Measuring Competition in Spatial Retail: An Application to Groceries*

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Abstract

We propose a framework for analyzing spatial competition between retailers of different formats that links the spatial distribution of consumers to a census of store-level revenues, revealing the degree of substitution between rival retailers while accounting for heterogeneity in location and tastes. Our approach yields localized measures of concentration and store-level diversion ratios that can be used to prospectively evaluate mergers in highly differentiated retail markets. Moreover, it does not require the analyst to define markets ex ante, collect prices or construct ad hoc price indices. We estimate the model using data from the supermarket industry and use the output to evaluate two representative mergers. Contrary to current conventional wisdom, we find substantial cross-format competition between supercenters, club stores, and traditional grocers. Our analysis cautions against ignoring the impact of new formats when evaluating mergers between traditional grocers.

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

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1 Introduction

Defining product markets and measuring market power are two of the most challenging aspects of merger analysis (Whinston, 2007; Baker and Bresnahan, 2008). Both are particularly difficult in markets with highly differentiated firms or products, as competition is then more localized. This is especially true in retailing, where firms compete (at the very least) over location, product selection, service, convenience, and price.[1] The diverse array of stores, and the continual blurring of retail formats, pose a challenge to both academics and policy makers seeking to analyze the competitive landscape of these markets and to understand how various policy interventions — including merger regulation, zoning restrictions and entry subsidies — affect market outcomes. Focusing on the grocery industry, we propose and estimate a model of store choice that eliminates the need to define markets ex ante and does not require information on price. While remaining relatively light on data requirements, our method recovers rich, spatially localized measures of retail competition that can be used to construct either the traditional (yet highly localized) measures of market concentration emphasized in the U.S. Horizontal Merger Guidelines or the more nuanced measures of competitive effects proposed by Farrell and Shapiro (2010a) and adoped by the U.K.'s Competition Commission.

The key issue in horizontal merger analysis is determining whether two merging parties have enough competitive overlap to substantially enhance market power.[2] The Horizontal Merger Guidelines, published by the Federal Trade Commission (FTC) and Department of Justice (DOJ), provide thresholds for increases in market concentration that are 'presumed likely to enhance market power' or 'warrant further scrutiny'. However, constructing the relevant market shares requires defining an appropriate anti-trust market. Choose too wide a definition, and you risk making it *ex ante* impossible to find concentration levels sufficient to cross the thresholds, but define markets too narrowly and it will be effectively impossible not to. For example, in the Whole Foods/Wild Oats case, the FTC proposed a market definition of "premium natural and organic groceries" while the firms argued for simply using "supermarkets". Similarly, in the Staples/Office Depot case, the FTC asserted a market for "the sale of consumable office supplies through office superstores", while the firms argued for "the overall sale of office products" (Farrell and Shapiro, 2010b). In both cases, the definition favored by the FTC implied that, in most geographies, the mergers would create monopolies essentially by definition.

An alternative to measuring concentration is to directly estimate consumer demand, and then use the

[1] Despite the constant attention afforded to e-commerce, most retail sales continue to take place through physical outlets, with new formats driving the continual evolution of the sector (Hortaçsu and Syverson, 2015). See footnote 5 for additional discussion of the role of e-commerce in retail markets.

[2] After establishing that firms sufficient have incentives to exercise market power (by internalizing demand interactions), the agencies must then assess whether there are offsetting changes on the supply side (e.g. cost synergies) that will counteract the implied market power effects. While the antitrust agencies typically favor a consumer surplus standard (e.g., that marginal cost must decreases enough to prevent consumer surplus from falling), arguments in favor of an aggregate surplus standard can be instead, which would involve offsetting changes in fixed costs as well (Williamson, 1968)

implied own and cross-product substitution patterns to either perform a full merger simulation (Werden and Froeb, 1994) or a conduct "partial simulation exercise" using simpler metrics based on the degree of "upward pricing pressure" (UPP) that arises from the elimination of direct competition between the merging parties. UPP, in turn, depends on the fraction of sales diverted to rival products, which reflects their proximity in product space.[3] The relevant diversion ratios can be computed either from an estimated demand system, or inferred from marketing studies or internal documents provided by the merging parties.

Our contribution is to estimate a spatially flexible model of retail store choice and show how it can be used to inform both concentration-based approaches and competitive effects analysis, thereby eliminating much of the distinction between the two. Our approach uses a census of store revenues, along with exact store locations and demographic information from their surrounding census tracts to estimate a model that links store revenues to consumer characteristics. Notably, our approach does not require information on prices, but can still produce store or firm diversion ratios and localized measures of concentration (down to the level of the census tract). By defining markets around consumers (and their local choice sets) instead of firms, we mitigate a central drawback of the concentration-based approach (Carlton, 2010).

Our framework is based on a simple nested-logit model of store choice by heterogeneous consumers, in which stores are collected into nests according to retail format (e.g. club store, supermarket, or supercenter). Consumers in each census tract allocate grocery expenditures across a group of nearby retail outlets that are differentiated by their in-store amenities, distance to the consumer's location, and chain affiliation. Critically, consumers' utility for all store characteristics—including chain affiliatoin—are allowed to vary with consumers' demographics, such as income. By accounting for multiple sources of consumer heterogeneity (i.e., location and income) and chain-level effects, we avoid the need to collect prices (for tens of thousands of products) or construct ad-hoc store level price indices while preserving the ability to quantify rich substitution patterns and to identify the degree of competitive overlap using either diversion or localized concentration measures.[4] We view our approach as providing a low-cost, "first-pass" method for analyzing store competition—including screening proposed retail mergers—that does not require ad hoc geographic market definitions, detailed price or product data, or *ex ante* judgements regarding which firms or formats should be included in the product market.

Using store-level data from the grocery industry, we demonstrate that our model can identify the key determinants of competitive overlap in this complex setting. Consistent with earlier studies (Smith, 2006), we

[3]While a full merger simulation yields a complete and precise accounting of economic impact, it involves predicting the complete equilibrium adjustment of the industry to the merger (Farrell and Shapiro, 2010a). This requires a fully-specified model of firm conduct, and depends on the curvature of the underlying demand system. Approaches based on UPP are simpler approximations that may also be more robust to alternative conduct assumptions (Jaffe and Weyl, 2013).

[4]Allowing these chain-level tastes to vary with income reflects the strong vertical aspects of differentiation in the grocery market (Ellickson, 2007).

find that consumers are only willing to travel a short distance for groceries, a willingness that declines quickly with income. While markets are geographically localized, store type matters as well. Consumers, particularly less affluent ones, are willing to travel significantly farther to shop at club stores than traditional grocers. This willingness to travel, along with additional, format-specific tastes, implies that the degree of cross-format competition in grocery markets is much larger than previously believed. This has direct implications for merger policy since, due to their more limited product selection, "club stores are typically not considered important substitutes to supermarkets by antitrust agencies in evaluating supermarket mergers" (Hosken et al., 2012). Our analysis suggests that this is a mistake, as club stores now compete on relatively equal footing with conventional supermarkets. More broadly, the model and associated competition measures serve to illustrate how particular firms segment the market, and which chains face the toughest competition from rivals, both within and across store formats. These patterns provide additional face validity for the framework's power in evaluating changes in market structure.

We then illustrate how our approach can inform antitrust policy directly, by examining two high-profile mergers. First, we revisit the aforementioned Whole Foods and Wild Oats case, which was challenged (and later approved) in 2007. We then consider another merger, between Delhaize and Ahold, that was recently proposed and is currently under review. Our analysis reveals that the grocery industry contains many submarkets and competition is indeed localized. Chains of the same format compete more strongly, but chains that target specific income segments are able to compete in relatively distinct niches. However, there remains substantial overlap, with traditional grocery stores attracting a diverse set of customers, and competing intensively with most stores in their local catchment area. Consistent with this latter point, we find evidence supporting 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 finding is driven by the high degree of substitution between premium organic firms and conventional supermarkets for most consumers. Due to this substitution, we find that only a tiny fraction of the tracts in which Whole Foods and Wild Oats overlapped should have raised antitrust concerns.

On the other hand, our store choice model also reveals strong cross-format competition from supercenters and club stores, which has important implications for the second merger we consider. It is now well-known that Wal-Mart has become a dominant force in the grocery industry. Not surprisingly, it exhibits the highest diversion ratio for 7 of the 30 supermarket chains we consider. However, we also find that club stores represent significant competitors to traditional grocers, due in large part to consumers' greater willingness to travel to them. We illustrate the importance of including clubs in the market by comparing the combined position of the two merging chains (Ahold and Delhaize) both with and without including club stores in the analysis. We find that the number of tracts where the thresholds provided in merger guidelines would raise anti-trust concerns is over 20 percent higher when clubs are ignored. This finding is intuitive, as 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. Turning to the analysis of diversion ratios, we find the exercise of market power to be more of a concern for Delhaize stores than for Ahold's. Moreover, since the Delhaize stores are more often located in remote and under-served locations, the raises additional concerns regarding access to affordable food.

While we consider our primary contributions to be in the area of antitrust, our store-choice model is also a natural input for a structural model of static or dynamic entry, where it might be used to evaluate zoning restrictions, entry subsidies or to aid in a firm's choice over where to locate. Finally, we note that our findings add to a recent literature on the importance of accounting for competition from new channels in retail markets, in this case the growing segment of supercenters and club stores (e.g., Hausman and Leibtag, 2007; Hortaçsu and Syverson, 2015).[5]

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 presents several elasticities and measures of competition that can be used to assess competitive effects. In section 4, we describe the data used in our empirical analysis and provides some background on the industry. Then in section 5, we discuss the empirical results, highlighting the ability of our framework to capture rich substitution patterns between firms. In section 6, we use our estimates to explore the impact of two high-profile mergers. Section 7 concludes.

2 Model

We develop a simple framework for analyzing competition between spatially differentiated, multi-product retailers. The emphasis on simplicity reflects our desire to see this method utilized as a tool for merger analysis and has three practical implications. First, we do not include price data in our model of store choice. Because supermarkets (and retail outlets more broadly) set prices for thousands of products, any price index used to model store-level demand is clearly an approximation. Recent work has emphasized the fact that, when different consumers purchase distinct baskets of goods (due to heterogeneous tastes), a one-size-fits-all price index is likely to provide an inadequate representation (Handbury, 2013). In lieu of prices, we include chain-level fixed effects in consumer utility that also vary with income. If the bulk of price and assortment variation is across rather than within chains — a reasonable assumption in our context,

[5] 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 by $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".

given the presence of firms as varied as Costco, Aldi, Whole Foods, and Kroger — these chain effects will capture the most important elements of firms' pricing differences (and how they differ over consumers).

Second, we do not specify a complete model of demand and supply, which would be necessary to conduct a full-fledged merger simulation, as in Nevo (2001). While clearly a simplification, the advantage lies in not requiring us to assume a particular model of conduct, or even to define the strategy space of firms. Instead, our framework provides direct measures of concentration changes and diversion ratios between merging parties. The former have been commonly used in merger analyses while the latter are the key inputs to the measures of upward pricing pressure that are used to quantify unilateral effects (e.g., Werden, 1996; Farrell and Shapiro, 2010a; Jaffe and Weyl, 2013).[6]

Third, we will not incorporate random coefficients (e.g. Berry et al. (1995)) — which capture unobserved heterogeneity in consumer tastes for product characteristics — into our store choice model, but instead rely on observed heterogeneity tied to consumer locations. While extremely powerful for generating rich substitution patterns, random coefficient demand models are challenging to estimate and typically infeasible to implement at the screening stage.[7] Moreover, by incorporating the joint geographic and income distribution of consumers, and allowing for closer competition between firms of the same format (via a generalized extreme value distributional assumption), we are able to flexibly estimate substitution patterns with a model that is relatively simple to estimate by non-linear least squares.

Our approach builds upon and extends the method proposed by Holmes (2011) to model revenue generation at Wal-Mart outlets both by incorporating competition and by including the full set of rival firms.[8] Consumers allocate grocery expenditure across a choice set of nearby stores, along with an outside good—which we take to be food purchases outside of nearby grocery or club stores (e.g., food purchases at restaurants, online grocers, convenience 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 purchasing groceries at that chain's stores. Consumers are heterogenous, differentiated most clearly by location and income.[9] As location is a primary driver of store choice, a consumer's utility for shopping at a

[6]We view our approach as consistent with principles laid out in the 2010 Merger Guidelines (U.S. Department of Justice and Federal Trade Commission, 2010):

> Diagnosing unilateral price effects based on the value of diverted sales need not rely on market definition or the calculation of market shares and concentration. The agencies rely much more on the value of diverted sales than on the level of HHI for diagnosing unilateral price effects in markets with differentiated sales. If the value of diverted sales is proportionately small, significant unilateral price effects are unlikely.
>
> Where sufficient data are available the agencies may construct economic models designed to quantify the unilateral price effects resulting from the merger. . . The Agencies do not treat merger simulation as conclusive in itself, and they place more weight on whether their merger simulations consistently predict substantial price increases than on precise prediction of any simulation.

[7]Some practical difficulties of working with these models are summarized in Knittel and Metaxoglou (2014).

[8]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.

[9]While our specification also allows consumers to be heterogeneous in household size, the framework can easily be extended

given store depends on their distance to it. Income impacts consumer spending in two ways, first through the overall budget allocated to groceries and second through the stores they choose to visit. This enables 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.

The remainder of this section presents the model and discusses the identification of its parameters. Section 3 uses the model to derive several measures of competition from the model that should be of direct interest to regulators, policy makers and academics.

2.1 Consumer Expenditure

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 tract-level demographic data drawn from the 2010 US Census, together with a model of consumer expenditure. Census tracts provide a very fine spatial disaggregation of consumers; there are over 70 thousand tracts in the United States containing roughly four to five thousand people each.[10] To model individual consumer expenditures, we assume the existence of a representative household in each census tract, indexing consumers according to the tract t in which they reside.[11] Consumers are thus endowed with a location (the tract centroid) and a vector of characteristics z_t (e.g. income) which affect their utility for groceries. 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 a choice set of nearby stores that are themselves endowed with a location and a vector of characteristics x_s (such as the size and chain affiliation of the store), as well as the outside good.

Each consumer makes a continuum of purchasing decisions to allocate their budget across stores. For

to other dimensions of consumer heterogeneity as well.

[10]Our analysis focuses on stores and consumers located in U.S. Metropolitan Statistical Areas (MSAs). Additional information regarding the data used in our analysis is provided in section 4.

[11]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.

each unit of expenditure i, a consumer in tract t's utility for spending at store s is,

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

The consumer's baseline utility for expenditure at store s is u_{st}, which is a function of the distance d_{st} from the centroid of the tract where the consumer lives to store s, as well as store characteristics x_s and tract-level consumer demographics z_t. Each purchase decision is subject to an idiosyncratic preference shock, ε_{sit}, that follows a Generalized Extreme Value (GEV) distribution with nesting structure described below.[12] 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, individuals are allowed to differ in tastes for distance and other characteristics though heterogeneity in the consumer's (tract-level) demographic variables z_t. This allows the utility of different store characteristics (including format type) to vary across observable consumer characteristics such as income.

Notably, we also include chain affiliation in x_s, thereby capturing *unobserved* characteristics of particular national chains such as assortment and price. Since we do not observe either prices or the actual set of products on offer, the chain affiliation of the store represents 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 low-price, limited-assortment grocery stores that cater to price sensitive consumers, while others may position themselves as "boutique" grocers that offer expensive, high-end organic products to a wealthier clientele. Alternatively, many "conventional" supermarket chains elect 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) 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.[13] Incorporating chain effects also accounts for the fact that the basket of goods received 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

[12] Note that this is equivalent to assuming a continuum of consumers within each tract who each consume a single unit of groceries and are differentiated only via the GEV shock.

[13] 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. Using store-level data from IRI, Nakamura (2008) finds that the vast majority (65 percent) of variation in overall price levels is attributable to variation at the level of a given chain, while only 16 percent is tied to the individual store. 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 homogeneity in chain policies, we do not take this approach in this paper.

that targets the urban poor). Moreover, by interacting these chain identifiers with consumer characteristics (e.g. income), we allow the utility tradeoff between expenditures at, say Aldi and Whole Foods, to vary across consumers.

Finally, a consumer's utility from 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 vicinity,

$$u_{0ti} = \lambda_0 w_t + \lambda_1 w_t z_t + \varepsilon_{0ti}. \tag{2}$$

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, $C_t = \{s : d_{ts} \leq D\} \cup 0$.[14] To allow for stronger competition between stores of similar format (e.g., supercenters, club stores, etc.) we organize all chains into K nests and allow ε_{sti} to be correlated across stores in the same nest. Similar formats offer more uniform retail experiences and therefore may compete more intensely within rather than across format, even after controlling for store characteristics. The nested GEV framework is able to capture this through correlation in ε_{sti} between stores of the same format (i.e., within the same nest). Let $0 \leq \mu_k \leq 1$ be the parameter that governs this correlation, where $\mu_k = 1$ represents independent shocks within nest k (the multinomial logit case) and $\mu_k = 0$ represents perfect correlation of ε_{sti} within nest.[15]

By integrating over the GEV shock, we can derive the share of their grocery budget that consumers in tract t spend at store s as a function of the parameter vector, $\theta = (\tau, \gamma, \lambda, \beta, \mu)$. Let $C_{t,k}$ be all the stores in the choice set of tract t belonging to nest k and $k(s)$ be the nest to which store s belongs. Next, define $C_{t,k(s)} = \{q \in C_t : k(s) = k(q)\}$ as the set of stores in the choice set of tract t that are in the same nest as store s. Finally, let ι_{ti} be the store in which consumer type t spends expenditure unit i. The share of spending at store s, as a fraction of all spending in tract t, can be decomposed into aggregate expenditure on nest $k(s)$ and the expenditure of store s as a proportion of all expenditure within $k(s)$,

$$p_{st}(\theta) \equiv \Pr(\iota_{ti} = s) = \Pr(\iota_{ti} \in C_{t,k(s)}) \Pr(\iota_{ti} = s | \iota_{ti} \in C_{t,k(s)}).$$

Given our distributional assumption, the share of expenditure on stores in $C_{t,k(s)}$ (e.g. any club store close

[14]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.

[15]We assume that the outside good belongs to its own distinct nest, so that ε_{0ti} is independent of all other GEV shocks. Without loss of generality, we normalize $\mu_0 = 1$.

to tract t) is

$$\Pr(\iota_{ti} \in C_{t,k(s)}) = \frac{\left(\sum\limits_{q \in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}\right)^{\mu_{k(s)}}}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q \in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}},$$

where u_{st} is the baseline utility that consumers in tract t obtain from visiting store s (a function of model parameters defined above). The probability of choosing a particular store s from the options included in $C_{t,k(s)}$ (e.g. a Sam's Club near t) is then

$$\Pr\left(\iota_{ti} = s | \iota_{ti} \in C_{t,k(s)}\right) = \frac{e^{u_{st}/\mu_{k(s)}}}{\sum\limits_{q \in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}}.$$

Finally, the unconditional share is given by

$$p_{st}(\theta) = \frac{e^{u_{st}/\mu_{k(s)}}\left(\sum\limits_{q \in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}\right)^{\mu_{k(s)}-1}}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q \in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}}. \tag{3}$$

In principle, we could allow for additional dimensions of unobserved heterogeneity that 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 observed heterogeneity and, as we will demonstrate later, yields rich substitution patterns across chains already, while retaining a simpler analytical structure.[16]

2.2 Store Revenues and Estimation

To connect consumer demographics and store characteristics to store revenues, we aggregate over the implied 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,

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

[16]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 in accommodating rich substitution patters suggests there is little to gain from this approach. The current approach has the added benefit of being directly tied to observable demographic variables.

where inc_t is per capita income in tract t and n_t is the total population residing in tract t. The final model parameter, α, captures the proportion of income that consumers allocate to total grocery expenditures (including the outside good).[17] 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 the choice set. A notable aspect of this modeling approach is that it does not impose ad-hoc geographic market boundaries. Instead, each store is located at the center of its own catchment area. Stores located nearby one another will have catchment areas that substantially overlap. As a result they will exert a stronger competitive effect on each other than stores that are further away, and will compete most intensely for 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 which is independent of the exogenous variables and across stores,[18]

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

where (θ_0, α_0) are the true parameters and η_s is the store-level measurement shock.[19] Given these assumptions, the parameters can be estimated via nonlinear least squares,

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

It is straightforward to show that this estimator is consistent and asymptotically normal, with the standard variance-covariance matrix implied by the nonlinear least squares objective function.

[17] While α is assumed to be constant for all consumers, our utility specification includes controls for consumer income which captures the fact that higher-income consumers are more likely to choose the outside good and hence spend a smaller proportion of their income in grocery and club stores.

[18] We have also estimated the model assuming that the measurement error enters via an additive shock; the qualitative results of both approaches are similar. We can relax the assumption that η_s is independent across stores as long as the dependence declines sufficiently fast as the distance between stores increases.

[19] Note that this is not a true structural error and, as such, we assume that firms do not condition their choices on its realized value (or even acknowledge its existence). In this sense, it is similar in spirit to the stochastic structure proposed by Pakes et al. (2015).

2.3 Identification

Having described 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. Identification of the model parameters comes from observing geographic variation in population demographics, store locations, and store revenues. We begin by assuming that ϵ_{its} and η_s are independent of stores' residential 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 the 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 prices for several tens of thousands of products per store, and it seems unrealistic to believe that consumers calculate store level price indices for each outlet. Instead, it's more likely that they have a rough perception of the price differences across *chains* and use this as a heuristic in selecting their primary 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, while also economizing on menu costs. This suggests that it is not efficient for chains to set policies at the level of the individual store. 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.[20] This latter variation is captured in our framework via the chain fixed effects.

Turning now to the identification of specific parameters, we focus first on α, the proportion of overall income allocated to grocery expenditures. 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 limit, α is simply the ratio of total revenue of all stores to the total income of the associated 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 while holding regional income fixed. This identifies the share of

[20] Analyzing store-level price data drawn from the IRI marketing dataset (Bronnenberg et al., 2008), which includes a random sample of roughly 10% of the supermarkets operating in the U.S., Gagnon and Lopez-Salido (2014) conclude that "the strong synchronization across stores in the level of prices and the timing of their adjustment indicates that stores play a relatively minor role in the determination of prices." Nakamura (2008) finds similar results using data from AC Nielsen.

the outside good so that the overall market size is known and can be used to identify 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.[21] For example, consider the impact of distance on store choice. Varying the distance between a tract and a store alters the share of expenditures 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. Finally, the nesting parameters of the model are identified through variation in the number and location of stores within versus across nests.

3 Analyzing the Retail Landscape

They key factor determining the value of our framework to merger analysis is its ability to deliver rich substitution patterns that can credibly identify the extent to which grocery competition is localized, both geographically and by firm and format type. In this section, we show how to compute several statistics that can reveal the impact of distance and demographics on the revenue of each firm. In section 5, we will use these statics to assess the model's performance. To aid in interpretation, we present a variety of elasticity measures, as well as the diversion ratios that are needed to compute measures of upward pricing pressure. We also provide several localized, share-based measures of concentration that can be directly compared to the 2010 Merger Guidelines' critical thresholds.

3.1 Demographic Effects

While the model parameters provide some insight into how consumers view different chains and value different store characteristics, it is easier to see how consumer demographics influence store revenues using various elasticities. With our model, we can directly compute the revenue elasticity of a single store with respect to the distance to or income of an individual tract.[22] For example, the distance elasticity for revenue at store

[21] 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 fixing the utility of the outside good (conditional on demographics). 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.

[22] We illustrate how to compute elasticities of revenue by focusing on distance, although a similar calculation could be carried out on other demographic or store features.

s from tract t is,[23]

$$\eta_{st} = \frac{\partial R_{st}}{\partial d_{st}} \frac{d_{st}}{R_{st}} = d_{st}(\tau_0 + \tau_1 z_t) \left(\frac{1}{\mu_{k(s)}} + \left(1 - \frac{1}{\mu_{k(s)}} \right) p_{st|k} - p_{st} \right). \tag{6}$$

Here $p_{st} = p_{st}(\theta)$ and $p_{st|k} = \Pr\left(\iota_{ti} = s | \iota_{ti} \in C_{t,k(s)}\right)$ are the probability of a consumer in tract t visiting store s unconditional on nest and conditional on choosing a store in nest $k(s)$, respectively.

To construct a measure of how chain-level revenue responds to increasing the distance to consumers, say by building additional stores in the remote suburbs, 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, $\eta^f = \sum_{s \in F_f} \eta_s \frac{R_s}{R^f}$, where F_f represents the set of stores that belong to chain f and R^f is total revenue for that chain. The resulting elasticities are best understood as marginal effects that establish the importance of distance to store profits, given the current configuration of stores and the estimated parameter values.

While most store and tract characteristics enter the model in a way that is analogous to distance (and therefore do not require separate derivations), the role of income is slightly more complicated. When income rises, there are two distinct effects on store revenues. First, consumers have more money to spend on food. Second, because income affects tastes for different stores differently, consumers substitute between stores and the outside good in distinct ways—these effects are captured by the inclusion of income in the tract-level demographic vector z_t. Overall, the store-tract level revenue elasticity with respect to the income of tract t is

$$\nu_{st} = 1 + \sum_{q \in C_t \setminus 0} (\tau_1 d_{qt} + \gamma_1 x_q) \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}} \right) p_{qt|k} - p_{qt} \right) - \lambda_1 w_t p_{0t}. \tag{7}$$

The first term reflects the fact that a 1 percent increase in income generates a 1 percent increase in all consumers' grocery budgets (by our proportionality assumption). The second term captures the own and cross substitution across stores due changes in income. Cross-substitution, is stronger when competing stores are in the same nest. The final term reflects the change in the appeal of the outside good due to changes in income. As 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, $\nu^f = \sum_{s \in F_f} \nu_s \frac{R_s}{R^f}$.

[23] The derivations for all elasticities shown in the text are provided in Appendix A.

3.2 Competitive Semi-Elasticities and Diversion Ratios

Identifying the degree of buyer substitution is critical to antitrust analysis as it determines the merging firm's incentives to internalize demand externalities. Note that, since our model does not include prices, we cannot calculate price elasticities between firms directly. However, we can construct semi-elasticities based on a differential improvement in the 'utility' offered by a particular store.[24] These semi-elasticities represent the change in revenue at store s due to a differential improvement in the utility of store q that is uniform across all consumers (i.e. increasing the level of a pure vertical characteristic). Intuitively, they reveal the degree to which firms compete for the same consumers, as well as the overall intensity of competition in the industry. The semi-elasticity of store s with respect to store q is,

$$\sigma_{s,q} = \frac{1}{R_s} \sum_{t \in L_s} R_{st} \sum_{q \in C_t} \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right), \tag{8}$$

As with the distance and income elasticities, semi-elasticities easily aggregate up to the chain level. The semi-elasticity for a chain f with respect to chain g is the percent decrease in revenue at f due to a differential improvement in the utility of all stores of chain g, and is given by

$$\sigma^{f,g} = \frac{1}{R^f} \sum_{s \in F_f} \sum_{t \in L_s} R_{st} \sum_{q \in F_g \cap C_t} \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right), \tag{9}$$

where R^f represents the total revenue for chain f and F_f and F_g are the set of stores that belong to chains f and g respectively. Recall that L_s is the set of tracts with store s in their choice set and that C_t is the choice set of consumers who live in tract t.

Note that at both the store and chain level, the semi-elasticities feature a symmetry property whereby the sum of $\sigma_{s,q}$ ($\sigma^{f,g}$) across all competing stores (chains) and the outside good exactly equals the own semi-elasticity $\sigma_{s,s}$ ($\sigma_{f,f}$). 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 either other chains or the outside share. As a result, we can define the store and chain level diversion ratios for each store (chain) as the proportion of increased revenue from an improvement

[24] Such an improvement represents a change in 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.

in the utility offered by store s (chain f) that is diverted from store q (chain j),[25]

$$D_{s,q} = \frac{\sigma_{s,q}}{\sigma_{s,s}} \qquad\qquad D^{f,g} = \frac{\sigma^{f,g}}{\sigma^{f,f}}$$

Because we do not observe prices, the diversion ratio we define is the ratio of revenue derivatives with respect to utility. Note that this is identical to the common definition of diversion ratios (namely the ratio of derivatives with respect to price) if consumers have homogeneous, quasi-linear utility for price. In a more complex model in which consumers price sensitivities are heterogeneous (e.g., a demand model with a random coefficient on prices), our diversion ratio will weight consumers *uniformly*, while a price-focused diversion ratio would weight them according to their marginal dis-utility of price.[26] While this could be viewed as a drawback if regulators are focused on price alone as the central single strategic variable of interest, it may instead be a feature in environments in which the strategic response to a merger is multi-dimensional—e.g., a store may raise/lower prices, expand/reduce product offerings, improve/degrade customer service or do such things in combination.[27] In that case, a single diversion ratio which places uniform weights on consumers might be preferred to separate diversion ratios focusing on different strategic responses.

The diversion ratio also reveals which chains are 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 determined by the *characteristics* of the stores and their affiliated chains, as well as their formats - similar chains will compete more closely with one another since they will both have high market shares in the same set of tracts.

3.3 Localized Concentration Measures

Concentration measures are commonly used by antitrust authorities to assess market power. Indeed, the 2010 merger guidelines explicitly list levels and changes in market concentration that might lead regulators to more closely scrutinize a proposed merger. The typical concentration measure is based on constructing the Herfindahl-Hirschman Index (HHI) from market shares of firms belonging to a pre-specified antitrust market. Baker (2007) succintly notes that "throughout the history of U.S. antitrust litigation, the outcome of more

[25]Note that this formula makes use of symmetry in the derivatives of the nested logit shares with respect to utilities, i.e., $\partial p_{st}/\partial u_{qt} = \partial p_{qt}/\partial u_{st}$.

[26]It is important to note that this assumption is also needed in order to approximate diversion ratios using ratios of market shares, as is sometimes suggested (Farrell and Shapiro, 2010a).

[27]For example, in his study of the impact of Wal-Mart's entry on grocery competition, Matsa (2011) found that incumbent firms responded by raising quality, rather than adjusting price.

cases has surely turned on market definition than on any other substantive issue." As a result, the market definition—what firms or stores are included in the HHI calculation—can be highly controversial. The model proposed here effectively solves this problem by defining markets around consumers (and their choice set) rather than firms (and their locations), and allowing the data to reveal the true extent of concentration over space. This is in line with Dennis Carlton's suggestion that the Guidelines "revise its approach to geographic market determination, shifting the focus of the analysis from one using supplier locations as a starting point to one based on the competitive alternatives faced by consumers at different geographic locations" (Carlton, 2010).

In particular, *for every census tract*, the model estimates the total revenue originating from that tract that accrues to each store in it's vicinity. Using these predictions, we construct tract-level Herfindhal-Hirschman indices (HHIs) to measure market concentration,

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

Rather than using an arbitrary geographic demarcation to define what stores to include in the market, these tract-level concentration indices can reveal how revenue is partitioned at a particular tract, yielding extremely localized measures of concentration. Moreover, because tract-level expenditures condition on tract-level demographics like income, our method also accounts for rich substitution patterns that are lost when aggregating store revenues to larger markets, such as MSAs. By centering the concentration measure on the consumer, rather than the stores, we avoid the need to make ad hoc decisions regarding which stores competes with whom, since these relationships are estimated within the store-choice model itself.

One issue with our tract-level HHI is that the same store serves multiple tracts, so even though HHI_t makes it clear that consumers in tract t reside in a concentrated retail environment, it is not clear whether a store that sells in s should be regarded as serving a concentrated market. To address this point, we can also construct a store-level concentration measure based on aggregating the tracts in the store's catchment area,

$$SHHI_s = \sum_{t \in L_s} \frac{R_{st}}{R_s} HHI_t. \tag{10}$$

The intuition behind this approach is straightforward, it simply weights each tract-level concentration by it's contribution to the store's total revenue. Note that a high $SSHI_t$ is a measure of concentration in the geographic and retail space centered on store s, not necessarily of the market power of store s itself. It is quite possible for a store with a small market share within its catchment area to be located in a concentrated area, particularly if it competes with a much stronger competitor. Getting at these more nuanced effects requires the diversion ratios discussed earlier.

3.4 Merger Analysis

We now turn to how the model can be used to screen potential mergers. Our goal is not necessarily to predict the specific outcome of a merger, but rather to provide guidance and tests as to whether a potential merger warrants further investigation. To that end, the 2010 Merger Guidelines provide input regarding how regulators view changes in concentration arising from proposed mergers (U.S. Department of Justice and Federal Trade Commission, 2010). According to the Guidelines, 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.[28] Mergers that raise the HHI by more than 100 points, and result 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." This evaluation can be directly applied to changes in either the tract-level or store-level concentration ratios provided above as a result of the merger. These tests could then aim to identify consumer groups who are likely to be adversely affected, and the stores that should be the focus of further analysis.

Recent work has argued that the impact of a merger can be directly related to upward pricing pressure, which can better account for head-to-head competition between merging parties than changes in market-wide concentration ratios (Werden, 1996; Farrell and Shapiro, 2010a). While we believe the localized concentration measures of this paper alleviate some of the concerns over applying HHI-based tests to evaluate mergers, our model can also assess the impact of mergers using store-level diversion ratios. In particular, if any efficiency gains arising from the merger are ignored,[29] the upward pricing pressure for store s merging with chain g is,[30]

$$UPP_s = \mu_q \sum_{q \in F_g} D_{s,q}$$

where μ_q is the pre-merger margin of store s and $D_{s,q}$ is the diversion ratio of store q with respect to store s. While μ_q is not identified by our model, it can often be approximated based on firm disclosures or industry reports. On the other hand, our model provides a precise, localized estimate of the diversion

[28] HHIs under 1,500 are considered un-concentrated and presumably competitive.

[29] The basic measure of UPP proposed by Farrell and Shapiro (2010a) is $D_{12}(P_2 - C_2) - EC_1$, where $(P_2 - C_2)$ is the pre-merger markup of product 2, D_{12} is the diversion ratio from product 1 to 2, and EC_1 is the efficiency gain accruing to product 1.

[30] The intuition for upward pricing pressure is discussed in detail in Werden (1996), Farrell and Shapiro (2010a), and Conlon and Mortimer (2013). Very briefly, it represents the additional terms that appear in a pricing first order condition for store s as a result of the merger, those that determine the impact of internalizing store s's pricing effect on the competing stores owned by the merging party. An analogous expression can be derived for non-price strategic variables as well. It is very simple to incorporate hypothetical efficiency gains into this measure, but we do not do so since measuring these gains is outside the scope of this paper.

ratio, which captures the closeness of competition between the merging parties, accounting for store and firm characteristics as well as geographic proximity of the competing stores. In the analysis presented in Section 6, we evaluate the impact of mergers based on the summation of store-level diversion ratios, though a full analysis could easily augment this with information on margins. In addition, we provide a side-by-side comparison of concentration-based and diversion-ratio-based metrics of two different mergers.

4 Data and Industry Background

For our empirical application, data on grocery revenues, locations, store features, and chain characteristics are drawn from the Trade Dimensions TDLinx dataset for calendar year 2006. Trade Dimensions collects information on every supermarket, supercenter,[31] 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.[32] 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.[33] 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.

Geographically, we focus on stores that are located within Metropolitan Statistical Areas (MSAs), excluding the 8 MSAs in the New York metro area.[34] Census tract information on population, per capita income, and average household size is drawn from the 2010 US Census, which also provides the precise location of the population weighted tract centroid.[35]

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

[31]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.

[32]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 what are effectively 'independent submarkets' (Ellickson, 2006).

[33]While the use of imputed data on store revenue is clearly not ideal, the TDLinx dataset is used by government agencies, academic researchers and the firms themselves to analyze competition and forecast demand. With the continuing growth of 'big data', we expect the quality and coverage of such data to increase with time.

[34]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. The reason for excluding the New York metro area is that these represent very dense markets that 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%).

[35]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.

those that operate more than 100 stores across all MSAs. We also include data on club stores, treating them as a special category.[36] In addition to groceries, clubs also carry a variety of additional consumer products such as electronics, clothing, prescription medication and eye wear. They offer larger pack sizes, typically at a reduced per unit cost, and appeal to suburban consumers with ample storage space. 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, supercenters, and club stores). Across all store types, the average outlet sells roughly \$20 million in groceries per year (\$391 thousand per week), with the largest stores topping out at over \$100 million. In terms of selling area, the average store includes just over 35 thousand square feet of floor space, while the average supercenter is 65 thousand square feet. Club stores are even larger and correspondingly generate the largest sales volumes.[37] Finally, both size and sales volume display sizable 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.[38] Having additional employees may reduce stock-outs or improve the customer service of the store (Matsa, 2011), while more checkouts allow faster service.

Most grocery stores are part of a regional or national chain. Summary statistics on chains are presented in Table 2. Though the average chain operates 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. Although we include all firms in our estimation, we focus our analysis on the three dominant firm types: large grocery chains (which operate almost half of total stores), supercenters, and clubs.

[36] Club stores are retail formats that require consumers to pay a membership fee to shop at the store and offer most items in bulk quantities.

[37] 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 meat and fish counters. 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.

[38] Note, Trade Dimensions collects, but did not provide, information on employees and checkouts for club stores as well. As such, we are forced to exclude these covariates from the utility function for club stores. We will evaluate robustness to the exclusion of these covariates for all stores when we discuss the results from the full model in section 5.

Table 1: Store Characteristics by Type of Chain

	Mean	St. Dev.	1st Quartile	Median	3rd Quartile
Small and Medium Grocery Chains					
39.02 % of all MSA stores, 18.16 % of MSA Revenue					
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
Revenue Per Square Feet	9.71	9.82	5.65	7.56	10.36
Large Grocery Chains					
49.87 % of all MSA stores, 47.17 % of MSA Revenue					
Store Size in 1000 sqft	36.74	15.51	25	37	48
Store Weekly Volume in 1000s	370.45	219.45	200	350	500
Full Time Employee Equivalents	69.34	43.61	37	64	93
Checkouts	9.56	3.96	7	9	11
Revenue Per Square Feet	10.46	5.72	6.67	9.29	12.50
Supercenters					
7.06 % of all MSA stores, 17.88 % of MSA Revenue					
Store Size in 1000 sqft	64.18	9.68	60	68	70
Store Weekly Volume in 1000s	991.51	333.48	725	1,025	1,225
Full Time Employee Equivalents	337.52	123.81	278	342	408
Checkouts	27.97	6.27	25	30	32
Revenue Per Square Feet	15.29	4.20	12.50	15.48	18.12
Club Stores					
4.03 % of all MSA stores, 16.76 % of MSA Revenue					
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
Revenue Per Square Feet	12.96	5.54	8.86	11.84	15.53
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
Revenue Per Square Feet	10.61	7.65	6.36	9.00	12.75

Though supercenters and clubs represent a smaller number of overall stores, their much higher per-store sales volume makes them significant players in the industry. Interestingly, despite occupying substantially different footprints, revenue per square feet is comparable across large chains, supercenters and club stores. All of these firms have much higher revenue per square feet than smaller chains, which operate much smaller *stores* on average. The top 4 chains each operate over 1000 stores. The largest of these is Wal-Mart—a national supercenter chain—which operates 1385 stores across 247 MSAs.

Since our primary goal lies in understanding local competition between the three dominant firm types, it is useful to highlight the characteristics of this set alone. Table 3 provides summary statistics for large grocery chains, supercenters and club stores. Wal-Mart is by far the largest player, both in terms of number of stores and average sales. The other two supercenter chains—Meijer and Target—are much smaller, although they still operate in more MSAs (and of course, operate larger stores) than most of the major grocery chains. Wal-Mart operates the largest (non-club) stores, due to both its large-scale supercenter format and the relatively

Table 2: Chain Characteristics by Type

	Mean	St. Dev.	1st Quartile	Median	3rd Quartile
Medium Grocery Chains					
13.91 % of all MSA stores, 9.92 % of MSA Revenue					
Number of Stores	24.50	20.03	12	17	28
Number of MSA operating	4.83	5.68	1	3	6
Large Grocery Chains					
49.87 % of all MSA stores, , 47.17 % of MSA Revenue					
Number of Stores	400.93	451.08	125	189.50	510
Number of MSA operating	34.70	36.41	12	17	46
Supercenters					
7.06 % of all MSA stores, 17.88 % of MSA Revenue					
Number of Stores	568	707.54	159	160	1,385
Number of MSA operating	107	121.74	26	48	247
Club Stores					
4.03 % of all MSA stores, 16.76 % of MSA Revenue					
Number of Stores	324.33	209.32	122	311	540
Number of MSA operating	113.67	97.44	36	82	223

young vintage of its store portfolio.[39] The set of large firms also includes the low-end limited-assortment chains Aldi and Save A Lot, mid-tier chains like Food Lion and Kroger, as well as more upscale grocers like Publix and Safeway. Notably, there is a large amount of variation both across and within firms in the distribution of store sizes and store level revenues. Some firms (e.g. Food Lion) include a fairly standardized store profile, while others (e.g. HE Butt) offer a far more heterogenous set of outlets. In our empirical model, we control for chain affiliation using both a fixed effect and a slope effect (the chain fixed effect interacted with consumer income). Finally, the club stores (BJ's, Costco, and Sam's) have a dramatically different profile from the mainline supermarket segments, offering larger but fewer stores per MSA. This suggests that consumers may travel much further on average to reach clubs. 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.

Table 4 presents summary information on the included census tracts. While census tracts are intended 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 tracts. This income heterogeneity is key to our identification strategy, which exploits variation in store revenues induced by differences across stores located near high- 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 given tract, of which 34 on average 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

[39]Note that the floor size for Wal-Mart stores reflects the size of the grocery sales floor only, and does not include the mass-merchandise portion of the supercenter (the sales volume figures also reflect grocery sales alone, rather than both grocery and mass merchandise revenues).

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	134	6	22.33	257.72	8.90	32.02
Delhaize America (Food Lion)	949	55	17.25	178.73	6.28	28.69
Fred Meyer	101	12	8.42	740.10	13.42	55.23
Giant Eagle	140	11	12.73	579.29	12.82	46.70
Giant Food (Ahold)	292	14	20.86	568.60	15.42	37.96
Great A & P Tea Co.	161	11	14.64	341.02	9.98	34.97
HE Butt	227	16	14.19	813.44	16.40	51.01
Hannaford Bros (Delhaizie)	108	9	12	528.47	12.61	42.05
Hy Vee Food Stores	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 (Bi-Lo)	238	21	11.33	225.29	6.03	37.38
Publix	845	36	23.47	419.70	11.07	38.81
Raleys	127	12	10.58	428.15	9.91	43.60
Roundys	125	10	12.50	496.60	12.03	41.91
Ruddick Corp (Harris Teeter)	138	17	8.12	407.79	11.25	36.56
Safeway	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	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 (Ahold)	312	17	18.35	563.78	12.18	47.31
SuperValu	1,194	58	20.59	460.74	9.51	49.02
Trader Joes	236	37	6.38	302.22	32.66	9.45
Weis Markets	120	12	10	242.58	6.62	37.22
Whole Foods	159	47	3.38	511.79	21.12	26.99
Wild Oats	108	38	2.84	185.28	9.29	20.71
Winn-Dixie	451	36	12.53	250.78	5.54	46.27
Supercenters						
Meijer	159	26	6.12	826.10	14.11	59.56
Target	160	48	3.33	526.25	8.79	60.66
Wal Mart	1,385	247	5.61	1,064.24	16.18	65.12
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
Sam's Club	540	223	2.42	1,451.67	11.17	130.05
Total	720.18	115.27	8.63	688.70	11.71	56.61

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

5 Empirical Specification and Estimation Results

To take the model to data, we must first 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, the level of customer service, and the speed of checkout, respectively. Unfortunately, our data do 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. We also categorize stores into one of three nests: traditional grocery stores, supercenters, and clubs. As discussed above, this allows the model to capture stronger substitution between stores in the same nest.[40]

The main consumer characteristic we include is log income. Income differences are intended to capture differences in price sensitivity and the opportunity cost of time across consumers. We also account for differences in household size, but only in how they affect a consumer's taste for the outside good.[41] Since our model operates at the individual shopper level, increased household size is expected to increase consumption of the outside good, as multi-person households typically spend 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 intended 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

[40] We have experimented with alternative nesting structures, such as a separate nest for natural/organic stores however the results did not indicate significantly stronger correlation between stores in this category relative to stores outside the category.
[41] In the notation of our model, household size enters as a tract level characteristic, w_t.

the utility of the outside good to be increasing and concave.

5.1 Parameter Estimates

Model estimates for four different specifications are presented in Table 5. The first column contains our preferred baseline specification, denoted (1). Specification (2) excludes the nesting structure, restricting consumer expenditure patterns within a tract to arise from a standard multinomial logit model that exhibits the independence of irrelevant alternatives across all stores. In specification (3), we exclude club stores from the analysis, but allow grocery stores and supercenters to occupy separate nests. 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. Interestingly, the parameters that govern utility of traditional grocery stores are not strongly affected by the inclusion of club stores. However, there are substantial changes in the estimates of the outside good and the proportion of income allocated to groceries. This is intuitive, since when grocery stores are excluded from the analysis, their absence will be accounted for by either a stronger outside good, or a lower overall grocery budget. As we will demonstrate below, including club stores in the choice set also has a significant impact on substitution patterns. Finally specification (4) excludes employment and checkouts from the set of grocery store characteristics so that grocery stores and supercenters are treated symmetrically to clubs. This is meant to gauge the impact of only including these covariates only for supermarkets in specifications (1) and (2). As expected, this increases marginal utility for store size, as size is likely to be correlated with employees and checkouts per store. However, it has little impact on the estimated utility of club stores or on the nesting parameters, so we opt to focus on the richer model that utilizes all available data.

Focusing initially on the estimate of α, we find that, in our preferred specification (1), the implied overall food budget is roughly 13 percent of total income. It is closer to 11 percent in the specifications that either eliminate the nesting structure (2) or exclude club stores (3). To gauge the face validity of this estimate, we compare it to the fraction of consumer income spent on food reported in the 2012 Consumer Expenditure Survey (CEX). The 2012 CEX reveals 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, and total expenses allocated to food should fall with income. Indeed, 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).

Table 5: Parameter estimates.

	Baseline (1)	Multinomial Logit (2)	No Clubs (3)	No FTE/Checkouts (4)
Grocery Stores and Supercenters				
dist	−0.169	−0.197	−0.177	−0.177
	(0.001)	(0.001)	(0.001)	(0.001)
dist*log(inc)	−0.109	−0.144	−0.115	−0.109
	(0.002)	(0.003)	(0.002)	(0.002)
log(size)	0.151	0.207	0.153	0.399
	(0.002)	(0.003)	(0.002)	(0.002)
log(size)*log(inc)	0.131	0.173	0.107	0.273
	(0.008)	(0.010)	(0.007)	(0.005)
log(fte)	0.240	0.317	0.244	
	(0.002)	(0.002)	(0.002)	
log(fte)*log(inc)	−0.117	−0.150	−0.124	
	(0.007)	(0.009)	(0.006)	
log(chk)	0.217	0.299	0.222	
	(0.003)	(0.004)	(0.003)	
log(chk)*log(inc)	0.255	0.339	0.263	
	(0.012)	(0.014)	(0.010)	
Club Stores				
dist	−0.050	0.021		−0.051
	(0.008)	(0.006)		(0.007)
dist*log(inc)	−0.184	−0.297		−0.175
	(0.019)	(0.017)		(0.018)
log(size)	0.680	0.844		0.622
	(0.054)	(0.058)		(0.051)
log(size)*log(inc)	0.127	0.376		0.111
	(0.176)	(0.183)		(0.169)
Outside option				
hhsize	0.472	0.650	0.506	0.455
	(0.005)	(0.008)	(0.005)	(0.005)
hhsize*log(inc)	0.553	0.642	0.700	0.546
	(0.011)	(0.018)	(0.010)	(0.010)
log(density)	1.482	2.207	1.780	1.438
	(0.134)	(0.148)	(0.129)	(0.122)
log(density)^2	−0.130	−0.237	−0.226	−0.141
	(0.054)	(0.064)	(0.052)	(0.048)
$\mu_{grocery}$	0.737		0.746	0.723
	(0.020)		(0.021)	(0.018)
$\mu_{supercenters}$	0.752		0.773	0.642
	(0.056)		(0.055)	(0.052)
μ_{club}	0.785			0.762
	(0.104)			(0.099)
α	0.132	0.112	0.113	0.133
	(0.004)	(0.002)	(0.003)	(0.004)
R^2	0.840	0.836	0.812	0.807

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

Recall that our model captures this pattern through the *outside good*, the utility of which is increasing in income.[42]

The nesting parameters, μ_{format}, are all between .7 and .8 in our baseline specification and significantly

[42] Note that we use per-capita income rather than household income, since we include household size information as a covariate as well.

different from both 0 (perfect correlation within nest) and 1 (independence within nest) across all specifications that include them. The results suggest that, while stores compete more intensely within nest, substitution across nest can be strong as well. When we eliminate the nesting structure in specification (2), the model fit deteriorates only slightly (judging by R^2). However, it is clear that ignoring format heterogeneity results in a stronger outside good. These restrictions also result in substantial changes in many of the utility parameters, particularly those pertaining to club stores, and dramatically alter substitution patterns (discussed below).

While not included in Table 5 due to space considerations, we also include fixed effects for each major chain that are each interacted with income. Appendix Table B.4 reports the chain fixed effects and income interactions for every large chain and club store firm. 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. Note that the impact of increasing income on the utility of almost every chain is negative, indicating that taste for the outside good grows faster with income than the utility of almost any inside good (i.e. grocery store, supermarket or club). This pattern represents 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. However, 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 both have income coefficients that are positive or close to zero, suggesting that they tend to target a high-income clientele, consistent with the public perceptions of these firms. Sam's Club, which targets small business owners, is similar. On the other hand, the supercenter firms (Wal-Mart, Target and Meijer) are among the lowest, indicating that these stores are particularly popular among low income consumers. 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. Not surprisingly, consumers clearly prefer grocery stores to be closer to their homes, presumably reflecting the monetary and opportunity costs of travel. This is consistent with earlier studies, which have found the catchment area of a supermarket (or supercenter) to be quite narrow, on the order of two or three miles (Ellickson and Grieco, 2013; Arcidiacono et al., 2016). The disutility of distance increases with income, suggesting that the opportunity cost of time is higher for high income consumers. These estimates are quite stable across specifications. Club store revenues are much less sensitive to distance than the revenues of grocery stores, while the interaction with income is even stronger. Consumers' greater tolerance for traveling to clubs likely reflects the fact that, unlike supercenters, club stores represent a fundamentally different shopping experience.[43] In particular, consumers purchase many more

[43]We have also experimented with allowing distance disutility to differ between supercenters and grocery stores, but found

items in bulk at club stores and therefore make correspondingly fewer trips to them. In all specifications, the disutility of distance with respect to income rises nearly twice as fast for club stores as for standard grocery stores (albeit from a lower base). This suggests that, overall, club stores are targeting consumers with lower opportunity cost of time. Finally, the estimates of the distance coefficients for grocery stores barely change when we add club stores to the model—compare specification (3) to (1).

Turning now to store features, the impact of all three store characteristics—sales floor size, full-time equivalent employment, and checkouts—are positive and highly significant in all specifications. Consumers prefer larger stores, staffed with more people, that provide more checkouts. The interactions of these 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 (4) 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 checkout covariates increases the impact of store size on grocery store utility. However, even in specification (4), 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 significantly more products than a one percent increase in the size of a grocery store. While the underlying utility parameters appear to be robust to the inclusion of club stores, we will see below that their exclusion 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 substitutes. Therefore, including them in the analysis of potential grocery mergers has a significant impact on the implied change in market structure: though still quite concentrated, the industry is less concentrated than we think. We will illustrate the relevance of this fact for merger analysis in Section 6.

5.2 Demographic Effects

We now present estimates of the demographic elasticities of firms at the chain level. Unless otherwise specified, we calculate these statistics using our preferred specification (1). The estimated distance and income elasticities for each chain are presented in Table 6. 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, Harris

no significant difference between these two classes of stores. These results are available from the author by request.

Table 6: Distance and Income Elasticities Large Chains and Clubs

	Distance Elasticity	Income Elasticity
Small Chains	−1.075	0.416
Medium Chains	−1.092	0.683
Albertsons	−1.074	0.693
Aldi	−1.103	0.516
Bashas Markets	−1.090	0.662
Delhaize America (Food Lion)	−1.089	0.631
Fred Meyer	−1.116	0.851
Giant Eagle	−1.101	0.870
Giant Food	−1.218	0.514
Great A & P Tea Co.	−1.145	0.613
HE Butt	−0.972	0.779
Hannaford Bros	−1.032	0.521
Hy Vee Food Stores	−0.990	0.789
Ingles Markets	−1.070	0.657
Kroger	−1.095	0.662
Lone Star Funds (Bi-Lo)	−1.058	0.792
Publix	−1.122	0.773
Raleys	−1.005	0.481
Roundys	−1.078	0.491
Ruddick Corp (Harris Teeter)	−1.182	0.749
Safeway	−1.151	0.484
Save A Lot	−1.056	0.549
Save Mart	−0.867	0.502
Smart & Final	−1.071	0.281
Stater Bros	−1.015	0.410
Stop & Shop	−1.169	0.702
SuperValu	−1.145	0.563
Trader Joes	−1.158	0.253
Weis Markets	−1.083	0.630
Whole Foods	−1.197	0.525
Wild Oats	−1.145	0.449
Winn-Dixie	−1.031	0.731
Meijer	−0.966	0.506
Target	−1.126	0.620
Wal Mart	−0.874	0.741
BJs	−0.491	0.191
Costco	−0.585	0.509
Sam's Club	−0.386	0.413

Teeter and Giant Foods, three chains that all 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, 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, presumably 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, Save Mart, and Meijer) also have distance elasticities above -1, reflecting their relative inelasticity with respect to distance, due perhaps to their one-stop shopping appeal. These elasticity estimates are consistent with these stores seeking to exploit a large-scale, large-catchment-area strategy that 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 an impact on grocery stores that are located even several miles away from their locations. As a result, club stores may represent a viable substitute to grocery stores, even when the two outlets are not nearby.

The estimated income elasticities are presented in the final column of Table 6. The median income elasticity is 0.59, implying that a one percent increase in income will increase store revenues by .59 percent. Since all of these elasticities are below 1, we find that consumers tend to spend a smaller percentage of their income on groceries as incomes rise. This is intuitive, as the share of food budgets going to the outside good (restaurants, etc.) should increase with income. Still, though perhaps not surprising, all firms clearly benefit from an increase in per capita income. Nonetheless, there is clear heterogeneity in how much they do so, with substitution between grocery stores also being important. For example, the limited assortment model of Smart & Final, Trader Joes, and Aldi appears to become less attractive as incomes rise, leading to very modest income elasticities. Notably, Wal-Mart has one of the highest income elasticities 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. The role of distance also seems to play a role here. Our parameter estimates show that as income rises, consumers prefer to shop closer to home, so stores near population centers should benefit, *ceteris paribus*. This effect seems to benefit suburban grocery chains such as Giant Eagle, Stop & Shop, and Publix.

5.3 Competitive Effects

Table 7 presents own semi-elasticities and cross semi-elasticities for the top two competitors for each firm, as well as the firm's substitution with the outside option. Recall that these measures represent 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 $1.16\Delta\%$. 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 $.133\Delta\%$. Stated another way—owing to the symmetry property—if Albertson's improves its perceived utility in a manner that is valued equally by all consumers, 11.5 percent (.133/1.16) of its increase in revenue will be due to revenue declines at Wal-Mart, 9.5 percent will be due to declines in Safeway's revenue, and 28.4 percent will be due to increases in overall grocery spending (i.e., a decline in the outside good). The remaining 50.6 percent of the increase will be due to revenue declines at other stores. Recall that these measures are identical to the diversion ratios typically used in antitrust analysis to quantify the incentives to exploit market power by internalizing demand externalities.

Several interesting patterns emerge from Table 7. With respect to own elasticity, the largest values correspond to Whole Foods, Aldi, and Trader Joe's. 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

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	1.112	Medium Chains	-0.104	Kroger	-0.082	-0.381
Medium Chains	1.002	Wal Mart	-0.097	Small Chains	-0.086	-0.324
Albertsons	1.162	Wal Mart	-0.133	Safeway	-0.110	-0.330
Aldi	1.360	Medium Chains	-0.178	Small Chains	-0.143	-0.323
Bashas Markets	1.026	Kroger	-0.241	Safeway	-0.146	-0.257
Delhaize America (Food Lion)	1.108	Wal Mart	-0.156	Medium Chains	-0.089	-0.331
Fred Meyer	1.078	Safeway	-0.198	SuperValu	-0.135	-0.329
Giant Eagle	1.104	Small Chains	-0.155	Medium Chains	-0.129	-0.332
Giant Food	1.099	Safeway	-0.116	Small Chains	-0.088	-0.451
Great A & P Tea Co.	1.256	Small Chains	-0.164	Kroger	-0.107	-0.385
HE Butt	0.710	Wal Mart	-0.163	Sam's Club	-0.062	-0.264
Hannaford Bros	0.890	Medium Chains	-0.165	SuperValu	-0.134	-0.319
Hy Vee Food Stores	0.948	Medium Chains	-0.194	Wal Mart	-0.170	-0.283
Ingles Markets	1.121	Wal Mart	-0.172	Lone Star Funds (Bi-Lo)	-0.123	-0.298
Kroger	0.956	Wal Mart	-0.112	Medium Chains	-0.076	-0.303
Lone Star Funds (Bi-Lo)	1.152	Wal Mart	-0.226	Delhaize America (Food Lion)	-0.105	-0.298
Publix	0.909	Wal Mart	-0.137	Winn-Dixie	-0.095	-0.305
Raleys	1.058	Safeway	-0.165	Small Chains	-0.088	-0.383
Roundys	1.060	Medium Chains	-0.153	SuperValu	-0.143	-0.405
Ruddick Corp (Harris Teeter)	1.161	Delhaize America (Food Lion)	-0.192	Medium Chains	-0.120	-0.361
Safeway	1.103	Kroger	-0.104	SuperValu	-0.084	-0.409
Save A Lot	1.297	Small Chains	-0.139	Medium Chains	-0.135	-0.310
Save Mart	1.041	Small Chains	-0.140	Safeway	-0.127	-0.378
Smart & Final	1.322	Kroger	-0.155	Safeway	-0.150	-0.422
Stater Bros	1.092	Kroger	-0.161	SuperValu	-0.131	-0.376
Stop & Shop	1.033	Medium Chains	-0.166	SuperValu	-0.130	-0.402
SuperValu	1.089	Medium Chains	-0.096	Small Chains	-0.095	-0.385
Trader Joes	1.305	Safeway	-0.151	Kroger	-0.116	-0.445
Weis Markets	1.203	Giant Food	-0.286	Small Chains	-0.144	-0.362
Whole Foods	1.323	Safeway	-0.119	Kroger	-0.102	-0.473
Wild Oats	1.286	Kroger	-0.180	Safeway	-0.102	-0.363
Winn-Dixie	1.119	Publix	-0.298	Wal Mart	-0.180	-0.300
Meijer	1.018	Kroger	-0.167	Wal Mart	-0.157	-0.299
Target	1.236	Wal Mart	-0.333	Sam's Club	-0.079	-0.344
Wal Mart	0.760	Kroger	-0.069	Sam's Club	-0.064	-0.270
BJs	1.156	Sam's Club	-0.125	Costco	-0.085	-0.380
Costco	0.920	Sam's Club	-0.096	Safeway	-0.057	-0.387
Sam's Club	0.958	Wal Mart	-0.121	Costco	-0.085	-0.315

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 costly (and raising quality would require an even greater marginal investment). For Aldi or Trader Joe's, 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 would then 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 9 of the 32 other large grocery chains, and the second largest competitor of an additional 3. It is also the largest competitor for medium chains. This unique overall positioning is consistent with Wal-Mart's enormous cost advantage (Basker, 2007). 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 identical to any other large footprint supermarket chain - their main differentiating factor is price. The results indicate that, for a given quality improvement, almost two-thirds of an increase in Wal-Mart revenue is drawn from rival grocery stores and clubs, with the remaining portion representing market expansion from the outside good. In particular, its impact is strongest on either mid-tier southern chains (Food Lion, Ingles, Bi-Lo, and Winn-Dixie) or firms that also operate supercenters (HE Butt, Target). In contrast, Wal-Mart is relatively insulated from competing with any particular chain. While Kroger is it's largest competitor, a Δ improvement in Kroger's overall appeal would result in only a $.091\Delta\%$ decline in Wal-Mart revenues. On the other hand, a Δ improvement in Wal-Mart's appeal would lead to a $.117\Delta\%$ decline in Kroger's revenues and a $.230\Delta\%$ decline for HE Butt. Furthermore, Wal-Mart actually owns its second largest "rival", the Sam's Club chain of club stores. More broadly, the chains hurt least by their largest rivals are those that are generally believed 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, and Aldi). An interesting exception is Safeway, which, despite a national presence, is able to avoid significant competition with Wal-Mart or other large 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., 2016), 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. By including club stores in a separate nest from grocery stores or supercenters, we are able to estimate the degree to which they compete with each other versus other store types. The estimate of the club store nesting parameter (0.785) does suggest stronger competition between club stores than with other formats, but certainly does not rule out significant cross-substitution between clubs and grocery stores. In examining the semi-elasticities of club stores, we see that they do represent each other's major competitors. However, Sam's Club is also a major competitor of HE Butt and Target, neither of which are club stores. Notably, this outcome is starkly different from when we adopt a multinomial logit specification which restricts substitution patterns between stores. According to a multinomial logit specification, Sam's Club represents a "top two" competitor of 10 non-club chains.[44] However, even in our preferred specification, substitution between club stores and grocery stores is evident. For example, the diversion ratio of Costco to non-club stores is 46.2 percent. As we will see below, including club stores in the analysis has a substantial impact on our assessment of potential grocery mergers.

5.4 Concentration

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 thresholds above, we find that 40.1% percent of all census tracts in the dataset are highly concentrated, while another 42.6% of tracts are moderately concentrated, confirming that the supermarket industry overall is quite 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 entirely surprising given the widespread importance of scale economies in chain retailing in general, and for supermarkets in particular. In fact, Table 8 reveals that the most concentrated

[44] The multinomial logit estimates are presented in Table 5, column 3 and are equivalent to fixing all nesting parameters at 1. The semi-elasticity table for this specification is available from the authors upon request.

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

Concentration	Number of Tracts	Income	Density	Mean Number of within 5/10 miles All Stores	Large Chain Stores	Large Chains	Club Stores
Low (< 1500)	9,196	26.76	6212.01	43.42	20.27	5.35	1.20
				134.22	65.77	7.09	4.20
Moderate	22,749	30.85	3017.46	21.79	13.43	4.44	0.95
				64.28	39.85	6.11	2.83
High (> 2500)	21,423	25.65	1261.35	8.52	5.18	2.39	0.39
				22.41	13.69	3.53	0.99
Total	53,368	28.05	2862.98	20.19	11.30	3.77	0.77
				59.52	33.82	5.24	2.33

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 fall somewhere in between.

6 Prospective Merger Screening

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. Fortuitously, 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 (assuming no own or competitive response in prices or store characteristics). As noted earlier, we view this exercise as a low-cost screening mechanism for evaluating potential mergers. We simply ask whether the competitive overlap between the merging parties is sufficient to warrant further scrutiny, at which point it would be important to consider whether the firms would be likely to raise prices, what, if any, the competitive response would be, and whether there exist large enough cost synergies to offset the potential price increase. This could be accomplished by evaluating the formulas for upward pricing power (using, for example, observed margins and a rule of thumb efficiency allocation) or by running a full-fledged merger simulation. Our key contribution lies in providing a highly localized measure of overlap that makes extremely weak ex ante assumptions regarding geographic market definition or which firms should be considered in or out of the competitive set.

Supermarket mergers have traditionally played an important role in antitrust enforcement. 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.[45] 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.[46]

6.1 Tract-Level Concentration Measures

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. Focusing first on the Whole Foods/Wild Oats case, 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 its impact, we examine how it would change concentration at each of these census tracts. We use the thresholds provided in the merger guidelines to identify highly-localized merger "hot spots," namely 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.

[45]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).

[46]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 results are presented in Table 9. Notably, our analysis of the Whole Foods/Wild Oats case overwhelming sides with the defense, as *almost all* tracts (99.5%) are classified as not raising concerns. In only 28 tracts does the HHI rise by a degree sufficient enough to warrant scrutiny and none of the tracts fall into the category of enhancing market power.[47] This is mainly driven by the fact that both Whole Foods and Wild Oats compete most intensely with conventional supermarkets, rather than with each other. This result is robust to expanding the nesting structure to include Whole Foods and Wild Oats in a distinct "natural/organic" nest.[48] 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 -.005 whereas Whole Food's own semi-elasticity is 1.234, equating to a diversion ratio of only 0.4 percent. In contrast Safeway and Kroger appear to be much stronger competitors to Whole Foods, with diversion ratios ranging of 8.9 and 7.7 percent respectively.[49] 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's 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 both firms operate, 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 2.5 million people in 2010. The areas of most significant concern are in Maryland, Massachusetts and Virginia.[50] 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

[47]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 54 and lifting 2 tracts into the 'enhancing market power" (see Table B.1 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).

[48]When we estimate the model with an "organic" nest, the nesting parameter on the natural/organic segment is 0.964 (0.121). Note that this is statistically insignificantly different from 1, which corresponds to tastes for Whole Foods and Wild Oats being independent. Other parameters are qualitatively unaffected. The full results from this specification are available from the authors upon request.

[49]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.

[50]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		Presumed Likely	
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	16	41.81	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	28	96.78	0	0

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

	Both Firms Present		Warrants Scrutiny		Presumed Likely	
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	349	1729.96	131	684.34
MD	1214	4999.43	389	1785.68	150	672.94
NH	124	587.62	49	245.98	58	256.56
PA	76	361.57	9	47.43	17	91.67
RI	19	69.11	4	15.35	15	53.76
VA	577	2550.94	297	1365.45	111	514.96
WV	31	163.93	0	0	31	163.93
Total	3118	13712.08	1098	5196.30	520	2484.16

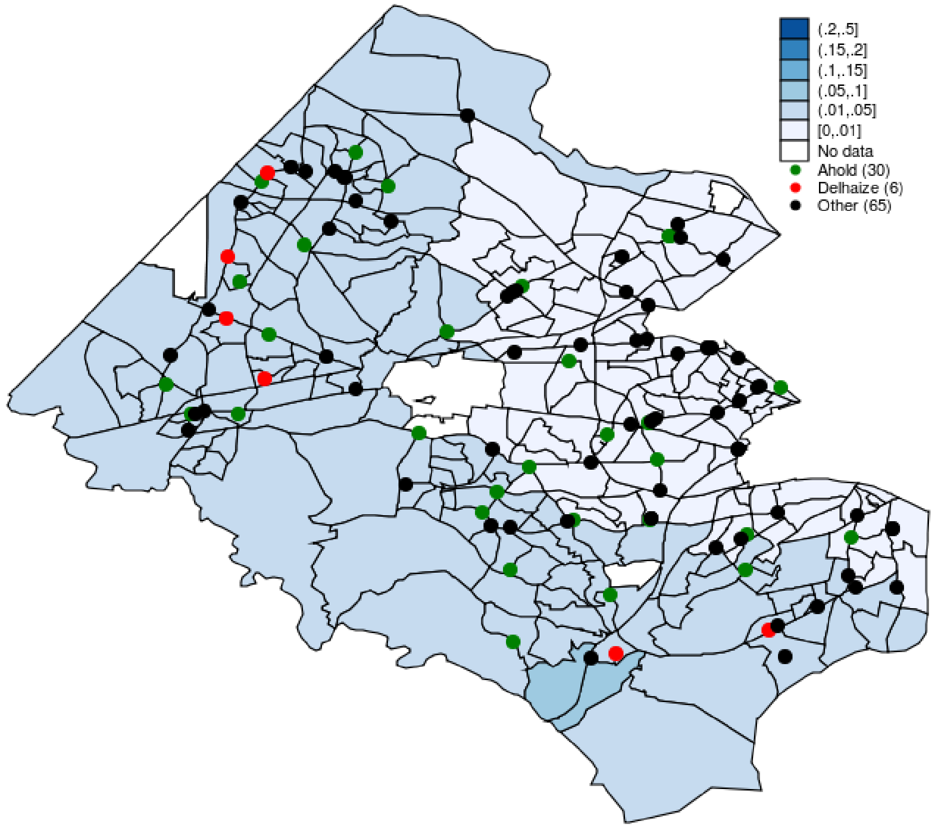

Figure 1: Post merger increases in HHI by tract: Fairfax County, VA

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 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, 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 an 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 cross the guidelines' critical thresholds, it is clear that population density alone is not the deciding factor.

6.2 Store-Level Analysis

The above analysis identifies those census tracts where the proposed merger raises concerns about market power. However, it is also useful to construct measures of merger impact that are focused on that individual stores that are party to the merger, especially since store divestitures are the typical remedy in contested

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

Population Density	No Concern	Merger Evaluation Warrant Scrutiny	Presumed Likely	Total
Low (<1500)	145	417	407	969
Medium (>1500 and <4000)	384	609	111	1104
High (>4000)	971	72	2	1045
Total	1500	1098	520	3118

mergers. We now provide two such measures. First, we consider the merging diversion ratio: the sum of the store level diversion ratio of store s to all stores in the merging chain. As discussed in Section 3.4, the diversion ratio is often viewed as the key factor in assessing unilateral effects. For both the Whole Foods/Wild Oats and the Ahold/Delhaize mergers, we calculate diversion ratios for every store in the chain. The results are reported in Table 12. The first column reports the number of stores in the chain which compete with the proposed merger partner in at least one census tract. The second column reports the average number of stores the merging partner has that compete in the initial store's catchment area.[51] Next, since there are no accepted rule-of-thumb thresholds for what constitutes a "high" diversion ratio[52], we report the number of stores where the diversion ratio with merging parties exceeds 5, 10, and 20 percent. Again, we find that the Ahold/Delhaize merger raises significantly stronger concerns regarding enhanced market power than Whole Foods/Wild Oats. Notably, we find that the merger is more likely to enhance the market power of Delhaize stores than Ahold stores, illustrating the advantage of using diversion ratios rather than just shares. More than half of the Delhaize stores which share at least one census tract with an Ahold store have a diversion ratio with Ahold of over 10 percent, while fewer than 10 percent of analogous Ahold stores have a diversion ratio this high. This asymmetry is explained by the difference in the number of competitors; Delhaizie faces almost twice as many Ahold stores in areas where they compete as vice versa.[53] Hence, the impact on Delhaizie stores of internalizing the effect of the merger is much larger, while the impact on Ahold stores, while still significant, is smaller. Since Delhaize stores are located in less dense areas (which typically have fewer fresh food options), this may be a particular concern if part of the policy concern is maintaining access to affordable food for consumers located in "food deserts".

The final two columns of Table 12 present an alternative store-level measure of merger impact: the merger guideline thresholds for HHI applied to the revenue-weighted average of the stores' tract-level HHIs using formula (10). In contrast to the diversion ratio measure, the store-level HHI does not directly measure

[51]That is, for Ahold store s that faces competition from Delhaize, there are 10.85 Delhaize stores in the choice set of tracts L_s.

[52]Since upward pricing pressure also depends on the actual margins of the acquired product(s), the relevant ratio is industry specific.

[53]We have verified that in the relevant area for the merger, Delhaize and Ahold stores have similar revenues on average.

Table 12: Store-Level Analysis of Potential Mergers

Chain	# of Competing Stores	Average # of Competitors	Diversion Ratios Div>.05	Div>0.1	Div>0.2	Concentration Warrants Scrutiny	Presumed Likely
Ahold	328	10.85	64	29	8	138	52
Delhaize	161	22.11	141	122	75	63	74
Whole Foods	69	2.92	1	0	0	2	0
Wild Oats	80	2.52	6	1	0	4	0

Notes: Each row contains information on the stores of a particular chain for whom the merger is relevant. # of Competing Stores is number of stores in the chain that compete in a tract where at least one store of the merging partner is present. Average # of Competitors is number of merger partner stores in the choice set of tracts that belong to the competing stores catchment area, L_s. "Warrant Scrutiny" and "Presumed Likely" indicate number of chain stores that would be classified as such according to the 2010 Merger Guidelines where HHI is calculated at the store level using (10).

Table 13: Comparison of Store Level Merger Evaluation and Diversion Ratios

	Div<.05	.05<Div<0.1	.1<Div<0.2	.2<Div
Ahold				
No Concern	137	1	0	0
Warrants Scrutiny	112	18	7	1
Raise Concerns	15	16	14	7
Delhaize				
No Concern	11	2	10	1
Warrants Scrutiny	5	7	19	32
Raise Concerns	4	10	18	42

the effects of the merger on a store's pricing incentives. Instead, it is best understood as the measure of concentration in the area that the store considers its relevant market. For this reason, we do not observe as much asymmetry in these measures as with the diversion ratios between Delhaize and Ahold. The merger causes increases in concentration in both Ahold and Delhaize centered-areas, although the increase in market power is stronger for Delhaize stores (who are merging with the larger party). Finally, we note that—as one would expect—the store level measures of HHI produce very similar results as the tract-level analysis from the previous section.

We next check to see whether the two measures of merger impact are identifying similar sets of stores as those on which to focus attention. As one would hope, this seems to be the case, the correlation between the diversion ratios and the change in HHI is over .75 for all chains.[54] Table 13 provides a cross-tabulation of the categorization of diversion ratios and concentration increase suggested by the Guidelines. Again, the correlation between the measures is apparent.

[54] The individual values are .88 for Ahold, .77 for Delhaizie, .85 for Whole Foods, and .82 for Wild Oats.

Table 14: **Effect of Excluding Club Stores on Evaluating the Ahold/Delhaize Merger**

	Without Club Stores			
With Club Stores	No Concern	Warrants Scrutiny	Presumed Likely	Total
No Concern	1,144	356	0	1,500
Warrants Scrutiny	1	426	671	1,098
Presumed Likely	0	2	518	520
Total	1,145	784	1,189	3,118

6.3 Do Club Stores belong in the market?

Last, we turn to the question of whether club stores should be included in the analysis of grocery mergers. It may be tempting to consider club stores a separate market, either because they seem sufficiently distinct as retail formats or because they tend to be located further away from consumers and therefore outside the standard geographic catchment area used by the FTC to define grocery markets. However, our empirical results reveal that club stores have much lower sensitivity to distance than grocery stores, suggesting that they may play a larger role even in relatively distant 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).

To see how including or excluding club stores from the analysis changes the outcome, we repeat our evaluation of the Delhaize-Ahold merger using the specification that excludes clubs. Table 14 presents a comparison of the two merger analyses in the form of a cross-tabulation of their resulting categorization of tracts.[55] The rows of this matrix represent the results of our preferred analysis (with club stores) while the columns show the results that exclude them. 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 with club stores included. The importance of club stores to the analysis is clear, as it results in a 56.2 percent decrease (from 1189 to 520) in the number of tracts where the merger is "presumed likely" to enhance market power under the merger guidelines. The results complement what we found earlier regarding the lower distance elasticity and popularity of club stores, as well as their high degree of diversion from grocery stores and supercenters. 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 be significantly more competitive once club stores are accounted for.

Overall, we view this framework as providing a natural first step in screening proposed mergers. In the

[55] The results using the store-store level measures of merger impact are qualitatively similar.

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.

7 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.

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A Derivations For Nested Logit

A.1 Derivative of Store-Tract Shares with Respect to Utility

Recall that the share of food expenditure from tract t spent at store s is,

$$p_{st}(\theta) = \Pr(\iota_{ti} = s) = \Pr\left(\iota_{ti} = s | \iota_{ti} \in C_{t,k(s)}\right) \Pr\left(\iota_{ti} \in C_{t,k(s)}\right)$$

Where C_t is the choice set of tract t, $k(s)$ is the nest to which store s belongs, and $C_{t,k}$ is the set of all stores in the choice set of tract t belonging to nest k. Given our distributional assumption, the probability of choosing a store in $C_{t,k(s)}$ is,

$$\Pr\left(\iota_{ti} \in C_{t,k(s)}\right) = \frac{\left(\sum\limits_{q \in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}\right)^{\mu_{k(s)}}}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q \in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}}$$

The probability of choosing store s given a store in $C_{t,k(s)}$ is chosen is,

$$\Pr\left(\iota_{ti} = s | \iota_{ti} \in C_{t,k(s)}\right) = \frac{e^{u_{st}/\mu_{k(s)}}}{\sum\limits_{q \in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}}$$

So the store choice probability is,

$$p_{st}(\theta) = \frac{e^{u_{qt}/\mu_{k(s)}}\left(\sum\limits_{q \in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}\right)^{\mu_{k(s)}-1}}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q \in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}}$$

For notational convenience, we suppress the dependence on the model parameters and denote:

$$p_{st|k} \equiv \Pr\left(\iota_{ti} = s | \iota_{ti} \in C_{t,k(s)}\right)$$

$$P_{t,k} \equiv \Pr\left(\iota_{ti} \in C_{t,k}\right)$$

Then the store choice probability is compactly written as, $p_{st} = p_{st|k} P_{t,k(s)}$. To derive the various elasticities from the model, we will repeatedly use the derivative of the share of store s in tract t with respect to utility of store $r \in C_t$,

$$\frac{\partial p_{st}}{\partial u_{rt}} = \frac{\partial p_{st|k}}{\partial u_{rt}} P_{t,k(s)} + \frac{\partial P_{t,k(s)}}{\partial u_{rt}} p_{st|k}.$$

The derivative of the probability of the total share of all stores in tract t, nest k with respect to the utility of store r from the perspective of tract t is,

$$
\begin{aligned}
\frac{\partial P_{t,k}}{\partial u_{rt}} &= \frac{\frac{\partial}{\partial u_{rt}}\left[\left(\sum\limits_{q\in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}\right)^{\mu_{k(s)}}\right]}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q\in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}} - \frac{\frac{\partial}{\partial u_{rt}}\left[\sum\limits_{v=0}^{K}\left(\sum\limits_{q\in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}\right]}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q\in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}} P_{t,k} \\
&= \mathbf{1}\left[r\in C_{t,k}\right] \frac{\mu_{k(r)}\left(\sum\limits_{q\in C_{t,k(r)}} e^{u_{qt}/\mu_{k(r)}}\right)^{\mu_{k(r)}-1} \frac{1}{\mu_{k(r)}} e^{u_{rt}/\mu_{k(r)}}}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q\in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}} - \\
&\quad - \frac{\mu_{k(r)}\left(\sum\limits_{q\in C_{t,k(r)}} e^{u_{qt}/\mu_{k(r)}}\right)^{\mu_{k(r)}-1} \frac{1}{\mu_{k(r)}} e^{u_{rt}/\mu_{k(r)}}}{\sum\limits_{v=0}^{K}\left(\sum\limits_{q\in C_{t,v}} e^{u_{qt}/\mu_v}\right)^{\mu_v}} P_{t,k} \\
&= \mathbf{1}\left[r\in C_{t,k}\right] p_{rt} - p_{rt}P_{t,k} \\
&= p_{rt}\left(\mathbf{1}\left[r\in C_{t,k}\right] - P_{t,k}\right)
\end{aligned}
$$

The derivative of the probability of choosing a store s given a store in $C_{t,k(s)}$ is chosen with respect to the utility of store r is,

$$
\begin{aligned}
\frac{\partial p_{st|k}}{\partial u_{rt}} &= \frac{\frac{\partial}{\partial u_{rt}} e^{u_{st}/\mu_{k(s)}}}{\sum\limits_{q\in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}} - \frac{\frac{\partial}{\partial u_{rt}} \sum\limits_{q\in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}}{\sum\limits_{q\in C_{t,k(s)}} e^{u_{qt}/\mu_{k(s)}}} p_{st|k} \\
&= \mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}} p_{st|k} - \mathbf{1}\left[r\in C_{t,k(s)}\right]\frac{1}{\mu_{k(s)}}\left(p_{rt|k}p_{st|k}\right) \\
&= \frac{1}{\mu_{k(s)}} p_{st|k}\left(\mathbf{1}\left[s=r\right] - \mathbf{1}\left[r\in C_{t,k(s)}\right] p_{rt|k(s)}\right)
\end{aligned}
$$

Substituting these into $\frac{\partial p_{st}}{\partial u_{rt}}$ yields,

$$
\begin{aligned}
\frac{\partial p_{st}}{\partial u_{rt}} &= \frac{\partial p_{st|k}}{\partial u_{rt}} P_{t,k(s)} + \frac{\partial P_{t,k(s)}}{\partial u_{rt}} p_{st|k(s)} \\
&= \frac{1}{\mu_{k(s)}} p_{st|k}\left(\mathbf{1}\left[s=r\right] - \mathbf{1}\left[r\in C_{t,k(s)}\right] p_{rt|k(s)}\right) P_{t,k(s)} + p_{rt}\left(\mathbf{1}\left[r\in C_{t,k(s)}\right] - P_{t,k(s)}\right) p_{st|k} \\
&= \frac{1}{\mu_{k(s)}} p_{st}\left(\mathbf{1}\left[s=r\right] - \mathbf{1}\left[r\in C_{t,k(s)}\right] p_{rt|k(s)}\right) + p_{rt}\left(\mathbf{1}\left[r\in C_{t,k(s)}\right] p_{st|k(s)} - p_{st}\right) \\
&= \mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}} p_{st} + \mathbf{1}\left[r\in C_{t,k(s)}\right]\left(p_{rt}p_{st|k(s)} - \frac{1}{\mu_{k(s)}} p_{st}p_{rt|k(s)}\right) - p_{st}p_{rt} \\
&= \mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}} p_{st} + \mathbf{1}\left[r\in C_{t,k(s)}\right]\left(1 - \frac{1}{\mu_{k(s)}}\right) p_{st}p_{rt|k(s)} - p_{st}p_{rt} \\
&= p_{st}\left(\mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}} + \mathbf{1}\left[r\in C_{t,k(s)}\right]\left(1 - \frac{1}{\mu_{k(s)}}\right) p_{rt|k(s)} - p_{rt}\right) \qquad (11)
\end{aligned}
$$

A.2 Elasticity with Respect to Distance

Revenue of store s from tract t is,

$$R_{st} = \alpha n_t inc_t p_{st}$$

The elasticity of store revenue from tract t with respect to the distance d_{st} to between the tract centroid and the store is,

$$\begin{aligned}\eta_{st} &= \frac{\partial R_{st}}{\partial d_{st}} \frac{d_{st}}{R_{st}} \\ &= \alpha n_t inc_t \frac{d_{st}}{R_{st}} \frac{\partial p_{st}}{\partial d_{st}}\end{aligned}$$

The derivative of the share with respect to distance is,

$$\begin{aligned}\frac{\partial p_{st}}{\partial d_{st}} &= \sum_{q \in C_t} \frac{\partial p_{st}}{\partial u_{qt}} \frac{\partial u_{qt}}{\partial d_{st}} \\ &= \frac{\partial p_{st}}{\partial u_{st}} \frac{\partial u_{st}}{\partial d_{st}} \\ &= p_{st} \left(\frac{1}{\mu_{k(s)}} + \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{st|k(s)} - p_{st} \right) \frac{\partial u_{st}}{\partial d_{st}} \\ &= p_{st} \left(\frac{1}{\mu_{k(s)}} + \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{st|k(s)} - p_{st} \right) (\tau_0 + \tau_1 z_t)\end{aligned}$$

Where $\frac{\partial p_{st}}{\partial u_{st}}$ follows from (11) and the derivative of utility with respect to distance follows from our linear utility specification. Substituting this into the elasticity yields,

$$\begin{aligned}\eta_{st} &= \alpha n_t \text{inc}_t \frac{d_{st}}{R_{st}} p_{st} \left(\frac{1}{\mu_{k(s)}} + \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{st|k(s)} - p_{st} \right) (\tau_0 + \tau_1 z_t) \\ &= d_{st} (\tau_0 + \tau_1 z_t) \left(\frac{1}{\mu_{k(s)}} + \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{st|k(s)} - p_{st} \right)\end{aligned}$$

We aggregate this elasticity to the store level,

$$\eta_s = \sum_{t \in L_s} \eta_{st} \frac{R_{st}}{R_s},$$

and then to the chain level,

$$\eta^f = \sum_{s \in F_f} \eta_s \frac{R_s}{R^f},$$

where $R^f = \sum_{s \in F_f} R_s$.

A.3 Elasticity with Respect to Income

The elasticity of store revenue with respect to income is,

$$\begin{aligned}
\nu_{st} &= \frac{\partial R_{st}}{\partial \log(inc_t)} \frac{1}{R_{st}} \\
&= \frac{\partial \text{inc}_t}{\partial \log(\text{inc}_t)} \frac{\alpha n_t p_{st}}{R_{st}} + \frac{\alpha n_t \text{inc}_t}{R_{st}} \frac{\partial p_{st}}{\partial \log(inc_t)} \\
&= 1 + \frac{\alpha n_t \text{inc}_t}{R_{st}} \frac{\partial p_{st}}{\partial \log(inc_t)}
\end{aligned}$$

In our specification of utility, $\log(\text{inc}_t)$ is an element of the vector z_t. Therefore,

$$\begin{aligned}
\frac{\partial p_{st}}{\partial \log(inc_t)} &= \sum_{q \in C_t \setminus 0} \frac{\partial p_{st}}{\partial u_{qt}} \frac{\partial u_{qt}}{\partial log(inc_t)} + \frac{\partial p_{st}}{\partial u_{0t}} \frac{\partial u_{0t}}{\partial log(inc_t)} \\
&= \sum_{q \in C_t \setminus 0} p_{st} \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right) \frac{\partial u_{qt}}{\partial log(inc_t)} \\
&\quad - p_{st} p_{0t} \frac{\partial u_{0t}}{\partial log(inc_t)} \\
&= p_{st} \Bigg(\sum_{q \in C_t \setminus 0} \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right) (\tau_1 d_{qt} + \gamma_1 x_q) \\
&\quad - \lambda_1 w_t p_{0t} \Bigg)
\end{aligned}$$

where second line uses (11) for the derivative of probability of going to the store s with respect to utility of store q. Substituting this into the elasticity and rearranging we have the formula presented in the text,

$$\nu_{st} = 1 + \sum_{q \in C_t \setminus 0} (\tau_1 d_{qt} + \gamma_1 x_q) \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right) - \lambda_1 w_t p_{0t}$$

Again, we aggregate up to the store and chain level by share-weighting,

$$\nu_s = \sum_{t \in L_s} \nu_{st} \frac{R_{st}}{R_s},$$

and

$$\nu^f = \sum_{s \in F_f} \nu_s \frac{R_s}{R^c},$$

where $R^f = \sum_{s \in F_f} R_s$.

A.4 Semi-elasticity of Store and Chain Revenue

We present the derivation chain level semi-elasticities as store-level semi-elasticities can be understood as special case where we consider the two stores as isolated chains. The revenue of a chain f is given by the formula,

$$R^f = \sum_{s \in F_f} \sum_{t \in L_s} R_{st}$$

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. It is given by the formula,

$$\sigma_{f,g} = \frac{1}{R^f} \sum_{q \in F_g} \frac{\partial R^f}{\partial u_{qt}}$$

Differentiating total revenue for chain f yields,

$$\begin{aligned}
\sigma_{f,g} &= \frac{1}{R^f} \sum_{q \in F_g} \sum_{s \in F_f} \sum_{t \in L_s} \frac{\partial R_{st}}{\partial u_{qt}} \\
&= \frac{1}{R^f} \sum_{s \in F_f} \sum_{t \in L_s} \sum_{q \in F_g \cap C_t} \frac{\partial R_{st}}{\partial u_{qt}}
\end{aligned}$$

Where the second equality uses the fact that stores outside of a tracts choice set have no impact on choices for tract t. Using the definition of R_{st} and (11) we complete the derivation to the formula that appears in the text.

$$\begin{aligned}
\sigma_{f,g} &= \frac{1}{R^f} \sum_{s \in F_f} \sum_{t \in L_s} \alpha \mathrm{inc}_t \, n_t \sum_{q \in F_g \cap C_t} \frac{\partial p_{st}}{\partial u_{qt}} \\
&= \frac{1}{R^f} \sum_{s \in F_f} \sum_{t \in L_s} \alpha \mathrm{inc}_t \, n_t \sum_{q \in F_g \cap C_t} p_{st} \left(\mathbf{1}\left[q = s\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[r \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right) \\
&= \frac{1}{R^f} \sum_{s \in F_f} \sum_{t \in L_s} R_{st} \sum_{q \in F_g \cap C_t} \left(\mathbf{1}\left[s = q\right] \frac{1}{\mu_{k(s)}} + \mathbf{1}\left[q \in C_{t,k(s)}\right] \left(1 - \frac{1}{\mu_{k(s)}}\right) p_{qt|k(s)} - p_{qt} \right).
\end{aligned}$$

B Additional Figures and Tables

Table B.1: **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	28	0	6,129
Warrants Scrutiny	0	26	2	28
Total	6,101	54	2	6,157

Table B.2: **Characteristics of the Tracts in Ahold/Delhaize Merger States**

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 B.3: Chain Effect Estimates, Intercepts

	Baseline	Multinomial Logit	No Club	Size Only
	(1) Intercepts	(2) Intercepts	(3) Intercepts	(4) Intercepts
Small Chains	−1.304	−1.217	−0.990	−0.885
	(0.015)	(0.021)	(0.013)	(0.013)
Medium Chains	−1.192	−1.065	−0.876	−0.703
	(0.016)	(0.022)	(0.014)	(0.014)
Albertsons	−1.106	−0.944	−0.794	−0.627
	(0.018)	(0.024)	(0.016)	(0.017)
Aldi	−1.404	−1.352	−1.085	−1.165
	(0.017)	(0.023)	(0.015)	(0.016)
Bashas Markets	−0.954	−0.744	−0.656	−0.532
	(0.020)	(0.026)	(0.017)	(0.017)
Delhaize America (Food Lion)	−1.245	−1.142	−0.929	−0.826
	(0.017)	(0.023)	(0.015)	(0.015)
Fred Meyer	−0.852	−0.603	−0.546	−0.103
	(0.033)	(0.038)	(0.028)	(0.034)
Giant Eagle	−0.873	−0.617	−0.532	−0.235
	(0.025)	(0.029)	(0.020)	(0.022)
Giant Food	−0.886	−0.629	−0.576	−0.244
	(0.023)	(0.028)	(0.020)	(0.021)
Great A & P Tea Co.	−1.108	−0.938	−0.795	−0.556
	(0.025)	(0.030)	(0.021)	(0.020)
HE Butt	−0.617	−0.308	−0.301	0.042
	(0.020)	(0.026)	(0.017)	(0.017)
Hannaford Bros	−0.910	−0.690	−0.614	−0.308
	(0.024)	(0.031)	(0.021)	(0.021)
Hy Vee Food Stores	−1.045	−0.849	−0.735	−0.293
	(0.032)	(0.036)	(0.027)	(0.027)
Ingles Markets	−1.298	−1.221	−0.977	−0.881
	(0.023)	(0.030)	(0.020)	(0.020)
Kroger	−0.826	−0.569	−0.511	−0.321
	(0.016)	(0.022)	(0.014)	(0.014)
Lone Star Funds (Bi-Lo)	−1.210	−1.084	−0.885	−0.729
	(0.019)	(0.025)	(0.017)	(0.018)
Publix	−1.002	−0.811	−0.689	−0.377
	(0.019)	(0.024)	(0.016)	(0.016)
Raleys	−0.882	−0.644	−0.564	−0.389
	(0.026)	(0.032)	(0.023)	(0.023)
Roundys	−0.807	−0.512	−0.501	−0.229
	(0.029)	(0.034)	(0.026)	(0.025)
Ruddick Corp (Harris Teeter)	−0.990	−0.784	−0.645	−0.450
	(0.030)	(0.035)	(0.025)	(0.027)
Safeway	−0.872	−0.631	−0.558	−0.377
	(0.016)	(0.022)	(0.014)	(0.015)
Save A Lot	−1.226	−1.114	−0.905	−0.910
	(0.016)	(0.022)	(0.014)	(0.014)
Save Mart	−0.858	−0.607	−0.537	−0.418
	(0.024)	(0.030)	(0.022)	(0.020)
Smart & Final	−0.893	−0.673	−0.578	−0.735
	(0.020)	(0.025)	(0.017)	(0.018)
Stater Bros	−0.627	−0.302	−0.307	−0.159
	(0.025)	(0.030)	(0.022)	(0.029)
Stop & Shop	−1.047	−0.851	−0.730	−0.464
	(0.021)	(0.026)	(0.018)	(0.018)
SuperValu	−0.963	−0.751	−0.646	−0.480
	(0.017)	(0.023)	(0.015)	(0.015)
Trader Joes	−0.549	−0.210	−0.226	−0.067
	(0.028)	(0.033)	(0.024)	(0.026)
Weis Markets	−1.315	−1.234	−0.999	−0.838
	(0.025)	(0.032)	(0.023)	(0.022)
Whole Foods	−0.913	−0.685	−0.594	−0.405
	(0.035)	(0.042)	(0.030)	(0.036)
Wild Oats	−1.265	−1.180	−0.952	−0.719
	(0.027)	(0.033)	(0.023)	(0.022)
Winn-Dixie	−1.271	−1.172	−0.962	−0.765
	(0.018)	(0.024)	(0.016)	(0.016)
Meijer	−1.145	−0.828	−0.832	0.024
	(0.020)	(0.027)	(0.017)	(0.016)
Target	−1.489	−1.225	−1.207	−0.362
	(0.025)	(0.035)	(0.022)	(0.021)
Wal Mart	−0.943	−0.595	−0.645	0.098
	(0.017)	(0.023)	(0.015)	(0.014)
BJs	−2.534	−2.364		−2.397
	(0.257)	(0.275)		(0.242)
Costco	−1.919	−1.629		−1.772
	(0.258)	(0.279)		(0.243)
Sam's Club	−2.121	−1.941		−1.959
	(0.266)	(0.286)		(0.251)

Table B.4: Chain Effect Estimates, Slopes

	Baseline	Multinomial Logit	No Club	Size Only
	(1) Slopes	(2) Slopes	(3) Slopes	(4) Slopes
Small Chains	−0.239	−0.519	0.123	−0.488
	(0.034)	(0.050)	(0.030)	(0.026)
Medium Chains	−0.242	−0.515	0.134	−0.482
	(0.037)	(0.052)	(0.032)	(0.028)
Albertsons	−0.339	−0.613	0.073	−0.797
	(0.050)	(0.065)	(0.043)	(0.044)
Aldi	−0.316	−0.687	0.000	−0.607
	(0.062)	(0.077)	(0.054)	(0.060)
Bashas Markets	−0.425	−0.729	−0.048	−0.778
	(0.046)	(0.063)	(0.040)	(0.038)
Delhaize America (Food Lion)	−0.436	−0.798	−0.079	−0.725
	(0.043)	(0.060)	(0.038)	(0.036)
Fred Meyer	−0.400	−0.712	0.021	−0.568
	(0.130)	(0.144)	(0.111)	(0.143)
Giant Eagle	−0.560	−1.040	−0.232	−0.709
	(0.108)	(0.122)	(0.087)	(0.085)
Giant Food	−0.204	−0.537	0.220	−0.527
	(0.051)	(0.068)	(0.045)	(0.044)
Great A & P Tea Co.	−0.426	−0.867	−0.033	−0.781
	(0.087)	(0.099)	(0.071)	(0.073)
HE Butt	−0.251	−0.447	0.204	−0.660
	(0.048)	(0.063)	(0.041)	(0.038)
Hannaford Bros	−0.753	−1.168	−0.345	−1.117
	(0.089)	(0.110)	(0.077)	(0.076)
Hy Vee Food Stores	−0.239	−0.503	0.202	−0.756
	(0.133)	(0.150)	(0.111)	(0.129)
Ingles Markets	−0.729	−1.232	−0.347	−1.057
	(0.106)	(0.127)	(0.093)	(0.089)
Kroger	−0.451	−0.781	−0.051	−0.735
	(0.039)	(0.055)	(0.034)	(0.030)
Lone Star Funds (Bi-Lo)	−0.328	−0.658	0.041	−0.693
	(0.069)	(0.083)	(0.061)	(0.068)
Publix	−0.194	−0.443	0.240	−0.547
	(0.048)	(0.064)	(0.041)	(0.039)
Raleys	−0.410	−0.707	−0.029	−0.890
	(0.091)	(0.108)	(0.081)	(0.074)
Roundys	−1.027	−1.747	−0.578	−1.342
	(0.118)	(0.129)	(0.099)	(0.100)
Ruddick Corp (Harris Teeter)	−0.130	−0.433	0.207	−0.379
	(0.077)	(0.095)	(0.068)	(0.066)
Safeway	−0.303	−0.582	0.100	−0.657
	(0.040)	(0.056)	(0.035)	(0.031)
Save A Lot	−0.302	−0.683	0.026	−0.740
	(0.050)	(0.066)	(0.044)	(0.048)
Save Mart	−0.153	−0.337	0.213	−0.464
	(0.079)	(0.089)	(0.070)	(0.061)
Smart & Final	−0.278	−0.521	0.101	−0.617
	(0.055)	(0.071)	(0.049)	(0.051)
Stater Bros	−0.403	−0.676	−0.052	−0.704
	(0.076)	(0.100)	(0.068)	(0.088)
Stop & Shop	−0.163	−0.481	0.217	−0.486
	(0.065)	(0.078)	(0.055)	(0.053)
SuperValu	−0.372	−0.710	0.011	−0.692
	(0.043)	(0.058)	(0.037)	(0.035)
Trader Joes	−0.386	−0.672	−0.038	−0.437
	(0.069)	(0.085)	(0.058)	(0.062)
Weis Markets	−0.304	−0.691	0.046	−0.517
	(0.107)	(0.133)	(0.094)	(0.085)
Whole Foods	−0.021	−0.204	0.379	−0.160
	(0.073)	(0.092)	(0.063)	(0.063)
Wild Oats	−0.195	−0.401	0.167	−0.650
	(0.072)	(0.088)	(0.061)	(0.059)
Winn-Dixie	−0.512	−0.875	0.005	−0.899
	(0.052)	(0.069)	(0.044)	(0.045)
Meijer	−1.301	−1.182	−0.784	−1.725
	(0.069)	(0.106)	(0.059)	(0.053)
Target	−0.818	−0.903	−0.357	−1.095
	(0.075)	(0.112)	(0.066)	(0.060)
Wal Mart	−0.657	−0.565	−0.128	−1.012
	(0.045)	(0.061)	(0.039)	(0.032)
BJs	−0.102	−0.795		−0.015
	(0.820)	(0.856)		(0.788)
Costco	0.471	−0.233		0.572
	(0.835)	(0.875)		(0.804)
Sam's Club	0.002	−0.535		0.049
	(0.843)	(0.883)		(0.809)

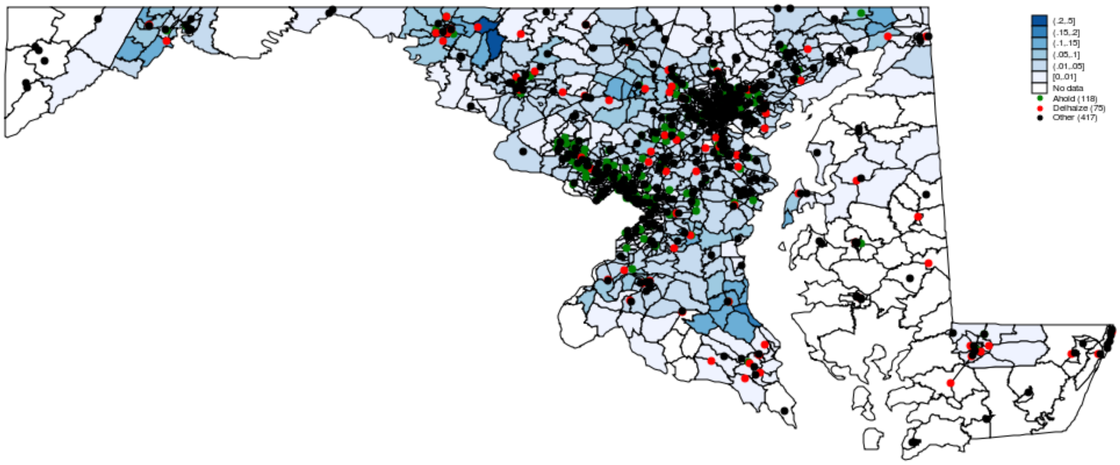

Figure B.1: Post merger increases in HHI by tract: Maryland

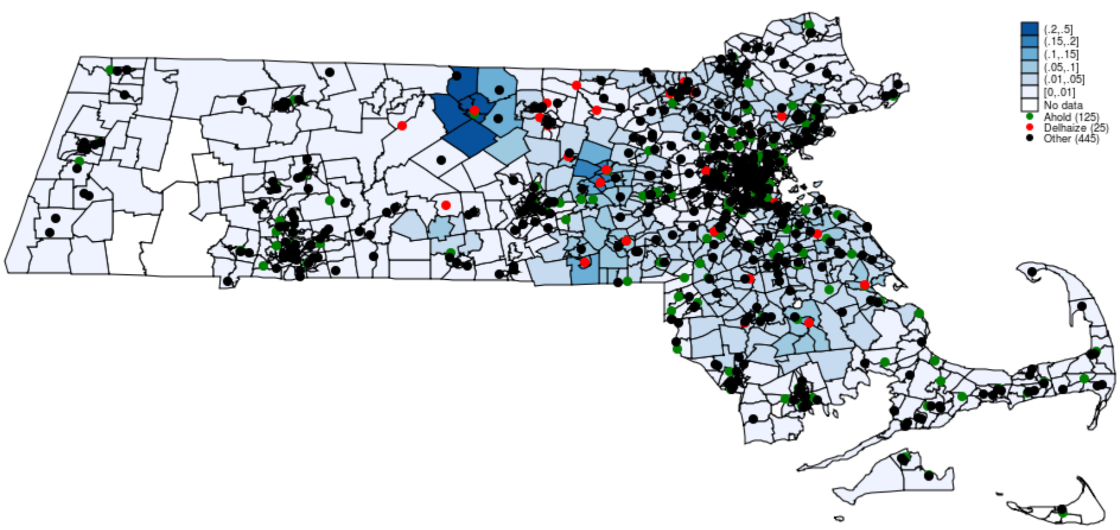

Figure B.2: Post merger increases in HHI by tract: Massachusetts

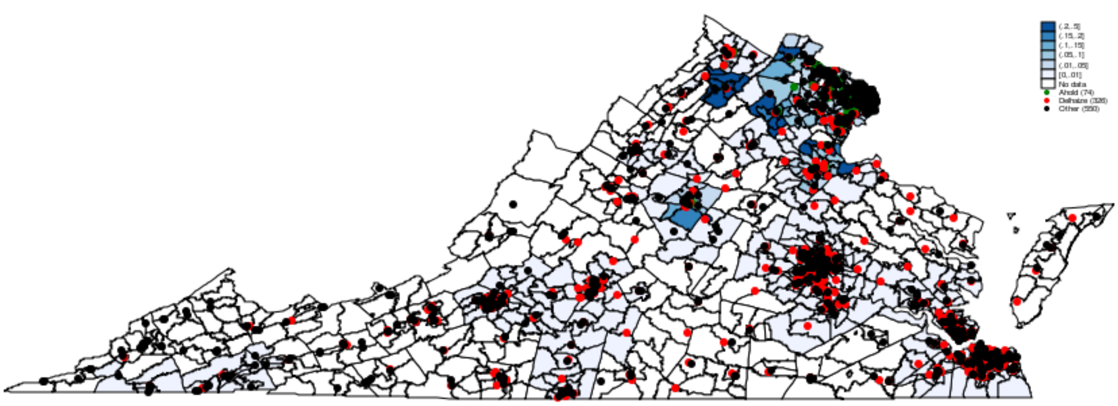

Figure B.3: Post merger increases in HHI by tract: Virginia