated variance of β_j from the pooled Tobit model for retailer j, $s^2_{\omega,j}$, because our model captures observed heterogeneity from several sources. We therefore specify $\overline{\omega}^2_j$ using a scaling constant, k_ω, and $s^2_{\omega,j}$ as follows

(W2.5) $$\overline{\omega}^2_j = k^2_\omega s^2_{\omega,j} .$$

Setting $k_\omega = 0.5$ would correspond to a prior belief that the residual standard deviation of the hierarchical equation, ω_j, is 50% of standard deviation of β_j from the pooled model. The same approach yields the following prior distributions for V_β and V_Σ

(W2.6) $$V_\beta = \text{diag}\left[k^2_\beta s^2_{\beta,1} \quad k^2_\beta s^2_{\beta,2} \quad \cdots \quad k^2_\beta s^2_{\beta,J}\right] \text{ and}$$

(W2.7) $$V_\Sigma = \text{diag}\left[k^2_\Sigma s^2_{\Sigma,1} \quad k^2_\Sigma s^2_{\Sigma,2} \quad \cdots \quad k^2_\Sigma s^2_{\Sigma,J}\right],$$

where $s^2_{\beta,j}$ and $s^2_{\Sigma,j}$ are empirical estimates of the variance of β_{ij} and the error variance of the pooled model for retailer j, respectively. We set the scaling constants $k_\beta = k_\Sigma = 0.5$ and $k_\omega = 0.25$.

Finally, we must select ν_β, ν_ω, and ν_Σ which weight our empirical priors. Because we are interested in individual differences and have limited intuition about the scaling constants, we choose not to shrink individual parameter estimates toward the priors too much. We therefore set $\nu_\beta = \nu_\omega = \nu_\Sigma = 5$. To determine how much the priors affect the posterior distributions, we tried doubling ν_β, ν_ω, and ν_Σ. Neither inferences nor predictions based on the posteriors were significantly affected.