Measuring Competition in Spatial Retail: An Application to Groceries*

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October 14, 2015

Abstract

We provide a simple framework for analyzing competition between multi-product retailers that can be used as a tool for evaluating potential mergers and judging their likely impact on market structure. Our aim is to provide a simple mechanism for identifying markets where concern may be warranted, and assessing the impact on market structure of allowing the parties to merge (along with the potential mitigating effects of potential divestitures). We estimate the model using data from the supermarket industry (including competition from both Wal-Mart supercenters and club stores) and use the output to evaluate two representative mergers, one that has already occurred and another that is currently in the negotiation stage.

Keywords: Retail Grocery, Club Stores, Store Choice, Anti-Trust Regulation, Demand Estimation.

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1 Introduction

Who competes with whom? In order to tackle almost any important question in industrial organization, whether it be the impact of competition, the effectiveness of advertising, or the benefits associated with new product introductions, you first need to determine the relevant market. Market definition, or more specifically, choosing the relevant set of substitute products, is especially difficult in the context of retail competition. Modern retailers differentiate themselves not just in where they choose to locate spatially, but also in the set of products they offer and in the amenities they offer to consumers. Consumers derive utility from store offerings that varies heterogeneously with their individual circumstances, most notably where they live and their level of income. As a result, the seemingly simple question of who stores actually compete with can be difficult to answer without a model of consumer choice that includes all possible competitors. The rise of "big box" formats like Wal-Mart and Best Buy and e-commerce firms like Amazon makes the problem even more challenging, as the increasing importance of both scale and scope economies blur the lines between traditionally distinct retail channels such as grocery and general merchandise, or consumer electronics and clothing.

The issue of market definition is especially relevant to antitrust analysis, where its choice can effectively determine whether a merger is approved or blocked by the relevant government agency. For example, in the recent Office Depot and Staples merger, the approval decision turned on whether "office supply superstore" constituted a distinct niche from mass merchandise or club store, while the analysis of the Whole Foods and Wild Oats merger relied on deciding whether "premium natural and organic supermarkets" (of which Whole Foods and Wild Oats were the only two relevant firms) competed in a distinct market from traditional grocery firms like Kroger and Safeway. The goal of this paper is to develop a framework for analyzing competition between multi-product, spatially differentiated retailers that can cleanly capture the degree of competition between highly differentiated firms. We apply the framework to data from the grocery industry, and then use it to evaluate the impact on market structure arising from two mergers, one that actually occurred and another that has recently been proposed. In so doing, we also highlight the importance of accounting for competition from new channels, in this case the growing segment of club stores.[1] We find that whether or not club stores are included in a model of grocery competition can have a dramatic impact on the outcome of a merger analysis involving two non-club grocery chains. This result is intuitive, the ex-ante exclusion of club stores results in a model that overlooks the presence of significant substitute outlets and consequently overstates the impact of the merger on ex post concentration.

[1] Hortaçsu and Syverson (2015) note that between 2000 and 2013, the club store Costco's sales alone increased by $50 billion. By comparison, sales at Amazon.com increased $38 billion over the same period. The authors go on to note that the four largest firms in the club sector (a category in which they include every type of Wal-Mart) accounted for almost 8% of total retail sales in 2012, a figure that is "almost 50 percent more than *all* e-commerce retail sales in that year".

We start by proposing a simple framework to connect information on consumer demographics to data on store-level outcomes. A central challenge in analyzing retailers stems from the fact that many of these firms carry a vast array of products, sometimes numbering in the tens or even hundreds of thousands. Constructing a representative basket of goods or price index for these firms can be prohibitively difficult. Rather than attempting to do so, we rely on revenue data (which is often readily available) and a rich set of store characteristics to characterize the firm side. By including both store characteristics and consumer demographic information, we are able to capture the fact that different consumers value different firms in heterogenous ways, without requiring information on individual products or prices. Importantly, some of this heterogeneity is unobserved to the researcher, but captured through firm level fixed effects that vary with consumer demographics.

We estimate our model using data from the supermarket industry, showing how our framework can flexibly capture rich substitution patterns that depend not only on spatial proximity, but systematic differences in tastes for particular types of firms. In particular, we find that consumers with differing levels of wealth have not only different travel costs, but choose to shop at distinct types of stores. We find that some store formats (e.g. clubs) are able to draw from a wider catchment area, while others (e.g. premium organic) can only attract consumers that live close by.

We then use the model to illustrate the impact of the spatial distribution of stores and consumers on store revenues. For each store, we are able to calculate the distance elasticity of revenue, a measure of how distance from the store affects store revenue, as well as an income elasticity of revenue, indicating how an outlet's revenue responds to the incomes of nearby consumers. The results indicate substantial heterogeneity across stores in their sensitivity to distance and income. For example, club stores—who tend to offer products in bulk at discount prices—are relatively insensitive to distance, while higher end grocery outlets such as Whole Foods—who emphasize prepared foods—are the most sensitive to distance. We are also able to provide a clear characterization of which firms compete for the same sets of consumers and which firms are most isolated in product space. These results confirm that club stores are often major competitors of major grocery chains, rather than competing in their own distinct market.

Next, we use the model to conduct a "first pass" horizontal merger analysis. Our aim is to provide a simple mechanism for identifying markets where concern may be warranted, and the likely impact on market structure of allowing the parties to merge (along with the potential mitigating effects of possible divestitures). Merger analysis is one of the largest areas of antitrust enforcement.[2] According to Hosken and Tenn (2016), it is also one of the most difficult, due to its inherently prospective nature. It is only made

[2]Hosken and Tenn (2016) note that, for the 2013 fiscal year, "roughly 62% of the budgeted antitrust resources were devoted to merger enforcement".

more difficult by the tight timelines involved. Under the Hart-Scott-Rodino Act of 1976, antitrust authorities have just thirty days to conduct a preliminary investigation of a merger upon notification of intent by the merging parties. If the government should choose to investigate further (by issuing a "second request"), the investigation typically occurs over just two to three months. During this period, the government reviews company documents, deposes the participants, and conducts econometric studies to measure the degree of substitution between the firms. Perhaps the most critical and controversial part of this analysis concerns the definition of the market.[3] Given the time constraint and difficulty of the problem, this is often done qualitatively (e.g. by relying on internal documents and interviews with industry participants) or by simply drawing circles of fixed radii around individual stores.[4] It is at this stage that we see our framework as most useful, since it allows the data to reveal the actual degree of substitution, obviating the need for ex ante judgement calls regarding who is in or out of the set or imposing a fixed distance cutoff.

We view our framework as most helpful in analyzing retail mergers. Due to the rising importance of scale and scope economies in driving retail efficiency, mergers are increasingly used as a mechanism for achieving scale. This is especially true in grocery markets. According to Hanner et al. (2015), from 1998 to 2007, the Federal Trade Commission (FTC) investigated supermarket mergers in 153 antitrust markets, ultimately challenging mergers in 134 of those markets. Perhaps not surprisingly, merger analysis in retail is especially challenging. The wide geographic spread of stores, their diverse set of product offerings and the continual blurring of both retail formats and sales channels renders it very difficult to establish who competes with whom, and to what degree. For example, in critiquing the government's challenge of the Whole Foods/Wild Oats merger, Lambert (2008) argued that the FTC sought to classify Whole Foods and Wild Oats as premium organic and natural supermarkets that exclusively targeted affluent consumers with a distinctive higher level of service, thus placing them in a separate market from conventional supermarket chains like Kroger and Safeway. This conclusion relied heavily on internal marketing documents obtained from the merging parties. Lambert argued that defining the market in this way implied that a merger between Whole Foods and Wild Oats was effectively a merger to monopoly.

Our framework provides a straightforward way of gauging the extent of competition that existed between these firms and their rivals using actual market outcomes. Using the estimates from our empirical analysis, we find evidence consistent with the court's opinion that "when Whole Foods does enter a new market where Wild Oats operates, Whole Foods takes most of its business from other retailers, not from Wild Oats." (Varner and Cooper, 2007) This conclusion is driven by the high degree of substitution between

[3] Varner and Cooper (2007) note that if the market is defined too narrowly, it is almost guaranteed that the government can make a prima facie case showing that the merger violates anti-trust laws. Similarly, if the market is defined too broadly, it is unlikely that the merger will be found unlawful.

[4] For supermarket mergers, economists at the Federal Trade Commission typically use a 3 to 5 mile radius to characterize the catchment area.

premium organic firms and conventional supermarkets for most consumers. We then consider a prospective merger involving Delhaize and Ahold. Here we do find areas of substantial anti-trust concern, which are mainly clustered in suburban and rural areas. We provide a simple method for identifying the markets (and stores) that should be the focus of more detailed analysis.

Finally, we highlight the importance of including club stores in the competitive set. Hosken et al. (2012) note that, due to their more limited product selection, "club stores are typically not considered important substitutues to supermarkets by antitrust agencies in evaluating supermarket mergers".[5] Our analysis suggests that this is a mistake, as club stores now compete on relatively equal footing with conventional supermarkets.

Apart from its role in guiding prospective merger analysis, we view our framework as making an important contribution to the empirical analysis of spatially differentiated multi-product firms. Retailing has been a source of robust productivity gains over the past few decades, mostly due to the replacement of small, low productivity firms with large, high productivity entrants (Foster et al., 2006). Much of these gains have been passed through to consumers in the form of lower prices and wider selection. These reallocation dynamics are mainly driven by the increasing importance of scale economies, which lead to ever-larger chains of ever-larger stores and increasing levels of concentration. Effective competition policy should carefully weigh the benefits of scale and consolidation and the potential cost of greater market power when evaluating mergers. We view our demand system as a key step in understanding how these markets function and as a key input to predicting how they will continue to evolve.

The paper is organized as follows. In section 2, we present our model of spatial competition and discuss the variation in the data needed to identify the parameters of interest. Section 3 describes the data used in our empirical analysis and provides some background on the industry. In section 4, we discuss the estimation results, highlighting the ability of our framework to capture rich substitution patterns between firms. In section 5, we use our estimates to explore the impact of two high-profile mergers. Section 6 concludes.

2 Model

Our goal is to provide a simple framework for analyzing competition between spatially differentiated retailers. The framework can be used to assess the degree to which firms compete in both geographic and product space and to evaluate the likely impact of mergers and acquisitions on market structure. In particular, we develop

[5] Hosken et al. (2012) further note that, in investigating supermarket mergers, the FTC has typically concluded that the primary competitor of supermarkets is other supermarkets (including supercenters like Wal-Mart and Target). With regard to other formats like mom and pop grocers, convenience stores, specialty food stores, club store, military commissaries, or mass merchants, the FTC has typically treated these firms as a collection of players that "do not individually or collectively effectively constrain prices at supermarkets".

a model of store choice and expenditure allocation that uses readily-available information on consumer demographics alongside a syndicated census of store-level data on store characteristics to predict observed (store-level) revenues. Our framework extends the approach proposed by Holmes (2011) for predicting the revenue of Wal-Mart stores to incorporate the impact of competition with stores operated by rival firms.[6] In our demand framework, consumers allocate grocery expenditure across a choice set of stores that includes all grocery and club stores within D miles of their location, along with an outside good—which can be understood to be food purchases outside of nearby grocery or club stores (e.g., food purchases at restaurants, online grocers, conveniences stores, farmers markets, etc). Stores are endowed with a set of characteristics, including possible affiliation with a major national chain (e.g. Kroger), which affect consumers' utility for spending money at the store. Consumers differ in their location, income and household size. As location is a primary driver of store choice, a consumer's utility for shopping at a given store will vary with that consumer's distance to the store. Income affects consumer spending in two ways, first through the overall budget that they allocate to groceries and second through the stores in which they choose to shop. This will allow us to capture the tendency for a consumer's share of budget devoted to food at home to fall with income (rich consumers spend more on food outside the home) and the mix of stores they visit to change as well (rich consumers are more likely to shop at Whole Foods than at Aldi). Store revenues are determined by aggregating up revenues across consumers in the store's catchment area; the degree to which these revenues decay with distance is estimated as part of the model. The result is a model which leverages the rich spatial and demographic variation in the data to identify who shops where, delivering a clear characterization of the competitive impact that stores exert on one other, as well as their degree of substitution with options outside that local market.

2.1 Consumer Store Choice

While we observe store-level revenue for every grocery store operating in the US, we do not have data on individual-level grocery expenditures. To connect store-level revenue to consumer-level tastes and implied choices, we use demographic data drawn from the 2010 US Census, measured at the census tract level. Census tracts provide a very fine spatial disaggregation of consumers, as there are over 70 thousand tracts in the United States containg roughly four to five thousand persons each.[7] To model individual consumer demand, we assume the existence of a representative household at every census tract, indexing consumers

[6] Holmes' analysis of Wal-Mart abstracted from competition to focus on how the dynamics of Wal-Mart's expansion decisions were impacted by the scale economies associated with operating a dense network of stores.

[7] Our analysis focuses on the Metropolitan Statistical Areas (MSAs) of the United States, more detail on the data used in our analysis is provided in section 3.

according to the tract t in which they reside.[8] Consumers are endowed with a location (the tract centroid) and a vector of characteristics z_t which affect their utility for groceries (e.g. income and household size). A consumer's weekly grocery budget (including spending on the outside good) is a fixed proportion α of his or her income, where α is a parameter to be estimated. Individuals allocate their budget according to a discrete-choice random utility model over nearby stores that are themselves endowed with a location and a vector of characteristics x_s (such as the size and brand of the store), as well as the outside good defined earlier.

Each consumer makes a continuum of purchasing decisions to allocate their budget across stores. For each unit of expenditure i, consumer t's utility for spending at store s is,

$$u_{sti} = \tau_0 d_{st} + \tau_1 d_{st} z_t + \gamma_0 x_s + \gamma_1 x_s z_t + \varepsilon_{sti}, \tag{1}$$

where d_{st} is the distance between store s and the tract centroid corresponding the representative consumer t. Each purchase decision is subject to an idiosyncratic preference shock, ε_{sit}, that is distributed according to the standard Type-I extreme value distribution (note that this is equivalent to assuming a continuum of consumers within each tract who consume only a single unit of groceries but who are differentiated only by the logit shock). This framework allows the utility of a given store to be a function of its proximity to consumers, as well as store characteristics capturing features like product availability, service quality, and convenience. Moreover, consumers are allowed to differ in tastes for distance and other characteristics though heterogeneity in the consumer's characteristics z_t. This enables the model to capture the fact that the utility of different store characteristics (including format type) will vary across consumers (captured here by demographic variation across census tracts).

Notably, we also include chain affiliation in x_s, capturing *unobserved* characteristics of national chains such as assortment and price. Since we do not observe actual prices or the particular set of products on offer, the chain affiliation proxies for the broad pricing, quality and assortment strategy of the firm, which we assume is set at the chain level. That is, some firms may choose to market themselves as limited-assortment, low-price grocery stores that cater to price sensitive consumers, while others may choose to be "boutique" grocers that offer expensive, high-end organic products to wealthy customers. On the other hand, many "conventional" supermarket chains attempt to serve a much broader segment of the market, with the subsequent lack of differentiation leading them to compete with a wider set of rivals. These different strategies will appeal to different consumers in heterogeneous ways. For example, Ellickson and Misra (2008)

[8] It would be conceptually straightforward to allow for unobserved heterogeneity at the census tract level, resulting in a random coefficients model in the spirit of Berry et al. (1995). We argue below that the current setup is flexible enough to capture quite rich substitution patterns based on observed heterogeneity alone.

find evidence that supermarkets use distinct price and positioning strategies to target different consumer segments based on purchase size and frequency of visits. While our approach does not control for pricing and quality decisions that are specific to the individual store, we believe these are second order to the average policy set by the chain.[9] Incorporating these individual chain effects also accounts for the fact that the basket of goods provided when you purchase a dollar's worth of goods at Whole Foods (a high-end grocer) is different from the basket of goods obtained from a dollar's expenditure at Aldi (a no-frills grocer that targets the urban poor). Moreover, by interacting these chain identifiers with consumer characteristics (e.g. income), we will account for the fact that the utility tradeoff between expenditures at Aldi versus Whole Foods varies by income.

Finally, a consumer's utility of spending on the outside good is determined by the representative consumer's (tract-level) demographic characteristics and a set of physical tract characteristics w_t, such as population density, that control for the availability of alternative consumption options in the tract's proximity,

$$u_{0ti} = \lambda w_t + \beta_t z_t + \varepsilon_{0ti}. \tag{2}$$

We assume that the household's choice set consists of all stores located within D miles of their resident tract, as well as the outside option, $C_t = \{s : d_{ts} \leq D\} \cup 0$.[10] By integrating over the idiosyncratic shock we can derive the share of their grocery budget that consumers in tract t spend at store s as a function of the model's parameters $\theta = (\tau, \gamma, \lambda, \beta)$,

$$p_{st}(\theta) = \frac{e^{u_{st}}}{\sum\limits_{q \in C_t} e^{u_{qt}}}, \tag{3}$$

where $u_{st} = u_{sti} - \epsilon_{sit}$. In principle, we could further allow for unobserved heterogeneity that could depend on store or tract characteristics, which would be equivalent to allowing for random coefficients in our utility framework—as in Berry et al. (1995). However, using the joint distribution of income and location accommodates a substantial amount of heterogeneity and, as we will see, yields rich substitution patterns across chains already, while retaining a simpler analytical structure.[11]

[9] For example, one could imagine adding to the model a "store level quality shock" that firms could observe and exploit in endogenously adjusting their quality-price offerings. While there is some evidence that firms do so, there are also strong branding and efficiency reasons for them to maintain uniformity. While exploring such a model is an interesting avenue for future work, given that we do not have explicit data on individual store prices or product offerings, and given that marketing campaigns enforce a large degree of heterogeneity in chain policies, we do not take this approach in this paper.

[10] In our application, we set D equal to 10 miles, we have experimented with higher and lower thresholds and have found little qualitative change in the resulting estimates.

[11] Moreover, since we do not directly observe tract-level revenue shares, identification of unobserved heterogeneity would rely on the aggregation of these preferences over tracts. While this heterogeneity may be identified in principle, the flexibility of the current model suggests there is little to gain from this approach, and the current approach has the benefit of being directly tied to observable demographic variables.

2.2 Store Revenues and Estimation

To connect consumer demographics and store characteristics to store-level outcomes, we aggregate over the choices of individual consumers to determine the revenue for each store as a function of the model parameters (and observed data). Revenue in store s resulting from expenditures in tract t is simply the total budget of all consumers in tract t times the proportion of those expenditures spent at store s by consumers in t,

$$\hat{R}_{st}(\theta, \alpha) = \alpha \text{inc}_t \cdot n_t \cdot p_{st}(\theta),$$

where inc_t is per capita income in tract t and n_t is the total population living in tract t. Store s collects revenue from all tracts for which it is included in the choice set (i.e. all tracts within 10 miles of its location). Therefore, predicted total revenue for store s is,

$$\hat{R}_s(\theta, \alpha) = \sum_{t \in L_s} R_{st}(\theta, \alpha), \tag{4}$$

where $L_s = \{t : s \in C_t\} = \{t : d_{st} \leq D\}$ is the set of tracts for which store s is included in some consumer's choice set. A notable aspect of this modeling approach is that we do not impose ad-hoc market boundaries. Instead, each store is located at the center of its own catchment area. Stores located nearby each other will have catchment areas that substantially overlap. As a result they will exert a stronger competitive effect on each other than stores that are farther apart, and will only compete intensively over customers located nearby each of them.

To estimate the model parameters, we compare the model-generated revenue predictions to the revenues observed in the data, choosing the parameters that make this fit as close as possible. To account for measurement error in the revenue data, we assume that the observed revenues for each store are perturbed by a multiplicative shock,[12]

$$R_s = e^{\eta_s} \hat{R}_s(\theta_0, \alpha_0),$$

where (θ_0, α_0) are the true parameters and η_s is the store level measurement shock. Assuming that η_s is mean zero and independent of the exogenous variables, the parameters can be estimated via nonlinear least squares,

$$(\hat{\theta}, \hat{\alpha}) = \underset{\theta, \alpha}{\text{argmin}} \sum_s \Big(\log(\hat{R}_s(\theta, \alpha)) - \log(R_s) \Big)^2. \tag{5}$$

It is straightforward to show that this estimator is consistent and asymptotically normal, with the standard

[12] We have also estimated the model assuming that the measurement error enters via an additive shock; the qualitative results of both approaches are similar.

variance-covariance matrix implied by the nonlinear least squares objective function.

2.3 Identification

Having detailed our model and estimation strategy, we now provide a short discussion of the variation in the data and required assumptions that are needed to identify the model parameters. We begin by assuming that ϵ_{its} and η_s are independent of stores' location and size decisions as well as consumers' chosen locations and observed incomes. In particular, we assume that consumers take store locations as given, and that consumers' perceptions of stores' pricing, quality and assortment policies are formed at the chain level, as opposed to the store level. This allows us to control for the endogeneity of these policies using chain fixed effects. Of course, it is possible that chains adjust their pricing policies store by store, based on local demographics. While there is some evidence that they do so (e.g. Hoch et al. (1995); Ellickson and Misra (2008)), we view this concern as second order here for two reasons. First, supermarket firms set several tens of thousands of prices per store, and it seems unrealistic to believe that consumers calculate store level price indices for each outlet. Instead, it seems much more likely that they have a rough perception of the price differences across chains and use this as a heuristic in selecting their focal store. Second, grocery stores usually do not set prices at the store level, but instead set the same price across broad "pricing zones" (Levy et al., 1998). The rationale for these zones is that stores can then jointly market their products (for example, though newspaper circulars and TV ads) to an area that is wider than a given store's catchment area, which also economizing on menu costs. This suggests that it is not efficient for chains to set policies at the level of the individual stores. While such "pricing-zones" are typically not nation-wide, it seems reasonable to assume that within-chain variation in pricing and product offerings across a pricing zone is less important than across-chain variation in these policies within the same zone. This latter variation is captured in our framework via chain fixed effects.

Identification of the parameters of utility comes from observing geographic variation in population demographics, store locations, and store revenues. We first consider identification of α, the proportion of overall income that enters the consumer's grocery budget. This parameter is identified by varying the total number of stores across otherwise identical markets and observing the change in total revenue across all stores. Intuitively, adding many stores to a market should drive the share of the outside good towards zero; eventually, adding additional stores won't add to total revenue but will only reallocate revenue across stores. In this situation, α is simply the ratio of total revenue of all stores to the total income of the associated total population of consumers. In general, the change in total revenue in response to the change in the number of stores reveals the substitution between the outside good and the new store, which, together with the changes

in other stores' revenue, pins down the utilities of all stores. With these utilities then known, the remaining revenue allocated to the outside good can be calculated, and used to determine α.

Having identified α, parameters governing store utility are identified by varying observable characteristics of both stores and consumers and observing the resulting changes in the share of total expenditure of the consumers within the catchment area, L_s, that are captured by each store. Of course, as in all discrete choice models, utility is only identified up to a location normalization: adding a unit to each element of u_{st} produces identical expenditure shares to the original formulation. We follow the standard normalization by setting the utility of the outside good to zero. To do this, we redefine utility as $\tilde{u}_{st} = u_{st} - u_{0t}$. Because consumer characteristics affect both the utility of the stores and that of the outside good, we can only identify changes in utility relative to the outside good. While measures of revenue and elasticities are invariant to this normalization, it does make it impossible to compare welfare across different consumers if those consumers value the outside good differently. However, with this normalization in place, identification of the parameters associated with individual store characteristics is straightforward. For example, consider the impact of distance on store choice. Varying the distance between a tract and a store alters the share of expenditure at that store relative to others in the tract's choice set. This will be reflected in the store's revenue relative to others in the same choice set, all of which are observed. A similar logic can be used to identify the parameters relating store and consumer characteristics.

3 Data

The data on grocery revenues, locations, store and chain characteristics are drawn from the Trade Dimensions TDLinx dataset for calendar year 2006. Trade Dimensions collects information on every supermarket, supercenter[13], grocery store and club store operating in the United States. Food stores that do not carry a "full-line of food products" or generate less than two million dollars in annual revenue are excluded from the dataset[14]. Data on store level sales volume is imputed using a proprietary scheme that incorporates store level transaction data for a subset of the full universe of stores (note that we have already accounted for the role of this measurement error in our empirical framework). We also observe the full ownership structure of each firm, allowing us to tie individual stores to either a high level holding company or a smaller collection of co-branded stores that operate under a single banner.

[13]Supercenters are combination grocery and mass merchandise stores that carry a full line of grocery products alongside a full line of mass merchandise products including clothing, electronics, housewares and sporting goods. Wal-Mart supercenters are the most recognizable example, but Target, Meijer and a few other firms operate these formats as well. Supercenters have always been included in the competitive set of supermarkets when considering grocery mergers.

[14]These cutoffs are the government and industry standards for distinguishing supermarkets and grocery stores from convenience stores and corner markets. The latter are believed to provide little competition to the former, as these two segments compete in effectively 'independent submarkets' (Ellickson, 2006).

Geographically, we focus on stores that are located within Metropolitan Statistical Areas (MSAs), excluding the 8 MSAs in the New York metro area.[15] Focusing exclusively on MSAs reduces concerns about how rural areas are treated in different parts of the country in terms of tract size. In particular, tracts are much larger in the rural west, which could lead to concerns regarding measurement error in the demographic variables indexing our representative consumers. We classify firms according to the number of stores they operate: small chains and independents are firms that operate 10 or fewer stores, medium chains are those that operate 10 to 100 stores, and large chains are those that operate more than 100 stores within all MSAs. We also include data on club stores, which are treated as a special category. Club stores are retail formats that require consumers to pay a membership fee to shop at the store and offer items in bulk quantities. In addition to groceries, they also carry a variety of additional consumer products such as electronics, clothing, prescription medication and eye wear. We include data on the three club store chains (Sam's Club, Costco, and BJ's) that operate in the US. Throughout, we treat Sam's Club as a distinct chain from Wal-Mart to account for the differences in product offerings and amenities across the two chains. We make no assumption as to whether these chains are operated jointly (internalizing their impact on each others revenue) or independently.

Table 1 provides summary statistics for the full set of 24,117 stores, broken out by store type (small and medium grocery chains, large grocery chains, and club stores). Across all store types, the average outlet sells roughly $20 million in groceries per year ($391.65 thousand per week), with the largest stores topping out at over $100 million. In terms of selling area, the average store is just over 35 thousand square feet, while the largest supercenters can be well over 150 thousand square feet. Looking across store types and formats, larger chains tend to operate larger stores and generate correspondingly greater sales volume. Club stores and supercenters generate the largest volumes. Larger stores allow firms to stock a deeper and wider selection of products, which can require large fixed investments at the level of the chain but increase consumer's willingness to pay for groceries (Ellickson, 2007). Consumers may benefit from increased variety in terms of reduced search and decreased shopping time (Messinger and Narasimhan, 1997), as well as a wider selection of prepared foods, fresh produce and service meats. Larger stores also allow firms to exploit store-level scale economies due to higher arrival rates of customers to the store (Oi, 1992) and complementary information technology investment (Holmes, 2001), while large *chains* are able to exploit economies of density (Holmes, 2011) and quantity discounts (Dobson, 2005). The collective effect of such scale leads to significant cost advantages for large chains. Turning to formats, club stores allow consumers to purchase larger pack sizes,

[15] The reason for this exclusion is that these very dense markets areas are far less reliant on automobile transportation than the rest of the country, so that outlet size and store density have far different meanings in these markets that in others. According to the 2000 US Census, New York City, Newark and Jersey City ranked 1-3 amongst large cities based on percentage of households without a car (more than 40%).

Table 1: Store Characteristics by Type of Chain

	Mean	St. Dev.	1st Quartile	Median	3rd Quartile
Small and Medium Grocery Chains					
40.76 % of all MSA stores					
Store Size in 1000 sqft	22.32	16.45	11	18	30
Store Weekly Volume in 1000s	182.34	174.40	80	125	225
Full Time Employee Equivalents	45.73	44.61	22	33	55
Checkouts	6.63	4.11	4	6	8
Large Grocery Chains					
55.20 % of all MSA stores					
Store Size in 1000 sqft	40.15	17.44	28	40	52
Store Weekly Volume in 1000s	447.52	312.89	225	375	575
Full Time Employee Equivalents	102.62	106.70	41	71	108
Checkouts	11.85	7.45	8	10	13
Club Stores					
4.03 % of all MSA stores					
Store Size in 1000 sqft	124.75	16.06	113	130	135
Store Weekly Volume in 1000s	1,627.90	742.22	1,125	1,500	1,975
All Stores					
24,117 stores in 317 MSAs					
Store Size in 1000 sqft	36.60	26.26	17	32	49
Store Weekly Volume in 1000s	391.65	412.74	125	250	500
Full Time Employee Equivalents	79.49	91.35	28	52	89
Checkouts	9.73	6.81	5	8	11

which are typically offered at a reduced per unit cost (and appeal to suburban consumers with ample storage space). Finally, both size and sales volume include a sizable amount of variation around their respective means, reflecting differences in both the age of stores and regional variation in zoning, land availability and consumer preferences. For non-club stores, we have data on the number of employees and checkouts operated in each store, which we include in the vector of store characteristics. Having additional employees may reduce stock-outs or improve customer service of the store (Matsa, 2011). A larger number of checkouts allows stores to offer shorter lines and faster checkout service.

Most grocery stores are part of a regional or national chain. Summary statistics on chains are presented in Table 2. While the average chain includes about five stores, the distribution is highly skewed, with a few very large chains and a large number of sole proprietorships. While 25% of the stores belong to firms operating less than 10 stores (the vast majority of which are single store enterprises), there are over 200 firms that operate at least 10 stores (the industry definition of a chain), 116 that operate at least 20, and 39 that operate more than 100. The top 4 chains each operate over 1000 stores. The largest of these is Wal-Mart, which operates 1385 stores across 247 MSAs.

Table 2: Chain Characteristics by Type of Firm

	Mean	St. Dev.	1st Quartile	Median	3rd Quartile
Medium Grocery Chains					
15.65 % of all MSA stores					
Number of Stores	24.50	20.03	12	17	28
Store Weekly Volume in 1000s	256.78	186.07	143.39	200	302.08
Store Size in 1000 sqft	31.26	17.31	20.82	27.83	37.54
Revenue Per Sqft	8.31	2.70	6.41	7.69	9.44
Number of MSA operating	4.83	5.68	1	3	6
Large Grocery Chains					
55.20 % of all MSA stores					
Number of Stores	416.12	466.97	127	162	510
Store Weekly Volume in 1000s	424.15	220.07	250.78	419.70	526.25
Store Size in 1000 sqft	38.64	13.92	32.02	38.81	46.70
Revenue Per Sqft	11.50	5.27	8.79	10.95	12.82
Number of MSA operating	41.27	50.73	12	21	47
Club Stores					
4.03 % of all MSA stores					
Number of Stores	324.33	209.32	122	311	540
Store Weekly Volume in 1000s	1,503.03	732.12	797.95	1,451.67	2,259.49
Store Size in 1000 sqft	119.34	13.29	104.47	123.50	130.05
Revenue Per Sqft	12.31	5.38	7.59	11.17	18.17
Number of MSA operating	113.67	97.44	36	82	223
All Chains and Clubs					
74.89 % of all MSA stores					
Number of Stores	104.40	256.84	13	21	64
Store Weekly Volume in 1000s	310.31	268.70	148.40	230	388.27
Store Size in 1000 sqft	34.20	20.30	22	31.78	41.59
Revenue Per Sqft	8.99	3.61	6.47	8.49	10.47
Number of MSA operating	13.67	31.58	2	4	11

Our primary goal is understanding local competition between regional and national chains. To that end, it is useful to highlight the characteristics of the largest players in the grocery industry. Table 3 provides summary statistics for the full set of large chains and club stores. Wal-Mart is by far the largest chain, both in terms of the number of stores and average sales. It also owns the largest stores, due to both its large-scale supercenter format and the relatively young vintage of its store porfolio. Note that the size of Wal-Mart stores reflects the size of the grocery sales floor only, not including the mass-merchandise portion of the supercenter (the sales volume figures also reflect grocery sales alone, rather than both grocery and mass merchandise revenues). The largest chains also include the low-end limited-assortment chains Aldi and Save A Lot, mid-tier chains like Food Lion and Kroger, as well as more upscale variants such as Publix and Safeway. Notably, there is a large amount of variation both across and within firms in the distribution

Table 3: Characteristics of Large Chains

	# Stores	# MSAs	Stores/MSA	Rev.	Rev. /sqft	Size
Large Grocery Chains						
Albertsons	510	71	7.18	357.94	6.75	54.16
Aldi	615	108	5.69	77.05	6.15	12.84
Bashas Markets I	134	6	22.33	257.72	8.90	32.02
Delhaize America	949	55	17.25	178.73	6.28	28.69
Fred Meyer Store	101	12	8.42	740.10	13.42	55.23
Giant Eagle	140	11	12.73	579.29	12.82	46.70
Giant Food	292	14	20.86	568.60	15.42	37.96
Great A & P Tea	161	11	14.64	341.02	9.98	34.97
H E Butt Grocery	227	16	14.19	813.44	16.40	51.01
Hannaford Bros C	108	9	12	528.47	12.61	42.05
Hy Vee Food Stor	102	15	6.80	513.48	11.59	45.82
Ingles Markets	112	11	10.18	205.27	5.02	41.59
Kroger	1,973	107	18.44	463.42	10.95	42.40
Lone Star Funds	238	21	11.33	225.29	6.03	37.38
Meijer	159	26	6.12	826.10	14.11	59.56
Publix Super	845	36	23.47	419.70	11.07	38.81
Raleys Supermark	127	12	10.58	428.15	9.91	43.60
Roundys Supermar	125	10	12.50	496.60	12.03	41.91
Ruddick Corp	138	17	8.12	407.79	11.25	36.56
Safeway Inc/HQ	1,339	46	29.11	424.96	11.98	37.33
Save A Lot	715	163	4.39	114.98	8.49	14.49
Save Mart Superm	118	13	9.08	385.81	10.18	37.84
Smart & Final	217	29	7.48	147.03	10.14	15.18
Stater Bros	162	3	54	388.27	16.10	24.22
Stop & Shop	312	17	18.35	563.78	12.18	47.31
SuperValu	1,194	58	20.59	460.74	9.51	49.02
Target	160	48	3.33	526.25	8.79	60.66
Trader Joes	236	37	6.38	302.22	32.66	9.45
Wal Mart Stores	1,385	247	5.61	1,064.24	16.18	65.12
Weis Markets	120	12	10	242.58	6.62	37.22
Whole Foods Mark	159	47	3.38	511.79	21.12	26.99
Wild Oats Market	108	38	2.84	185.28	9.29	20.71
Winn-Dixie Store	451	36	12.53	250.78	5.54	46.27
Club Stores						
BJs	122	35	3.49	797.95	7.59	104.47
Costco	311	82	3.79	2,259.49	18.17	123.50
Sams	540	223	2.42	1,451.67	11.17	130.05
Total	720.18	115.27	8.63	688.70	11.71	56.61

of store sizes and store level revenues. Some firms, such as Food Lion, include a fairly standardized store profile, while others, such as HEB, offer a far more heterogenous set of outlets. In our estimation, we will control for chain affiliation using both a fixed effect and a slope effect (the chain fixed effect interacted with consumer income). Club Stores BJ's, Costco, and Sam's Club have a dramatically different profile from the mainline supermarket segments, they offer larger stores with fewer stores per MSA. Which implies consumers must travel further on average to reach club stores. Revenue per store at Costco and Sam's Club is much higher than any grocery store, while BJ's—by far the smallest of the club store chains—appears to be less successful on this dimension.

Data on consumer demographics are drawn from the 2010 US Census.[16] Table 4 presents summary information on the included tracts. While census tracts are designed to be fairly uniform in terms of total population size, there is still a great deal of variation across tracts (reflecting difference in regional growth rates and migration). In addition, there is substantial heterogeneity in the level of average income across census tracts. This income heterogeneity is key to our identification strategy, which exploits variation in store revenues induced by differences across stores located near high-income versus low-income tracts. Finally, note that the effective choice set of consumers is quite large. On average 60 stores lie within the choice set of a tract, of which 34 are large chain stores. Club stores are much more sparse; the average tract has only 2.33 club stores to choose from, reflecting the club store strategy of relying on less frequent store visits with much larger purchase sizes.

Table 4: Census tracts: Demographic and choice set variation

	Mean	St. Dev.	1st Quartile	Median	3rd Quartile
Population	4,381.67	1,984.38	3,001	4,119	5,444
Average income	28.05	14.02	18.96	25.29	33.59
Population Density	2,862.98	3,013.04	846.48	2,043.98	3,733.49
Household size	2.43	0.59	2.11	2.38	2.69
Stores within 5 miles	20.19	19.70	6	15	28
Stores within 10 miles	59.52	58.57	16	41	84
Large chain within 5 miles	11.30	10.51	3	9	17
Large chain within 10 miles	33.82	31.99	9	25	50
Club stores within 5 miles	0.77	0.89	0	1	1
Club stores within 10 miles	2.33	2.11	1	2	4

[16] Census tracts are defined by the decennial census, we opt to use the 2010 tract-level data as it is the closest decennial census to our 2006 store-level dataset. While this introduces some measurement error, we believe that population dynamics are small enough that this error is small.

4 Specification and Estimation Results

To take the model to data, we must specify a set of store, consumer, and tract characteristics to include in the analysis. For standard grocery stores (regardless of chain size), we use size, employment and the number of checkouts as characteristics. These covariates are intended to proxy for the breadth of the product assortment, level of customer service, and speed of checkout respectively. Unfortunately, our data does not include employment counts or the number of checkouts for club stores. For this reason, and because club stores represent a fundamentally different retail experience from standard grocery stores, we estimate a separate set of distance and size parameters for club stores.

The main consumer characteristic we include is the log of income. Income differences are intended to capture differences in price sensitivity and the opportunity cost of time across different consumer types. We also consider differences in household size, but only in how it affects a consumer's taste for the outside good. Since our model operates at the individual consumer level, increased household side is expected to increase consumption of the outside good, since multi-person households typically spends less on groceries on a per-capita basis. Finally, our main tract characteristic is population density, defined as density within a 5 mile radius of the centroid of the focal census tract. We include a linear and quadratic term in density, which is meant to proxy for congestion within the tract as well as differences in the number of restaurants and other non-grocery options for consuming food either at or away from home. We expect the impact of population density on the utility of the outside good to be increasing and concave.

4.1 Parameter Estimates

Model estimates for three different specifications are presented in Table 5. In specification (1), we exclude club stores from the analysis. As noted earlier, club stores are typically not included in anti-trust challenges of mergers in the grocery industry as they are not considered important enough substitutes to significantly constrain supermarket prices (Hosken et al., 2012). Part of our goal is to evaluate the validity of this assumption, by comparing predictions from our analysis both with and without club stores. In the current context of our search for a favored specification, we start with a model with no clubs—specification (1)—and add club stores in specification (2). In specification (2), we initially exclude employment and checkouts from the set of grocery store characteristics so that grocery and club stores are treated symmetrically to clubs (to help gauge the impact of then including these covariates only for supermarkets in specification (3)). Finally, specification (3), our preferred specification, includes the full set of available characteristics for both grocery and club stores.

Focusing initially on the estimate of α, we find that the implied overall food budget is roughly 11 percent

Table 5: Parameter estimates.

	Grocery Stores Only (1)	Grocery and Club Stores (2)	(3)
Grocery Stores			
dist	−0.210	−0.207	−0.197
	(0.001)	(0.001)	(0.001)
dist*log(inc)	−0.147	−0.144	−0.144
	(0.003)	(0.003)	(0.003)
log(size)	0.206	0.553	0.207
	(0.002)	(0.001)	(0.003)
log(size)*log(inc)	0.153	0.391	0.173
	(0.008)	(0.005)	(0.010)
log(fte)	0.318		0.317
	(0.002)		(0.002)
log(fte)*log(inc)	−0.141		−0.150
	(0.007)		(0.009)
log(chk)	0.301		0.299
	(0.003)		(0.004)
log(chk)*log(inc)	0.346		0.339
	(0.012)		(0.014)
Club Stores			
dist		0.020	0.021
		(0.006)	(0.006)
dist*log(inc)		−0.289	−0.297
		(0.016)	(0.017)
log(size)		0.777	0.844
		(0.055)	(0.058)
log(size)*log(inc)		0.360	0.376
		(0.178)	(0.183)
Outside option			
hhsize	0.707	0.650	0.650
	(0.007)	(0.007)	(0.008)
hhsize*log(inc)	0.744	0.656	0.642
	(0.017)	(0.017)	(0.018)
log(density)	2.595	2.155	2.207
	(0.137)	(0.137)	(0.148)
$\log(\text{density})^2$	−0.382	−0.242	−0.237
	(0.061)	(0.059)	(0.064)
α	0.096	0.110	0.112
	(0.002)	(0.002)	(0.002)
R^2	0.809	0.803	0.836

Notes: All specifications include chain effects which vary with income. Standard errors in parentheses.

of total income. To gauge the face validity of this estimate, we compare it to an estimate of the fraction of consumer income spent on food reported in the 2012 Consumer Expenditure Survey (CEX). The 2012 CEX reports that, on average, consumers spent 12.8 percent of their income on food, which accords closely with our estimate of α. To be clear, this is the population average, unconditional on income. Of course, total expenses allocated to food certainly falls with income. The CEX estimates range from 15.5% for low-income consumers (those with less than $10,000 in annual pre-tax household income) to 11.8% for high-income consumers (those with greater than $70,000 in annual pre-tax household income). Our model captures the fact that high-income consumers spend a smaller share of their income in grocery and club stores through

the *outside good*, the utility of which is increasing in income. Because the outside good is normalized, the impact of income on each chain encompasses that firm's change in utility with income, relative to the outside good. In Table 15 (included in the Appendix) we report the chain fixed effects and slopes (interactions with income) for every large chain and club store firm. Note that the impact of increasing income on the utility of every chain is negative, indicating that taste for the outside good grows faster with income than the utility of any inside good (i.e. grocery store, supermarket or club). This pattern reflects the increased share of food purchased in restaurants, farmers markets, and specialty food stores for consumers in high-income tracts, as well a tendency for wealthier consumers to spend a larger fraction of their income on non-food items. Note that there is also significant heterogeneity in the impact of income on the choice of inside goods (i.e. different store brands). For example, Costco and Whole Foods have the two highest (least negative) income effects, suggesting that they tend to target a high-income clientele, consistent with the public perceptions of both firms. On the other hand, Save-A-Lot and Aldi are among the lowest, indicating that these stores are particularly popular among low income consumers (again reflecting the stated positioning strategies of these chains). Overall, the model seems to do a credible job of capturing the impact of income on food expenditure allocation, both amongst stores as well as between all stores and the outside good.

We now turn to the impact of distance on a consumer's utility for grocery and club stores. Not surprisingly, consumers prefer grocery stores to be closer to their homes, presumably reflecting the monetary and opportunity costs of travel. The disutility of distance gets stronger with income suggesting that the opportunity cost of time is higher for high income consumers. Notably, club store revenues are much less sensitive to distance than the revenues of grocery stores (for clubs, the effect of distance is positive but insignificant at low income levels). Figure 1 plots the marginal utility of distance for club and grocery stores by income. This is quite different from earlier studies of both the grocery industry alone, as well as the more recent impact of competition from supermarkets. In both cases, the catchment area of a supermarket (or supercenter) has been found to be quite narrow, on the order of two or three miles (Ellickson and Grieco (2013)). Consumers' greater tolerance for traveling to clubs likely reflects the fact that, unlike supercenters, club stores represent a fundamentally different business model. In particular, consumers purchase many more items in bulk at club stores and therefore make correspondingly fewer trips to them. Moreover, the disutility of distance with respect to income rises nearly twice as fast for club stores compared with standard grocery stores suggesting that, overall, club stores are targeting consumers with lower opportunity cost of time. Interestingly, the estimates of distance coefficients for grocery stores changes barely change when we add club stores to the model.

Turning next to store characteristics, the impact of all three store characteristics are positive and highly significant. Consumers prefer larger stores, staffed with more people, that provide more checkouts. The

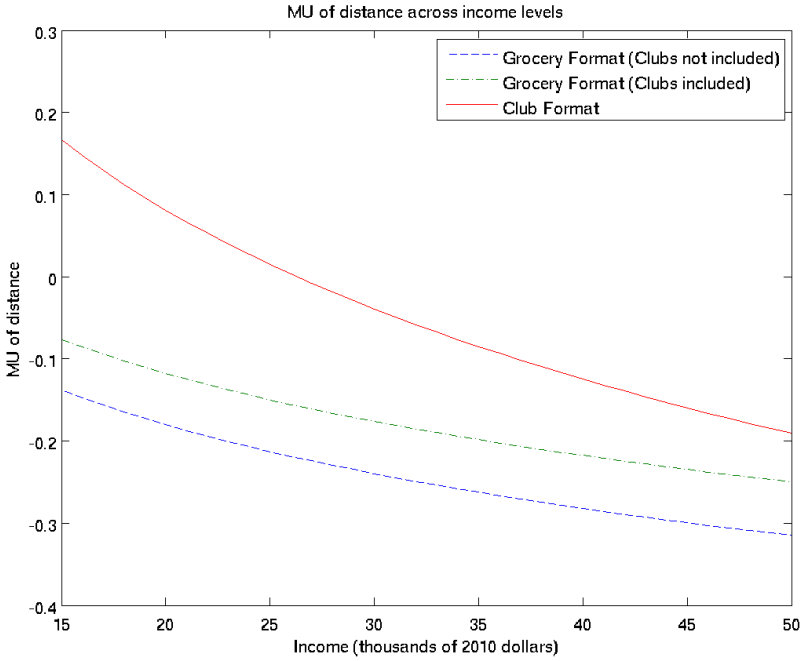

Figure 1: Marginal Utility of Distance by Consumer Income.

interaction of characteristics with income are also important. For grocery stores, taste for both size and checkouts is increasing in income, while taste for employees is decreasing. The decline in taste for employees with respect to income, controlling for size and checkouts, may reflect preferences among high-income consumers for investments in labor-saving technologies, such as self-checkout lanes.

Since we do not have employment or checkout data for club stores, specification (2) is used to illustrate how this omission affects the estimates (as it relates to grocery stores). As size, employment and checkouts are correlated, omitting the employment and checkouts increases the impact of size on grocery store utility. However, even in this specification, club stores' sensitivity to size is larger than that of grocery stores. Since club stores tend to be larger than grocery stores, this may be because a one percent increase in the size of a club store allows the store to offer dramatically more products than a one percent increase in the size of a grocery store. Turning to specification (3) we find that the utility parameters of grocery stores are similar to those in (1) whereas the utility parameters in club stores closely match specification (2). This suggests that the estimates of utility for grocery stores are robust to whether club stores are accounted for and the estimates of club stores are robust to how grocery store utility is modeled. While the underlying utility parameters appear to be robust to the inclusion of club stores, we will see below that the inclusion of club stores can have a substantial impact on the competitive landscape implied by the model's estimates. While club stores do not alter consumers' preferences for conventional supermarkets, consumers do view the two

formats as close substitutes. Therefore, including them in the analysis of potential grocery mergers has a significant impact on the implied impact on market structure: the industry is less concentrated than we think. We will illustrate the relevance of this fact for merger analysis in Section 5.

4.2 Demographic Effects

While the model parameters give us some insight into how consumers view different chains and value different store characteristics, it is easier to see how demographics drive store revenues by directly computing elasticities. We now turn from competition between firms to an analysis of the determinants of how firms locate (in both product and geographic space) relative to consumers. Recall that the two key elements of consumer heterogeneity in our framework are location and income. Our model enables us to directly compute the revenue elasticity of a single store with respect to the distance to or income of an individual tract. For example, the distance elasticity for revenue at store s from tract t is

$$\eta_{st}^{d} = \frac{\partial R_{st}}{\partial d_{st}} \frac{d_{st}}{R_{st}} = (\tau_0 + \tau_1 \log(\text{inc}_t))(1 - p_{st})d_{st}.$$

To construct a measure of how chain-level revenue responds to increasing the distance to consumers, say by building more remote stores in suburban locations, we aggregate these store-tract level elasticities first to the store and then to the chain level. In particular, we calculate the store-level elasticity as $\eta_s = \sum_{t \in L_s} \eta_{st} \frac{R_{st}}{R_s}$ and the chain level elasticity as, $\eta_c = \sum_{s \in F_f} \eta_s \frac{R_s}{R_c}$, where F_f represents the set of stores which belong to chain f. The resulting elasticities are best understood as marginal effects that establish the importance of distance for store profits, given the current configuration of stores and the underlying parameter estimates.

The estimated elasticities are presented in the first column of Table 6. The distance elasticities are presented first in column 2. For grocery stores, the distance elasticities are mostly clustered around -1, indicating that a 1 percent increase in distance to a store is associated with a roughly 1 percent decline in store revenue. The highest distance elasticities are for Whole Foods and Giant Foods, two chains that each have an upscale focus and serve high-income consumers (who we earlier found to have a high disutility of distance). Firms with a clear urban focus, such as Target and Trader Joes, also tend to have distance elasticities that are lower than -1. In contrast, Wal-Mart has one of the highest distance elasticities, -.875, indicating that it is able to overcome being located further away from consumers by offering larger size and other amenities (such as low prices and an assortment of complementary non-grocery products). Other supercenter chains (H E Butt, Hy Vee, and Meijer) also have distance elasticities above -1, reflecting their relative inelasticity with respect to distance. This may reflect their one-stop shopping based appeal. These elasticity estimates are consistent with these stores seeking to exploit a large-scale, large catchment area

Table 6: Distance and Income Elasticities Large Chains and Clubs

	Distance Elasticity	Income Elasticity
Small Chains	−0.979	0.277
Medium Chains	−0.994	0.565
Albertsons	−0.979	0.476
Aldi	−0.985	0.281
Bashas Markets	−0.988	0.418
Delhaize America	−0.987	0.306
Fred Meyer Stores	−1.018	0.667
Giant Eagle	−0.996	0.478
Giant Food	−1.122	0.387
Great A & P Tea	−1.033	0.271
H E Butt Grocery	−0.887	0.678
Hannaford Bros	−0.953	0.101
Hy Vee Food Stores	−0.902	0.648
Ingles Markets	−0.953	0.131
Kroger	−0.995	0.389
Lone Star Funds	−0.954	0.577
Meijer	−0.949	0.290
Publix Super Mkts	−1.023	0.684
Raleys Supermarkets	−0.921	0.257
Roundys Supermarkets	−0.973	−0.295
Ruddick Corp	−1.080	0.684
Safeway	−1.058	0.318
Save A Lot	−0.939	0.302
Save Mart Supermarkets	−0.785	0.517
Smart & Final	−0.972	0.165
Stater Bros Markets	−0.914	0.252
Stop & Shop	−1.071	0.649
SuperValu	−1.046	0.341
Target Corp	−1.078	0.463
Trader Joes	−1.060	0.023
Wal Mart Stores	−0.875	0.799
Weis Markets	−0.984	0.405
Whole Foods Market	−1.108	0.573
Wild Oats Markets	−1.044	0.412
Winn-Dixie Stores	−0.931	0.339
BJs	−0.163	0.194
Costco	−0.311	0.720
Sams	−0.098	0.608

strategy. This strategy is even more apparent when we consider the distance elasticities of club stores. Since we earlier found that consumers have a lower disutility of distance for traveling to clubs, it is not surprising that club store distance elasticities are much lower than traditional grocery chains. This fact allows club stores to have a far-reaching impact on grocery stores that are located even several miles away from the club's location. As a result club stores may represent a viable substitute to grocery stores even when the two outlets are several miles apart.

The role of income in the model is slightly more complicated. When consumers' income rises, there are two distinct effects on store revenues. First, consumers have more money to spend on groceries. Second, because income affects tastes for stores differently, consumers substitute between stores and the outside good. Overall, the store-tract level revenue elasticity with respect to the income of tract t is

$$\nu_{st} = 1 + (\tau_1 d_{st} + \gamma_1 x_s)(1 - p_{st}).$$

The first term reflects the fact that a 1 percent increase in income generates a 1 percent increase in all

consumers' grocery budgets, while the second term is the effect of substitution across stores due to that same change in income. Like with the distance elasticity, we can aggregate the income elasticity to both the store level, $\nu_s = \sum_{l \in L_s} \nu_{st} \frac{R_{st}}{R_s}$, and chain level, $\nu_f = \sum_{s \in C_f} \nu_s \frac{R_s}{R_f}$.

The estimated income elasticities are presented in the final column of Table 6. All of these elasticities are below 1, indicating that a 1 percent increase in total consumer income results in a less than 1 percent increase in store revenues. This is largely due to substitution towards the outside good as incomes rise. That is, consumers tend to spend a smaller percentage of their income on groceries as incomes increase. However, substitution between grocery stores is also important. While most firms benefit from an increase in their consumer's income (perhaps not surprisingly) there are a few at the extreme low end that do not. The most prominent example is Roundy's, which was experiencing severe financial problems at this time due to increased competition from higher-end firms—and was attempting to arrange a buyout (Hajewski, 2011). The limited assortment model of Aldi and Trader Joes also appears to become less attractive as income rises, leading to very modest income elasticities. Notably, Wal-Mart has the highest income elasticity among grocery formats. This is indicative of Wal-Mart's strong market share and surprisingly broad appeal across income groups. HE Butt, which uses a similar business model to Wal-Mart but operates exclusively in Texas, also has a high income elasticity. More generally, the firms that target the wealthy (Publix, Target, Giant) have the high elasticities as consumers tend to substitute to these stores as their income rises. For example, Whole Foods, which emphasizes high service and a wide variety of prepared foods has a income elasticity of .58. At the other end of the spectrum, Kroger, Winn-Dixie, Ingels, and Smart & Final are among the lowest values. The latter three are firms that expressly target the less affluent. Interetingly, Wal-Mart and the two major club chains Sam's and Costco, are among the highest income elasticities. It appears that these formats which emphasize one-stop shopping become more attractive as incomes increase.

4.3 Competitive Effects

We can also use the model to gain a better understanding of how chains compete with each other for revenue. Since our model does not include prices, we are unable to calculate price elasticities between firms. However, we can construct semi-elasticities based on a differential improvement in the utility offered by a particular chain.[17] These semi-elasticities serve to illustrate which firms compete for the same consumers, as well as the overall intensity of competition in the industry. Specifically, the semi-elasticity for a chain f with respect to chain g is the percent decrease in revenue for f due to a differential improvement in the utility of the stores of chain g. Formally, the semi-elasticity at the chain level is just the percentage change in f's revenue

[17] Such an improvement represents a change in chain quality which is viewed equally by all consumers. If we were to assume consumers all had the same price sensitivity, this improvement could be accomplished by a uniform decrease in prices.

for a differential increase in the utility of all stores in chain g is given by

$$\begin{aligned}
\sigma_{f,g} &= \frac{1}{R_f} \sum_{s \in F_f} \sum_{t \in L_s} \alpha \text{inc}_t \, n_t \sum_{q \in F_g \cap C_t} \frac{\partial p_{st}}{\partial u_{qt}} \\
&= \frac{1}{R_f} \sum_{s \in F_f} \sum_{t \in L_s} \alpha \text{inc}_t \, n_t \sum_{q \in F_g \cap C_t} \left(\mathbf{1}\{s = q\} \, p_{qt}(1 - p_{qt}) - \mathbf{1}\{s \neq q\} \, p_{st} p_{qt} \right) \\
&= \frac{1}{R_f} \sum_{s \in F_f} \sum_{t \in L_s} R_{st} \sum_{q \in F_g \cap C_t} \left(\mathbf{1}\{s = q\} \, (1 - p_{qt}) - \mathbf{1}\{s \neq q\} \, p_{qt} \right),
\end{aligned}$$

where R_f represents the total revenue for chain f and F_f and F_g are the set of stores that are members of chains f and g respectively. Recall that L_s is the set of tracts with store s inside their choice set and that C_t is the choice set of consumers who live in tract t. The second line makes use of the well known derivative of the logit share formula.

Note that this formula features a symmetry property whereby the sum of $\sigma_{f,g}$ across all firms $g \neq f$ and the outside good exactly equals the own semi-elasticity $\sigma_{f,f}$. This is intuitive since it is only utility *differences* that matter, and raising the utility of all firms and the outside good together results in no change in firm revenues. Since altering chain utilities (or the utility of the outside good) does not affect the overall grocery budget, any gain in revenue will come at the expense of other chains or the outside share. The semi-elasticity indicates which chains will be hurt the most by improvements in competing chains, and which are most likely to expand the market by drawing consumers away from the outside good. Note that the main competitor status (i.e. who is hurt the most) will be partially driven by geography, since the closer two firms' stores are to each other physically, the more revenue they can steal from one another. However, main competitor status will also be affected by the *characteristics* of chains - similar chains will compete more closely with one another since they will both have high market shares in the same set of tracts.

Table 7 presents the semi-elasticities and top competitors for each firm, as well as the firm's substitution with the outside option. Intuitively, these are the percentage change in revenue of firm f for a differential increase in the quality of firm g. For example, a Δ increase in Albertson's chain fixed effect will increase it's own revenue by $87\Delta\%$. On the other hand, Albertson's revenue decreases most sharply with an increase in Wal-Mart's quality. The same Δ increase in Wal-Mart's fixed effect decreases Albertson's revenue by $14.2\Delta\%$. Stated another way, if Albertson's improves its perceived utility in a manner that is valued equally by all consumers, 16.3 percent (.142/.870) of its increase in revenue will be due to revenue declines at Wal-Mart, 7.8 percent will be due to declines in Safeway's revenue, and 26.3 percent will be due to increases in overall grocery spending (i.e., a decline in the outside good). The remaining 49.6 percent of the increase will be due to revenue declines at other stores. Note that these measures are identical to the "diversion ratios"

Table 7: Competition Between Chains: Own and Cross Semi-elasticities

Chain	Own Semi-Elasticity	First Comp	Cross Semi-Elasticity	Second Comp	Cross Semi-Elasticity	Outside Cross Semi-Elasticity
Small Chains	0.849	Wal Mart Stores	-0.083	Medium Chains	-0.070	-0.277
Medium Chains	0.768	Wal Mart Stores	-0.103	Sams	-0.059	-0.222
Albertsons	0.870	Wal Mart Stores	-0.142	Safeway	-0.068	-0.229
Aldi	1.011	Medium Chains	-0.118	Wal Mart Stores	-0.113	-0.210
Bashas Markets	0.777	Kroger	-0.161	Wal Mart Stores	-0.120	-0.166
Delhaize America	0.847	Wal Mart Stores	-0.164	Sams	-0.065	-0.221
Fred Meyer Stores	0.831	Safeway	-0.148	Costco	-0.113	-0.224
Giant Eagle	0.840	Small Chains	-0.111	Sams	-0.106	-0.201
Giant Food	0.858	Safeway	-0.081	Small Chains	-0.063	-0.337
Great A & P Tea	0.947	Small Chains	-0.111	Sams	-0.072	-0.263
H E Butt Grocery	0.567	Wal Mart Stores	-0.168	Sams	-0.066	-0.177
Hannaford Bros	0.695	Medium Chains	-0.119	SuperValu	-0.099	-0.217
Hy Vee Food Stores	0.739	Wal Mart Stores	-0.189	Medium Chains	-0.121	-0.176
Ingles Markets	0.843	Wal Mart Stores	-0.177	Lone Star Funds	-0.086	-0.186
Kroger	0.736	Wal Mart Stores	-0.118	Sams	-0.066	-0.203
Lone Star Funds	0.872	Wal Mart Stores	-0.245	Sams	-0.075	-0.181
Meijer	0.853	Kroger	-0.179	Sams	-0.093	-0.184
Publix Super Mkts	0.706	Wal Mart Stores	-0.143	Winn-Dixie Stores	-0.063	-0.200
Raleys Supermarkets	0.808	Safeway	-0.112	Costco	-0.096	-0.283
Roundys Supermarkets	0.811	Medium Chains	-0.108	Sams	-0.105	-0.278
Ruddick Corp	0.884	Delhaize America	-0.130	Wal Mart Stores	-0.112	-0.235
Safeway	0.846	Costco	-0.082	Kroger	-0.067	-0.310
Save A Lot	0.966	Wal Mart Stores	-0.127	Small Chains	-0.094	-0.202
Save Mart Supermarkets	0.788	Costco	-0.108	Small Chains	-0.098	-0.284
Smart & Final	0.981	Kroger	-0.104	Costco	-0.101	-0.327
Stater Bros Markets	0.821	Kroger	-0.110	Costco	-0.090	-0.273
Stop & Shop	0.801	Medium Chains	-0.125	SuperValu	-0.097	-0.285
SuperValu	0.838	Medium Chains	-0.068	Small Chains	-0.066	-0.280
Target Corp	0.957	Wal Mart Stores	-0.148	Sams	-0.085	-0.220
Trader Joes	0.976	Safeway	-0.097	Costco	-0.093	-0.346
Wal Mart Stores	0.659	Kroger	-0.073	Medium Chains	-0.065	-0.165
Weis Markets	0.913	Giant Food	-0.204	Wal Mart Stores	-0.107	-0.238
Whole Foods Market	0.994	Safeway	-0.073	Kroger	-0.066	-0.373
Wild Oats Markets	0.956	Kroger	-0.116	Costco	-0.081	-0.264
Winn-Dixie Stores	0.844	Publix Super Mkts	-0.197	Wal Mart Stores	-0.189	-0.196
BJs	1.022	Medium Chains	-0.102	Stop & Shop	-0.079	-0.261
Costco	0.813	Safeway	-0.066	Kroger	-0.063	-0.276
Sams	0.845	Wal Mart Stores	-0.123	Kroger	-0.078	-0.208

(Shapiro (1996)) typically used in antitrust analysis to measure the degree of similarity between merging parties offering differentiated products.

Several interesting patterns emerge from Table 7. With respect to own elasticity, the largest values correspond to Whole Foods, BJ's, Aldi, and Save-a-Lot. To the extent that a high elasticity indicates that a firm's return to increasing quality is high, this suggests that these firms cost to improving quality must also be high. There are several possible explanations for this. For Whole Foods, which is already known to offer high quality, this may simply reflect the fact that the products sold there are already very high cost (and raising quality would require an even greater marginal investment). For Aldi or Save-a-Lot, the explanation might be that their limited-assortment format makes it very difficult to improve quality (without altering their entire business model). On the other hand, the lowest own semi-elasticities are for HE Butt and Wal-Mart. A low semi-elasticity suggests that while quality increases could be achieved relatively easily, they are foregone because they would not result in a substantial revenue increase for the firm (given the market segment they are targeting). Again, this likely reflects the fact that these firms will be forced to compete directly with other firms that offer much higher levels of service should they choose to shift up market.

Turning to the cross elasticities, it is striking just how large a shadow Wal-Mart casts. It is the largest competitor of 10 of the 32 other large grocery chains, and the second largest competitor of an additional 5. It is also the largest competitor for both medium and small chains. Interestingly, among club stores, Wal-Mart is only a major competitor of its own Sam's Club chain, which is almost certainly due to their tendency to co-locate. While part of this large overall impact is clearly driven by Wal-Mart's enormous scale and national presence, it also reflects its close proximity in product space to many of these conventional chains. Indeed, the supermarket portion of a Wal-Mart supercenter is essentially the same as any other large footprint supermarket chain - their main differentiating factor is price. The results indicate that over three quarters of an increase in Wal-Mart revenue is drawn from rival grocery outlets, with the remaining portion representing market expansion from the outside good. In particular, its impact is strongest on either mid-tier regional chains (Delhaize, Ingles, Lone Star, and Winn-Dixie) or firms that also operate super centers (HEB, Hy Vee). In contrast, Wal-Mart is relatively insulated from competition from any particular chain. While Kroger is it's largest competitor, a Δ improvement in Kroger's overall appeal would result in only a $.073\Delta\%$ decline in Wal-Mart revenues. On the other hand, a Δ in Wal-Mart's appeal would lead to a $.118\Delta\%$ decline in Kroger's revenues and a $.189\Delta\%$ decline for Hy Vee. Furthermore, Wal-Mart actually owns its second largest "rival", the Sam's Club chain of club stores. This unique overall positioning is consistent with Wal-Mart's enormous cost advantage (Basker, 2007). More broadly, the chains that are hurt the least by their largest rivals are the firms that are generally thought to have significant market power, either due to regional monopoly (Giant Food, Giant Eagle, and SuperValu) or their isolated position in product space

(Whole Foods, Trader Joe's, Aldi). An interesting exception is Safeway, which, despite a national presence, is able to avoid significant competition with Wal-Mart or other chains.

While Wal-Mart's impact on the supermarket industry has been studied in detail elsewhere (Matsa, 2011; Ellickson and Grieco, 2013; Arcidiacono et al., 2009), the extent of competition between club stores and supermarkets is much less well-understood (a notable exception is Courtemanche and Carden (2014), who find that rival supermarkets tend to raise prices in response to entry by Costco, but have no measurable price response to Sam's Club). As noted earlier, club stores have not been included in the competitive set when analyzing supermarket mergers, though there is mounting agreement among industry analysts that the firms themselves consider clubs to be important rivals. A key feature of our model is that it can allow the data to speak to whether club stores are operating in their own market or whether they are in fact a significant rival to traditional grocery firms. Notably, from Table 7, it is clear that club stores, particularly Costco and Sam's Club are primary or secondary competitors of several grocery chains including national chains Delhaize, Kroger, and Safeway who manage to avoid direct competition with each other. Moreover, club stores do not appear to have each other as primary competitors despite some geographic overlap in their locations. Overall, club stores appear to compete on relatively equal footing with more traditional formats. This suggests that including them in merger analysis could have a substantial impact on outcomes. We turn to this exercise next.

5 Using the Model to Assess the Impact of Grocery Mergers

To illustrate how our model can be used as an input to merger analysis, we consider two representative cases. The first is the actual merger between Whole Foods and Wild Oats which was proposed in 2007 and actively contested by the FTC that same year. Our data corresponds to the period just before the merger was announced. The second is a potential merger between Ahold and Delhaize, which was recently announced. Note that in this second case our data corresponds to a period far before the actual merger (2006 versus 2015) so it should appropriately be considered a hypothetical exercise. Our model will allow us to determine the degree of overlap between the competing firms, the extent of competition with existing rivals, and the predicted market structure (concentration ratios) that would obtain should the merger occur.

Supermarket mergers have traditionally played an important role in antitrust. Due to the importance of maintaining access to affordable food and the ever-present role of scale in distributing groceries, the supermarket industry is a constant focus for anti-trust review. Hanner et al. (2015) note that, from 1998 to 2007, the FTC investigated supermarket mergers in 153 antitrust markets, ultimately challenging mergers

in 134 of those markets.[18] It is also a particularly challenging industry in which to assess the impact of mergers, since competing firms are differentiated geographically, as well as in the set of products they offer and the particular consumer segments that they target (Hosken et al. (2012)). This makes market definition especially difficult. While the Horizontal Merger Guidelines published by the FTC and DOJ provide a framework for assessing the degree of overlap, the implementation can be quite challenging (e.g. choosing the set of competing stores and the radius of competition). In many cases these decisions are made qualitatively, relying on internal documents, industry case studies and trade publications. Moreover, in some cases the market definition essentially determines the outcome. For example, in the Whole Foods/Wild Oats case, the FTC argued that the two firms competed in the narrowly-defined category of *premium natural and organic supermarkets*, whereas the defense argued for a broader definition that would include all rival supermarkets (*premium natural and organic* or otherwise). Under the more narrow definition, the merger was effectively a merger to monopoly in most geographic markets, while under the broader definition, the conclusion would depend on the extent to which Whole Foods and Wild Oats in fact compete with chains outside this narrow segment. The merging parties ultimately prevailed, with the presiding judge concluding that "when Whole Foods does enter a new market where Wild Oats operates, Whole Foods takes most of its business from other retailers, not from Wild Oats" (Lambert, 2008).

The model proposed in this paper can be used to address these thorny issues of market definition in a straightforward manner that allows the data to reveal the true extent of overlap. In particular, for every census tract, the model recovers the total revenue originating from that tract that accrues to each store in it's vicinity. Therefore, rather than using total store revenues alone, we construct indices of concentration that can reveal exactly how revenue is divided at a particular point in space. Specifically, we construct tract-level Herfindhal-Hirschman indices (HHIs) as a measure of market concentration,

$$HHI_t = \sum_{s \in C_{t \setminus 0}} \left(100 \cdot \frac{p_{st}}{1 - p_{0t}} \right)^2 .$$

According to the 2010 Merger Guidelines (U.S. Department of Justice and Federal Trade Commission, 2010), a market is considered moderately concentrated if it's HHI is between 1,500 and 2,500, and highly concentrated if the HHI is over 2,500. HHIs under 1,500 are considered un-concentrated and presumably competitive. Focusing on the industry as a whole, we compute these HHI's for every census tract in all 317 MSAs included in our earlier analysis and present the results in Table 8. Using the above cutoffs, we find that

[18] The role of anti-trust concerns in shaping the development of the grocery industry goes back to the early attempts to curtail the growth of the Great Atlantic and Pacific Tea Company (which led to the passage of the Robinson-Patman Act in 1936) and includes the landmark Von's Grocery decision of 1966, the passage of the Food Distribution Merger Guidelines in 1973 and the Hart-Scott-Rodino Act of 1976, as well as the Whole Foods/Wild Oats merger considered here (Ellickson (2016); Hosken and Tenn (2016)).

38.7% percent of all census tracts in the dataset are highly concentrated, while another 43.5% of tracts are moderately concentrated, confirming that the supermarket industry indeed tends to be highly concentrated. This result is particularly stark since we are including all stores within 10 miles of the tract centroid as part of the choice set, so even the most concentrated tracts have a choice set that includes more than 20 stores (Table 8). Of course, this is not surprising given the widespread importance of scale economies. In fact, Table 8 reveals that the most concentrated tracts are those that are least dense in terms of population, as these tracts tend to have the fewest stores of all types in their nearby vicinity. This is consistent with levels of fixed cost sufficiently high to leave these low demand markets served by relatively few firms. Income plays less of a clear role, as both the most and least concentrated tracts are lower income. This reflects the fact that low income tracts tend to be either very urban (with lots of nearby stores) or very rural (with very few nearby stores), whereas the higher-income suburbs lie somewhere in between.

Table 8: **Firm concentration computed at the level of the tract**

				Mean Number of within 5/10 miles			
Concentration	Number of Tracts	Income	Density	All Stores	Large Chain Stores	Large Chains	Club Stores
Low (< 1500)	9,415	26.59	6078.52	42.70	19.90	5.33	1.20
				132.19	64.66	7.06	4.15
Moderate	23,219	30.08	3000.29	21.64	13.30	4.43	0.94
				63.34	39.23	6.06	2.79
High (> 2500)	20,643	26.43	1240.61	8.28	5.10	2.32	0.38
				22.05	13.62	3.49	0.97
Total	53,368	28.05	2862.98	20.19	11.30	3.77	0.77
				59.52	33.82	5.24	2.33

Having characterized the competitive landscape overall, the tract level HHIs derived from the model can also be used to forecast the potential change in market structure associated with a particular merger. Starting with the Whole Foods/Wild Oats example, we compute the implied tract-level impact of the merger for the 6,157 tracts in which both chains appear in the tract choice set in 2006 (the year just prior to the proposed merger). To assess the impact of the merger, we examine how it would change concentration at each of these census tracts. According to the merger guidelines, mergers that raise the HHI by more than 100 points in moderately or highly concentrated markets "potentially raise significant competitive concerns and often warrant scrutiny," while mergers that raise the HHI by more than 200 points and result in highly concentrated markets are "presumed to be likely to enhance market power." We use these guidelines to identify merger "hot spots," tracts where the increase in HHI due to the merger either warrants scrutiny or is presumed likely to enhance market power. The remaining markets are characterized as not raising significant anti-trust concerns. The results are presented in Table 9. Notably, our analysis of the Whole

Foods/Wild Oats example overwhelming sides with the defense, as the vast majority of tracts (99.5%) are classified as not raising concerns. In only 30 tracts does the HHI rise by a degree sufficient enough to "warrant scrutiny" and none of the tracts fall in to the category of "enhancing market power".[19] This is mainly driven by the fact that both Whole Foods and Wild Oats compete strongly with conventional supermarkets. In fact, we find that even when we consider only those Whole Foods stores with a Wild Oats in the vicinity, the semi-elasticity of Wild Oats on Whole Foods is only -.0131 whereas Whole Food's own semi-elasticity is .912, equating to a diversion ratio of only 1.4 percent. In contrast Safeway, Kroger, and Costco all appear to be much stronger competitors to Whole Foods, with diversion ratios ranging from 6.5 to 8.7 percent even for this selected sample of stores.[20] These results confirm the intuition behind the judicial decision in the Whole Foods/Wild Oats merger case that general grocery retailers are close substitutes for Whole Foods and Wild Oats and complement our findings in Table 7. From those results, we can see that the top competitor of Whole Foods is actually Safeway, while for Wild Oats it is Kroger.

We next consider a potential merger between Delhaize (Food Lion and Hannaford) and Ahold (Giant Food and Stop & Shop). This merger was announced on June 24, 2015 and is currently under review by the FTC. If approved, it would create one of the largest supermarket firms in North America, and one that would rank fourth in overall market share.

Table 10 presents the results of this second analysis. For each state in which the two firms are active, we list the total number of tracts in which the two merging firms are both present, the number of tracts which warrant further scrutiny and those where the merger is presumed likely to enhance market power. In all, this analysis indicates that the merger would be presumed likely to enhance market power in tracts totaling a population of 2.4 million people in 2010. The areas of most significant concern are in Maryland, Massachusetts and Virginia.[21] It is evident from the figures that the largest increases are predicted to occur in the least densely populated areas (i.e. the areas with the fewest overall stores). This is most clearly illustrated by looking at particular counties. For a concrete example, we focus on Fairfax County, VA in the Washington, DC suburbs. Figure 2 illustrates that, within Fairfax County, there is little reason for concern in the more densely populated areas of the county, which are mainly in the east (around the Capital Beltway). In contrast, the less densely populated western and southern portions of the county show Herfindahl increases

[19] Interestingly, excluding the impact of competition due to club stores has a relatively small impact for this merger, increasing the total number of tracts in the "warrant scrutiny" category to 52 and lifting 4 tracts into the 'enhancing market power" (see Table 13 in the Appendix). This likely reflects the fact that there is little direct competition between either Whole Foods and Wild Oats and the three club store firms (presumably due to the fact that they are rarely geographically close enough together to have a significant impact on one another).

[20] We have carried out the converse analysis of the effect of Whole Foods on Wild Oats Stores in the vicinity of a Whole Foods and the qualitative results are even stronger in indicating that Wild Oats competes most intensely with stores outside the "organic" segment.

[21] Figures 3-5 in the appendix show the existing set of stores operated by each firm (Ahold in green and Delhaize in red), as well as the locations of all competing stores operated by rival chains (shown in black). The tracts themselves are color coded according to the expected level of increase in HHI should the merger occur (the darkest areas represent the largest increases).

Table 9: **Tract-level Impact of the Whole Foods/Wild Oats merger**

	Both Firms Present		Warrants Scrutiny		Enhance Market Power	
State	Number of Tracts	Population	Number of Tracts	Population	Number of Tracts	Population
AZ	411	1676.24	0	0	0	0
CA	1427	6353.02	0	0	0	0
CO	641	2643.28	12	54.97	0	0
CT	142	538.18	0	0	0	0
FL	245	1041.83	0	0	0	0
IA	7	22.56	0	0	0	0
IL	708	2908.50	0	0	0	0
IN	18	66.97	0	0	0	0
KS	126	493.86	0	0	0	0
KY	142	545.66	0	0	0	0
MA	451	1940.66	0	0	0	0
MO	301	1094.88	0	0	0	0
NE	178	609.34	0	0	0	0
NM	164	642.11	18	48.80	0	0
NV	373	1494.98	0	0	0	0
OH	138	562.23	0	0	0	0
OR	229	1042.37	0	0	0	0
TX	428	1958.68	0	0	0	0
WA	28	103.57	0	0	0	0
Total	6157	25738.92	30	103.77	0	0

Table 10: **Tract-level Impact of the Ahold/Delhaize merger**

	Both Firms Present		Warrants Scrutiny		Enhance Market Power	
State	Number of Tracts	Population	Number of Tracts	Population	Number of Tracts	Population
DC	58	194.13	0	0	0	0
DE	45	238.05	1	6.46	7	46.00
MA	974	4547.29	360	1754.07	137	722.34
MD	1214	4999.43	402	1859.54	136	601.70
NH	124	587.62	52	257.86	57	251.96
PA	76	361.57	22	83.07	17	91.67
RI	19	69.11	3	10.57	16	58.53
VA	577	2550.94	303	1391.58	108	502.91
WV	31	163.93	0	0	31	163.93
Total	3118	13712.08	1143	5363.15	509	2439.04

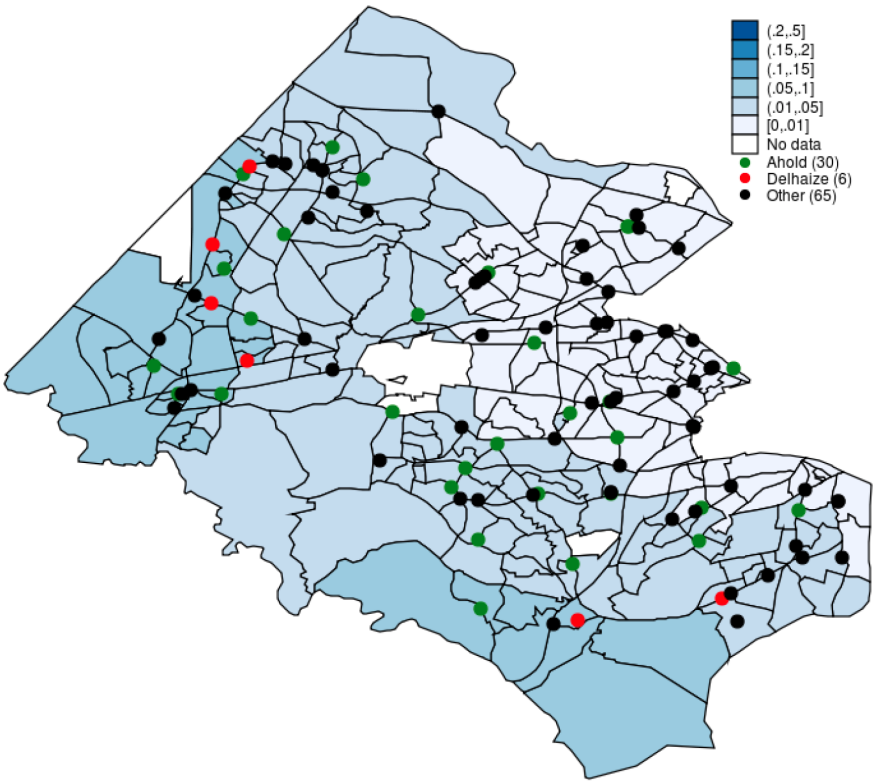

Figure 2: Post merger increases in HHI by tract: Fairfax County, VA

of more than 100 points, which would trigger anti-trust concerns under the guidelines. The map also clearly shows that while Ahold stores (in this case, the Giant Food chain) are spread throughout the county, whereas Delhaize stores are located only in the less urban areas. To further investigate the relationship between population density and the likelihood of our model indicating a tract is a anti-trust "hot-spot", we present the cross-tab of population density with the indicated merger evaluation in Table 11. While it confirms that rural areas are more likely to trip the guidelines critera, it is clear that population density alone is not the deciding factor.

Table 11: **Population Density and Ahold/Delhaize Anti-Trust Concern**

	Merger Evaluation			
Population Density	No Concern	Warrant Scrunity	Enhance Market Power	Total
Low (<1500)	142	428	399	969
Medium (>1500 and <4000)	366	629	109	1104
High (>4000)	958	86	1	1045
Total	1466	1143	509	3118

We now turn to the question of the importance of including club stores in the analysis of this merger. It

may be tempting to consider club stores a separate market, either because they are fundamentally different retail formats or because they tend to be located further away from consumers and therefore outside the standard geographic catchment area for grocery markets. However, our estimation results indicate that club stores have much lower sensitivity to distance than grocery stores, suggesting that they may play a larger role even in relatively distant census tracts. Also, because of their large size, club stores may represent an attractive substitute to grocery stores for some consumers, particularly those with high income (Courtemanche and Carden (2014)).

Table 12: **Effect of Excluding Club Stores on Evaluating the Ahold/Delhaize Merger**

	Without Club Stores			
With Club Stores	No Concern	Warrants Scrutiny	Enhance Market Power	Total
No Concern	1,122	341	3	1,466
Warrants Scrutiny	1	436	706	1,143
Enhance Market Power	0	3	506	509
Total	1,123	780	1,215	3,118

To see how the presence or absence of club stores in the analysis affects outcomes, we redo the analysis of the Delhaize-Ahold merger using the specification of our model that excludes club stores. Table 12 presents a comparison of the two merger analyses in the form of a cross-tabulation of their resulting categorization of tracts. The rows of this matrix represent the results of our preferred analysis with club stores while the columns represent the results excluding club stores. Recall that the estimates for these specifications were presented in columns (1) and (3) of Table 5, respectively. The diagonal contains the counts of tracts where the two analyses agree on categorization, cells above the diagonal contain tracts where concerns are higher excluding club stores, while cells below the diagonal contain tracts where concerns are higher when club stores are included. The importance of club stores to the analysis is clear, as it results in a 58.1 percent decrease (from 1215 to 509) in the number of tracts where the merger is "presumed likely" to enhance market power under the merger agreement guidelines. The results are consistent with what we have presented earlier regarding the lower distance elasticity and popularity of club stores. Due to their size and attractiveness for larger purchases, club stores represent strong competitors to grocery stores even when they are a significant distance away. As a result, markets which appear concentrated when club stores are ignored may actually appear significantly more competitive once club stores are taken into account.

Overall, we view this framework as providing a natural first step in evaluating prospective mergers. In the case of Whole Foods and Wild Oats, it would suggest allowing the merger to proceed uncontested. In the case of Delhaize and Ahold, it identifies the areas of potential concern and highlights the importance of including club stores in the competitive set. Most importantly, it eliminates the need to rely on ad

hoc or qualitative methods of defining markets and instead leverages the data to reveal the true extent of competition.

6 Conclusion

This paper provides a simple framework for analyzing competition between multi-product retailers that can be used as a tool for evaluating potential mergers and judging their likely impact on market structure. Using readily available information on store locations, characteristics and revenues, we propose a spatial model of competition that reveals the extent to which rival firms compete and does not require choosing geographic overlap ex ante or making a binary decision over whether to include or exclude particular firms. We illustrate the utility of the framework using two examples of recent mergers. Apart from its role in analyzing prospective mergers, this model is a natural input to structural models of entry and expansion. This is the focus of our future research.

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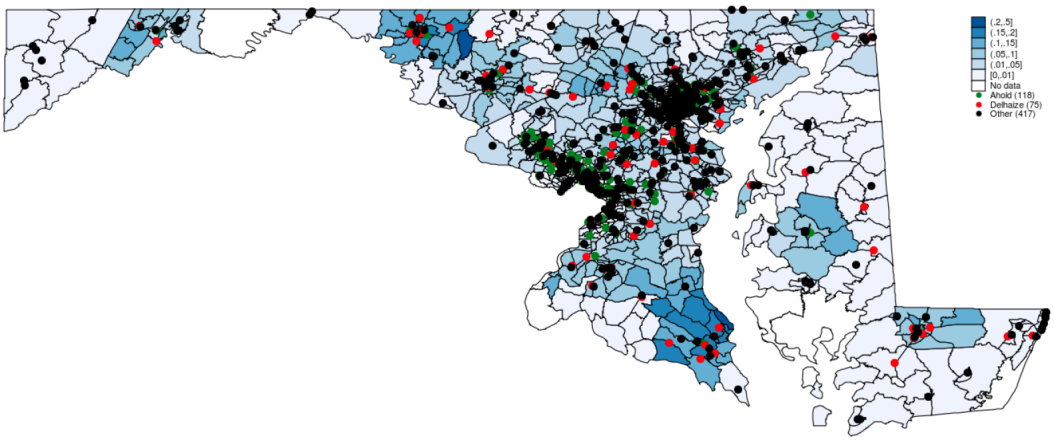

Figure 3: Post merger increases in HHI by tract: Maryland

7 Appendix

Table 13: **Effect of Excluding Club Stores on Evaluating the Whole Foods/Wild Oats Merger**

	Without Club Stores			
With Club Stores	Both Firms Present	Warrants Scrutiny	Enhance Market Power	Total
Both Firms Present	6,101	26	0	6,127
Warrants Scrutiny	0	26	4	30
Total	6,101	52	4	6,157

Table 14: **Characteristics of the tract**

State	Number of Tracts	Income	HH size	Density	Population	HF After	HF change	Competing Stores
All Tracts								
DC	176	40.84	2.10	8,474.26	3,375.59	0.18	0	11.37
DE	170	29.25	2.49	1,772.97	4,360.99	0.23	0	0.66
MA	1,434	33.76	2.38	3,847.88	4,515	0.24	0.01	11.45
MD	1,309	34.69	2.49	3,228.52	4,165.07	0.22	0.02	18.43
NH	223	32.40	2.36	744.64	4,600.81	0.36	0.04	3.76
PA	2,816	27.45	2.32	2,851.76	3,990.71	0.23	0	0.17
RI	238	28.92	2.34	2,846.88	4,394.27	0.26	0	0.70
VA	1,537	34.91	2.48	2,431.56	4,267.09	0.29	0.02	9.46
WV	231	23.07	2.15	601.75	3,891.88	0.43	0.01	0.59
All Tracts with competition								
DC	58	32.90	2.19	7,559.91	3,347.14	0.18	0	34.50
DE	45	27.90	2.74	1,682.87	5,290	0.18	0.02	2.49
MA	974	36.42	2.48	5,011.14	4,668.68	0.21	0.02	16.86
MD	1,214	34.97	2.49	3,400.28	4,118.15	0.19	0.02	19.87
NH	124	33.95	2.39	1,056.50	4,738.89	0.30	0.06	6.76
PA	76	24.46	2.43	1,096.14	4,757.47	0.32	0.04	6.16
RI	19	23.19	2.23	1,063.03	3,637.26	0.29	0.04	8.79
VA	577	44.66	2.66	2,978.30	4,421.04	0.24	0.04	25.19
WV	31	27.42	2.33	379.39	5,288.06	0.39	0.07	4.39
Tracts with competition (require consideration)								
DE	8	29.12	3.38	359.64	6,556.62	0.42	0.08	2.88
MA	515	33.01	2.55	2,289.04	4,967.37	0.25	0.03	10.97
MD	560	38.93	2.59	1,663.52	4,553.41	0.25	0.03	15.16
NH	111	33.38	2.38	1,072.87	4,661.23	0.31	0.07	6.94
PA	57	23.69	2.42	1,118.16	4,573.98	0.35	0.05	6.04
RI	19	23.19	2.23	1,063.03	3,637.26	0.29	0.04	8.79
VA	411	41.33	2.76	1,951.44	4,609.48	0.26	0.06	20.07
WV	31	27.42	2.33	379.39	5,288.06	0.39	0.07	4.39
Tracts with competition (don't require consideration)								
DC	58	32.90	2.19	7,559.91	3,347.14	0.18	0	34.50
DE	37	27.64	2.60	1,968.98	5,016.14	0.13	0	2.41
MA	459	40.25	2.40	8,065.35	4,333.55	0.18	0.01	23.47
MD	654	31.57	2.40	4,887.41	3,745.45	0.15	0.01	23.90
NH	13	38.82	2.44	916.76	5,402	0.23	0.01	5.23
PA	19	26.79	2.45	1,030.08	5,307.95	0.24	0	6.53
VA	166	52.93	2.42	5,520.70	3,954.50	0.19	0	37.86

Table 15: Chain Effect Estimates

	(1) Intercepts	(2) Intercepts	(3) Intercepts	(1) Slopes	(2) Slopes	(3) Slopes
Small Chains	−0.776	−0.629	−1.217	−0.379	−0.887	−0.519
	(0.019)	(0.020)	(0.021)	(0.045)	(0.043)	(0.050)
Medium Chains	−0.622	−0.381	−1.065	−0.374	−0.872	−0.515
	(0.020)	(0.020)	(0.022)	(0.047)	(0.045)	(0.052)
Albertsons	−0.512	−0.268	−0.944	−0.427	−1.291	−0.613
	(0.022)	(0.023)	(0.024)	(0.058)	(0.059)	(0.065)
Aldi	−0.903	−1.011	−1.352	−0.617	−1.118	−0.687
	(0.020)	(0.022)	(0.023)	(0.068)	(0.074)	(0.077)
Bashas Markets	−0.342	−0.133	−0.744	−0.578	−1.278	−0.729
	(0.023)	(0.024)	(0.026)	(0.055)	(0.055)	(0.063)
Delhaize America	−0.697	−0.561	−1.142	−0.692	−1.230	−0.798
	(0.020)	(0.021)	(0.023)	(0.054)	(0.053)	(0.060)
Fred Meyer Stores	−0.177	0.448	−0.603	−0.519	−0.976	−0.712
	(0.032)	(0.038)	(0.038)	(0.120)	(0.146)	(0.144)
Giant Eagle	−0.136	0.288	−0.617	−0.926	−1.304	−1.040
	(0.024)	(0.026)	(0.029)	(0.093)	(0.101)	(0.122)
Giant Food	−0.200	0.274	−0.629	−0.308	−1.026	−0.537
	(0.025)	(0.027)	(0.028)	(0.061)	(0.060)	(0.068)
Great A & P Tea	−0.493	−0.163	−0.938	−0.746	−1.400	−0.867
	(0.026)	(0.026)	(0.030)	(0.082)	(0.087)	(0.099)
H E Butt Grocery	0.131	0.623	−0.308	−0.210	−1.063	−0.447
	(0.023)	(0.023)	(0.026)	(0.056)	(0.053)	(0.063)
Hannaford Bros	−0.284	0.155	−0.690	−0.979	−1.703	−1.168
	(0.027)	(0.029)	(0.031)	(0.095)	(0.098)	(0.110)
Hy Vee Food Stores	−0.415	0.189	−0.849	−0.278	−1.168	−0.503
	(0.030)	(0.032)	(0.036)	(0.122)	(0.141)	(0.150)
Ingles Markets	−0.764	−0.644	−1.221	−1.060	−1.726	−1.232
	(0.026)	(0.027)	(0.030)	(0.109)	(0.108)	(0.127)
Kroger	−0.133	0.151	−0.569	−0.609	−1.224	−0.781
	(0.020)	(0.020)	(0.022)	(0.049)	(0.047)	(0.055)
Lone Star Funds	−0.626	−0.422	−1.084	−0.554	−1.193	−0.658
	(0.022)	(0.024)	(0.025)	(0.074)	(0.083)	(0.083)
Meijer	−0.374	0.646	−0.828	−0.931	−1.824	−1.182
	(0.024)	(0.025)	(0.027)	(0.088)	(0.097)	(0.106)
Publix Super Mkts	−0.375	0.063	−0.811	−0.243	−0.975	−0.443
	(0.022)	(0.022)	(0.024)	(0.056)	(0.055)	(0.064)
Raleys Supermarkets	−0.201	0.052	−0.644	−0.585	−1.410	−0.707
	(0.028)	(0.029)	(0.032)	(0.097)	(0.089)	(0.108)
Roundys Supermarkets	−0.091	0.300	−0.512	−1.439	−2.240	−1.747
	(0.030)	(0.031)	(0.034)	(0.108)	(0.115)	(0.129)
Ruddick Corp	−0.287	−0.038	−0.784	−0.399	−0.794	−0.433
	(0.030)	(0.033)	(0.035)	(0.083)	(0.083)	(0.095)
Safeway	−0.198	0.072	−0.631	−0.399	−1.118	−0.582
	(0.020)	(0.021)	(0.022)	(0.051)	(0.048)	(0.056)
Save A Lot	−0.666	−0.666	−1.114	−0.597	−1.318	−0.683
	(0.020)	(0.021)	(0.022)	(0.059)	(0.063)	(0.066)
Save Mart Supermarkets	−0.158	0.017	−0.607	−0.202	−0.806	−0.337
	(0.027)	(0.026)	(0.030)	(0.078)	(0.072)	(0.089)
Smart & Final	−0.236	−0.429	−0.673	−0.353	−1.030	−0.521
	(0.023)	(0.024)	(0.025)	(0.064)	(0.067)	(0.071)
Stater Bros Markets	0.140	0.369	−0.302	−0.583	−1.156	−0.676
	(0.026)	(0.032)	(0.030)	(0.087)	(0.115)	(0.100)
Stop & Shop	−0.401	−0.033	−0.851	−0.361	−0.952	−0.481
	(0.023)	(0.024)	(0.026)	(0.067)	(0.067)	(0.078)
SuperValu	−0.306	−0.069	−0.751	−0.580	−1.198	−0.710
	(0.020)	(0.021)	(0.023)	(0.052)	(0.051)	(0.058)
Target Corp	−0.791	0.065	−1.225	−0.735	−1.203	−0.903
	(0.032)	(0.035)	(0.035)	(0.099)	(0.109)	(0.112)
Trader Joes	0.235	0.490	−0.210	−0.544	−0.769	−0.672
	(0.029)	(0.032)	(0.033)	(0.073)	(0.079)	(0.085)
Wal Mart Stores	−0.178	0.747	−0.595	−0.297	−1.105	−0.565
	(0.021)	(0.021)	(0.023)	(0.054)	(0.049)	(0.061)
Weis Markets	−0.786	−0.572	−1.234	−0.594	−1.027	−0.691
	(0.029)	(0.029)	(0.032)	(0.118)	(0.108)	(0.133)
Whole Foods Market	−0.237	0.033	−0.685	−0.039	−0.411	−0.204
	(0.036)	(0.044)	(0.042)	(0.080)	(0.081)	(0.092)
Wild Oats Markets	−0.742	−0.416	−1.180	−0.274	−1.059	−0.401
	(0.028)	(0.028)	(0.033)	(0.075)	(0.074)	(0.088)
Winn-Dixie Stores	−0.732	−0.469	−1.172	−0.658	−1.473	−0.875
	(0.022)	(0.023)	(0.024)	(0.060)	(0.061)	(0.069)
BJs		−2.147	−2.364		−0.701	−0.795
		(0.259)	(0.275)		(0.831)	(0.856)
Costco		−1.371	−1.629		−0.079	−0.233
		(0.263)	(0.279)		(0.851)	(0.875)
Sams		−1.669	−1.941		−0.455	−0.535
		(0.269)	(0.286)		(0.857)	(0.883)

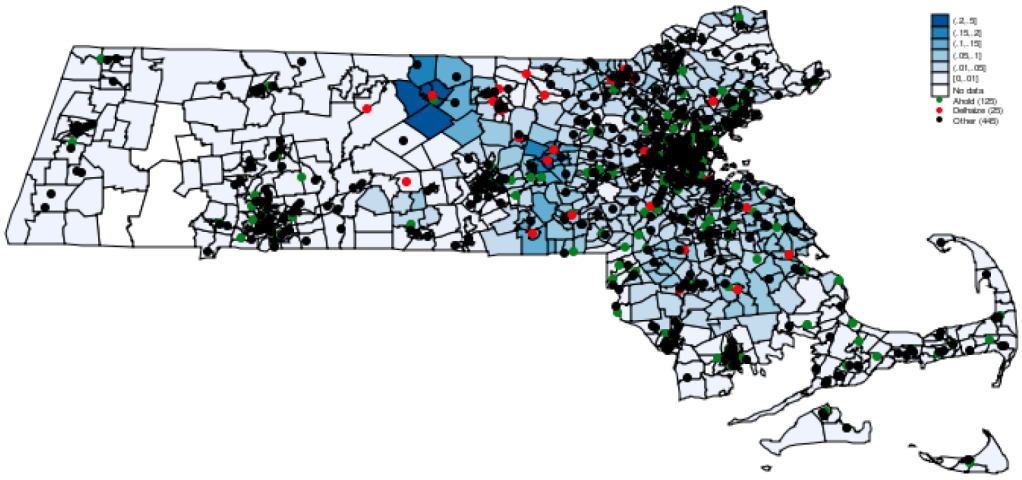

Figure 4: Post merger increases in HHI by tract: Massachusetts

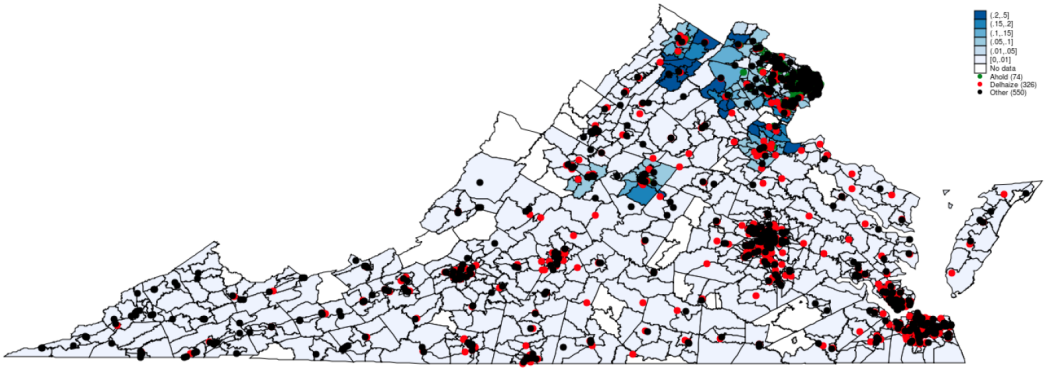

Figure 5: Post merger increases in HHI by tract: Virginia