Measuring Competition in Spatial Retail*

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Abstract

We propose a framework for analyzing spatial competition between retailers of different formats. Our spatially-aggregated discrete choice model incorporates overlapping consumers' choice sets and avoids the need for researchers to define markets ex ante. In addition, we leverage the relative uniformity of pricing, assortment, and amenity strategies within retail chains to estimate flexible substitution patterns without accounting for the many thousands of product prices within a store or constructing ad hoc price indices. We apply our model to the grocery retail industry in the United States to illustrate how it identifies the importance of location, format and the spatial distribution of consumers in determining the competitiveness of a market. Contrary to conventional wisdom, we find substantial cross-format competition between supercenters, club stores, and traditional grocers. We use our estimates to evaluate two representative mergers between supermarket chains to show how our estimates can inform antitrust policy.

Keywords: Grocery Retail; Store Choice; Anti-Trust Regulation; Demand Estimation.

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1 Introduction

Measuring competition requires specifying the relevant consumer choice set, accounting for overlap in ownership across products, and identifying the degree of substitution between the relevant options. In the case of spatial retail competition, both the choice set and the extent of differentiation depend on how consumers value the trade-off between travel distance and store features (assortment, amenities and prices). How far are consumers willing to travel to obtain better or cheaper products? And how are these choices shaped and constrained by the retail environment that surrounds them? To answer these questions, we propose and estimate a model of spatial demand that flexibly captures these tradeoffs and provides concrete measures of both substitution patterns and competitive pressures. We illustrate our approach by evaluating the anti-trust implications of two high-profile grocery mergers.

While one could, in principle, tackle the richness of spatial retail demand (e.g. firms offering distinct bundles of heterogenous products to multi-homing shoppers choosing how often to shop and how much to buy) with a fully articulated structural model of supply and demand, we take a simpler approach that abstracts away from much of this complexity while retaining the ability to flexibly estimate substitution patterns between stores. To do so, we exploit two key institutional features of modern retail chain competition, namely that prices and assortments are primarily firm rather than store level decisions (Della Vigna and Gentzkow, 2017; Hitsch et al., 2019). This regularity allows us to capture several of the key aspects of the underlying consumer choice problem via chain-level fixed effects, interacted with income, that reflect the overall pricing, assortment and service levels of rival outlets, without requiring information on their actual values. While the significant reduction in complexity (and data requirements) this provides is not without cost, it permits a relatively simple framework for analyzing spatial competition that still captures the rich manner in which demand is allocated across space and how firms choose to carve up this landscape. Absent information on prices, we exploit the rich covariation between store locations and local consumer demographics to pin down substitution patterns and quantify the extent of market power at varying levels of geographic aggregation.[1]

This paper fills a void between two existing approaches for estimating retailer demand. Traditional aggregate-demand models, which divide the spatial landscape into independent markets, are forced to ignore distance effects, as measuring these would require specifying over-lapping choice sets. While micro-level choice models can include direct information on travel distance, choice-based sampling often leads individual-

[1] In our application, the main motivation for pursuing this alternative source of variation is the fact that we do not observe prices at all, a feature of many retail datasets (total revenues are far easier to collect than individual prices and quantities). However, the widespread practice of uniform grocery pricing in at least the U.S. and U.K. (Thomassen et al., 2017) suggests that price effects may not be well-identified from cross-sectional variation alone, even if prices were in fact observed. In this sense, our approach is similar to Conlon and Mortimer (2013), who use variation in the availability of products in lieu of price changes to measure diversion.

level analyses to omit several components of the choice set - namely the stores that were not visited - thereby obscuring the role of competition. Estimating retail demand is further complicated by the large number of products and complex set of prices that comprise a given shopping basket, often requiring the construction of ad hoc price indices and/or the omission of relevant components of the product line.

To bridge this gap, we develop a model of spatial demand that links store-level aggregate revenues to consumer choices by exploiting the relationship between the exact location of every store and the distribution of consumer demographics in the residential geography that surrounds it. Our empirical model builds upon and extends the approach proposed by Holmes (2011) for sales volumes at Wal-Mart outlets, by incorporating competition from rival firms.[2] This spatially-aggregated discrete choice framework extends the simple nested-logit model of store choice, in which stores are grouped into nests according to retail format (e.g. club store, supermarket, or supercenter), by aggregating over spatially-heterogeneous consumer types. Shoppers differ by their location, income, family size and vehicle ownership status, allowing us to capture flexible substitution patterns across stores by leveraging geographic variation in these observed preference shifters. Consumers in each census tract allocate grocery expenditures across a group of nearby retail outlets that are distinguished by their in-store amenities, distance from the consumer's location, and chain affiliation. Critically, consumers' utility for all store characteristics—including chain affiliation—are allowed to vary with observed demographics, such as income and vehicle ownership. This flexibility ensures the ability to compute highly localized measures of competitive overlap, including the store and chain level diversion ratios that are key inputs to competition policy.

As location is a primary driver of store choice, a consumer's utility for shopping at a given store depends on their distance from it, and whether they own a car. Income impacts consumer spending in two ways, first through the overall budget allocated to food and second through the stores they choose to shop at. The model captures the well-known tendency for a consumer's share of income spent on food at home to fall with income (e.g. via either basic 'Engel's law' type effects or the fact that wealthy consumers tend to spend proportionately more on food outside the home) and the mix of stores they frequent to change as well (e.g. high income consumers are more likely to shop at Whole Foods than at Aldi). By leveraging the rich spatial distribution of stores and consumer demographics, the model delivers a clear characterization of which consumers prefer which stores, the competitive impact that stores exert on one another, and the degree of substitution with between stores and the outside option.

Using a store-level census of the grocery industry, we demonstrate that this model can identify the key determinants of store choice and competitive overlap in this complex setting. Our results highlight the

[2] Holmes' analysis of Wal-Mart abstracted from competition to focus on how the dynamics of Wal-Mart's expansion decisions were influenced by the scale economies associated with operating a dense network of stores. A similar approach is used by Seim and Waldfogel (2013) to model the Pennsylvania state liquor monopoly.

importance of distance, format, and consumer heterogeneity in shaping the competitive landscape of retail trade. Consistent with earlier studies, we find that consumers prefer to travel relatively short distances for groceries, a willingness that declines quickly with income but is moderated by vehicle ownership (Smith, 2006; Eizenberg et al., 2016). While markets are geographically localized, store type matters as well. Consumers, particularly less affluent ones and almost exclusively those with cars, are willing to travel significantly farther to shop at club stores rather than traditional supermarkets. This accords with the empirical analysis of Lagakos (2016), who finds that car ownership alone explains roughly two-thirds of the cross-country differences in the relative use of modern (and far more productive) big box retail technologies, and provides further evidence that the benefits of these innovations may be regressive (Lagakos, 2016; Atkin et al., 2018; Eizenberg et al., 2016), perhaps even leaving some transportation-constrained consumers un-served. The greater spatial reach enjoyed by club stores also has direct implications for merger policy. Due to their more limited product selection, club stores have previously been excluded from the competitive set (Hosken et al., 2012); our analysis suggests that this is a mistake, as club stores now compete on relatively equal footing with conventional supermarkets.

We illustrate how our approach can inform antitrust policy in practice, by examining two high-profile mergers. First, we revisit the contentious Whole Foods and Wild Oats case, which was challenged (but eventually approved) in 2007. We then consider another merger, between Delhaize and Ahold, that was recently approved in 2016. Our analysis reveals that the grocery industry contains many submarkets with localized competition: 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. We 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, because the Delhaize stores are more often located in remote and under-served locations, this raises additional concerns regarding access to affordable food.

While we consider the primary application of our framework to be in the area of antitrust, our flexible spatial demand system is also relevant to urban economists and other researchers seeking to understand how urban agglomeration and consumer heterogeneity affect the provision of local amenities. In particular, by providing a flexible measure of distance disutility that accounts for vehicle ownership, while also including unobserved quality differences, our framework delivers a rich characterization of key demand-side drivers of density economies. These demand-side factors have been shown to be a key determinant of food deserts (Allcott et al., 2018), as well as the variety-based benefits of larger cities (Handbury, 2013; Handbury and Weinstein, 2015) or dedicated shopping districts (Eizenberg et al., 2016). Our store-choice model is also a natural input to a structural model of static or dynamic market entry, where it might be used to evaluate zoning restrictions or entry subsidies, or to inform a firm's choice over where to place its stores. 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).[3]

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 derives 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

The goal of this paper is to provide a framework for measuring competition between retail outlets. To maintain computational tractability and accommodate some limitations of our data, we make a few key

[3] 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".

simplifying assumptions that differ from more conventional aggregate demand treatments. Before presenting our framework, we highlight the reasoning behind our decisions.

First, we do not include price as a covariate in our choice model. Part of this is clearly by necessity, as we do not observe prices. This is undoubtably a limitation. For example, we will not have a money metric to address questions related to consumer welfare. However, proposing a framework that doesn't require prices also yields significant advantages. Because supermarkets (and retail chains more broadly) set prices for thousands of products, any price index used to model store-level demand is, by necessity, 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 of the underlying choice problem (Handbury, 2013). Thus, even if we observed prices, it is not clear how best to include them. More importantly, there is now strong evidence that, at least amongst retail chains, prices exhibit surprisingly little within-firm variation (Della Vigna and Gentzkow, 2017; Hitsch et al., 2019; Adams and Williams, 2019). If the bulk of price and assortment variation is indeed across rather than within chains, our chain effects, which are further interacted with income, should capture the most important elements of firms' pricing differences, while operating at the actual level at which prices are set. In addition, utilizing chain-level effects to control for price variation reduces the need to instrument for price. As we discuss below, this then avoids the need to invert market shares to recover unobserved store quality (Berry, 1994; Berry et al., 1995) as part of a nested estimation routine.

Avoiding a BLP-style share inversion also relates to our second simplification: we do not include the usual product (here, store) level structural error in our indirect utility function. There are two reasons for this. First, using chain fixed-effects in lieu of prices mitigates the key endogeneity problem that this error term is designed to address. Second, including such an error so would be quite complicated in our setting, as this would effectively require assigning all stores to a single market. While one could, in principle, do so, it is computationally impractical for two reasons. First, the dimension of the shares in the "quality inversion" would be very large, adding significant computational complexity to the estimation procedure. Second, the resulting market shares would then be extremely small and likely sensitive to measurement error in our revenue data (Gandhi et al., 2017). Instead, we include a non-structural error in the spirit of Pakes et al. (2015), which we discuss in detail below.

Third, we do 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 (and census-based demographic information). While this puts some limitations on the nature of substitution, by incorporating the joint geographic and income distribution of consumers, and allowing for closer competition between firms of the same format (via an explicit nesting structure), we are able to flexibly estimate substitution patterns with a model that is relatively simple to estimate by non-linear least squares, thereby reducing the computational burden. Moreover, our spatially aggregated nesting structure allows for stronger substitution within formats and between chains that target similar consumers (e.g., high versus low income), which is precisely the sort of substitution patterns that one might hope to capture using random coefficients. Of course, one could easily extend the model to include random coefficients on observed characteristics. We note that this extension would be much simpler to estimate than a typical aggregate random coefficient model, as it would not require a share inversion.

Finally, we do not specify or estimate a structural supply model, which would be necessary to conduct a full-fledged merger simulation, as in Nevo (2001), or to evaluate other counterfactual policy changes. While clearly a restrictive simplification, the advantage lies in allowing us to quantify the key demand-side aspects of product substitution without having to specify a particular model of conduct, or even to define the strategy space of firms. This might be important if firms primarily react to changes in their environment using other levers than price, say by adjusting assortment or service, or by adding or removing outlets. Critically, our framework can still provide direct measures of concentration changes and identify key diversion ratios between merging parties or competing chains. The former have been commonly used in merger analyses while the latter are the central inputs to the measures of upward pricing pressure that are now used to quantify unilateral effects (e.g., Werden, 1996; Farrell and Shapiro, 2010; Jaffe and Weyl, 2013).[4]

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 of direct interest to regulators, policy makers and academic researchers.

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.[5] To connect store-level revenue to consumer-level tastes and implied

[4]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.

[5]There are clearly benefits to having individual data on grocery expenditures and product-level prices. Knowing the exact stores a consumer frequents provides direct information on distance travelled, which is critical for understanding the impact of policies aimed at eliminating spatial frictions (Figurelli, 2012; Eizenberg et al., 2016). Richer data can also allow researchers to tackle questions related to how often people shop and how much they buy, which are important for assessing the degree and

choices, we use tract-level demographic data drawn from the 2010 US Census, together with a model of consumer expenditure allocation. 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.[6] 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. Consumers are thus endowed with a location (the tract centroid) and a vector of characteristics z_t (e.g. income, family size, car ownership) which affect their utility for grocery purchases. A consumer's 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. Our model allows individuals' tastes for stores, as well as for the outside good, to vary with income. Therefore, we can capture the empirical fact that the proportion of income spent at grocery stores (e.g. *expenditures* on groceries, rather than the outside good) falls with income (Engel's law).

Each consumer makes a continuum of purchasing decisions over the course of the year that allocate their overall food budget across stores. For each unit of expenditure i, a consumer in tract t's utility for spending at store s is

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

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.[7] 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 variety and service level. Moreover, individuals can differ in their tastes for distance and other characteristics though observed heterogeneity in the consumer's (tract-level) demographic variables z_t. This allows the utility of different store features to vary across observable customer characteristics such as income and family size.[8] These interaction terms are important for providing the flexibility required to capture rich substitution patterns. For example, they will highlight the stores that

importance of search and stockpiling behavior (Griffith et al., 2009). One benefit of our more aggregate approach is that we are able to include the full set of stores that consumers are choosing between, while retaining the ability to identify flexible aggregate substitution patterns.

[6] 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.

[7] 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.

[8] Note that we use a Kronecker product here as both x_s and z_t are vectors

are preferred by high-income consumers, and allow for substitution between these stores to be stronger than with stores whose characteristics are preferred by low income consumers.

Notably, we also include chain affiliation in x_s, which will capture *unobserved* characteristics of a given national chain, such as assortment and price. These taste shifters are further allowed to vary by income. Because 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. Della Vigna and Gentzkow (2017) and Hitsch et al. (2019) each provide evidence consistent with this assumption. Exploiting high-frequency store-level data covering over 20,680 food, drug and mass merchandise stores, Della Vigna and Gentzkow (2017) find that "chains in fact set uniform or nearly-uniform prices across their stores." Prices do vary by market, but this variation is mainly driven by variation in the types and identities of chains that choose to enter different local markets. Hitsch et al. (2019) similarly find a large degree of homogeneity within, but not across chains, and argue that chain-level assortment and package sizes play a central role in explaining across-chain variation in price. Ellickson and Misra (2008) provide additional evidence that supermarkets use distinct price and positioning strategies to target different consumer segments based on purchase size and frequency of visits. Thus, while our approach does not control for pricing and quality decisions that are specific to the individual store, these appear to be of second order importance to the average policy set by the chain.[9] 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 spent at Aldi (a no-frills grocer that targets the urban poor). Moreover, by interacting these chain identifiers with income, we allow the utility tradeoff between expenditures at, say Aldi versus Whole Foods, to vary across consumer types.

Finally, a consumer's utility from the outside good is determined by the (tract-level) representative consumer's demographic characteristics z_t 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,

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

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, $C_t = \{s : d_{ts} \leq D\} \cup 0$. While the choice of D may appear similar to the arbitrary choice of geographic market definition we aim to avoid, the inclusion of an explicit disutility

[9] Alternatively, one could imagine adding to the model a "store level quality shock" that firms could observe and exploit in endogenously adjusting their local quality-price offerings. While there is some evidence that firms occasionally do so, there are strong branding and efficiency reasons for chains to maintain uniformity, at least at the level of an overall metropolitan area (e.g. zone pricing). Note that, in principle, the chain fixed effect could instead be specified at a lower level of aggregation (e.g. chain-MSA) to account for this possibility, at the cost of including many more parameters.

of distance in consumer's utility will capture the tendency of consumers to avoid traveling to distant stores, even when they are included in the choice set. Hence, D should be chosen to be at least as large or larger than one would expect consumers to travel. 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.[10]

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). Leting $0 \leq \mu_k \leq 1$ be the parameter that governs this correlation, $\mu_k = 1$ then represents independent shocks within nest k (the multinomial logit case) and $\mu_k = 0$ represents perfect correlation of ε_{sti} within nest.[11]

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, $\theta = (\tau, \gamma, \lambda, \mu)$. 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 the GEV distributional assumption, the share of expenditure on stores in $C_{t,k(s)}$ (e.g. any club store close 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

[10] The median number of stores within 10 miles of given tract is 41. In their analysis of the U.K. grocery market, Thomassen et al. (2017) assume that the choice set is the nearest 30 stores, noting that the fraction of expenditures outside that set is only 1.2%. In our setting, the presence of the logit shock could add an element of mis-specification if D is set too large, since all outlets in the choice set will attract at least some consumers. In our application, the choice of D had little material impact, but, in other settings, this choice could have more bite.

[11] 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 $\mu_0 = 1$.

$C_{t,k(s)}$ (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

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

As noted above, we could in principle allow for additional dimensions of unobserved heterogeneity that depend on store or tract characteristics—i.e. random coefficients as in Berry et al. (1995). However, leveraging the joint distribution of observed consumer characteristics accommodates a substantial amount of observed heterogeneity already and, as we will demonstrate later, yields quite rich substitution patterns across chains in our application, while retaining a simpler analytical structure.[12] In particular, store-to-store substitution patterns will depart from the proportional substitution (IIA) property in two ways. First, within a tract, the nesting structure allows for greater substitution within format, in a manner that it not directly tied to overall shares. Second, because store-level revenue is generated by aggregating over tracts—which themselves vary in average income, distance to each store in the market and other consumer characteristics— our spatially-aggregated logit structure then allows for stronger substitution patterns between stores that are either closer together or cater to similar income groups (as revealed by the estimated chain-income effects). We turn now to detailing how this spatial aggregation takes place.

2.2 Store Revenues and Estimation

To connect tract-level consumer demographics and store characteristics to store-level 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 allocated to store s,

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

[12] Moreover, because 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—indeed, it is precisely the variation which identifies the nesting parameters—the flexibility of the current model in accommodating rich substitution patterns suggests there is little to gain from incorporating additional unobserved heterogeneity. 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 could potentially assign to grocery expenditures. Consumers will allocate this proportion between grocery expenditures and the outside good. Store s collects revenue from all tracts that include s in their 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 overlap, often substantially. 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 to minimize squared error loss. 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 uncorrelated with the exogenous variables and across stores,[13]

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

where (θ_0, α_0) are the true parameters and η_s is the store-level measurement shock.[14] 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.

[13] 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.

[14] 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 (as it is not material to their decision problem). In this sense, it is similar in spirit to the stochastic structure proposed by Pakes et al. (2015). As noted above, the fact that we do not condition on prices, but instead include interacted fixed effects, mitigates many of the classic endogeneity concerns associated with aggregate demand estimation. The fact that prices and assortments are predominately chain-level decisions should bolster this argument.

2.3 Identification

Having described our model and estimation strategy, we now provide a short discussion of the variation in the data and the additional assumptions that are needed to identify the model parameters. Identification comes from observing geographic co-variation in population demographics, store locations, and store revenues. We assume 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, rather than the store. 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 or, more realistically, market by market, based on local demographics. While there is some evidence that they sometimes do so (e.g., Hoch et al., 1995; Ellickson and Misra, 2008), we view this concern as being of second order importance 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 would calculate store level price indices for each outlet, even if such variation were indeed present. 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, as noted earlier, grocery stores rarely set prices at the store level, but instead maintain uniform price across broad "pricing zones", which can and often do extend to the level of the entire chain (Levy et al., 1998; Della Vigna and Gentzkow, 2017). One 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 mitigating menu costs and/or fairness concerns.

Turning now to the identification of specific parameters, we focus first on α, the proportion of overall income potentially allocated to grocery expenditures. This proportion is distinguished from the outside good in our model because changes in the choice set of grocery stores could lead consumers to substitute expenditure from the outside good to observed stores, while the $1-\alpha$ proportion of income is not substitutable with grocery expenditures. The parameter α is thus 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 it 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. Of course, this limiting case is unlikely to be observed in the data; firms will enter only if it remains profitable to do so. In practice, we instead rely on the nonlinearities in the functional form of market shares to distinguish α from the outside good. Given the parametric assumptions laid out earlier, the model provides a prediction regarding the change in total revenue (of all stores in an MSA) in response to the change in the number of stores in that MSA (holding all else equal). Therefore, variation in the number of stores across MSAs, conditional on other characteristics, can be used to trace out the utility of the outside good. Given these utility parameters, the model then implies a share for the outside good. The overall market size is then known, and can be used to identify α by comparing this quantity to total market income.

Next, we turn to the parameters governing store and chain level utility. Recall that we do not observe individual-level store choices or tract-level shares.[15] Instead of exploiting such micro-variation, these utility parameters are identified in our setting 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.[16] 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 from variation in the number and location of stores within versus between nests across the choice sets of differing census tracts. This variation, together with the model structure, implies corresponding variation in the observed revenue of stores due to the observed composition of competitors. This strategy is broadly similar to that used to identify unobserved heterogeneity in Berry et al. (1995).

3 Analyzing the Retail Landscape

A key deliverable of our framework lies in its ability to recover 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 store or chain. In section 5, we will use these statistics 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

[15] As noted earlier, data on consumer-level choice is sometimes available either from syndicated panels or credit card transaction data (Griffith et al., 2009; Dubois and Jódar-Rosell, 2010; Figurelli, 2012). While such data has the advantage of more clearly pinning parameters like travel costs, it often lacks relevant information regarding alternative choices to the ones actually selected (i.e. the other stores in the choice set).

[16] 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.

localized, share-based measures of concentration that can be directly compared to the critical thresholds provided in the 2010 Merger Guidelines.

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 elasticities. With our model, we can directly compute the revenue elasticity of a single store with respect to either store or consumer characteristics.[17] For example, the distance elasticity for revenue at store s from tract t is,[18]

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

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 suburbs rather than the center-city, 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

[17] 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.

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

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

3.2 Competitive Semi-Elasticities and Diversion Ratios

Identifying the degree of buyer substitution is critical to antitrust analysis because it determines the merging firm's incentives to internalize demand externalities. It is also germane to a broader set of questions including the existence and importance of food deserts, the impact of zoning restrictions, and the structural determinants of firms' entry and exit decisions. Note that, because our model does not include prices, we cannot directly compute *price* elasticities between firms, or diversion ratios *with respect to price*. Instead, we compute semi-elasticities and diversion ratios with respect to *utility*.[19] These semi-elasticities with respect to utility represent the percent change in revenue caused by a differential change in u_{sti} for store s across all consumers in all tracts, as opposed to a differential change in price. In the special case where price sensitivity is homogeneous across consumers, our semi-elasticities and diversion ratios with respect to *utility* would be equivalent to those with respect to *price*.[20] If price sensitivity instead varies by consumer characteristics, the two measures will differ. In Appendix B we show how these two measures differ and discusses how, with outside knowledge of how price sensitivity varies with income (or other demographics), it would be possible to use our model to construct substitution patterns and diversion ratios with respect to price as well.

We first construct semi-elasticities based on a differential improvement in the utility offered by a particular store. Intuitively, the semi-elasticities 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 the utility of store q is,

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

The semi-elasticity equation (8) illustrates how the model captures substitution effects. The nesting parameter directly raises substitution within format as μ_k decreases (which can even operate within a tract). Second, given that demand is aggregated across tracts, leveraging the estimated tract-store choice

[19] When considering differential utility across consumer types, we implicitly assume that the scale of the distribution of the idiosyncratic error term ε_{sti}, which is typically normalized in discrete choice applications, is constant across consumers.

[20] To be precise, our semi-elasticities are identical up to scale (converting utils to dollars) while the diversion ratios are exactly identical since they are scale-free by construction. These results are provided in Appendix B

probabilities rather than aggregated market shares allows stores that are attractive to similar consumer types (in location and income) to exhibit stronger substitution than stores that are not. 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: 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. Because 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 in the utility offered by store s (chain f) that is diverted from store q (chain j),[21]

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

As noted above, because we do not observe prices, the diversion ratios we define are ratios of revenue derivatives with respect to utility (rather than price). As we show in Appendix B, our measure is identical to the standard diversion ratio (namely the ratio of derivatives with respect to price) if consumers have homogeneous, quasi-linear utility for price.[22] 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 ratios are based on elasticity measurements which weight the differential effects of utility *uniformly* across consumers, while a price-focused diversion ratio would weight according to marginal dis-utility of price instead (Appendix B). 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

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

[22]It is worthwhile noting that homogeneous price sensitivity is also needed in order to approximate diversion ratios using ratios of market shares, as is frequently done in the antitrust literature (e.g., Farrell and Shapiro, 2010).

to a merger is multi-dimensional—e.g., a store may raise/lower prices, expand/reduce product offerings, improve/degrade customer service or do several such things in combination. 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 (via reduced stock-outs), rather than adjusting price. On the other hand, Ellickson and Grieco (2013) find that they primarily respond by reducing employment (service). Given this recent evidence that retail stores compete on multiple dimensions, a single diversion ratio, which places uniform weights on consumers based on scaled utility, might be preferred to separate diversion ratios capturing different strategic responses or a single diversion ratio focused only on price competition.

Diversion ratios also reveal 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: 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 because they will each 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 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 addresses 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 HHIs to measure market concentration, at the chain level.[23]

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

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 within 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, because these relationships are estimated within the store-choice model itself.

3.4 Aggregated Measures

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 t should be regarded as serving a concentrated market (since almost all stores derive revenue from more than a single tract). To address this point, we can easily construct concentration measures for a larger area based on aggregating the tracts within its boundaries. Suppose we want to construct a concentration measure for the collection of tracts L; we can simply calculate

$$AHHI_L = \sum_{t \in L} \rho_t HHI_t, \tag{10}$$

where ρ_t is a tract-level weight, to be defined shortly. This can be done to analyze arbitrary combinations of tracts including the catchment area of a particular store or set of stores, a city, county, or entire MSA. Typically, one would weight tracts by their population. However, if we are interested in the catchment area of a particular store, it may be preferable to weight tracts by the share of revenue that tract provides to the store (as estimated by our model). This would give us a better measure of whether the store itself is operating in a concentrated environment.

Aggregating tract level HHIs also provides a way to compare our concentration estimates to the traditional HHI measure based on an area-level market share. While the traditional measure considers how the revenues of outlets within an area are divided, our measure considers how the average tract within an area divides

[23] Here we define $p_{ft} = \sum_{s \in F_f \cap C_t} p_{st}$ as the chain f's total share from the tract and in a slight abuse of notation sum overall chains (as opposed to stores) in the choice set.

its expenditures. Note that our measure may be either higher or lower than the traditional measure. It may be higher if outlets are differentiated into submarkets such that aggregate substitution patterns differ dramatically from the independence of irrelevant alternatives (as is likely to be the case if location is an important determinant of store choice and consumers face significant travel costs relative to market size). It could also be lower because our method accounts for the presence of stores outside the area's geographic boundary when determining concentration.

It is similarly straightforward to aggregate store level diversion ratios to higher geographic units than individual stores. To do so, we follow (9), which calculates diversion at the chain level, but re-define F_f and F_g to be the set of stores for each chain within the geographic area of interest. Doing so will be of interest when analyzing a potential merger of two chains whose stores only compete in a subset of the markets served by either firm. A regional diversion ratio would also be relevant if we believe that firms implement pricing or assortment strategies at the regional level, rather than at the level of the individual store.

3.5 Merger Analysis

We now turn to demonstrating how the framework can be used to assess proposed mergers. Our main focus is on providing sharper guidance at the screening stage, first by computing more nuanced predictions regarding potential changes in concentration, and then by providing the key empirical constructs required for computing upward pricing pressure, namely store and chain-level diversion ratios. Merger analysis has traditionally focused on market concentration, utilizing thresholds at which concerns regarding either unilateral or coordinated effects might arise.[24] In particular, the 2010 Merger Guidelines (U.S. Department of Justice and Federal Trade Commission, 2010) flag a market as moderately concentrated if it's HHI is between 1,500 and 2,500, and highly concentrated if the HHI is over 2,500.[25] 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." These thresholds can be directly applied to merger-induced changes in either the tract-level or store-level concentration ratios laid out above. One could then further identify the consumer groups (geographic submarkets) that are likely to be most adversely affected, and the stores that should be the focus of further analysis (and perhaps divested).

Recent work has argued that the unilateral effects of a merger are better quantified by measuring upward pricing pressure (UPP), as it accounts more directly for head-to-head competition between merging parties

[24] Coordinated effects refer to anti-competitive forces arising from a merger that make collusion (either tacit or explicit) *between the merged firm and its rivals* more likely. Unilateral effects refer to forces that give the merged firm a *unilateral* incentive to raise prices.

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

than changes in market-wide concentration ratios (Werden, 1996; Farrell and Shapiro, 2010). The idea behind UPP is that mergers between rival firms involve two opposing forces that determine the post-merger prices charged by the merged entity: upward pressure stemming from the loss of direct competition between each firm's products and downward pressure arising from marginal cost efficiencies enabled by the merger. Farrell and Shapiro (2010) provide a measure of the net effect. The upward force, which operates via an additional term that appears in the first order condition of the Bertrand pricing problem for each product, can be interpreted as an increase in the opportunity cost of selling that product. This increased shadow cost can then be compared to the potential cost reduction arising from the merger to determine whether the net effect is positive. In the simple single-product, two-firm, Bertrand-pricing case with prices P_1 and P_2, costs C_1 and C_2, and efficiency "credits" E_1 and E_2, a merger between the two firms creates net upward pricing pressure for product 1 if $D_{12}(P_2 - C_2) > EC_1$, where D_{12} is the diversion with respect to price from product 1 to product 2. An analogous formula applies to product 2. Assuming symmetric prices and costs, the condition further simplifies to

$$D_{12}\frac{m}{1-m} > E_1, \tag{11}$$

in which $m = \frac{P-C}{P}$ is the (constant) relative margin and all variables are now conveniently unit-free. A slightly more complicated formula applies to the asymmetric case (Farrell and Shapiro, 2010). Although the margin m is not identified by our model, this information is typically available to agencies via a "second request" under the Hart-Scott-Rodino Act. Different levels for the "efficiency credit" E_1 play an analogous role to the HHI thresholds utilized in the traditional concentration-based approach. Critically, our spatial demand model provides precise, localized information on diversion accounting for store and firm characteristics, as well as geographic proximity of the competing stores. This is the component of UPP that is typically considered the most difficult to obtain. However, it is the diversion ratio with respect to *utility* can be computed directly from our model, not price. Of course, the two measures are when consumers have homogeneous price sensitivity (Appendix B). When price sensitivity varies by consumer characteristics, the appendix shows the relation to the two diversion measures. For screening purposes, we propose using the diversion ratio with respect to utility as an approximation of the diversion with respect to price. These diversion ratios can be computed at the level of the store, region or chain, meaning that UPP can be computed for either a given store or a particular collection of stores (e.g. all the stores in a particular market, all stores for which the relevant catchment areas overlap). Moreover, because neither prices nor costs appear to vary much within chain (Della Vigna and Gentzkow, 2017; Stroebel and Vavra, 2019), margins are relatively constant, making the computation of UPP at different levels of aggregation fairly undemanding from a data perspective. In the empirical analysis presented below, we compute predicted changes in concentration, along with diversion-ratio based evaluations, for two different grocery 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,[26] 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.[27] Data on store level sales volume is imputed for roughly half of the stores using a proprietary scheme that incorporates store level transaction data for a subset of the full universe of stores.[28] 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.[29] 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.[30]

We classify firms according to the number of stores they operate: small chains and independents are firms that operate 10 or fewer stores, medium chains are those that operate 10 to 100 stores, and large chains are those that operate more than 100 stores across all MSAs. We also include data on club stores, treating them as a special category.[31] In addition to groceries, clubs also carry a variety of additional consumer products

[26] 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.

[27] 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).

[28] Unfortunately, we observe neither the imputation method, nor the identities of the stores for which revenues are imputed. 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.

[29] 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%).

[30] 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.

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

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.[32] Finally, both size and sales volume display meaningful 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.[33] 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. 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

bulk quantities.

[32]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.

[33]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

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.

Because 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 young vintage of its store portfolio.[34] 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

[34] 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 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

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 be willing to 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 designed to be fairly uniform in terms of total population size, there is still a great deal of variation across tracts (reflecting differences 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 relying on less frequent store visits with much larger purchase sizes.

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

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 per Person	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
Proportion of Households with Vehicle	0.915	0.101	0.892	0.950	0.979
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 include size, employment and the number of checkouts. 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 signficantly different retail experience from standard grocery stores, we estimate a separate set of distance and size parameters for these firms. We also categorize stores into one of three nests: traditional grocery stores, supercenters, and clubs. As discussed earlier, this allows the model to capture stronger substitution between stores of the same format.[35]

The main consumer characteristic we include is tract-level log average income. Income differences are intended to capture heterogeneity in price sensitivity and the opportunity cost of time. We also account for tract-level differences in average household size, vehicle ownership, and population density.[36] We interact these demographic characteristics with taste for store characteristics (size, fte and distance) and allow them to moderate taste for the outside good. However, apart from income, we do not interact them with the chain effects, as this would substantially increase the number of parameters to estimate. Because 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.

[35] 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.

[36] Population density is 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 the utility of the outside good to be increasing and concave.

5.1 Parameter Estimates

Table 5 presents five alternative specifications of our empirical model. The first column contains our preferred (and richest) specification, denoted (1), we which refer to as the baseline specification in what follows. Note that we have demeaned all characteristics, so the parameter estimates can be interpreted as marginal utilities at the average characteristic levels across tracts and outlets.

We begin by providing a high-level discussion of the various empirical specifications we use as robustness checks, and then turn to a more granular discussion of individual parameter estimates from our preferred one. Specification (2) removes the nesting structure from the baseline model, restricting consumer expenditure patterns *within a tract* to arise from a plain multinomial logit model that exhibits the undesirable independence of irrelevant alternatives (IIA) property across all stores for a given consumer type. Note that, because it continues to account for the spatial distribution of consumer characteristics across tracts, even this more restrictive specification will not exhibit proportional substitution at the aggregate level.

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 parameters indexing the outside good and the proportion (α) of income allocated to groceries. This is intuitive; when grocery stores are excluded from the analysis, their absence will be accounted for by either a stronger outside good, a lower overall grocery budget, or a combination of each. While the underlying utility parameters appear to be robust to the inclusion of club stores, we demonstrate below that their exclusion would have a substantial impact on the competitive conditions 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 it might at first appear. We illustrate the relevance of this fact for merger analysis in Section 6.

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 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 includes all available data.

Finally, specification (5) evaluates the robustness of our results to dropping interactions between tract and store characteristics. Not surprisingly, these estimates, which are reported for specifications (1-4) in Appendix Table C.1, complicate the interpretation of individual coefficients. We find their inclusion to have a meaningful impact on only the club store parameters relating to distance and vehicle ownership. This is likely due to the added flexibility of allowing distance disutility to vary with population density and family size.

Returning now to our preferred specification (1), the estimate of α 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 (inside and outside the home) 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 is in line with our estimate of α.[37] 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). Our model captures this pattern through the *outside good*, the utility of which is increasing in income relative to almost all outlets, with the only statistically significant exception being Whole Foods.[38]

The nesting parameters, μ_{format}, are all between .7 and .8 in our baseline specification and significantly 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, although the richer specification is preferred based on both the Akaike and Bayesian information criteria.

While not reported in Table 5 due to space considerations, we also include fixed effects for each major chain and interact them with income. Appendix Tables C.2 and C.3 reports the chain fixed effects and income interactions respectively for every large chain and club store firm. Because the outside good is normalized, the impact of income on each chain reflects a given firm's change in utility as income increases, relative to the outside good. Note that the impact of increasing income on the utility of almost every chain is negative; this indicates that the utility of the outside good grows faster with income than that of almost any chain.

[37]The comparison here is imperfect. Our parameter α measures the proportion of income that potentially substitutes with groceries, which may include non-food expenditures, or even savings. We thank an anonymous referee for pointing this out.

[38]The income-chain utility effects reported in Appendix Table C.3 are reported relative to the outside good.

Table 5: Parameter estimates.

	Baseline (1)	Multinomial Logit (2)	No Clubs (3)	No FTE/Checkouts (4)	Drop Interactions (5)
Grocery Stores and Supercenters					
dist	−0.146	−0.173	−0.153	−0.153	−0.174
	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)
vehicle	1.378	1.728	1.087	1.222	1.991
	(0.042)	(0.050)	(0.037)	(0.041)	(0.038)
dist*vehicle	0.243	0.493	0.165	0.198	0.015
	(0.015)	(0.019)	(0.012)	(0.013)	(0.013)
dist*log(inc)	−0.142	−0.193	−0.140	−0.142	−0.106
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
log(size)	0.154	0.199	0.154	0.353	0.151
	(0.003)	(0.004)	(0.003)	(0.002)	(0.003)
log(size)*log(inc)	0.126	0.168	0.121	0.309	0.124
	(0.009)	(0.010)	(0.007)	(0.005)	(0.008)
Club Stores					
dist	0.020	0.045		−0.002	−0.051
	(0.012)	(0.012)		(0.012)	(0.009)
vehicle	7.974	8.634		7.376	4.020
	(1.051)	(1.057)		(1.069)	(0.846)
dist*vehicle	−0.564	−0.729		−0.375	−0.238
	(0.158)	(0.145)		(0.173)	(0.131)
dist*log(inc)	−0.169	−0.212		−0.180	−0.177
	(0.022)	(0.021)		(0.021)	(0.020)
log(size)	0.698	0.822		0.664	0.693
	(0.052)	(0.058)		(0.051)	(0.056)
log(size)*log(inc)	0.086	0.202		0.122	0.264
	(0.162)	(0.187)		(0.159)	(0.182)
$\mu_{grocery}$	0.740		0.733	0.716	0.747
	(0.021)		(0.149)	(0.019)	(0.021)
$\mu_{supercenters}$	0.779		0.779	0.662	0.761
	(0.058)		(0.058)	(0.052)	(0.057)
μ_{club}	0.733			0.729	0.807
	(0.149)			(0.145)	(0.109)
α	0.133	0.112	0.114	0.134	0.132
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Tract Characteristics in Outside Option	X	X	X	X	X
Additional Store Characteristics	X	X	X		X
Additional Interactions	X	X	X	X	
R2	0.842	0.839	0.814	0.809	0.841
AIC ($\times 10^4$)	−4.854	−4.801	−4.595	−4.402	−4.834
BIC ($\times 10^4$)	−4.763	−4.713	−4.519	−4.318	−4.753

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

Overall, 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 purchases. Whole Foods is the notable exception: this is consistent with the high-quality, high-price public perception of the Whole Foods brand and its focus on prepared food. Club stores also exhibit positive, albeit insignificant income effects relative to the outside good. This is consistent with these firms' broader assortment, focus on packaged meals, and a membership format that caters to a wealthier clientele.[39] On the other hand, the supercenter firms (Wal-Mart, Target and Meijer) are among the lowest income interactions, indicating that these stores are especially 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 the set of all stores and the outside good.

We now turn to the impact of distance and vehicle ownership. Not surprisingly, consumers clearly prefer grocery stores that are closer to their homes, presumably reflecting the monetary and opportunity costs of travel. This is consistent with earlier studies, which have found the primary catchment area of a supermarket (or supercenter) to be quite narrow, on the order of two or three miles (Ellickson and Grieco, 2013; Figurelli, 2012). The disutility of distance increases with income, suggesting that the opportunity cost of time is higher for high income consumers. Vehicle ownership leads consumers to be more willing to utilize grocery stores and less sensitive to distance. This is consistent with consumers facing lower travel costs if they own a car.[40] The effects of geography on the utility of club stores appears to be substantially different from grocery stores. First, utility from club stores is extremely sensitive to car ownership, yet appears to be insensitive to distance at mean levels. However, consumers who shop at club stores tend to have high incomes and high levels of vehicle ownership, both of which are associated with stronger distance disutility for clubs. While the coefficients are difficult to interpret individually, when we calculate the revenue elasticity of distance in Table 6 we find substantially lower but still negative effects of distance for club stores. Consumers' greater tolerance for traveling to clubs likely reflects the fact that, unlike supercenters, club stores represent a fundamentally different shopping experience.[41] In particular, consumers purchase many more items in bulk at club stores and therefore make correspondingly fewer trips to them. This places a premium on both storage and transportation. 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 a lower opportunity cost of time (albeit with high income). 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). Overall, these findings have important implications for understanding cross-format competition across space. Different formats appear to have substantially different catchment areas that arise from targeting consumers with differing travel costs (due to car ownership). As a

[39] It is interesting to note that this result reverses itself in specification (5) which drops tract-store interactions.

[40] Vehicle ownership is measured as a probability between 0 and 1 and then demeaned to the tract-level average, so although the coefficient on vehicle ownership is large, very few tracts have positive taste for distance to grocery stores.

[41] In an earlier draft of this paper, we experimented with allowing distance disutility to differ between supercenters and grocery stores, but found no significant difference between these two classes of store.

result, a single geographic market definition is likely to exclude club format outlets from consideration when they are in fact substantial competitors for suburban and exurban grocery expenditures.

Turning now to store features, we first examine the impact of store size separately, which is positive and highly significant for both grocery stores and club stores, though notably much larger for club stores. This may be due to a 1 percent increase in a club store (which averages 124 thousand square feet) resulting in a much larger increase in variety than a 1 percent increase in a grocery store or supercenter (36 and 64 thousand square feet respectively). Income effects exhibit a stronger impact on utility for grocery stores, and are positive but insignificant for club stores.

In Appendix Table C.1 we present estimates for two additional grocery store and supercenter characteristics: full-time employment equivalents and checkouts. Not surprisingly, 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.

5.2 Heterogeneous Effects of Income and Distance

While the model coefficients are informative about sign and relative magnitude, their overall effect on stores' revenues are difficult to interpret directly. Instead, we calculate a rich set of revenue elasticities that reveal how consumer characteristics surrounding a store affect its revenue. Table 6 presents revenue elasticities of distance and income at the chain level.[42] 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.[43] The chains that are most sensitive to distance elasticities are Giant Foods, Stop & Shop, Harris Teeter, and Whole Foods, four 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, also tend to have distance elasticities that are lower than -1. In contrast, Wal-Mart has one of the highest distance elasticities, -.875, indicating that it is able to overcome being located further away from consumers, presumably by offering larger size and other amenities (such as low prices and

[42] Unless otherwise specified, all results in the remainder of the paper are calculated using our preferred specification (1) in Table 5.

[43] While it not easy to directly compare their results with ours, Eizenberg et al. (2016) find that for grocery consumers in Jerursalem, a 1 kilometer increase between origin and destination would decrease demand by 35 percent. Given that consumers in the US likely travel further than those in Jerusalem, a reasonable comparison might be a 1 mile increase in our setting. Given that US shoppers travel about 3 miles to a grocery store on average (Figurelli, 2012), this 33 percent increase in travel distance would lead to a 33 percent decrease in revenues, according to our results, which seems broadly consistent with Eizenberg et al. (2016).

Table 6: Distance and Income Elasticities Large Chains and Clubs

	Distance Elasticity	Income Elasticity
Small Chains	−1.066	0.251
Medium Chains	−1.099	0.550
Albertsons	−1.051	0.570
Aldi	−1.085	0.335
Bashas Markets	−1.019	0.532
Delhaize America (Food Lion)	−1.086	0.493
Fred Meyer	−1.126	0.789
Giant Eagle	−1.082	0.757
Giant Food	−1.261	0.399
Great A & P Tea Co.	−1.116	0.470
HE Butt	−0.987	0.667
Hannaford Bros	−1.078	0.403
Hy Vee Food Stores	−0.998	0.695
Ingles Markets	−1.083	0.528
Kroger	−1.081	0.546
Lone Star Funds (Bi-Lo)	−1.065	0.677
Publix	−1.052	0.657
Raleys	−1.021	0.357
Roundys	−1.069	0.341
Ruddick Corp (Harris Teeter)	−1.194	0.633
Safeway	−1.144	0.351
Save A Lot	−1.027	0.386
Save Mart	−0.940	0.371
Smart & Final	−1.052	0.126
Stater Bros	−1.065	0.284
Stop & Shop	−1.188	0.573
SuperValu	−1.151	0.422
Trader Joes	−1.138	0.109
Weis Markets	−1.136	0.484
Whole Foods	−1.160	0.387
Wild Oats	−1.099	0.302
Winn-Dixie	−0.969	0.613
Meijer	−0.936	0.340
Target	−1.101	0.463
Wal Mart	−0.862	0.605
BJs	−0.292	0.036
Costco	−0.312	0.214
Sam's Club	−0.222	0.227

an assortment of complementary non-grocery products). Other big-box 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. Club stores, which are even larger outlets, are even more insensitive to distance from their consumers. Distance elasticities range from -.222 for Sam's Club to -.312 for Costco. Because 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. However, this result illustrates that club stores are able to draw revenue from a significantly larger geographic area than traditional grocers. Hence, club stores are relevant substitutes for grocery stores even if they are located even several miles away, a fact that could easily be overlooked in an analysis in which stores are simply clustered by geographic market.

The estimated income elasticities are presented in the final column of Table 6. The median income elasticity is 0.422, implying that a ten percent increase in income will increase store revenues by 4.2 percent.

However there are large differences in income elasticities across chains; they range from 0.036 for BJs (a club store) to 0.789 for Fred Meyer. It appears that the stores with the highest income elasticities tend to target the middle-range of the income scale, whereas chains that target high-income customers (Whole Foods and Wild Oats) as well as the limited-assortment stores that serve low-income consumers (Aldi and Save A Lot), have lower income elasticities. This is consistent with low-income consumers substituting towards traditional grocery stores in response to an increase in income while high-income consumers tend to substitute towards the outside good (e.g. restaurants). The fact that these elasticities are below 1 indicates 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. 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. Notably, Wal-Mart has a relatively high income elasticity of 0.605. 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.

Finally, we note that distance also seems to play a role in determining income elasticities. 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 with respect to utility for the top two competitors for each firm, as well as the firm's substitution with the outside good. 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 its own revenue by $1.21\Delta\%$. 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 $.139\Delta\%$. Stated in terms of diversion ratios—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 (.139/1.213) of its increase in revenue will be due to revenue declines at Wal-Mart, 9.4 percent will be due to declines in Safeway's revenue, and 28.2 percent will be due to increases in overall grocery spending (i.e., a decline in the share of the outside good). The remaining 50.9 percent of the increase will be due to revenue declines at other stores. Recall that, assuming a homogeneous marginal utility of income, these measures are identical to the diversion ratios with respect to

Table 7: Own and Cross Semi-elasticities with respect to Utility

Chain	Own Semi-Elasticity	First Comp	Cross Semi-Elasticity	Second Comp	Cross Semi-Elasticity	Outside Cross Semi-Elasticity
Small Chains	1.141	Medium Chains	-0.105	Kroger	-0.084	-0.398
Medium Chains	1.081	Wal Mart	-0.105	Small Chains	-0.092	-0.354
Albertsons	1.213	Wal Mart	-0.138	Safeway	-0.114	-0.342
Aldi	1.321	Medium Chains	-0.171	Small Chains	-0.139	-0.323
Bashas Markets	1.133	Kroger	-0.265	Safeway	-0.162	-0.280
Delhaize America (Food Lion)	1.103	Wal Mart	-0.156	Medium Chains	-0.089	-0.330
Fred Meyer	1.113	Safeway	-0.203	SuperValu	-0.140	-0.345
Giant Eagle	0.986	Small Chains	-0.138	Medium Chains	-0.116	-0.303
Giant Food	1.050	Safeway	-0.108	Small Chains	-0.082	-0.446
Great A & P Tea Co.	1.203	Small Chains	-0.155	Kroger	-0.104	-0.376
HE Butt	0.798	Wal Mart	-0.181	Sam's Club	-0.070	-0.299
Hannaford Bros	1.001	Medium Chains	-0.184	SuperValu	-0.152	-0.371
Hy Vee Food Stores	0.980	Medium Chains	-0.198	Wal Mart	-0.176	-0.295
Ingles Markets	1.102	Wal Mart	-0.171	Lone Star Funds (Bi-Lo)	-0.121	-0.294
Kroger	1.014	Wal Mart	-0.118	Medium Chains	-0.080	-0.320
Lone Star Funds (Bi-Lo)	1.087	Wal Mart	-0.216	Delhaize America (Food Lion)	-0.099	-0.282
Publix	0.931	Wal Mart	-0.141	Winn-Dixie	-0.098	-0.304
Raleys	1.116	Safeway	-0.175	Small Chains	-0.092	-0.408
Roundys	0.956	Medium Chains	-0.136	SuperValu	-0.126	-0.373
Ruddick Corp (Harris Teeter)	1.076	Delhaize America (Food Lion)	-0.178	Medium Chains	-0.112	-0.336
Safeway	1.142	Kroger	-0.108	SuperValu	-0.087	-0.426
Save A Lot	1.298	Small Chains	-0.137	Medium Chains	-0.132	-0.320
Save Mart	1.102	Small Chains	-0.146	Safeway	-0.135	-0.408
Smart & Final	1.321	Kroger	-0.159	Safeway	-0.148	-0.417
Stater Bros	1.081	Kroger	-0.161	SuperValu	-0.130	-0.367
Stop & Shop	1.024	Medium Chains	-0.163	SuperValu	-0.127	-0.411
SuperValu	1.124	Medium Chains	-0.098	Small Chains	-0.097	-0.402
Trader Joes	1.311	Safeway	-0.151	Kroger	-0.117	-0.449
Weis Markets	1.171	Giant Food	-0.273	Small Chains	-0.138	-0.364
Whole Foods	1.302	Safeway	-0.114	Kroger	-0.102	-0.469
Wild Oats	1.330	Kroger	-0.186	Safeway	-0.107	-0.374
Winn-Dixie	1.142	Publix	-0.306	Wal Mart	-0.184	-0.302
Meijer	0.914	Kroger	-0.151	Wal Mart	-0.134	-0.274
Target	1.138	Wal Mart	-0.292	Sam's Club	-0.075	-0.320
Wal Mart	0.785	Kroger	-0.072	Sam's Club	-0.066	-0.279
BJs	1.114	Sam's Club	-0.139	Costco	-0.097	-0.365
Costco	0.978	Sam's Club	-0.122	Safeway	-0.059	-0.395
Sam's Club	0.966	Wal Mart	-0.119	Costco	-0.104	-0.311

price 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, Wild Oats, Aldi, Smart & Final 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 of improving quality must also be high. There are several possible explanations for this. For Whole Foods, which is already known to offer high quality, this may simply reflect the fact that the products sold there are already very 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 single largest competitor of 7 of the 32 other large grocery chains, and the second largest competitor of an additional 2. 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 $.069\Delta\%$ decline in Wal-Mart revenues. On the other hand, a Δ improvement in Wal-Mart's appeal would lead to a $.118\Delta\%$ decline in Kroger's revenues and a $.181\Delta\%$ 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 (0.733) does suggest stronger competition within the club store format than across 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 clubs. Notably, these results are starkly different when we adopt a multinomial logit specification that 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 BJs to non-club stores is 46.1 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

5.4.1 Tract-Level Measures

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 MSAs included in our earlier analysis and present the results in Table 8. Using the thresholds above, we find that

[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

				Mean Number of within 5/10 miles			
Concentration	Number of Tracts	Income	Density	All Stores	Large Chain Stores	Large Chains	Club Stores
Low (< 1500)	9,289	26.83	6253.26	43.69	20.41	5.36	1.20
				134.71	65.93	7.09	4.20
Moderate	22,607	30.73	3017.90	21.77	13.45	4.46	0.95
				64.21	39.93	6.11	2.85
High (> 2500)	21,472	25.77	1233.21	8.36	5.08	2.37	0.38
				22.06	13.48	3.53	0.97
Total	53,368	28.05	2862.98	20.19	11.30	3.77	0.77
				59.52	33.82	5.24	2.33

40.2% percent of all census tracts in the dataset are highly concentrated, while another 42.4% of tracts are moderately concentrated, confirming that the supermarket industry overall is quite concentrated. This result is particularly stark because 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 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.

Overall, our results indicate that, despite allowing for a relatively large choice set for consumers, the estimated disutility of distance leads low-density areas to exhibit significant concentration, despite having access to several outlets. This reflects the tension between scale efficiencies and market power concerns that dominates the debate over retail mergers in rural areas, as well as the more general discussion of food deserts and equal access to healthy food.

5.4.2 Aggregated Measures and Comparison to Standard HHI

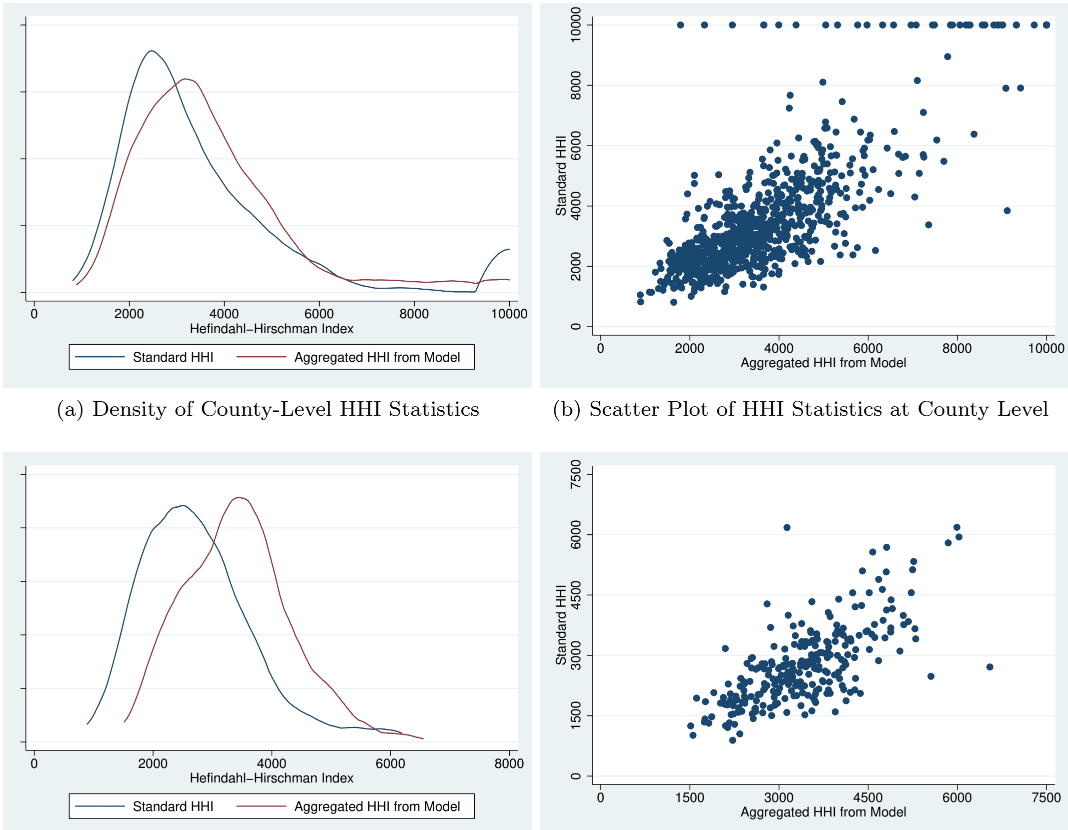
Finally, we aggregate our concentration measures to the county and MSA level to compare them to the standard HHI measure calculated using revenue shares over geographic boundaries. Our aggregated HHI measures are the population weighted average of tract level HHIs defined in equation (10). The standard HHI measure is simply the sum of squared market shares for all firms within the county or MSA respectively, where market shares are calculated based on county or MSA boundaries.

Figure 1 presents the comparisons at both the county and MSA level. Panel 1a contains a plot of the density of concentration statistics using the standard HHI measure in blue, and our aggregated HHI measure in red. Our measure reports slightly higher concentration and slightly less dispersion. On average, county level HHI is 125 points higher using our aggregated measure (3730 versus 3605). However, the most notable difference in the two measures is the mass point of fully monopolized counties (HHI = 10,000) under the standard HHI definition. This is an artifact of the inclusion of some very small counties (with populations less than 15,000) on the periphery of MSAs.[45] Our aggregated measure does not exhibit such a mass point because it is able to account for competition from stores located near to, but not within, these peripheral counties. The effect is also apparent in panel 1b, which presents a scatter plot of the county level concentration statistics. The mass point of small counties which look like monopolies using county boundaries turn out to be fairly heterogeneous under our measure, with a handful even having below-average concentration levels. Overall, the two measures appear to be highly correlated ($\rho = 0.80$), as we would expect.

At the MSA level, the gap in the average HHI is substantially larger between the two measures. Our aggregated measure is 668 points higher than the traditional measure on average (3411 versus 2743). Comparing the MSA level densities in panel 1c, this difference appears to reflect a rightward shift in the traditional HHI distribution between as we move from county to MSA market definitions. It is intuitive that the standard measure of HHI falls substantially when we move to a larger region definition while our own measure is more robust to geographic market boundaries. At the MSA level, there is no longer a mass point of "monopolies" due to artificially small markets. However, when we move to a larger market definition, the standard measure is likely to overstate the degree of competition if establishments located in different parts of the MSA do not in fact compete. Still, as panel 1d indicates, the correlation between the two measures remains strong at the MSA level, the correlation coefficient is 0.70.

We conclude this section by re-iterating that neither county nor MSA level market definitions are likely to be appropriate for the grocery industry. In at least in some cases, the county level appears too small, while MSAs seem consistently too large. These comparisons simply point out that our aggregated HHI measure—which takes into count differentiation between products internal to the market and competition from stores located outside the market boundary—is able to deliver measures of competition that are more robust to the level of aggregation and account for more localized aspects of spatial substitution.

[45] Recall that our analysis only uses census tracts within an MSA.



(a) Density of County-Level HHI Statistics

(b) Scatter Plot of HHI Statistics at County Level

(c) Density of MSA-Level HHI Statistics

(d) Scatter Plot of HHI Statistics at MSA Level

Figure 1: Comparison of Standard and Model Aggregated HHI Measures at County and MSA levels.

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 window correspond to the period just before the merger was announced. The second is a merger between Ahold and Delhaize, which was approved in 2016. Note that in this second case our data correspond to a period far before the actual merger (2006 versus 2016) so it should be viewed as illustrative. 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 first 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 what, if any, the competitive response would be (e.g., raising prices, reducing variety, or even closing stores to avoid canibalization), and whether there exist large enough cost synergies to offset the effects of enhanced market power. This could be accomplished by evaluating the formulas for upward pricing pressure (using, for example, observed margins and a standard efficiency credit) 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.[46] It is also a particularly challenging industry in which to assess the impact of mergers, because 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.[47]

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 this merger 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

[46] 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).

[47] 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).

HHI due to the merger either "warrants scrutiny" or is "presumed likely to enhance market power". The remaining markets are characterized as not raising significant anti-trust concerns.

The results are presented in Table 9. Notably, our analysis of the Whole Foods/Wild Oats case overwhelming sides with the defense, as *almost all* tracts (99.5%) are classified as not raising concerns. In only 31 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.[48] 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.[49] 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 -0.028 whereas Whole Food's own semi-elasticity with respect to utility is 1.324, equating to a diversion ratio with respect to utility of only 2.1 percent.[50] In contrast Safeway and Kroger appear to be much stronger competitors to Whole Foods, with diversion ratios of 8.8 and 7.8 percent respectively.[51] Although we do not have information on the actual margins for either firm, typical margins for grocery firms in the U.S. tend to be around 30%.[52] If we assume this margin and evaluate equation (11), the positive contribution to net UPP would be merely 0.9%, suggesting only minimal cost synergies would be needed to counteract the market power effects of the merger.[53] 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 merger between Delhaize (Food Lion and Hannaford) and Ahold (Giant Food and Stop & Shop). This merger was announced in June of 2015 and approved one year later (after review by the FTC). The merger created one of the largest supermarket firms in North America, with the combined

[48] 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 50 and lifting 2 tracts into the "enhancing market power" (see Table C.4 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).

[49] In a previous version of the paper, we also estimated the model with an additional "organic" nest. We found the corresponding baseline parameters to be unaffected, and the additional nesting parameter on the natural/organic segment to be 0.964 (0.121), making it statistically insignificantly different from 1. This corresponds to tastes for Whole Foods and Wild Oats being independent, providing an additional test of the government's claim that the PNOS segment was distinct.

[50] The diversion ratio of Whole Foods to Wild Oats is an even weaker 1.0 percent.

[51] 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.

[52] For example, the 2006 Annual Retail Trade Survey conducted by the U.S. Census reports average margins of 28.9% for grocery stores (https://www.census.gov/programs-surveys/arts.html). Similarly, Stroebel and Vavra (2019) compute average margins of 31% using detailed price and wholesale cost data from a large U.S. supermarket chain observed from 2004 to 2007. They further argue that marginal costs are relatively constant across stores within a chain which, together with the uniform pricing results of Della Vigna and Gentzkow (2017), implies that margins are essentially fixed at the chain level.

[53] This calculation takes our diversion ratios with respect to utility as an approximation of the diversion ratio with respect to price.

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	14	66.87	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	17	43.70	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	31	110.57	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
MA	974	4547.29	335	1676.56	126	654.80
MD	1214	4999.43	370	1713.74	149	662.99
NH	124	587.62	46	229.54	58	256.56
PA	76	361.57	10	47.81	16	89.99
RI	19	69.11	4	15.35	15	53.76
VA	577	2550.94	285	1303.54	122	573.66
WV	31	163.93	0	0	31	163.93
Total	3118	13712.08	1051	4992.99	524	2501.69

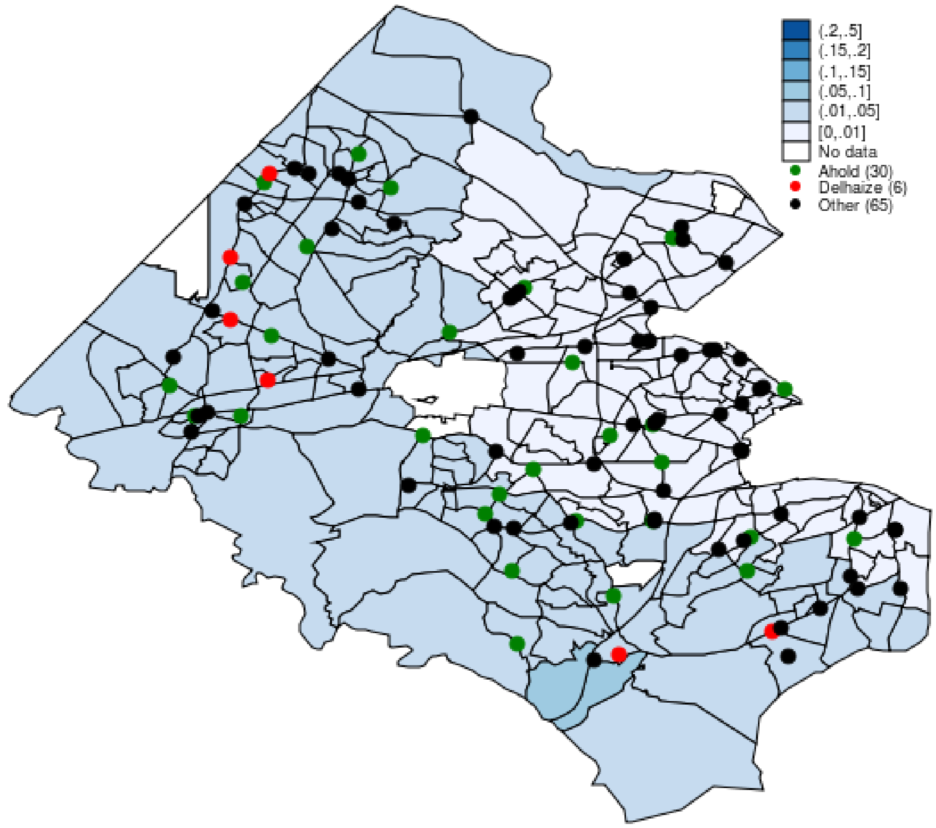


Figure 2: Post merger increases in HHI by tract: Fairfax County, VA

entity ranking 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.

We use our model to compute the diversion ratio with respect to utility between Ahold and Delhaizie stores in areas where the two compete. We find the diversion of Delhaizie to Ahold to be substantial, 19.7 percent.[54] If we again assume margins of roughly 30 percent, the positive contribution to net UPP would be 8.44 percent, which is likely higher than any reasonable "efficiency credit".[55]

The areas of most significant concern are in Maryland, Massachusetts and Virginia.[56] It is evident from

[54]The opposite diversion, from Ahold to Delhaizie is 5.1 percent. The asymmetry in diversion ratios, which is also present at the store level in Table 13, stems from Ahold being a much larger chain with several stores located relatively far away from Delhaizie stores, even in areas that broadly overlap.

[55]Again, for this back of the envelope calculation it is important to keep in mind we have calculated diversion ratios with respect to *utility* rather than price. As we show in Appendix B, the two are equivalent if price sensitivity is homogeneous in the population. In the same appendix we show how our diversion ratio could be adjusted using outside measures of heterogeneity in price sensitivity.

[56]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 11: Population Density and Ahold/Delhaize Anti-Trust Concern

	Merger Evaluation			
Population Density	No Concern	Warrant Scrutiny	Presumed Likely	Total
Low (<1500)	162	397	410	969
Medium (>1500 and <4000)	391	599	114	1104
High (>4000)	990	55	0	1045
Total	1543	1051	524	3118

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 clearly illustrated by looking at particular counties. For a concrete example, we focus on Fairfax County, VA in the Washington, DC suburbs. Figure 2 illustrates that, within Fairfax County, there is little reason for concern in the more densely populated areas of the county, which are mainly in the east (around the Capital Beltway). In contrast, the less densely populated western and southern portions of the county show Herfindahl increases 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 because store divestitures are the typical remedy in contested mergers. We now provide two such measures. First, we consider the merging diversion ratio with respect to utility: the sum of the store level diversion ratio of store s to all stores in the merging chain. As discussed in Section 3.5, 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 with respect to utility 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

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	63	30	8	134	56
Delhaize	161	22.11	137	122	72	61	75
Whole Foods	69	2.92	2	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) where weights are revenue shares of the store under consideration computed from the model.

store's catchment area.[57] Next, because there are no accepted rule-of-thumb thresholds for what constitutes a "high" diversion ratio, we report the number of stores where the diversion ratio with merging parties exceeds 5, 10, and 20 percent.[58] 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.[59] 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. Because 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

[57] 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.

[58] Because upward pricing pressure also depends on the actual margins of the acquired product(s), the relevant ratio is industry specific. Assuming 30 percent margins (and equating diversion ratios with respect to utility and price), diversion ratios of 5, 10 and 20 percent would require cost savings of roughly 2.1, 4.3, and 8.6 percent respectively to completely offset the impact of enhanced market power.

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

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	111	17	5	1
Raise Concerns	17	15	17	7
Delhaize				
No Concern	14	0	10	1
Warrants Scrutiny	6	6	20	29
Raise Concerns	4	9	20	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 upon 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.[60] 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.

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

[60] The individual values are .88 for Ahold, .78 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	1,217	326	0	1,543
Warrants Scrutiny	2	424	625	1,051
Presumed Likely	0	0	524	524
Total	1,219	750	1,149	3,118

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.[61] 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 an over 50 percent decrease (from 1149 to 524) 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 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

Using readily available information on store locations, characteristics and revenues, we propose a spatially-aggregated nested-logit model of competition. Importantly, the model does not require the researcher to partition firms into independent markets. The model can be used to analyze the degree of spatial retail

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

competition across a variety of retail chains and to evaluate the impact of potential mergers. We illustrate the utility of the framework using two examples of recent mergers.

We designed our framework to have parsimonious data requirements. In particular, we do not require the analyst to observe individual consumer expenditures or even tract-specific expenditure shares. While the low data requirement is an advantage in many settings, researchers with access to micro-level data should be able to obtain more precise estimates of substitution patterns. Because our model includes an equation for location-specific expenditure shares (3), we are optimistic that it would be possible to incorporate such micro-moments into our estimator were these data available. We leave this exercise future research.

Apart from its role in analyzing prospective mergers, this model is a natural input to structural models of entry and expansion. We believe our results clearly establish that there is substantial heterogeneity in consumer preferences for groceries, and illustrates how that heterogeneity shapes the competitive environment. Clearly income, location, and vehicle ownership play an important role, and the model could be extended to include additional demographic variables. By characterizing the revenue response of firm location, size and quality, our model provides a key ingredient towards estimating the essential revenue side components driving firms location decisions. Revealed preference could then identify the cost side implications. We see our model as an important first step to establishing how preferences, distribution technology, and retail technology (such as novel formats) determine market structure in retail industries.

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A Derivations

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,

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

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,

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

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,

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

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

$$\begin{aligned}
\frac{\partial p_{st}}{\partial u_{rt}} &= \frac{\partial p_{st|k}}{\partial u_{rt}}P_{t,k(s)} + \frac{\partial P_{t,k(s)}}{\partial u_{rt}}p_{st|k(s)} \\
&= \frac{1}{\mu_{k(s)}}p_{st|k}\left(\mathbf{1}\left[s=r\right] - \mathbf{1}\left[r\in C_{t,k(s)}\right]p_{rt|k(s)}\right)P_{t,k(s)} + p_{rt}\left(\mathbf{1}\left[r\in C_{t,k(s)}\right] - P_{t,k(s)}\right)p_{st|k} \\
&= \frac{1}{\mu_{k(s)}}p_{st}\left(\mathbf{1}\left[s=r\right] - \mathbf{1}\left[r\in C_{t,k(s)}\right]p_{rt|k(s)}\right) + p_{rt}\left(\mathbf{1}\left[r\in C_{t,k(s)}\right]p_{st|k(s)} - p_{st}\right) \\
&= \mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}}p_{st} + \mathbf{1}\left[r\in C_{t,k(s)}\right]\left(p_{rt}p_{st|k(s)} - \frac{1}{\mu_{k(s)}}p_{st}p_{rt|k(s)}\right) - p_{st}p_{rt} \\
&= \mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}}p_{st} + \mathbf{1}\left[r\in C_{t,k(s)}\right]\left(1 - \frac{1}{\mu_{k(s)}}\right)p_{st}p_{rt|k(s)} - p_{st}p_{rt} \\
&= p_{st}\left(\mathbf{1}\left[s=r\right]\frac{1}{\mu_{k(s)}} + \mathbf{1}\left[r\in C_{t,k(s)}\right]\left(1 - \frac{1}{\mu_{k(s)}}\right)p_{rt|k(s)} - p_{rt}\right) \qquad (12)
\end{aligned}$$

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 (12) and the derivative of utility with respect to distance follows from our linear utility specification. Substituting this into the elasticity yields,

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

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 (12) 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 (12) we complete the derivation to the formula that appears in the text.

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

B Diversion Ratios with Respect to Price Versus Utility

In this appendix, we elaborate on the difference between semi-elasticities and diversion ratios with respect to utility, which we introduce, and the standard measure, which is computed with respect to price. Our focus on the former arises here from the fact that we do not observe price in our data, but it is also relevant in environments like ours where price is observed but does not vary across products conditional on other characteristics. We exploit the existence of uniform pricing in our setting in order to use chain-income effects as appropriate controls for price effects Here, we make further use of this assumption to illustrate how these two measures relate to one another.

The distinction between the two measures is most straightforward when considering substitution patterns directly. Our measure for semi-elasticity of revenue for f with respect to utility of chain g is,

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

If we assume that chains price uniformly at the chain level, the (revenue) cross-price elasticity is,

$$\rho^{f,g} = \frac{P_g}{R^f} \sum_{q \in F_g} \sum_{t \in L_q} \frac{\partial R^f}{\partial u_{qt}} \frac{\partial u_{qt}}{\partial P_g}$$

Comparing $\sigma^{f,g}$ to $\rho^{f,g}$ we see that they are both sums over store-tract derivatives of revenue with respect to utility. However, $\sigma^{f,g}$ weights these values uniformly while $\rho^{f,g}$ weights them according to the price sensitivity of tracts. That is, more price sensitive tracts will receive stronger weight in $\rho^{f,g}$ since the same shift in u_{qt} can be achieved with a smaller reduction in prices for these tracts. However, if price sensitivity is constant across all consumers, then $\frac{\partial u_{qt}}{\partial P_g}$ can be factored out of the summation and the two measures are equivalent up to a multiplicative constant.

Turning to the calculation of diversion ratios, the diversion ratio with respect to utility (DRU) is,[62]

$$D^{f,g} = \frac{\sigma^{g,f}}{\sigma^{f,f}} \frac{R^g}{R^f} = -\frac{\sum_{q \in F_f} \sum_{t \in L_f} \frac{\partial R^g}{\partial u_{qt}}}{\sum_{q \in F_f} \sum_{t \in L_q} \frac{\partial R^f}{\partial u_{qt}}}$$

Whereas the diversion ratio with respect to price (DRP) is,

$$E^{f,g} = \frac{\rho^{g,f}}{\rho^{f,f}} \frac{R^g}{R^f} = -\frac{\sum_{q \in F_f} \sum_{t \in L_q} \frac{\partial R^g}{\partial u_{qt}} \frac{\partial u_{qt}}{\partial P_f}}{\sum_{q \in F_f} \sum_{t \in L_q} \frac{\partial R^f}{\partial u_{qt}} \frac{\partial u_{qt}}{\partial P_f}}$$

Similar to the substitution patterns, these ratios are identical if $\frac{\partial u_{qt}}{\partial P_f}$ does not vary over q, t. When is this assumption likely to hold? If we continue to assume that prices are uniform (i.e., set at the chain level), then the effect of price is totally absorbed in the chain effects we estimate, which are allowed to vary by income. The question becomes how does a change in prices affect these chain effects. If all consumers value price equally, then the chain effects could be decomposed as follows

$$\xi_f^0 + \xi_f^i \Delta inc_t = \tilde{\xi_f} - \alpha P_f + \xi^i \Delta inc_t$$

where Δinc_t indicates the deviation of tract t's income from the national average. In this case $\frac{\partial u_{qt}}{\partial P_f} = -\alpha$ and DRU = DRP. However, it is more likely that price sensitivity varies across tracts. If price sensitivity is related to income, as is commonly assumed, we would have

$$\xi_f^0 + \xi_f^i \Delta inc_t = \tilde{\xi_f} - \alpha^0 P_f + \tilde{\xi^i} \Delta inc_t + \alpha^i \Delta inc_t P_f$$

and so $\frac{\partial u_{qt}}{\partial P_f} = -\alpha + \alpha^i \Delta inc_t$. In this case, price elasticity is related to utility semi-elasticity by,

$$\rho^{f,g} = -P_g \left(\alpha^0 \sigma^{f,g} + \frac{\alpha^i}{R^f} \sum_{q \in F_g} \sum_{t \in L_q} \Delta inc_t \frac{\partial R^f}{\partial u_{qt}} \right)$$

The DRP is,

$$E^{f,g} = -\frac{R^g \sigma^{g,f} + \frac{\alpha^i}{\alpha^0} \sum_{q \in F_g} \sum_{t \in L_q} \Delta inc_t \frac{\partial R^f}{\partial u_{qt}}}{R^f \sigma^{f,f} + \frac{\alpha^i}{\alpha^0} \sum_{q \in F_f} \sum_{t \in L_q} \Delta inc_t \frac{\partial R^f}{\partial u_{qt}}}$$

Therefore, DRP differs from DRU by correction terms in the numerator and denominator which capture how different tracts value price differently. Unfortunately, our model is unable to identify α_i separately from chain-income effects. However, outside information on how price sensitivity varies with income could in principle be paired with our results to compute diversion ratios with respect to price under these assumptions. These correction terms will be small if either α^i/α is small in magnitude (so income does not affect price sensitivity) or if the correlation between income and substitutability with respect to utility is small.

To conclude, we note that for characteristics for which we do observe within chain variation, such as distance or store size, it would be straightforward to calculate both substitution elasticities (or semi-elasticities) and diversion ratios using our model. These patterns may also be of interest to when studying non-price strategic interaction between retail firms.

C Additional Figures and Tables

[62] Note that because $\sigma^{f,g} R^g = \sigma^{g,f} R^f$ it is also true that $D^{f,g} = \sigma^{f,g}/\sigma^{f,f}$ as presented in the paper (see footnote 25).

Table C.1: Additional Parameter Estimates.

	Baseline (1)	Multinomial Logit (2)	No Clubs (3)	No FTE/Checkouts (4)	Drop Interactions (5)
Tract Characteristics in Outside Option					
hhsize	0.347	0.517	0.406	0.335	0.547
	(0.015)	(0.019)	(0.013)	(0.011)	(0.006)
hhsize*log(inc)	0.643	0.809	0.680	0.642	0.566
	(0.011)	(0.019)	(0.010)	(0.010)	(0.011)
log(density)	1.577	2.398	1.846	1.358	1.565
	(0.153)	(0.198)	(0.143)	(0.129)	(0.134)
log(density)^2	−0.198	−0.348	−0.281	−0.172	−0.206
	(0.056)	(0.066)	(0.054)	(0.049)	(0.054)
Additional Store Characteristics					
log(fte)	0.242	0.343	0.241		0.243
	(0.003)	(0.003)	(0.002)		(0.002)
log(fte)*log(inc)	−0.120	−0.169	−0.116		−0.113
	(0.008)	(0.009)	(0.007)		(0.007)
log(chk)	0.172	0.250	0.175		0.219
	(0.005)	(0.005)	(0.004)		(0.003)
log(chk)*log(inc)	0.306	0.413	0.302		0.269
	(0.012)	(0.015)	(0.011)		(0.012)
Additional Tract-Store Interactions					
Grocery Stores and Supercenters					
hhsize*dist	−0.058	−0.074	−0.053	−0.058	
	(0.002)	(0.002)	(0.002)	(0.002)	
log(density)*dist	0.032	0.041	0.028	0.028	
	(0.002)	(0.003)	(0.002)	(0.001)	
hhsize*log(size)	0.041	0.054	0.045	0.012	
	(0.006)	(0.007)	(0.005)	(0.002)	
log(density)*log(size)	0.008	−0.012	0.010	−0.061	
	(0.003)	(0.004)	(0.003)	(0.001)	
hhsize*log(fte)	−0.052	−0.055	−0.053		
	(0.005)	(0.006)	(0.004)		
log(density)*log(fte)	0.008	0.043	0.008		
	(0.002)	(0.003)	(0.002)		
hhsize*log(chk)	0.048	0.069	0.052		
	(0.008)	(0.010)	(0.007)		
log(density)*log(chk)	−0.075	−0.074	−0.074		
	(0.004)	(0.005)	(0.004)		
Club Stores					
hhsize*dist	0.032	0.061		0.013	
	(0.018)	(0.016)		(0.018)	
log(density)*dist	0.043	0.052		0.024	
	(0.011)	(0.011)		(0.012)	
hhsize*log(size)	−0.108	−0.140		−0.089	
	(0.021)	(0.021)		(0.021)	
log(density)*log(size)	−0.014	0.008		−0.022	
	(0.013)	(0.013)		(0.013)	

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

Table C.2: Chain Effect Estimates, Intercepts

	Baseline (1)	Multinomial Logit (2)	No Clubs (3)	No FTE/Checkouts (4)	Drop Tract-Char (5)
Small Chains	−1.669	−1.579	−1.262	−1.302	−1.205
	(0.036)	(0.047)	(0.031)	(0.027)	(0.016)
Medium Chains	−1.558	−1.431	−1.150	−1.125	−1.093
	(0.036)	(0.047)	(0.031)	(0.027)	(0.017)
Albertsons	−1.464	−1.302	−1.061	−1.039	−1.004
	(0.037)	(0.048)	(0.032)	(0.029)	(0.019)
Aldi	−1.760	−1.708	−1.351	−1.564	−1.305
	(0.037)	(0.047)	(0.031)	(0.029)	(0.018)
Bashas Markets	−1.322	−1.106	−0.936	−0.952	−0.850
	(0.038)	(0.049)	(0.033)	(0.029)	(0.021)
Delhaize America (Food Lion)	−1.613	−1.513	−1.204	−1.248	−1.146
	(0.037)	(0.047)	(0.031)	(0.028)	(0.018)
Fred Meyer	−1.234	−0.981	−0.840	−0.531	−0.745
	(0.047)	(0.057)	(0.039)	(0.042)	(0.033)
Giant Eagle	−1.247	−0.987	−0.816	−0.668	−0.774
	(0.041)	(0.051)	(0.035)	(0.032)	(0.026)
Giant Food	−1.279	−1.031	−0.877	−0.692	−0.798
	(0.040)	(0.051)	(0.035)	(0.032)	(0.024)
Great A & P Tea Co.	−1.455	−1.294	−1.047	−0.957	−1.014
	(0.041)	(0.052)	(0.035)	(0.031)	(0.026)
HE Butt	−0.981	−0.674	−0.580	−0.382	−0.507
	(0.038)	(0.049)	(0.033)	(0.029)	(0.021)
Hannaford Bros	−1.297	−1.062	−0.906	−0.763	−0.804
	(0.041)	(0.052)	(0.035)	(0.032)	(0.025)
Hy Vee Food Stores	−1.416	−1.202	−1.014	−0.729	−0.940
	(0.046)	(0.055)	(0.039)	(0.036)	(0.033)
Ingles Markets	−1.676	−1.611	−1.259	−1.317	−1.201
	(0.040)	(0.051)	(0.035)	(0.031)	(0.024)
Kroger	−1.189	−0.928	−0.786	−0.737	−0.720
	(0.036)	(0.047)	(0.031)	(0.027)	(0.017)
Lone Star Funds (Bi-Lo)	−1.576	−1.452	−1.157	−1.162	−1.111
	(0.038)	(0.049)	(0.033)	(0.030)	(0.020)
Publix	−1.361	−1.173	−0.956	−0.799	−0.900
	(0.038)	(0.049)	(0.032)	(0.028)	(0.020)
Raleys	−1.249	−1.014	−0.845	−0.811	−0.777
	(0.041)	(0.052)	(0.035)	(0.032)	(0.027)
Roundys	−1.159	−0.869	−0.766	−0.637	−0.703
	(0.044)	(0.054)	(0.038)	(0.035)	(0.031)
Ruddick Corp (Harris Teeter)	−1.360	−1.152	−0.927	−0.884	−0.889
	(0.044)	(0.055)	(0.038)	(0.036)	(0.030)
Safeway	−1.230	−0.990	−0.829	−0.785	−0.768
	(0.036)	(0.047)	(0.031)	(0.027)	(0.018)
Save A Lot	−1.583	−1.470	−1.172	−1.309	−1.125
	(0.036)	(0.047)	(0.031)	(0.027)	(0.017)
Save Mart	−1.226	−0.982	−0.818	−0.834	−0.754
	(0.040)	(0.051)	(0.035)	(0.030)	(0.025)
Smart & Final	−1.285	−1.039	−0.882	−1.159	−0.795
	(0.038)	(0.049)	(0.033)	(0.030)	(0.020)
Stater Bros	−0.994	−0.665	−0.590	−0.579	−0.519
	(0.042)	(0.052)	(0.036)	(0.037)	(0.026)
Stop & Shop	−1.421	−1.234	−1.010	−0.894	−0.957
	(0.039)	(0.050)	(0.033)	(0.030)	(0.022)
SuperValu	−1.321	−1.115	−0.914	−0.883	−0.861
	(0.036)	(0.047)	(0.031)	(0.027)	(0.018)
Trader Joes	−0.898	−0.544	−0.492	−0.501	−0.442
	(0.044)	(0.054)	(0.037)	(0.035)	(0.029)
Weis Markets	−1.691	−1.615	−1.280	−1.270	−1.218
	(0.042)	(0.053)	(0.036)	(0.032)	(0.026)
Whole Foods	−1.256	−1.045	−0.845	−0.802	−0.812
	(0.048)	(0.060)	(0.041)	(0.042)	(0.037)
Wild Oats	−1.622	−1.534	−1.217	−1.131	−1.167
	(0.042)	(0.053)	(0.036)	(0.032)	(0.028)
Winn-Dixie	−1.635	−1.534	−1.227	−1.188	−1.174
	(0.038)	(0.048)	(0.032)	(0.029)	(0.019)
Meijer	−1.562	−1.191	−1.155	−0.452	−1.033
	(0.038)	(0.050)	(0.033)	(0.028)	(0.021)
Target	−1.909	−1.590	−1.532	−0.841	−1.381
	(0.041)	(0.054)	(0.035)	(0.031)	(0.026)
Wal Mart	−1.349	−0.960	−0.962	−0.372	−0.828
	(0.037)	(0.048)	(0.032)	(0.027)	(0.018)
BJs	−3.234	−2.605		−3.299	−2.505
	(0.255)	(0.282)		(0.249)	(0.266)
Costco	−2.625	−1.810		−2.685	−1.858
	(0.258)	(0.286)		(0.252)	(0.269)
Sam's Club	−2.850	−2.125		−2.895	−2.074
	(0.266)	(0.294)		(0.260)	(0.277)

Table C.3: Chain Effect Estimates, Slopes

	Baseline (1)	Multinomial Logit (2)	No Clubs (3)	No FTE/Checkouts (4)	Drop Tract-Char (5)
Small Chains	−0.020	−0.099	0.024	−0.262	−0.319
	(0.036)	(0.053)	(0.031)	(0.027)	(0.035)
Medium Chains	−0.025	−0.100	0.016	−0.252	−0.323
	(0.038)	(0.055)	(0.033)	(0.028)	(0.037)
Albertsons	−0.141	−0.231	−0.078	−0.606	−0.428
	(0.050)	(0.067)	(0.044)	(0.044)	(0.050)
Aldi	−0.099	−0.245	−0.085	−0.379	−0.396
	(0.065)	(0.080)	(0.055)	(0.061)	(0.064)
Bashas Markets	−0.222	−0.358	−0.167	−0.573	−0.534
	(0.047)	(0.064)	(0.040)	(0.037)	(0.047)
Delhaize America (Food Lion)	−0.226	−0.384	−0.201	−0.498	−0.520
	(0.045)	(0.062)	(0.039)	(0.037)	(0.044)
Fred Meyer	−0.122	−0.273	−0.053	−0.319	−0.505
	(0.125)	(0.142)	(0.106)	(0.135)	(0.130)
Giant Eagle	−0.386	−0.654	−0.399	−0.498	−0.626
	(0.108)	(0.123)	(0.086)	(0.084)	(0.110)
Giant Food	0.067	−0.043	0.144	−0.259	−0.254
	(0.053)	(0.070)	(0.046)	(0.044)	(0.053)
Great A & P Tea Co.	−0.247	−0.421	−0.213	−0.612	−0.462
	(0.084)	(0.100)	(0.069)	(0.071)	(0.088)
HE Butt	−0.057	−0.052	0.046	−0.461	−0.349
	(0.049)	(0.065)	(0.042)	(0.039)	(0.048)
Hannaford Bros	−0.491	−0.732	−0.440	−0.824	−0.845
	(0.090)	(0.112)	(0.078)	(0.075)	(0.091)
Hy Vee Food Stores	−0.017	−0.121	0.070	−0.512	−0.333
	(0.135)	(0.153)	(0.114)	(0.131)	(0.135)
Ingles Markets	−0.540	−0.871	−0.495	−0.823	−0.820
	(0.108)	(0.129)	(0.094)	(0.089)	(0.108)
Kroger	−0.249	−0.405	−0.188	−0.547	−0.548
	(0.040)	(0.057)	(0.035)	(0.031)	(0.040)
Lone Star Funds (Bi-Lo)	−0.107	−0.240	−0.079	−0.459	−0.418
	(0.069)	(0.085)	(0.060)	(0.068)	(0.070)
Publix	−0.025	−0.081	0.042	−0.352	−0.288
	(0.049)	(0.067)	(0.042)	(0.039)	(0.049)
Raleys	−0.201	−0.303	−0.150	−0.683	−0.496
	(0.090)	(0.108)	(0.081)	(0.072)	(0.093)
Roundys	−0.864	−1.326	−0.751	−1.179	−1.094
	(0.121)	(0.134)	(0.101)	(0.101)	(0.121)
Ruddick Corp (Harris Teeter)	0.080	−0.022	0.084	−0.150	−0.213
	(0.076)	(0.094)	(0.066)	(0.063)	(0.078)
Safeway	−0.101	−0.188	−0.035	−0.462	−0.385
	(0.042)	(0.059)	(0.036)	(0.032)	(0.041)
Save A Lot	−0.061	−0.186	−0.053	−0.520	−0.375
	(0.052)	(0.068)	(0.045)	(0.048)	(0.051)
Save Mart	0.079	0.075	0.124	−0.224	−0.226
	(0.079)	(0.091)	(0.069)	(0.061)	(0.080)
Smart & Final	−0.053	−0.134	0.013	−0.405	−0.366
	(0.056)	(0.072)	(0.049)	(0.051)	(0.055)
Stater Bros	−0.221	−0.326	−0.192	−0.509	−0.516
	(0.075)	(0.099)	(0.066)	(0.082)	(0.075)
Stop & Shop	0.067	0.000	0.091	−0.249	−0.203
	(0.066)	(0.082)	(0.056)	(0.054)	(0.067)
SuperValu	−0.173	−0.299	−0.135	−0.518	−0.452
	(0.044)	(0.061)	(0.038)	(0.035)	(0.043)
Trader Joes	−0.195	−0.311	−0.150	−0.209	−0.472
	(0.073)	(0.090)	(0.061)	(0.064)	(0.072)
Weis Markets	−0.076	−0.237	−0.061	−0.290	−0.379
	(0.111)	(0.135)	(0.097)	(0.086)	(0.109)
Whole Foods	0.166	0.195	0.217	0.023	−0.099
	(0.074)	(0.094)	(0.063)	(0.062)	(0.075)
Wild Oats	−0.012	−0.031	0.026	−0.447	−0.284
	(0.074)	(0.091)	(0.063)	(0.058)	(0.074)
Winn-Dixie	−0.313	−0.483	−0.236	−0.709	−0.617
	(0.054)	(0.071)	(0.046)	(0.046)	(0.053)
Meijer	−1.105	−0.805	−0.978	−1.528	−1.389
	(0.072)	(0.110)	(0.060)	(0.054)	(0.071)
Target	−0.691	−0.587	−0.598	−0.928	−0.920
	(0.079)	(0.115)	(0.069)	(0.061)	(0.077)
Wal Mart	−0.499	−0.210	−0.343	−0.818	−0.759
	(0.046)	(0.064)	(0.040)	(0.033)	(0.045)
BJs	0.163	−0.100		0.104	−0.806
	(0.765)	(0.876)		(0.758)	(0.859)
Costco	0.556	0.196		0.532	−0.336
	(0.779)	(0.901)		(0.770)	(0.873)
Sam's Club	0.168	−0.051		0.057	−0.787
	(0.787)	(0.909)		(0.778)	(0.883)

Table C.4: Effect of Excluding Club Stores on Evaluating the Whole Foods/Wild Oats Merger

	Without Club Stores			
With Club Stores	Both Firms Present	Warrants Scrutiny	Presumed Likely	Total
Both Firms Present	6,105	21	0	6,126
Warrants Scrutiny	0	29	2	31
Total	6,105	50	2	6,157