Balancing profitability and customer welfare: an application to zone-pricing by a supermarket chain[1]

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March 2002.
This is a rough draft. Comments are welcome.

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Abstract

We investigate the impact of price discrimination by a large Chicago supermarket chain. Using a structural econometric approach, we are able to measure the impact on prices, profits and consumer welfare of shifting from a uniform chain-level pricing policy to a regionally-segmented zone-pricing policy. We estimate demand systems for two different product categories using a database containing store-level information on sales, prices, promotions and demographic profiles for each of the stores' market areas.. As wholesale prices are observed in our data, we investigate the ability of our estimated demand system to generate reasonable approximations of the true data on retailer markups with a zone category management model. Using the structurally-derived retailer and consumer valuation metrics, we study the impact of moving from a zone pricing scheme to an individual store-level pricing policy. Further, we propose alternatives to the store pricing policy in order to address some potential practical implementation problems of that policy.

Our results seem to provide reasonable estimates of the underlying pricing decisions in the chain. Specifically, the retail rmarkups obtained from the estimated elasticity structure reasonably approximate the markups observed in the data. In assessing the impact of zone-pricing, we find that benefits (to the store) and costs(to the consumer) of price discrimination vary by product category. Thus, certain products are better-suited to zone-pricing than others. Our recommended alternative pricing policies seem to alleviate some of the losses to consumers, due to store-pricing, while still offering notable profit gains to the retailer.

1   Introduction

In recent years, the practice of "zone pricing" has become increasingly popular for retailers. This form of third-degree price discrimination is a spatial pricing policy whereby a firm selects various delivered prices and the geographic zones in which they apply. In some instances, the definition of a zone may be sufficiently narrow that nearby outlets of a common retail chain may charge noticeably different prices. For instance, some large supermarket chains allow prices to vary across clusters of stores within a given metro-market. Similarly, retail gasoline stations in a given city often charge higher prices at outlets near freeways and fast food chains charge different prices at airports.

Recently, policy researchers have begun investigating the legality of zone pricing practices in industries such as wholesale gasoline (LA Times 2000) and dairy (Milwaukee Journal Sentinel 1999). In wholesale channels, zone pricing could potentially inflate prices in certain markets at the expense of retailers. Alternatively, in the case of dairy, government-imposed zone pricing could depress prices in certain markets at the expense of individual farmers. These are typical outcomes of the well-known monopoly third-degree price discrimination problem (e.g. Schmalensee 1981 and Varian 1985). In particular, uniform prices tend to lie somewhere between the extremes of the discriminatory prices. For supermarket price zones, similar "fairness" policy concerns as those above could arise if price discrimination raises shelf prices in zones catering predominantly to lower-income consumers with lower access to search for the "best" price.

In practice, supermarket pricing decisions tend to be made weekly on a category-by-category basis by independent category managers. As a result, most supermarket pricing studies (e.g. Slade 1995 and Chintagunta 2002) consist of a short-run partial equilibrium model of the category in question, rather than a broader model of the store-wide pricing decisions. Consumer losses within a category may be small from the category manager's perspective when going from a uniform to a zone level pricing policy. From a store manager's perspective, aggregating the impact of zone-pricing across categories could generate non-trivial consumer welfare losses that, in the long-run, could translate into losses in store traffic as consumers switch to other stores. This possibility generates a strategic motivation for identifying categories in which zone-pricing generates substantial additional profits without extracting too much consumer surplus.

We investigate the implications of zone-pricing by using a rich scanner data set for a large supermarket chain in the Chicago area. The data consist of weekly store-level SKU prices, quantities, margins, traffic and promotional information for 2 of the product

categories available.[1] The data also contain an index that classifies clusters of stores into pricing zones according to the chain's definition. To complement the store data, we use competitive information from Spectra marketing that characterizes the demographic profile for each store's consumer base as well as the proximity to local competitors. One of the unique features of the data is the availability of weekly store margins, which we use to back out a measure of the wholesale price. Combining wholesale prices with the zone designations provides another interesting aspect of the data. Unlike previous empirical work on price discrimination, we are better able to attribute cross-sectional price variation to discrimination as opposed to alternative explanations, such as cost differences. Thus, we are in a better position to measure the welfare implications from third-degree price discrimination.

Using the data for 2 product categories available in the database, refrigerated orange juice and liquid laundry detergent, we estimate structural demand systems. Access to retail margins as described above allows us to validate the ability of our demand system to recover the true underlying data-generating process by comparing the margins observed in the data to those predicted using the estimated demand system. This validation is similar to Nevo (2001) and Slade (2002) except that we observe a full time-series of margins rather than a single observation of the approximate mean margin for each alternative. Using a static category management pricing model, we then simulate the prices and sales consistent with uniform weekly chain-level pricing. Since the data contain the chain's definition of the retail zones, we are able to compute the price and welfare impacts of zone pricing relative to chain level pricing. Moreover, we are able to assess which local consumer segments benefit and which are hurt by this geographic price discrimination and how these effects vary across product categories. We then repeat the exercise at the store level by implementing a profit-increasing store-level pricing model and simulate its impact on prices, profits and consumer welfare. Finally, given the practical limitations of implementing a store level pricing policy, we propose an alternative pricing scheme that alleviates this problem.

A key feature of our estimation approach is the ability to identify flexible substitution patterns while controlling for the endogeneity of prices. We estimate systems of demand equations, allowing the shape of demand to vary across stores. As in Berry, Levinson and Pakes (BLP hereafter, 1995), we use an aggregate mixed logit demand specification. The demand model allows for category expansion by including a "no purchase" option in

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[1]The analysis has been carried out for 7 product categories. In the interests of space, we have focused two categories that differ in terms of their implications.

the specification. The parsimony of the BLP approach comes, partially, from the use of measurable product characteristics. This "characteristics approach" involves projecting consumer preferences onto a set of product attributes and, thus, using these attributes to help explain aggregate substitution patterns. As with many of the typical supermarket product categories, our data do not include an exhaustive set of measurable product attributes. Our solution is to estimate a richer correlation structure in the distribution of brand valuations. To preserve some of the parsimony of the mixed-logit specification, we use a factor-analytic approach. An interesting by-product of this approach is the ability to produce a map of the brands based on intangible product attributes (Elrod 1988 and Chintagunta 1994).

A recent body of empirical research has attempted to identify and measure the implications of price discrimination. Existing work has emphasized the identification of the practice of price discrimination versus cost-based differences (Borenstein 1991, Shepard 1991 and Cohen 2001). Others have looked at the underlying sources of price discrimination and their magnitude (Verboven 1996 and Goldberg 1996). Only recently has empirical work emerged documenting the welfare impact of price discrimination. Leslie (2001) simulates the impact of several counterfactual price discrimination schemes for tickets at a Broadway theatre. Cohen (2000) measures the impact of second-degree price discrimination across brands in the paper towel industry. A related literature on coupons has focused predominantly on the likelihood of consumer usage, rather than impact on equilibrium welfare (e.g. Chiang 1995, Gonul and Srinivasan 1996 and Erdem, Keane and Sun 1999). Nevo and Wolfram (2000) investigate the impact of manufacturer's coupons on retail prices for breakfast cereals. Similarly, Besanko, Dubé and Gupta (2001a) demonstrate empirically the potential for profit-enhancing targeted coupons in a competitive environment.

Several studies have used the data set used in this paper although with different objectives (e.g. Peltzman 2000 and Chevalier, Kayshap and Rossi 2000). Two papers using these data are closely-related to our work. Hoch et al. (1995) find that a large proportion of the variation in category-level consumer price elasticities across stores is explained by local consumer demographics and, to a much lesser extent, to local competitive variables. In a follow-up study, Montgomery (1997) looks at the profit-implications of zone and store pricing for the supermarket chain in one specific product category.

Our work differs from these two papers in several ways. Our main objective is to study the implications of zone pricing on consumer welfare (besides profits), the results of which should interest policy workers, strategists and marketers. We then use the

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underlying structure of the model to propose alternative pricing strategies that address customer welfare due to store pricing and the computational complexity for the store manager. Our work also differs from a practical point of view. Similar to Montgomery (1997), we find that estimation of standard demand models (double-log, linear etc.) underpredicts the price sensitivity of demand: implied margins are much higher than the observed levels. The parsimony of the current model enables us to solve this problem in two ways. First, we estimate flexible substitution patterns with a relatively small number of parameters. As a result, we do not observe "incorrect" signs in our cross-elasticities.[2] At the same time, we are able to control for the potential endogeneity of prices. Previous work with various weekly supermarket data and discrete choice modeling consistently finds that instrumenting for prices leads to noticeably higher magnitudes in the price response parameter (Besanko, Gupta and Jain 1998, Villas-Boas and Winer 1999 and Chintagunta 2002).[3] We find our model provides reasonable estimates of the zone-level margins. Finally, we validate the fit of our model using the observed retail margins.

Consistent with the zone structure, we observe substantial price variation across stores within a given week in the raw data. In fitting the demand curves, we find both the price-sensitivity as well as the no-purchase probability vary tremendously across stores. Interestingly, our estimates of zone-specific prices provide a reasonably accurate representation of the true prices reported in the data. This finding gives us confidence in our ability to capture the underlying data-generating process. As in Hoch et al. (1995), we find that demographic variables consistent with willingness-to-pay are the most influential for market shares and elasticities. Thus, we conclude that zone classification is based primarily on discriminating across consumer types. However, we do find evidence that measures of competition and consumer search matter, but to a lesser extent. To assess the welfare implications of zone-pricing, we compute the prices and quantities that would prevail if the retailer adopted a uniform chain-level pricing policy for products. As expected, category profits are higher under the zone pricing relative to chain pricing. Consumer welfare effects vary across stores. We then compute the prices and quantities that would prevail if the stores adopted a store-specific pricing policy. Now prices rise substantially more than under the current zone pricing. Interestingly, while consumer welfare effects vary across stores, we note that the store-pricing seems to target higher

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[2]Note that previous work has often estimated negative cross-price elasticities of demand in categories which one would expect to consist of substitute products. These incorrect signs will bias simulated profit-maximizing prices upwards.

[3]Montgomery and Rossi (1997) do not find noticeable effects from instrumental variables. However, their specification uses aggregate price indices for a category rather than shelf prices.

prices to less-affluent areas with larger ethnic populations and higher search costs. In contrast, zone-pricing seems to target high prices to more affluent areas. We also conclude that shifting from uniform pricing to either zone or store-level pricing may be better suited in some categories than others. For example, in liquid laundry detergent, we find only modest gains from zoning. We also note the importance of balancing store profits with consumer welfare. For example, in the orange juice category, we do find sizeable losses in consumer welfare, especially if the chain moves to store pricing.

Two practical considerations arise with such profit-enhancing pricing policies. First, a store manager could be concerned about the overall losses to consumers in stores where prices are expected to rise. To mitigate these losses, we propose a constrained pricing procedure that makes use of the underlying economic structure of the model. The approach restricts the new store prices to offer the population of consumers in each store at least the same level of welfare as under a uniform chainwide pricing policy. We find that this constraint still enables the store manager to capture a large portion of the gains from unconstrained pricing in both categories. The second practical consideration involves the potential complexity of computing store-level prices for a chain which, like Dominicks, has a large number of stores. We address this computational complexity by suggesting an improved zone structure. Using our store-specific price levels, we cluster the stores into 5 zones. We find that these zones offer substantially more profit than the existing zone configuration.

The paper is structured as follows. Section 2 presents the model. Section 3 discusses the main aspects of the estimation procedure. Section 4 provides an overview of the data we use for estimation. Section 5 presents results, including the demand parameters, the perceptual maps and finally the welfare implications of zone-pricing. We conclude in section 6.

2   Model

To develop a viable pricing framework for a category manager, we begin by specifying an economic model of individual choice behavior in a supermarket category. We then derive the expected aggregate demand facing the category manager. Using the derived demand, we then model the category manager's pricing problem.

This structural approach presents several advantages. From a modeling perspective, we are able to compute a theory-based measure of consumer well-being based on their willingness-to-pay. This measure permits us to compute consumers' monetary valuations

of various pricing policies by the retailer. At the same time, the structural approach simplifies our treatment of the retailer's pricing problem. The derivation of aggregate demand from first principles yields a "well-behaved" specification. Typically, popular approximations of aggregate demand, such as the log-log model, generate non-concave regions in the profit function. The non-concavity makes it impossible to maximize profits without imposing additional (ad hoc) constraints (Anderson and Vilcassim 2001) on the set of profit-maximizing prices. Similarly, the parsimony of the model helps us identify "reasonable" aggregate substitution patterns. In contrast, studies using standard linear or log-linear approximations of demand have typically provided unsatisfactory substitution patterns, such as negative cross-price elasticities for products that are substitutes. For instance, Hoch et al. (1995) report category price elasticities that are larger than the individual brand elasticties. This outcome implies underlying complementarity between some of the brands (negative cross-price elasticities). Finally, the structural derivation helps us understand potential sources of bias in the estimation problem. Several researchers have noted the tendency for regression models to understate consumer price-sensitivity with comparable retail data, which leads to over-confidence in the pricing recommendations. One solution to this problem has been to impose constraints on the parameters during the estimation process (Bradlow and Montgomery 1999). We believe that one source of estimation bias derives from unobserved (to the econometrician) covariates that influence consumer choice and, thus, pricing. In developing the model, we indicate how such unobservables could affect consumer choices and, potentially, bias estimation. Following the recommendation of Berry (1994), we solve this problem with an instrumental variables procedure.

2.1   Utility and Demand

In this section, we describe the underlying consumer choice model generating the observed aggregate purchases in each store-week. We use the mixed logit specification (McFadden and Train 1998), which adds normally-distributed random coefficients to the standard conditional logit choice model. For a more general discussion of discrete choice models and their aggregation we refer the reader to BLP (1995). One of the main advantages of this specification is parsimony. Consumer preferences are projected onto a set of exogenous product attributes, which greatly reduces the dimension of the estimation problem. For industries with a large number of alternatives, correlations in valuations of products is characterized by heterogeneous tastes for the attributes. In many product markets, researchers are easily able to collect a sufficient set of attributes to capture

the underlying market segments in the category. For example, this approach has been applied to aggregate data for automobiles (BLP 1995, Petrin 1999 and Sudhir 2001a), PCs (Bresnahan, Stern and Trajtenberg 1997), ready-to-eat cereals (Nevo 2001) and movie theaters (Davis 2000). In packaged goods product markets such as one would find in supermarkets, much of the correlation derives from intangible sources such as brand perceptions. Since intangibles are not easily measured by the econometrician, we model the joint distribution of brand valuations explicitly. We use a parsimonious factor-analytic approach to recover the impact of intangible attributes, as is typically used with individual data (Elrod 1988, Chintagunta 1994 and Elrod and Keane 1995) as well as with aggregate data (Chintagunta, Dubé and Singh 2002).[4]

Formally, we assume that on a given shopping trip in week t ($t = 1, \ldots, T$), M_t consumers each select one of J brands in the category or opt for the no-purchase alternative, whose mean utility is normalized to 0. We discuss the validity of this single-unit purchase assumption in Appendix A. In a store-week t, each brand j has attributes: (x_{jt}, ξ_{jt}). The vector x includes a brand-specific fixed-effect as well as an indicator for the incidence of a promotion and the size of the SKU (e.g. ounces). The vector, ξ encompasses the effects of unobserved (to the econometrician) in-store product attributes, such as advertising, shelf-space and coupon availability that vary across store-weeks (BLP 1995, BGJ 1998)[5]. These unobserved factors generate deviations from the mean utility for a product across weeks and stores. In the estimation section below, we explain how these deviations from the mean might bias estimation. Finally, the variable p_{jt} denotes brand j's shelf-price in week t.

For a shopping trip during week t, the conditional utility consumer h derives from purchasing product j is given by:

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\begin{aligned}
u_{hjt} &= \alpha_{hj} + x_{jt}\beta_h + \theta_h (Y_h - p_{jt}) + \xi_{jt} + \varepsilon_{hjt}, \\
h &= 1, ..., H, j = 0, ..., J, t = 1, ..., T.
\end{aligned}
$$

The coefficients β_h capture consumer h's tastes for attributes, x, which includes marketing mix variables. The parameter θ_h captures consumer h's marginal utility for income. In

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[4]Additional methods exist for identifying flexible substitution patterns using similar data with aggregate choices. For instance, Nevo (2001) samples consumer demographic profiles from the empirical joint distribution provided by the census at the MSA level. BLP (1998) construct additional moments of the data-generating process by combining additional micro data with their aggregate data.

[5]Since we estimate a full set of product fixed-effects, we do not need to worry about unmeasured physical product attributes, as in BLP 1995. We are nonetheless concerned with unobserved (to the econometrician) weekly in-store product-specific effects.

the current context, income consists of the shopping budget for a trip during week t.[6] The parameter α_{hj} captures household h's idiosyncratic perception of brand j. The term ε_{hjt} is an i.i.d. mean-zero stochastic term capturing consumer h's idiosyncratic utility for alternative j during week t. We assume that ε_{hjt} has a type I extreme value distribution. Previous work has also explored the use of correlated errors, such as the multivariate normal, giving rise to the probit choice model (McCullough and Rossi 1994). Below we discuss some of the limitations of an i.i.d. additive error.

The formulation allows for an outside good, "no purchase", the utility of which is given by

$$u_{ht0} = \alpha_{h0} + \theta_h Y_h + \varepsilon_{ht0}.$$

In the current context, this alternative represents the allocation of the shopping budget, Y_h, to other goods in the store outside the category. For practical reasons, this outside good is important for the retailer pricing exercise. In the absence of this alternative, the total category size would be invariant to the prices of all brands increasing or decreasing by the same amount. Hence, allowing for the outside good allows the category sales to be influenced by the prices of the inside goods. For identification purposes, α_{h0} is normalized to zero.

Since we do not observe the true distribution of consumer preferences, we assume tastes, brand perceptions and the marginal utility of income are drawn from a multivariate normal distribution. For simplicity, we treat the taste parameters as i.i.d:

$$\begin{bmatrix} \beta_h \\ \theta \end{bmatrix} = \begin{bmatrix} \overline{\beta} \\ \overline{\theta} \end{bmatrix} + \lambda' \nu_h, \nu_h \sim N(0, I)$$

where the vectors of means, $\begin{bmatrix} \overline{\beta} \\ \overline{\theta} \end{bmatrix}$, and the standard deviations, λ, are parameters to be estimated.

We do allow for a richer covariance structure for the vector of brand perceptions:

$$\alpha_h \sim N(\overline{\alpha}, \Sigma).$$

In theory, we could estimate the the full $(J \times J)$ matrix Σ directly. In practice, as the number of brands grows, Σ becomes increasingly difficult to identify. Instead, we use the factor structure:

$$\Sigma = L\omega\omega'L', \ \omega \sim N(0, I).$$

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[6]In the following analysis, we do not address formally how households allocate total income to their weekly shopping budgets.

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One interpretation for this structure is that L is a $(J \times K)$ matrix of latent attributes for each of the J brands, and ω is a $(K \times 1)$ vector of consumer tastes for these attributes. The vector of mean brand perceptions, $\overline{\alpha}$, and the matrix of latent attributes, L, consist of parameters to be estimated. In addition to its parsimony, this approach allows us to estimate standard errors for the latent attributes. In the current context, we assume $K = 2$. For identification purposes, we do the following (see Elrod 1988):

1. The outside or "no purchase" option is located at the origin of the map (translational invariance).

2. One of the brands is located along the horizontal axis (rotational invariance).

3. We set the variances of ω above to 1 in the estimation (scale invariance).

As is now the convention in the literature, we simplify our notation by re-writing the consumer's indirect utility in terms of mean tastes and deviations from the mean:

$$u_{hjt} = \delta_{jt} + \mu_{hjt} + \varepsilon_{hjt}$$

where $\delta_{jt} = \overline{\alpha}_j + x_{jt}\overline{\beta} - \overline{\theta}p_{jt} + \xi_{jt}$ is common to all consumers and $\mu_{hjt} = x_{jt}\lambda\nu_h + L\omega_h$ is consumer-specific[7]. An advantage of this mixture of the normally-distributed taste shocks with the extreme value disturbance, is that we can integrate out the latter analytically. The unconditional probability q_{jt} that a consumer chooses a particular product j in week t, after integrating out individual heterogeneity, has the following form:

$$q_{jt} = \int_{-\infty}^{\infty} \frac{\exp(\delta_{jt} + \mu_{hjt})}{1 + \sum_{i=1}^{J} \exp(\delta_{it} + \mu_{hit})}\phi(\nu)\,\partial\nu, \tag{1}$$
$$h = 1, ..., H, j = 0, ..., J, t = 1, ..., T.$$

where $\phi(\cdot)$ is the pdf of a multivariate standard normal. From the store manager's perspective, (1) represents the share of consumers entering the store in week t that purchase a unit of product j. Thus, the manager's expected demand for product j in store-week t is :

$$Q_{jt} = q_{jt}M_t. \tag{2}$$

Our main motivation for using this random coefficients specification, as opposed to a simpler conditional logit (or homogeneous logit), is the need for flexibility. The homogeneous logit generates the IIA property (the independence of irrelevant alternatives

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[7]Note that we remove the term $\theta_h Y_h$ from the equation as it will not be identified in the share equations below. This term drops out of the share equation as it is common to all the alternatives including no-purchase.

property) at the consumer level. The IIA property could manifest itself into our aggregate analysis in several ways. First, it can be shown that the assumption leads to aggregate cross-elasticities that are driven by market shares (see BLP 1995 for a thorough discussion). For instance, products with similar market shares are predicted to be close substitutes. In addition to the potentially unrealistic predicted substitution patterns, the cross-elasticities also restrict the implied retailer behavior in equilibrium. Multiproduct firms are restricted to set a uniform margin for each of the products in their line (Besanko, Dubé and Gupta 2001a). Since our analysis focuses on category management, this property would imply that all of the products in a category have the same mark-up over their wholesale prices. To alleviate the restrictive substitution patterns generated by the IIA property, we allow for consumer-specific deviations from mean tastes. As a result, the demand function in 2 above does not suffer from restrictive substitution patterns.

We use random taste coefficients to generate correlations in utilities for the various alternatives and, thus, relax the restrictive substitution patterns generated by the IIA property. As discussed above, one could also use a correlated additive error, such as the probit model, which avoids the IIA property directly. In general, the probit strictly dominates the logit as it allows for freely-varying covariances. The random coefficients probit also enables one to disentangle heterogeneity from simple non-IIA behavior at the consumer level. We use the "mixed" logit instead of a multinomial probit due to the relative ease of estimating the former versus the latter. McFadden and Train (2000) show that the mixture of normals with the type I error, the *mixed logit*, is sufficiently flexible to approximate a broad set of parametric indirect utility functions, including the probit (see Dalal and Klein 1988 for a related finding). In practice, the flexibility depends on the restrictions placed on the correlations in the random coefficients, Σ. With aggregate data, the ability to integrate out the logit disturbance, as in (1), vastly increases the ease of implementation versus a multinomial probit. Thus, we choose the mixed logit due to its relative ease of use.

One of the complications of the mixed logit specification (1) is the lack of an analytic form for the multidimensional integral. While it is true that for a simple model with fewer than three random parameters one could solve the expression numerically (Hausman and Wise 1978), most categories consist of more than three alternatives. Instead, we use direct Monte Carlo simulation, as in Nevo (2001).

2.2 Local Interactions

Other than marketing mix variables, we have not yet discussed store-specific covariates that allow expected demand to vary across stores. In practice, we do not expect each store in a chain to face the same distribution of consumers. Stores in different neighborhoods typically face different demographic distributions of consumers. Moreover, the presence of local competitors could alter the sensitivity of consumers to a store's marketing effort. We expect differences in both the distribution of consumer types and the presence of local competitors to alter the derived demand for goods facing each store. For instance, one might expect wealthier neighborhoods to be less price-sensitive, on average, for some categories. Similarly, one might expect proximity of competitors to increase the price sensitivity of derived aggregate demand in a store. We use a detailed set of variables that proxy for both differences in the mean demographic profiles and levels of competition facing each store. These proxies fall into three categories: willingness-to-pay, consumer search and competition. A more precise description of these covariates appears in the data section below.

For each of the $s = 1, ..., 83$ stores, we summarize these store-specific characteristics in the vector D_s. These terms shift both the price sensitivities, θ, and the probability of purchasing in the category by influencing each of the brand preferences, α_j, equally for each of the store areas. We decompose the parameters across the $s = 1, ..., 83$ stores as follows:

$$\begin{aligned} \theta_{hs} &= \overline{\theta} + D'_s\gamma + \lambda'\nu_h \\ \alpha_{jhs} &= \overline{\alpha_j} + D'_s\delta + L_j\omega_{hj}, j = 1, ..., J \end{aligned}$$

where $\overline{\theta}$ is the mean marginal utility of income across stores, weeks and households; $D'_s\gamma$ is the mean marginal utility of income across consumers and weeks in store s; and $\lambda'\nu_h$ is the idiosyncratic component of marginal utility of income for some consumer h. Similarly, $\overline{\alpha_j}$ is the mean brand preference for alternative j across stores, weeks and households; $D'_s\delta$ is the mean across consumers and weeks in store s; and $L_j\omega_{hj}$ is the idiosyncratic component for some consumer h. The vectors δ and γ consist of parameters to be estimated. Note that the vector δ is common across brands so that store characteristics will shift the category size (brand qualities relative to no purchase). In principle, one could estimate a separate θ and α parameter for each of the 83 stores in our sample. However, this approach is infeasible since it would require estimation of 166 parameters. The proposed decomposition has additional potential benefits, such as the ability to forecast demand in a new store based on its characteristics.

Nevo (2001) captures differences in consumer profiles across city-markets by sampling individual households from the empirical joint distribution of demographics collected by the Census. One of the disadvantages of our disaggregate data is that comparable joint-demographic distributions are not available at the store-level. Only marginal distributions are reported publicly by the census. In general, the zip-code and census block level data collected for the Current Population Survey are too thin to provide credible representations of the true underlying demographic distribution. So we use mean demographics in each store area instead.

To the best of our knowledge, no study has modeled store competition explicitly in determining aggregate demand for a retailer. In modeling demand for yogurt, Berto Villas-Boas (2001) treats the same brands in different stores as substitutes. However, she finds extremely small cross-price elasticities across stores, suggesting that store competition has little impact within the yogurt category. Due to data restrictions, most applications of store-level data treat retailers as local monopolists (e.g. Slade 1995, BGJ 1998). Slade justifies her assumption on phone interviews with store managers in a given market who claim that consumers do not shop across stores on a product-by-product basis. We also conducted telephone interviews with Chicago area store managers and our findings were consistent with this claim. Stores do condition on their competitors' actions in a limited way by collecting a weekly sample of half a dozen SKUs from the local competitors' entire store offerings. However, this behavior seems more consistent with competition on overall offerings rather than on a category-by-category basis[8]. For instance, Chevalier, Kayshap and Rossi (2000) find that prices for items exhibiting holiday or seasonal demand peaks tend to be priced in a manner consistent with loss-leader competitive pricing (Lal and Matutes 1994). Therefore, we try to limit our focus to product categories that are less likely to drive overall store traffic[9]. Since we do not observe competitors' prices in our data, we cannot model competition explicitly. Instead, we assume that any local market power is captured, on average, by proximity to competitors. We discuss this assumption further in the data section below.

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[8]Stores do, however, collect a "full book" of about 600 to 1000 prices from local competitors on an annual basis. This practice is not likely to generate inter-store competition at the category level and weekly frequency we consider in our analysis.

[9]In the section measuring the impact of zone pricing, below, we provide empircal support for the assumption that the categories we use do not drive store traffic significantly.

2.3 Measuring Consumer Welfare

One of our main objectives in using a structural demand system is the ability to measure the change in consumer welfare associated with altering the pricing policy. An attractive feature of the discrete choice model is the ability to compute consumer welfare explicitly. A popular measure for welfare in such contexts is the Hicksian, or compensating, variation, which captures the dollar amount by which consumers would need to be compensated to maintain the same level of utility after the change in pricing policy (e.g. Trajtenberg 1989, Nevo 2001 and Petrin 1999). We denote an individual h's utility net of the extreme value taste shock as V_h (expected utility) and their marginal utility of income as θ_h. Suppose a zone-pricing policy is introduced that changes consumer valuations for each alternative from V_h^{chain} to V_h^{zone}. As derived in Small and Rosen (1981), assuming individual marginal value of income is held constant, individual $h's$ associated change in welfare can be computed as:

$$CV_h = \frac{\log\left(\sum_{j=0}^{J}\exp\left(V_h^{zone}\right)\right) - \log\left(\sum_{j=0}^{J}\exp\left(V_h^{chain}\right)\right)}{\theta_h}. \tag{3}$$

The numerator of (3) captures the expected change in utility. Dividing through by the marginal utility of income, θ_h, makes this change money-metric. Integrating across the distribution of consumer preferences, we can compute the expected aggregate change in consumer welfare:

$$\Delta W = M \int CV_h \phi\left(\nu\right)\partial\nu. \tag{4}$$

In the next section, we model the supermarket category manager's pricing decision. Using variable profits as the measure of the manager's valuation, we are able to compare the dollar value of gains of various pricing policies both to the supermarket and to consumers. Similarly, we can compute the change in customer value in going from zone to store level pricing.

2.4 Category Management

We now describe our model of retail behavior. Our data comprise stores from a single retail chain in a large metropolitan area. We have no reason to expect store-level pricing decisions to elicit a competitive response from manufacturers. Therefore, we treat wholesale prices as exogenous to the retailer. We discuss the validity of this assumption in the data section below. In other contexts, marketers have modeled the vertical channel to capture the strategic interaction between retail and wholesale prices using a logit

demand model (e.g. Besanko, Gupta and Jain 1998, Sudhir 2001b and Villas-Boas and Zhao 2001). Typically, these studies do not have access to retail margins and, thus, use the channel structure to help identify a time-varying wholesale price (see for example, Berto Villas Boas 2001). Kadiyali et. al. (2000) use information on retail margins. However, their objective was to identify the nature of interactions between manufacturers and a single retailer.

We assume that each week the retailer jointly sets the profit-maximizing prices, p_j, of each of the J products in a category (see for example, Sudhir 2000b, Kadiyali et. al. 2000). Based on our phone conversations with local chain managers, we believe that weekly price decisions are made by category managers rather than by a store-wide manager[10]. In contrast, most promotional decisions (newspaper features, in-aisle displays etc.) are determined at the store-level. While promotions are funded almost entirely by manufacturers, the timing and format are determined by the retailer. Typically, the promotional calendar is determined in advance so that category pricing decisions are made conditional on the promotion. Therefore, we treat the promotion level as exogenous to category pricing[11].

We also assume that the retailer's variable costs consist solely of wholesale prices, w_j. We treat all store and/or category-related overhead as fixed costs, F_t. Thus, in week t, a retailer[12] solves the following optimization problem:

$$\max_{\{p_j\}_{j=1}^J} \Pi = \sum_{j=1}^J (p_{jt} - w_{jt})Q_{jt} - F_t.$$

Using (2)above, the first-order condition for a typical brand i is:

$$\sum_{j=1}^J (p_{jt} - w_{jt})\frac{\partial Q_{jt}}{\partial p_{it}} + Q_{it} = 0.$$

We re-write the system of first-order conditions for brands $1, \ldots, J$ in matrix form as:

$$\Omega(\mathbf{p} - \mathbf{w}) + \mathbf{Q} = \mathbf{0}, \tag{5}$$

[10]The retailer's definition of a category may differ from that of academic research. The latter typically relies on the definitions used by Nielsen and IRI, the two traditional suppliers of comparable scanner databases.

[11]Our phone conversations revealed that category managers may in fact request additional promotional funds if they feel the performance of the category or a specific brand therein is sluggish. However, we were informed that the incidence of such endogenous (to the category manager) promotions are quite unusual.

[12]To simplify notation, we drop the subscript for the retailer and the category. In our empirical work, a retailer may be the store-manager, the zone manager or the chain manager depending on the context.

where

$$p - \mathbf{w} \equiv \begin{bmatrix} p_{1t} - w_{1t} \\ \vdots \\ p_{Jt} - w_{Jt} \end{bmatrix}_{J \times 1}$$

$$\Omega_{jk} = \begin{cases} \frac{\partial Q_{jt}}{\partial p_{jt}}, j = k \\ \frac{\partial Q_{jt}}{\partial p_{jt}}, j \neq k \end{cases}_{J \times J}$$

$$\mathbf{Q} = \begin{bmatrix} Q_{1t} \\ \vdots \\ Q_{Jt} \end{bmatrix}_{J \times 1}.$$

This represents a system of J equations, one for each brand. The optimal set of prices for the retailer are determined by solving:

$$\mathbf{p} = \mathbf{w} - \Omega^{-1}\mathbf{q} \tag{6}$$

where $\Omega^{-1}\mathbf{q}$ is the retail mark-up. By checking the second order sufficient conditions, one can verify that the solution to (6) represents an optimum for the retailer. The actual value of Q_{jt} depends on the level of aggregation considered. For the store-level problem, this will take the form (2), where M_t is weekly store traffic. However, for a zone pricing problem, Q_{jt} would be obtained by integrating across the store-level demand for each of the stores in the zone in week t. Similarly, chain-level pricing would involve integrating across all the store-level demand curves.

As we mentioned in the demand section, the assumption of homogeneous tastes leads to restrictive pricing behavior by retailers. When consumer tastes for attributes are homogeneous, the optimal retail prices satisfying (5) become:

$$p_{jt} = w_{jt} + \frac{1}{\theta q_{0t}},$$

where $q_{0t} = 1 - \sum_{j=1}^{J} q_{jt}$ is the share of the no-purchase alternative. Therefore, when consumer heterogeneity is characterized solely by the extreme value taste shock, the amounts by which a retailer sets its mark-ups over the wholesale prices are the same for all the products carried. This property is not consistent with our data in which margins vary across alternatives.

3 Estimation

We now outline the estimation procedure for the aggregate mixed logit. Since one of our objectives in this analysis is the determination of the level of aggregation at which

stores determine prices, we estimate demand alone. This approach also ensures that our demand-side estimates are not subject to specification error from incorrectly assuming static category management by retailers. Our estimation methodology is quite similar to that used by BLP (1995). Therefore, we refer the more interested reader to BLP (1995) for a more technical description and to Nevo (2001) for a more practical discussion of the implementation of the methodology.

A primary concern in empirical papers using similar discrete choice models is the potential for estimation bias due to correlation between prices and the unobserved product attribute, ξ. Using weekly store-level data, our primary concern lies in unmeasured store-specific covariates that influence demand and also shift prices at a weekly frequency. Even after including a full set of alternative-specific intercepts, several papers have documented evidence of an estimation bias in models that do not control for this problem using weekly supermarket data (BGJ 1998, Chintagunta 2001, Villas-Boas and Winer 1999 and Villas-Boas and Zhao 2001). For instance, we do not observe shelf-space; however, increasing shelf-space allocation typically incurs costs that raise prices, such as allocation fees and opportunity costs. At the same time, it is well known that shelf-space influences consumer brand choices (Dreze, Hoch and Purk 1994). While characterizing the precise nature of measurement error in our data is beyond the scope of the paper, we use standard instrumental variable techniques to avoid estimation biases.

In order to facilitate the direct instrumentation of prices, we use the inversion procedure proposed by Berry (1994). We then set up a generalized method of moments (GMM) procedure to estimate the system of mean utilities. Due to the treatment of heterogeneity in the model, we use Monte Carlo simulation methods to compute the moment conditions. McFadden (1989) and Pakes and Pollard (1989) both show that the method of simulated moments (MSM) still produces consistent estimates. However, the efficiency of these estimates is reduced due to simulation error. Only with sufficiently many simulation draws can one reach asymptotic efficiency with MSM. We use 30 draws and assume this number is sufficient to eliminate any noticeable simulation noise. Alternatively, one could implement variance-reducing simulation methods as in BLP (1995).

4 Data

We use data from Dominick's Finer Foods (DFF), which is the second largest supermarket chain in the Chicago metropolitan area. DFF operates close to 100 stores in the Chicago area. Our data consist of weekly sales, prices, promotions, and profit margins at the

individual UPC-level for 83 of these stores during the 52-week period of 1992. In the current analysis, we look at the liquid laundry detergent and refrigerated orange juice categories. We present the descriptive statistics for the products included in the analysis for each of the respective categories in table 4. These data consist of means across store-weeks. The column labelled "unit share" corresponds to the conditional shares, or share of unit sales, for each brand. The actual market shares used for estimation are computed as total brand sales divided by the total weekly store traffic. Effectively, our model implies that each time consumers visit the store, they either purchase a unit of one of the alternatives within the category of interest or they elect not to purchase. In the current context, a unit corresponds to a UPC code (e.g. a 64 oz Tropicana Premium vs. a 96 oz). The promotion variable is an indicator for whether the given product had an in-aisle display or newspaper feature that week. As mentioned previously, the promotion decision is assumed to be exogenous to category management within a store or zone. In Appendix B, we provide a precise description of how we construct the relevant brands for analysis.

In table 5, we summarize the sources of variation in our price and share data. For each SKU in our data, we run separate regressions of prices and shares on store and week fixed-effects. In the table, we report the median R-square across products for each category. We find that cross-week variation accounts for roughly 72% of the variation in a product's price, in the laundry detergent category, and 77% in refrigerated orange juice (78% and 76% respectively for shares). Similarly, cross-store variation explains roughly 11% of the price variation, in laundry detergent, and 6% in orange juice (2% and 5% respectively for shares). As explained below, we are able to explain a substantial portion of the intertemporal price variation using the wholesale prices. To help capture the cross-store variation, we use characteristics of a store's trading area.

We supplement our store data with an extensive set of descriptive variables, from Spectra (see Hoch et. al. 1995), characterizing the underlying consumer base and local competition associated with each store. ZIP code level demographic data was obtained from the 1990 census. To capture heterogeneity across stores in terms of the types of households they face, we include the following demographic variables: INCOME (log median income), AGE60 (% of population over age 60), ETHNIC (%of population that are Black or Hispanic) and HVAL (mean household value). We also include SHOPINDX (ability to shop–% of population with car and single family house) to capture the relative ability of local consumers to travel. The two competitive variables used in the study are distance from the nearest Jewel (the largest supermarket in the area), JEWEL, and

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minimum of the distance from the nearest Cubfoods and Omni, EDLP, (the two main EDLP operations). Our preliminary work also included variables on competitor volume but these had limited explanatory power and were dropped in the subsequent stages of analysis.

Summary statistics for the demographic and competitive variables are provided in table 6. We find considerable variation in the demographic and competitive characteristics across stores. For example, DFF stores cater to market areas with Black and Hispanic representation ranging from 2 to 99% of the population. In terms of consumer wealth, income levels range from $19,000 to over $75,000 (note we report INCOME in logs). Similarly, average house values range from $64,000 to over $267,000. In terms of competition, some stores are located right next to rival supermarkets. Others locate over 4 miles from the nearest Jewel and 18 miles from the nearest EDLP store. We expect these differences to generate noticeable differences in the levels and price-sensitivities of demand across stores. Note that the demographics explain, on average, 6.7% of the price variation for detergent and 3% for refrigerated juice. Thus, we are able to explain over half of the price variation across stores using these demographic variables. Since the estimation of store-specific parameters would generate an unmanageable number of parameters for the given data sets, we are confident that the demographics do a reasonable job explaining store-specific differences.

As discussed in the model section, we classify the demographics and competitive variables into three categories: willingness-to-pay, consumer search and competition. The demographic variables are used to capture consumer heterogeneity in tastes across stores. The extent to which these factors influence shares at a store are attributed to price discrimination. The Spectra measure SHOPINDX measures the ability of a consumer to shop and, thus, to search for the "best" price in the local market. Finally, proximity to competitors provide a crude measure of the extent of local competition. We classify the impact of consumer search and competition on a store's brand shares as sources of price dispersion.

4.1   Zones

An important feature of our data is the ability to disentangle price discrimination and differences in cost. In general, wholesale prices are virtually identical across stores in a given week. On average, the standard deviation of wholesale prices across stores in a given week is 0.008. Unlike previous work (e.g. Shepard 1991) we can rule out explanations

for price variation based on wholesale costs.[13]

Despite the roughly identical unit costs across the stores in our data, prices and margins vary substantially within most weeks. Using the liquid laundry detergent data, the average range in prices for a given product across stores in a given week is 81 cents. By contrast, the average range within a Dominicks-classified zone is about 16 cents. Given that the mean price in the category is $5.58, the average weekly price range across stores overall is 14% of the mean price, versus only 3% within a zone. For certain products, the price differences are significantly higher. For example, in the refrigerated orange juice category, the price of Minute Maid (64 oz.) is 38% higher in the highest price zone, compared to the stores that fall in the lowest price zone.

As mentioned earlier, our data set contains an index that groups stores into pricing zones. In figure 1, we plot the stores on the Chicago area map, labeling each according to its zone affiliation from 1 to 16. In practice, the chain does not always appear to respect the specified zones in its weekly pricing decision. Looking across products, we observe that many items appear to use a coarser zone definition. For instance, prices of small share items often have a uniform price across stores. Similarly, in some categories, prices may only reflect three or four zones, rather than the full 16 that we observe later in the data. Other studies that have used this data (for example Hoch et al. 1995) also suggest that the actual number of zones might be fewer than those provided in the data. We investigate this issue by looking at the prices of several products across randomly selected weeks. Consistent with Hoch et al., we find only 3 levels of prices in the early years of the total available data (e.g. 1989-1990). However, the number of zones increases over time. By the time of our sample, 1992, we begin to observe substantially more prices for many large-share products in any given week. For some of the large share items, we often observe between 9 and 16 different shelf prices across stores within a given week. To illustrate this point, figure 2 has the distribution of prices for 128 oz Tide laundry detergent for a given week. Looking across stores, we see prices ranging from as low as $3.80 to as high as $4.90.[14]

In table 7 we report the average laundry detergent prices and demographics by zone.

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[13]One explanation that we have not ruled out is differences in the opportunity cost of shelf space in areas with expensive real estate. In areas with high property values and/or high property taxes, stores may have more rigid capacity constraints that could affect pricing. In this regard, zone pricing could reflect differences in these shelving costs.

[14]The explanation for this increase in the number of zones over time remains an empirical question. Two possibile explanations are that either the chain is facing a changing competitve environment (entry of mass-merchandisers and club stores) or that Dominicks management is varying its pricing policy. We refer the interested reader to Singh (2001) for a more thorough discussion.

These data demonstrate the ability of our store characteristics to explain some of the observed price differences across zones. For instance, the highest prices are in zone 7, where we observe the highest household values as well as fairly high search costs. In contrast, zone 16 has the lowest prices and exhibits fairly high incomes with very few elderly or ethnic households. Note also that zone 6 has the closest EDLP store and, at the same time, has very low prices.

To illustrate the role of demographics in explaining Dominicks' 16-zone configuration, we map the stores in figure 3. Each store is labeled by its zone affiliation. The size of the dot corresponding to each store is proportional to the distance from the nearest EDLP competitor (Cub Foods). Also, we have used colored-shading of areas of the city to indicate differences in the average income level of households. The map demonstrates how distance to EDLP, coupled with underlying income of the population appear to capture a large portion of the zone strategy. Zones 1 and 7 consist of stores quite far from EDLP competitors. Zone 7 stores face some of the lowest median income areas, whereas zone one stores are located in slightly higher to medium income areas. In contrast, most zone 2 and zone 6 stores are relatively close to EDLP stores.

4.2   Instruments

Another interesting feature of our data is the availability of wholesale prices. As discussed in the model section, we treat these data as exogenous.[15] We use the wholesale price as an instrument for in-store shelf prices. Although not reported, a pooled regression of shelf prices on wholesale prices alone gives an R^2 of 0.71 (refrigerated juice) and 0.74 (laundry detergent). Running the regression by SKU, we find that the wholesale prices do a much better job of explaining the larger-share brands of detergent (R^2 of about 0.6 on average) than the smaller brands (R^2 of about 0.1 on average). For refrigerated juice, the costs alone explain about 25% of the variation, on average, regardless of share. Introducing the additional exogenous covariates used in the instrument matrix for the GMM procedure tends to explain an additional 10% of the variation in the prices. Given the reasonably strong explanatory power of these instruments, we are able to identify the structural demand parameters without using supply-side moments. To illustrate the ability of our cost data to explain price variation, we plot the time-series for prices and

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[15]Since prices appear to be determined at the zone level, aggregate demand for the chain requires integrating across 16 different zone demand curves. Moreover, the chain only accounts for 25% of the Chicago supermarket sales. Therefore, it is not likely that marginal changes in price at one of the zones would have a noticeable impact on aggregate demand for the Chicago market. As a result, we assume that a zone pricing decisions do not impact the wholesale price.

wholesale prices of 128 oz Tide Laundry Detergent for one of the stores in figure 4. The figure shows that retail price movements generally coincide with changes in wholesale prices. However, it does appear that retail passthrough rates exceed 100% in certain weeks. In appendix C, we briefly discuss the implications of not instrumenting for prices, which generates noticeable biases in both the model parameters and in the predicted zone prices.

5 Results

We now present the estimated demand systems for each of the two categories. Demand parameters are reported in tables 8 and 9. We report the corresponding latent brand factors in table 11. Rather than reporting the implied brand correlation matrices, Σ, we plot the brand "locations" using the factors as a coordinate system. We also report the elasticities of store characteristics on each of the category sizes (probability of purchase) in table 10.

Before describing the empirical results, we first explain what the parameters in tables 8 and 9 mean. We use table 8 (laundry detergent) as an illustration. The first five parameters correspond to the mean intrinsic preferences, $\overline{\alpha_j}$, for the J brands included in the category. This is followed by the mean price effect, $\overline{\theta}$, and the standard deviation of the distribution of price sensitivities across consumers, λ. This is followed by the effects of promotion and the interaction between price and promotion. Following this is the effect of the dummy variable that distinguishes between 64 and 128 ounce pack sizes of detergents. This variable takes the value 1 for the 64 ounce size. A holiday dummy variable is also included and its effect on category demand is presented next. This is followed by a set of parameters, δ, that correspond to the effects of store characteristics on the preferences of the brands in the category. Recall from our earlier discussion that these effects are the same for all the brands within the category. The coefficient 0.412 corresponding to the income variable implies that a higher income household has a greater probability of purchasing laundry detergents than a lower income household. The last set of parameters are the interactions between the store characteristics and prices, γ. In other words, they represent the observed component of price heterogeneity across stores.

In the laundry detergent category, table 8, we find that Tide is the highest-valued brand in the category. We also observe a preference for 64 oz versus 128 oz size packages. As expected, promotions increase the likelihood of purchase, as does the incidence of a holiday week. Price sensitivity has the correct negative sign and we do observe significant

heterogeneity. Interestingly, we find the price sensitivity rises for promoted items. Using the estimated factors, in table 11, we plot the brand map for detergents in figure 5. The map highlights the perceived similarities and differences across brands in the market. The horizontal axis seems to separate out brands manufactured by P&G (Tide and Cheer) from those manufactured by Unilever (Wisk, Surf and All). Further, the two P&G brands, Tide and Cheer are perceived to be similar to one another whereas the Lever brands appear a lot more differentiated in the minds of consumers. By positioning All close to the P&G brands, Lever may be using it as a "fighting" brand in the marketplace. We discuss the effects of store characteristics subsequently.

In the orange juice data, table 9, we find that Tropicana premium has the highest mean preference effect, which is consistent with its dominant position in the category. We also observe a preference for the smaller 64-oz size, versus the larger 96 oz. As before, promotions increase the likelihood of purchase, but at the same time, they increase consumers' sensitivity to price. In figure 6, we present the perceptual map for orange juice brands. Once again, we find the map of the brand preferences to be quite revealing. There appear to be 3 distinct groups of brands in the market. The first set, consisting of the Tropicana and Florida brands, is perceived as being different from the other brands. We do however, observe slight differences between the product not from concentrate (premium) and the product from concentrate (SB). The second group consists of Minute Maid, a Coca-Cola product, and the third group consists only of the store brand (Dominicks). This finding is good news for the national brands as it does appear that they have effectively differentiated themselves from the store brand.

In table 10, we report the elasticities of the store characteristics on category size (the probability of purchase). Since characteristics enter the demand systems both as intercept-shifters and as price-slope-shifters, we feel the elasticity is more revealing as a summary statistic. Median income seems to have a strong negative effect on category size for laundry detergents. In contrast, higher income areas are more likely to purchase refrigerated orange juice. Interestingly, the proportion of retired households tend to increase the size of both categories. Ethnicity has an almost negligible effect on both categories. The ability to shop increases the size of the laundry category; but, it has a very small negative impact on the size of orange juice. Both categories tend to be larger in areas with higher average household values. Finally, neither of the competitive variables seem to have a strong effect on category size. Even doubling the distance from a competitor (a 100% increase in distance) will not generate more than about half a percent increase in the probability of purchase.

5.1 Goodness-of-Fit

Our next objective is to try and assess the ability of our demand system to predict the store-level margins. Using the observed wholesale prices, we compute the shelf prices for chain-level, zone-level and store-level pricing by solving the system of equations defined by (1) and (6). Since our main objective is to study the implications of pricing, we need to verify that our demand estimates and our category management model produce realistic measures of the category managers' market power.

The first step involves determining which model seems to come the closest to approximating the observed margins in the data. One way to think of this problem would be to solve a minimum distance procedure in which one minimizes the distance between true and estimated margins, using the covariance of the observed margins as a metric:

$$\min_{\mu} \left(\text{margin-}\mu\right) \Phi \left(\text{margin-}\mu\right) \tag{7}$$

where μ is the estimated margin and Φ is the covariance matrix of the observed margins. In table 12, we take the margins implied by the store-level, zone-level and chain-level pricing policies and compute the corresponding criterion (7). The zone-pricing model seems to provide the best fit according to the minimum distance criterion.

We now compare the mean predicted margins for each brand under the three pricing policies considered and compare these to the true margins observed in the data. To illustrate, in tables 13 and 14, we report the margins as a percentage of prices for the laundry detergent and refrigerated juice categories. These tables capture how well we can reproduce the levels within stores. For the laundry detergent data, the levels are reasonably close to the true values and the correlations are fairly high, especially for the largest-share items (Tide and All). For juice, our mean margins look, for the most part, fairly reasonable. The main exception is the store brand for which we over-predict the margin and for which price estimates are very poor. Our sense is that store-brand pricing may not fit well with the category management model. In fact, store-brands may well be priced below the category manager's level if they are set at a store-wide level to generate store traffic (Chintagunta 2002).

6 Impact of Zone Pricing

Using the demand systems estimated in the previous section, we now set-out to measure the implications of zone-pricing. Our analysis measures the impact on consumer welfare and retail profitability. Measuring consumer welfare allows us to assess the dollar value

of losses or gains to consumers from the various pricing policies. Similarly, retail profits provide a dollar value of the losses and gains to the category manager.

6.1 Welfare implications for retailers and consumers

As discussed above, we use Hicksian compensating variation, as in equation 3, to measure welfare changes. First, we evaluate the impact of zone-pricing by comparing the zone prices and welfare with those computed at the chain level. In conducting this analysis, we need to make certain assumptions. First, we assume that shifting from chain to zone pricing does not alter the nature of promotions in the category. This assumption is analogous to Nevo (2000) and Petrin (2001) who assume that mergers and product-introductions respectively do not impact (in the short-run) the mix of observed product attributes. Similarly, we assume that zone-pricing does not impact the unobserved attribute, ξ. Finally, we also assume that changes in pricing for the product categories in question will not alter the levels of store traffic each week. To support this assumption, we present results for a simple model of store-choice, in table 16. Assuming that each household in a store's market makes a single weekly store-choice decision, this model captures the binary probability that a households visits the local DFF or not. We measure the share of households that visit DFF as store traffic divided by the total number of local households. We explain this choice using local market characteristics as well as a price index for each of the 33 product categories available. Our results may be biased due to the lack of competitors' prices. However, the fact that both laundry detergent and refrigerated juices are not significantly affecting the store choice probability makes us more confident in our assumption above.

In table 15, we report the total annual chain-wide welfare implications of various pricing policies for both of the categories studied. As expected, allowing for more flexible pricing increases a category's profitability, so that zone-pricing and store-pricing both generate gains to the store. In general, the incremental gain from store-pricing far exceeds the gains from zone-pricing. At the same time, the impact on consumers varies by category. Recall that one interpretation of these consumer welfare numbers is the total dollar amount the chain would need to pay consumers to make them as well off under some new pricing policy as they were under uniform chain-wide prices. One must keep in mind that the main reason why Dominicks did not pursue a store-specific pricing policy was due to the lack of technology at the time for implementation. Thus, the current analysis illustrates ways in which structural econometric methods can be applied to a standard retail database to execute more profitable pricing strategies.

We begin with the impact from a shift from uniform chain-pricing to the zone pricing practice that appears to be generating the observed data. Then, we will discuss the impact of a hypothetical move towards store-level pricing. For laundry detergent, we observe fairly small total effects from zone-pricing on the chain profits (only 0.6% gain) or on consumers; although consumers do gain overall by $2,158. Given the high-necessity oriented nature of laundry detergent, it seems intuitive that such an item would not exhibit tremendous variation in willingness-to-pay across store markets. In contrast, the orange juice category benefits reasonably well, generating a $52,400 (1.6%) gain in profits. At the same time, total consumer welfare falls $19,791. Figure 9 plots the total compensating variation by store, indicating that the negative impact on total annual consumer welfare is misleading. In fact, in many stores, consumers benefit from the price change.

Now we demonstrate how our demand system can be used to implement a more profitable store-specific pricing scheme. As above, we compare the prices and welfare levels from the zone model with those of the store-level model. As expected, the store-pricing leads to much larger profit gains than the zone pricing. We observe an almost $542,000 (16.3%) gain in profits relative to chain pricing for orange juice, and $109,700 (9.6%) for laundry detergent. At the same time, we observe $158,100 in losses to consumers in juice, which is small relative to the profit gains, but much larger than the losses from zone pricing. For detergent, consumers do in fact gain overall by $16,215. As before, we can see that the low consumer welfare losses are misleading once we look at each store. In figure 10, we plot the compensating variation for orange juice by store.

The intuition for why consumers in some stores gain value while others lose welfare, or value, from these more flexible pricing policies relates to the ability of the store to re-align its product line pricing according to local demand. For instance, in store 75, most laundry detergent prices are raised, on average, about 2-3% (e.g. 128 oz price rises by 26 cents). At the same time, the price of 64 oz Tide (the category leader in the store with roughly 15% more share than the 2nd-ranked alternative) is lowered by one percent. As a result, the conditional share of 64 oz Tide rises almost 16%, while the conditional shares of most of the other brands fall by 1-3%. Note that store 75 in zone 7, one of the high-price zones in which consumers have fairly high search costs and there are no nearby EDLP stores. As a result, demand is fairly inelastic, which explains why the store would want to raise its price level. In contrast, in store 128, 64 oz Tide has a much smaller lead, dominating the 2nd-ranked alternative by only 4% in category share. Interestingly, store 128 holds the prices of its top 3 products almost fixed, while lowering

the prices of the remaining brands in the category 1-2%. As a result, shares become much more equalized in store 128, with the two largest-share goods falling 2-3%. At the same time, the conditional share of 64 oz Wisk rises almost 9 percent, making it (by a narrow margin) the new category leader, on average. Note that store 128 is in zone 11, which caters to households with relatively low incomes and house values. The area also caters to a higher proportion of ethnic households with larger families. As a result, demand is much more elastic, which explains why the store reduces most prices, allowing for a better-value brand to gain more relative share.

An interesting question for customer relationship management involves which types of consumers end up better versus worse off after the chain adopts a more flexible pricing policy. In general, we find that both store and, to a much lesser extent, zone pricing decrease welfare in lower income neighborhoods. Similarly, welfare rises in areas with greater mean household values for all categories. We also observe welfare falling in areas with larger ethnic populations. In general, we do not find much relationship between age and welfare changes. Interestingly, zone-pricing appears to lower welfare in areas where households have a higher ability to shop. But, store-pricing raises welfare in stores catering to consumers with greater ability to shop. This outcome is not surprising since the store-pricing will clearly favor stores with more price-elastic demand. In terms of competition, the welfare implications of proximity to a Jewel varies across categories and are quite small. The impact of proximity to an EDLP store is even smaller. Overall, it would appear that demographics are more influential for driving patterns in welfare changes than proximity to competitors.

While our results showing greater profits from the store pricing are consistent with those from Montgomery (1997), as noted before our analysis is different in nature. Most importantly, we note the trade-offs of zone and store-pricing in terms of the impact on consumer welfare. While it may be profitable to implement geographic price discrimination within a city market, as consumer losses across categories accumulate, one could eventually expect losses in traffic as shoppers switch to other stores. We view store-switching as a longer-run implication based on store-wide prices and therefore beyond the scope of our analysis. Naturally, higher prices could also encourage new entry by a competing chain not currently in the territory. Lower prices, on the other hand, could evoke competitive retaliation, although they could also deter entry into the market. These issues are more long-term considerations that need to be balanced carefully with our short run findings if they are to be used as inputs into chain strategy. Based on our current results, it would appear that managers would be better off allowing for price

discrimination in the laundry detergent category than refrigerated juice.

6.2 Alternative Recommended Pricing Policies

In the current section, we address some of the limitations of the pricing policies analyzed in the previous section. In particular, we address potential managerial concerns with losses in consumer value, on the demand-side, and complexity of price-determination on the retailer-side. To address each of these issues, we propose alternative pricing policies.

As demonstrated in the previous section, one of the main advantages of using a structural econometric approach is the ability to measure explicit economic metrics. In the current context, two such metrics are the category manager's valuation of a pricing policy, variable profits, as well as consumers' valuations, Hicksian compensating variation. In this section, we leverage both these metrics to propose an overall welfare-enhancing pricing strategy for the retailer. Store managers may be concerned that extracting too much value from consumers could generate store-switching in the long-run. Previous research has experimented with ad hoc constraints on pricing, such as holding the average price level fixed. In the current context, we are able to propose pricing such that consumer value is fixed. The structural approach generates a natural theory-based constraint - consumer welfare. We propose profit-maximizing store-level prices that are constrained to offer consumers at least as much surplus as a chain-level pricing policy. The prices under this policy will, by construction, make consumers better off than under chain-pricing or, at the very least, leave them indifferent between the two policies. Formally, the problem involves solving the following problem for each store s in each week t:

$$\max_{\{p_{sjt}\}_{j=1}^{J}} \Pi_{st} = \sum_{j=1}^{J}(p_{sjt} - w_{jt})Q_{sjt}$$

subject to the constraint:

$$\Delta W \geq 0.$$

In the above problem, ΔW measures the aggregate change in consumer welfare associated with switching from chain pricing to store-pricing, as in expression (4).

In table 15, we report the resulting change in profits and consumer welfare associated with such a policy in row labeled "constr. store". As expected, the constraint prevents the category manager from generating the same additional profits as under the unconstrained store-specific pricing policy of the previous section. However, even with the constraint, the manager is able to generate roughly half the gains of the store-pricing, an improvement in profits of 5.6% over a uniform chain-pricing policy, in the laundry

detergent category, and 7.4% in the refrigerated orange juice. At the same time, overall consumer welfare rises, especially in the refrigerated juice category where unconstrained pricing led to overall losses to consumers.

A second consideration regarding the unconstrained pricing of the previous section is the potential complexity of coordinating a store-specific pricing policy across the 83 stores. Clearly, one advantage of a zone policy is the simplification of price-determination. The previous section demonstrates the ease with which an aggregate database can be leveraged to learn about differences in consumer willingness-to-pay. However, changing item prices in 83 stores could be costly from an implementation point of view. Therefore, we propose an alternative zone pricing policy. Using the store prices computed in the previous section, we construct share-weighted price indexes for both the refrigerated juice category and the laundry detergent category. Using the 83 price indexes, we then run a simple non-hierarchical cluster analysis[16] to generate 5 zones. Constraining prices to be the same across all stores within each of these 5 zones, we then re-compute the profits and welfare levels that would prevail. In the row labeled "cluster" in table 15, we find that this simple 5-zone structure still generates substantial profit gains relative to the 16-zone pricing policy used by Dominicks during the time the data were collected. An interesting point is the fact that while the clusters offer notable gains to the retailer (relative to chain-pricing and the actual zone-pricing), consumers are better-off with 16-zone pricing policy used by Dominicks. Of course, the welfare-constrained policy proposed above could serve as a means of offsetting these losses to consumers. To attempt to characterize these zones, we plot the map of stores in figure 11. In the current context, the size of the dot for a given store is proportional to the mean household value of consumers in the store's market. Since we do not find much effect from distance to Cub stores, we do not include this information in the plot. As we can see, household values seem to explain a fair amount of the 5-zone configuration. Zone 5 caters to markets with fairly low average household values, whereas zones 2 and 4 cater to high and medium range household values respectively.

7   Conclusions

Using a detailed database including weekly store-specific margins, we are able to estimate flexible demand systems capable of generating reasonable approximations of the true data-generating process in several product categories. Rather than impose parameter

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[16]We use the non-hierarchical k-means-based cluster function in Stata version 7.

restrictions, as in Montgomery (1997), we resolve the typical store over-pricing problem by controlling for weekly store-specific endogeneity in prices due to unmeasured demand covariates. We use the demand system to investigate the impact of zone pricing on firm profits and consumer welfare. Our results suggest that zone-pricing is primarily a method for the supermarket chain to price discriminate based on geographic differences in consumer characteristics. However, we do find evidence for consumer search and local competition to influence the variation in zone margins to a lesser extent. These results are consistent with the findings of Hoch et al. (1995). As expected, flexible-pricing improves store profits, especially in the case of store-specific pricing. The magnitude of the gains depends on the category. For a necessity item like laundry detergent, we find conservative gains in profits with small effects on consumers. However, for categories like refrigerated orange juice, which exhibits far more demand heterogeneity across stores, we find fairly large profit implications. At the same time, consumers experience differential welfare effects. In particular, we find that DFF's existing zone-pricing seems to target high prices to less affluent areas. Allowing DFF to use store-pricing exacerbates this effect. Interestingly, the shift to store pricing would also raise prices in areas where consumers are less able to shop.

Our results add to the growing literature measuring the sources and welfare impact of price discrimination and price dispersion. Unlike most previous structural analyses using aggregate data, we are able to measure the fit of our model. With regards to the price discrimination literature, we are also able to control more accurately for alternative explanations of price variation. Our results are relevant to policy workers concerned with consumer welfare in the context of food prices. However, our findings are also relevant for strategists and marketers concerned with improving store profitability and managing their relations with consumers. In particular, we find that not all categories benefit noticeably from zone-pricing. We also find that managers must be weary of the impact on consumer welfare when implementing a zoning scheme. In some stores, the losses to consumers may in fact outweigh the profit gains.

In our current specification, we have only focused on the impact on consumers and retailers. An interesting area for future research is the impact on retail pass-through. While we expect wholesale prices to be determined at the market level, it may be of interest to see how zone pricing alters the extent that exogenous changes in wholesale prices are passed-through to consumers. Recently, Besanko, Dubé and Gupta (2001b) document that, in the same data, retail pass-through rates are fairly high, especially for large-share items. They also find that pass-through rates vary across stores based on

similar store characteristics as we use in our model. Using our structural model, we could measure the impact of zone-pricing on pass-through relative to a uniform chain-level price mechanism. This analysis could be interesting for manufacturers who are interested in identifying which consumers benefit the most from promotional wholesale discounts.

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A   The single-unit purchase assumption

In some product categories, the single unit purchase assumption may be inappropriate. Consumers may purchase varying quanitites of a single brand or assortments consisting of multiple brands and varying quantities of each. A small marketing literature has explored the benefits of models that account for consumers' quantity decisions for a single brand (Chiang 1991 and Chintagunta 1993) and for consumers' assortment decisions (Dubé 2001 and Kim, Allenby and Rossi 2001). Assuming single-unit purchases in such categories could understate the own and cross-price elasticities. When looking at pricing, the model would tend to overstate the extent to which prices could be raised above costs profitably.

For the categories used in the current analysis, we believe the single-unit purchase assumption is not overly restrictive. To illustrate, we have assembled household purchase data for both of the categories used. We report the distribution of total brands purchased and total quantities of each on a given trip. While these data do not match the Chicago market or the precise time period, we have no reason a priori to expect Dominicks consumers to purchase these categories in vastly different proportions.

We use data for 2108 households in Denver between January 1993 and May 1995. For Laundry Detergent, we observe 12,287 trips during which an item was purchased in the category. Of these trips, fewer than 2% involve the purchase of multiple product alternatives and fewer than 10% involve the purchase of more than a single unit of any alternative. For Refrigerated Orange Juice, we observe 9719 trips during which an item was purchased in the category. Of these trips, fewer than 1% involve the purchase of multiple product alternatives and fewer than 10% involve the purchase of more than a single unit of any of the alternatives.

B   The data

Descriptive statistics for the five product categories used in the analysis are shown in Table 1. These product categories differ in terms of within category competition as well as the role of store brand. For example, in the laundry detergent category, the top three brands capture 60% share, while a single brand accounts for over 44% share in the beer and orange juice. The store brand has negligible presence in beer and laundry detergents, while it is a major player in the juice and paper towel categories.

One of the problems with the scanner data is the large number of products in most categories. In general, each product category contains between 30 to 100 separate UPCs. For computational feasibility, the large number of products requires some aggregation across UPCs and some truncation. Selecting the set of brands for empirical analysis requires a balance between category representation and aggregation bias. Our approach was to run a correlation of prices across stores and weeks, and bundling those UPCs within a brand-size that had a price correlation of over .8. In other words, we only aggregate across UPCs whose prices co-move highly enough to believe they are priced jointly. As an example in table 3, we present the UPCs, their sizes, category shares, prices, and the price correlation for Tropicana brand in the orange juice category. Based on the unit price and the price correlations, 6 UPCs for this brand were included as 3 separate products in our empirical analysis. In table 2 we present the number of products (brand-size combinations), total number of UPCs, and the category representation for the 5 product categories used in the analysis.

Category	Top brand[1] share	3-brand share	Store brand share	Avg. margin	Store brand margin
Laundry deterg.	32%	60%	1%	17%	23%
Refrig. O.J.	44%	80%	16%	25%	23%

[1]Brand here represents all items of different sizes, flavors etc. carried under the single brand name. This is different from "brand" definition used in the paper as described below.

Table 1: Category Descriptive Statistics

Category	# of products	# of UPCs	% UPCs used
Laundry detergent	9	18	60%
Refrigerated Orange Juice	7	14	67%

Table 2: Product Aggregation

C   Price Endogeneity

An important feature of our analysis is the explicit treatment of the regression error, ξ. Unlike many standard aggregate modeling techniques, we have explicitly derived a structural error. In doing so, we recognize how this unobserved (to the econometrician) component of consumer choices could influence prices and, thus bias our demand estimates. To assess this problem, we estimate a demand system that circumvents the bias using instrumental variables techniques (two-stage least squares). We compare the results to those obtained using simple ordinary least squares. Note that we do not incorporate the random coefficients so that estimation can be performed with standard linear regression techniques (see for instance Besanko, Gupta and Jain 1998). In general, we find that the mean price sensitivity across stores and weeks (including demographic interactions) is 8% lower using OLS. These results are consistent with other studies cited in this paper that have found similar downward tendencies from OLS estimates. When we use the model to simulate zone prices, we find that the zone prices from the OLS framework are between 7 and 10% lower with OLS than 2SLS. This finding illustrates our concern that failure to account for the potential endogeneity of prices could generate misleading managerial predictions.

Product	Size	Price	Cat. Share	Price Correlation									
TROP PURE PRM OJ	32 oz	1.65	2.60%	1									
TROP PURE PRM OJ	16 oz	1.09	2.00%	0.83	1								
TROP PURE PRM OJ	64 oz	2.68	9.60%	0.17	0.21	1							
TROP ORNGE JCE	32 oz	1.45	1.30%	0.8	0.84	0.23	1						
TROP SB OJ	64 oz	2.37	8.00%	0.18	0.22	0.16	0.38	1					
TROP PURE PRM	64 oz	2.68	6.40%	0.17	0.2	0.98	0.23	0.16	1				
TROP SB HOMEST	64 oz	2.38	5.70%	0.19	0.23	0.16	0.38	0.98	0.16	1			
TROP PURE PRM	96 oz	4.51	4.30%	0.7	0.75	0.03	0.77	0.21	0.03	0.22	1		
TROP PURE PRM	96 oz	4.51	2.30%	0.7	0.75	0.03	0.77	0.21	0.03	0.22	1	1	
TROP PURE PRM OJ	3/8 oz	1.58	2.10%	0.58	0.8	0.2	0.61	0.09	0.2	0.1	0.55	0.55	1

Table 3: Aggregation of Tropicana UPCs

Category	Brand	Size	Share	Price	Cost	Prom
Refrigerated OJ	MM	64 oz	21.2%	2.24	1.69	0.37
	MM	96 oz	4.1%	4.09	1.99	0.31
	Dom	64 oz	24.4%	1.65	1.15	0.39
	Trop Prm	64 oz	20.5%	2.66	1.88	0.39
	Trop SB	64 oz	17.7%	2.37	1.62	0.29
	Trop Prm	96	7.7%	4.51	2.18	0.14
	Florida	64 oz	4.3%	2.18	1.90	0.22
Laundry Detergent	SURF	64	6.2%	4.09	3.01	0.27
	WISK	128	7.0%	8.10	3.31	0.13
	WISK	64	14.1%	4.14	3.53	0.17
	ALL	64	12.8%	3.11	2.41	0.24
	ALL	128	10.9%	5.72	2.19	0.13
	CHEER	64	6.3%	4.20	3.62	0.16
	CHEER	128	5.3%	8.20	3.42	0.25
	TIDE	128	18.9%	8.30	3.52	0.41
	TIDE	64	18.4%	4.38	3.79	0.25

Table 4: Descriptive Statistics

	Laundry Det.	Rfj. OJ
Price Variation across weeks	0.72	0.77
Price Variation across stores	0.11	0.06
Share Variation across weeks	0.78	0.76
Share Variation across stores	0.02	0.05

Table 5: R-square values are medians across each of the products in the category

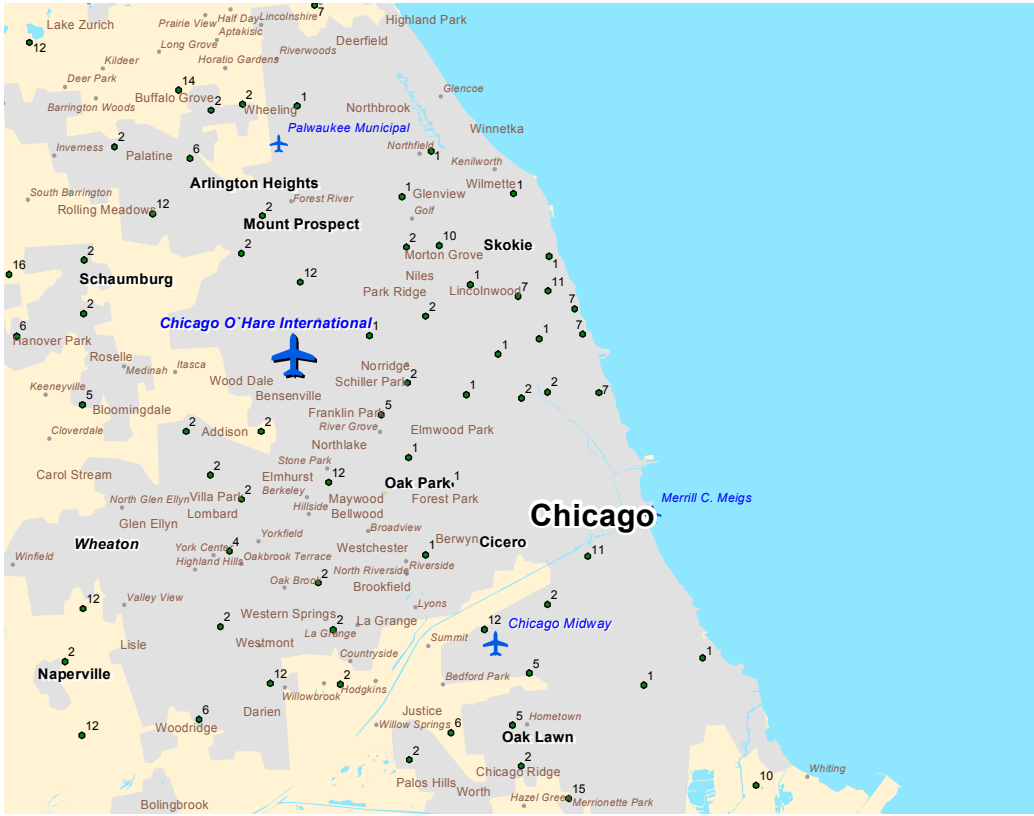| Variable	Mean	Std Dev	Minimum	Maximum
AGE60	17%	6%	6%	31%
ETHNIC	15%	19%	2%	99%
HHLARGE	12%	3%	1%	22%
HVAL150	34%	24%	0.40%	92%
SHOPINDX	74%	24%	0%	99%
JEWELDIST	1.29 (mi)	0.86	0.06	3.96
EDLPDIST	5.03 (mi)	3.48	0.13	17.85

Table 6: Demographic and Competitive Variables

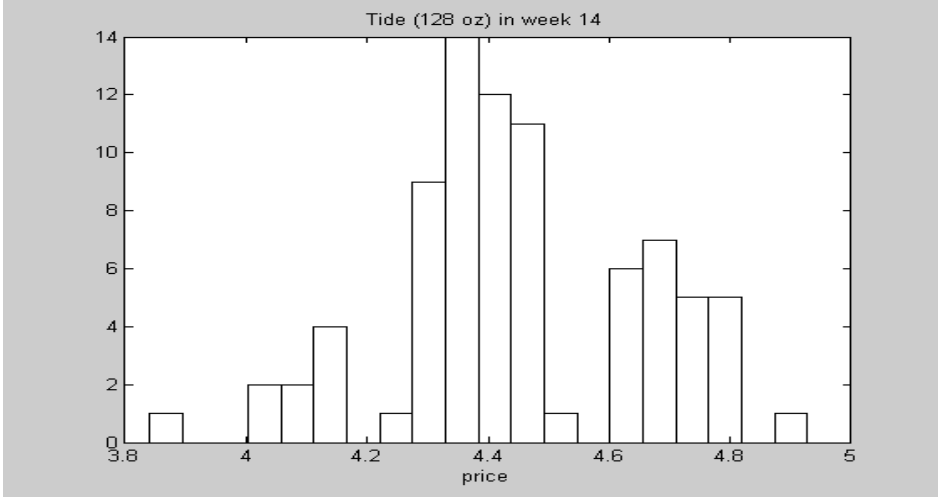Figure 1: 16-Zone configuration used by DFF

Figure 2: Distribution of shelf prices across stores for 128 oz Tide in a given week.

| ZONE | Price | Demographics | | | | | Jewel | EDLP |
| | | Income | Age60 | Ethnic | Shopindx | HVAL | | |
	($)	(log $)	(%)	(%)	(%)	($'000)	(miles)	(miles)
1	3.48	10.56	0.20	0.26	0.62	166.52	1.29	7.24
2	3.27	10.66	0.17	0.11	0.79	147.37	1.19	4.20
3	3.38	10.62	0.18	0.03	0.89	143.83	1.04	2.10
4	3.28	10.80	0.21	0.05	0.80	160.00	2.47	1.63
5	3.26	10.59	0.22	0.07	0.83	111.59	1.76	2.80
6	3.20	10.71	0.14	0.08	0.87	135.32	1.26	1.14
7	3.48	10.43	0.21	0.23	0.42	190.35	1.35	8.51
8	3.27	10.56	0.13	0.15	0.88	121.19	0.34	11.65
10	3.46	10.57	0.26	0.15	0.75	116.41	1.83	7.28
11	3.38	10.10	0.15	0.46	0.25	97.37	1.58	9.53
12	3.26	10.74	0.16	0.14	0.84	152.75	0.93	4.89
13	3.26	10.72	0.09	0.11	0.94	151.07	3.91	6.68
14	3.26	10.88	0.09	0.07	0.76	179.07	1.43	3.10
15	3.25	10.57	0.14	0.21	0.88	100.39	1.80	4.41
16	3.19	10.78	0.06	0.08	0.81	139.06	1.72	2.60
MEAN	3.31	10.62	0.16	0.15	0.76	140.82	1.59	5.18

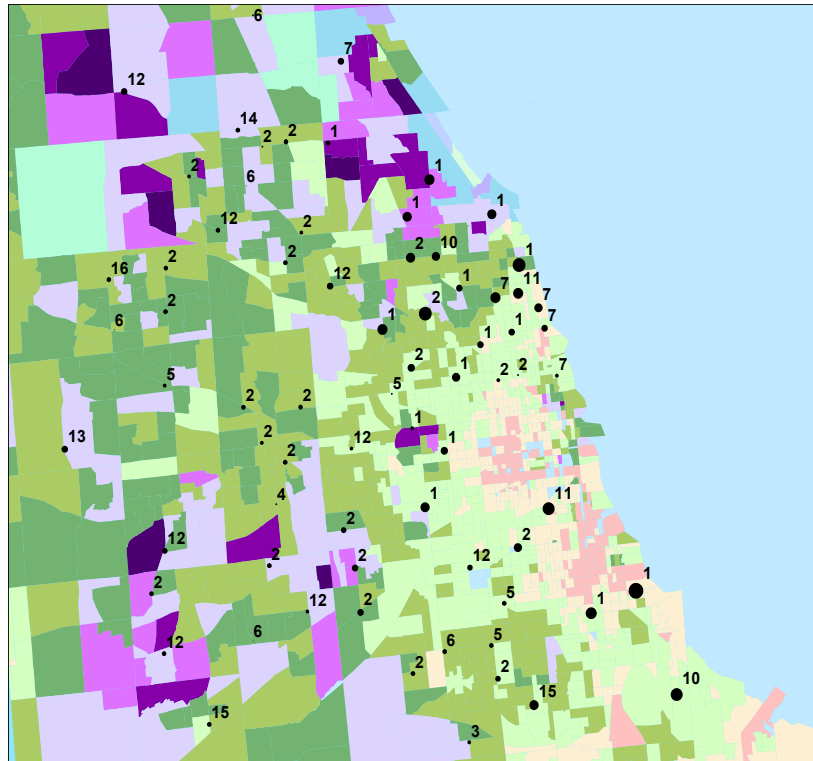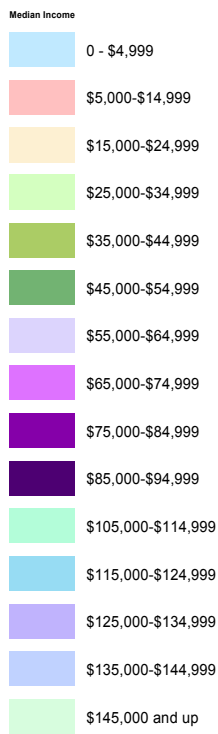Table 7: Demographics and Competitive Variables by Zone

Figure 3: 16-zone configuration used by DFF: Role of median income level and proximity to Cub Foods, the main EDLP competitor. (Note dots are proportional to the distance to the nearest Cub Foods).
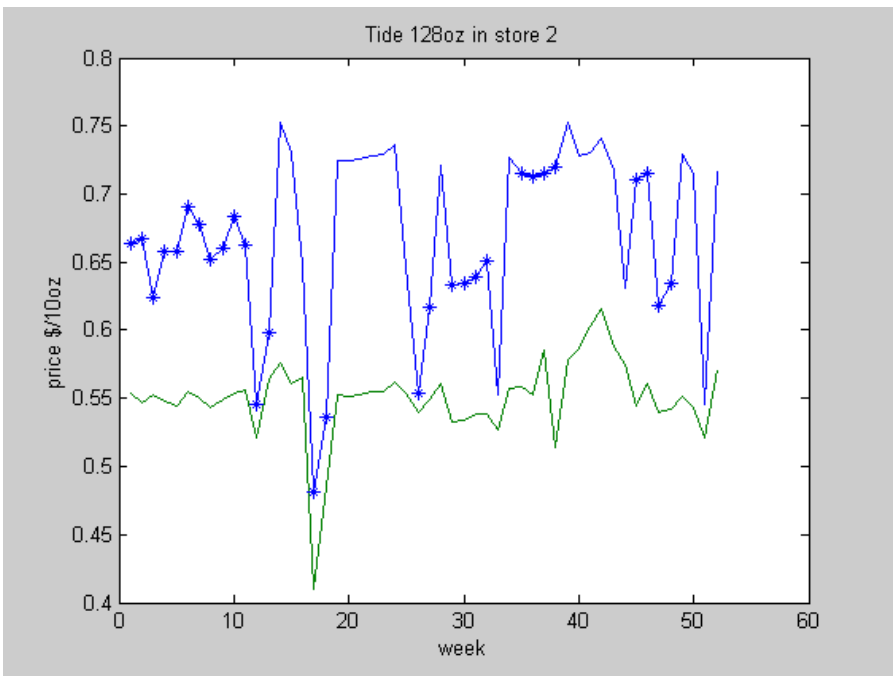
Figure 4: Shelf Prices and Wholesale Prices (* indicates promotion week)

	param	s.e.
Surf	-6.273	2.654
Wisk	-7.216	2.786
All	-5.316	2.554
Cheer	-3.305	2.550
Tide	-1.866	2.541
price	-7.843	4.082
s.d. price	0.348	0.393
promo	0.749	0.068
price*promo	-1.106	0.112
64-oz	0.742	0.008
holiday	0.227	0.026
income	0.412	0.262
age60	-0.907	0.420
ethnic	0.064	0.207
shopindx	0.436	0.255
hval	-0.009	0.001
Jewel	-0.002	0.029
EDLP	-0.010	0.008
price* income	-0.713	0.421
price*age60	3.296	0.672
price*ethnic	-0.641	0.324
price*shopindx	-0.273	0.410
price*hval	0.020	0.002
price*Jewel	0.050	0.046
price*EDLP	0.053	0.013

Table 8: Demand for Laundry Detergent
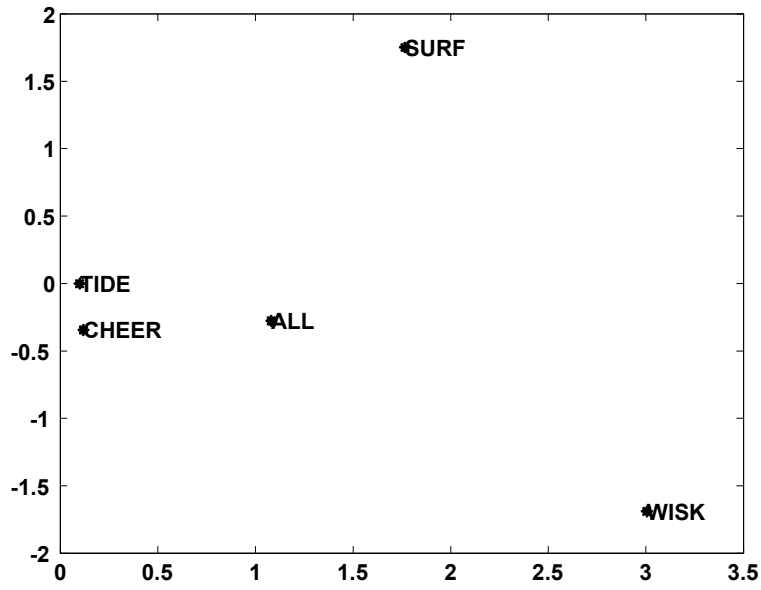
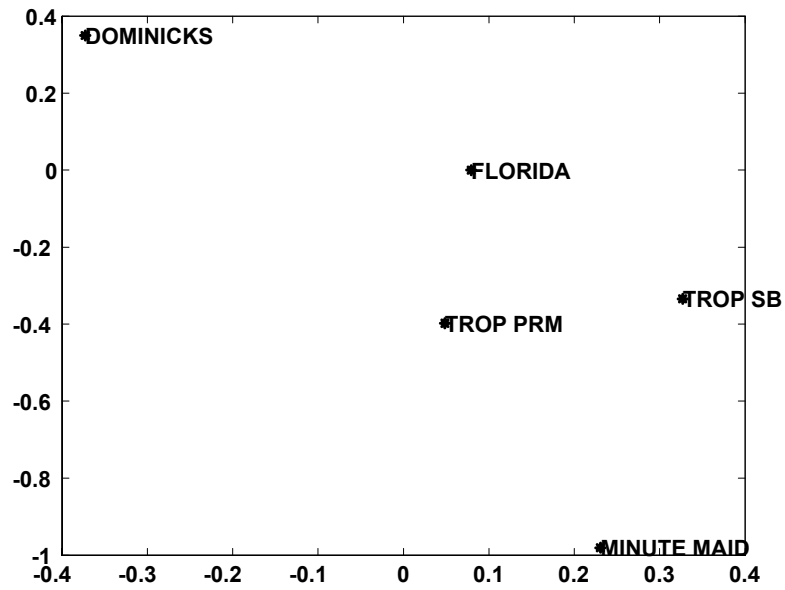Figure 5: Perceptual Map for Laundry Detergent

Figure 6: Perceptual Map for Refrigerated Orange Juice

	param	s.e.
MM	10.858	1.823
Dom	9.802	1.924
Trop Prm	11.953	1.817
Trop SB	11.008	1.814
Florida	8.724	1.969
price	-50.389	4.443
s.d. price	-0.033	0.874
promo	1.632	0.079
price*promo	-3.694	0.211
96-oz size	-0.485	0.011
holiday	0.198	0.031
income	-0.921	0.186
age60	-1.933	0.284
ethnic	0.375	0.147
shopindx	-0.062	0.170
hval	-0.015	0.001
Jewel	0.012	0.020
EDLP	-0.029	0.006
price* income	2.950	0.459
price*age60	8.096	0.693
price*ethnic	-0.436	0.346
price*shopindx	-0.004	0.419
price*hval	0.049	0.002
price*Jewel	-0.062	0.049
price*EDLP	0.120	0.013

Table 9: Demand for Refrigerated Orange Juice

Category	Income	Age60	Ethnic	Shopindx	Hvalmean	Jewel	EDLP
Laundry Detergent	-0.107	0.126	-0.018	0.160	0.301	0.024	0.067
Refrigerated OJ	0.751	0.109	0.010	-0.026	0.205	0.003	0.036

Table 10: Marginal Effects of Store Characteristics on Category Size (purchase prob.)

Category	Brand	dim 1	s.e.	dim 2	s.e.
Laundry Detergent	Surf	1.766	0.396	1.750	0.421
	Wisk	3.005	0.592	-1.689	0.582
	All	1.080	0.252	-0.277	0.387
	Cheer	0.120	0.463	-0.344	0.653
	Tide	0.100	0.368		
Refrigerated OJ	MM	-0.138	0.678	0.763	0.338
	Dom	0.056	1.207	1.226	0.512
	Trop Prm	0.008	0.444	-0.341	0.418
	Trop SB	-0.020	1.160	0.117	0.591
	Sunny D	-0.440	1.002		

Table 11: Latent Brand Factors

	Laundry Det.	Rfj. OJ
store	1.844	2.499
zone	1.210	1.463
chain	1.329	3.025

Table 12: Minimum Distance Criterion

Brand	Size (oz)	Conditional Share	TRUE	Store	Zone	Chain
Surf	64	6.2%	25.8%	19.5%	22.1%	22.3%
Wisk	128	7.0%	17.9%	22.8%	26.4%	26.6%
Wisk	64	14.1%	14.9%	21.5%	25.2%	25.4%
All	64	12.8%	22.3%	22.1%	24.2%	24.3%
All	128	10.9%	23.2%	23.9%	26.1%	26.2%
Cheer	64	6.3%	13.6%	14.4%	15.6%	15.7%
Cheer	128	5.3%	16.4%	15.1%	16.3%	16.4%
Tide	128	18.9%	14.7%	14.4%	15.5%	15.6%
Tide	64	18.4%	13.5%	13.8%	14.6%	14.8%

Table 13: Predicted Margins for Laundry Detergent

Brand	Size (oz)	Conditional Share	TRUE	Store	Zone	Chain
MM	64 oz	21.2%	23.7%	32.2%	30.6%	30.5%
MM	96 oz	4.1%	26.2%	30.1%	26.9%	26.5%
Dom	64 oz	24.4%	28.2%	38.7%	38.8%	38.4%
Trop Prm	64 oz	20.5%	28.1%	30.8%	28.4%	27.8%
Trop SB	64 oz	17.7%	30.1%	33.4%	30.7%	30.6%
Trop Prm	96	7.7%	27.0%	28.9%	25.4%	24.7%
Florida	64 oz	4.3%	31.6%	41.8%	42.4%	42.1%

Table 14: Predicted Margins for Refrigerated Orange Juice

Category	Aggregation	Profit	Change in Profit	Change in Profit ($)	Change in Cons. Welfare ($)	Total Change in Welfare ($)
Laundry	Chain	$1,148,500				
Detergent	Zone	$1,155,400	0.6%	$6,900	$2,158	$9,058
	Store	$1,258,200	9.6%	$109,700	$16,215	$125,915
	Constr. Store	$1,212,500	5.6%	$64,000	$39,381	$103,381
	cluster	$1,192,500	3.8%	$44,000	$1,082	$45,082
Refrig.	Chain	$3,336,000				
OJ	Zone	$3,388,400	1.6%	$52,400	-$19,791	$32,609
	Store	$3,878,200	16.3%	$542,200	-$158,100	$384,100
	Constr. Store	$3,582,400	7.4%	$246,400	$48,613	$295,013
	cluster	$3,623,400	8.6%	$287,400	-$156,900	$130,500

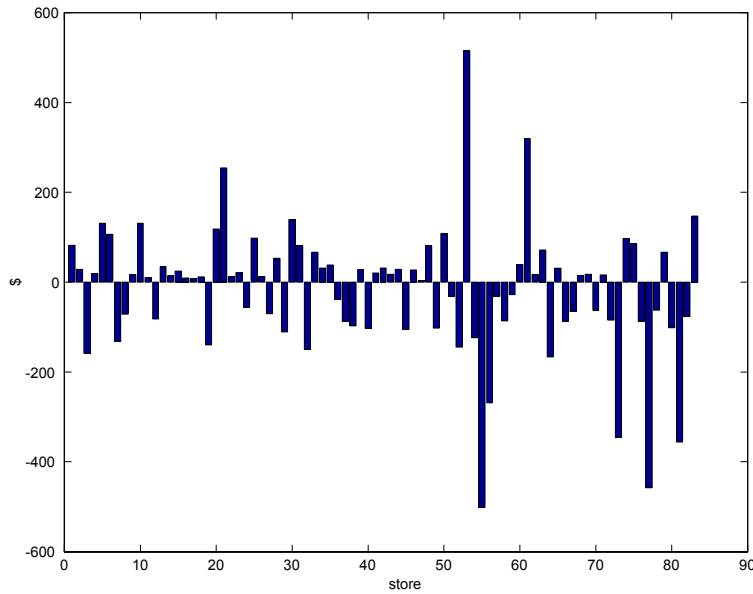Table 15: Welfare Implications of Pricing Policies

Figure 7: Consumer Welfare Gains and Losses with Zone-Pricing (Laundry Detergent)
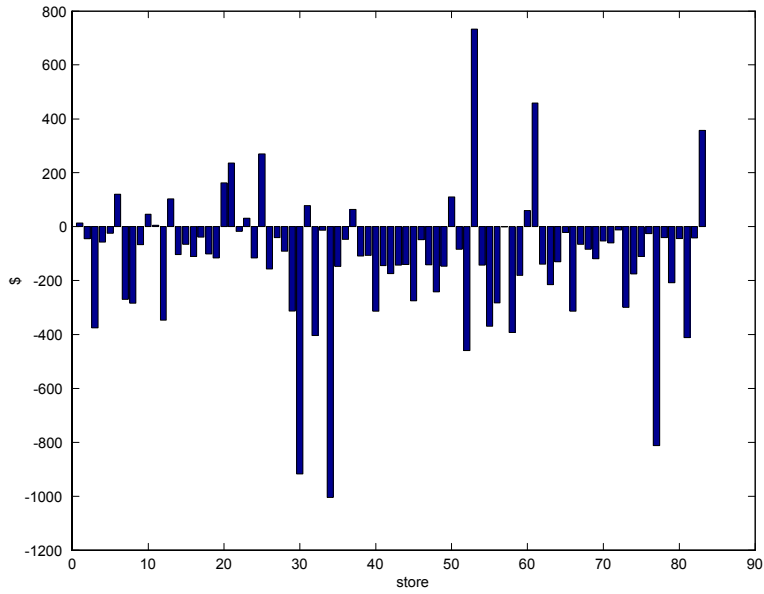
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Figure 8: Consumer Welfare Gains and Losses with Store-Pricing (Laundry Detergent)
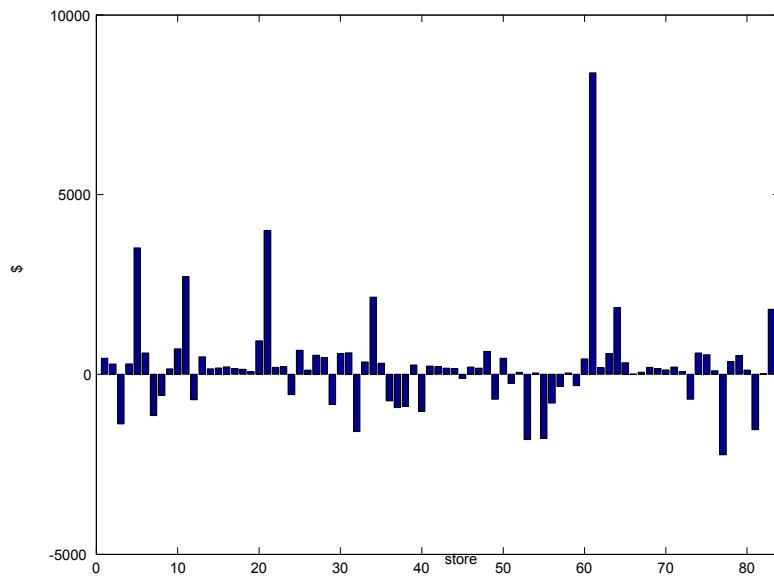

Figure 9: Consumer Welfare Gains and Losses with Zone-Pricing (Refrigerated Orange Juice)
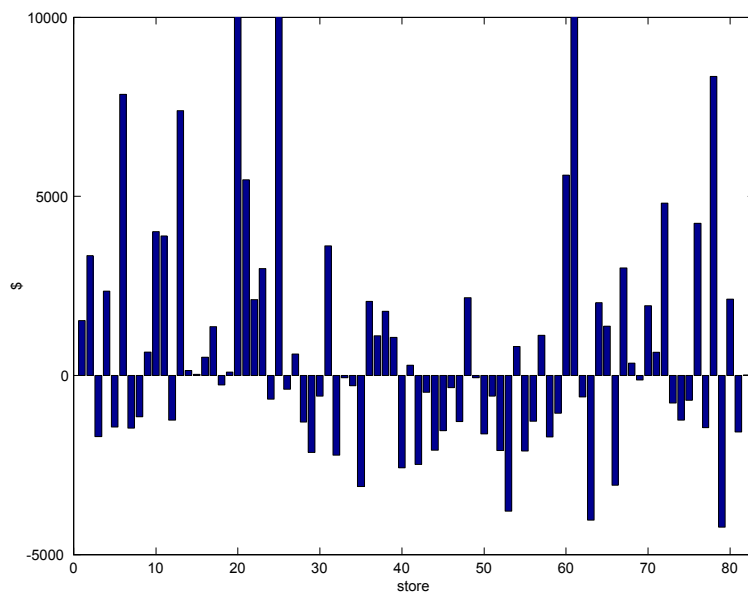
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Figure 10: Consumer Welfare Gains and Losses with Store-Pricing (Refrigerated Orange Juice)
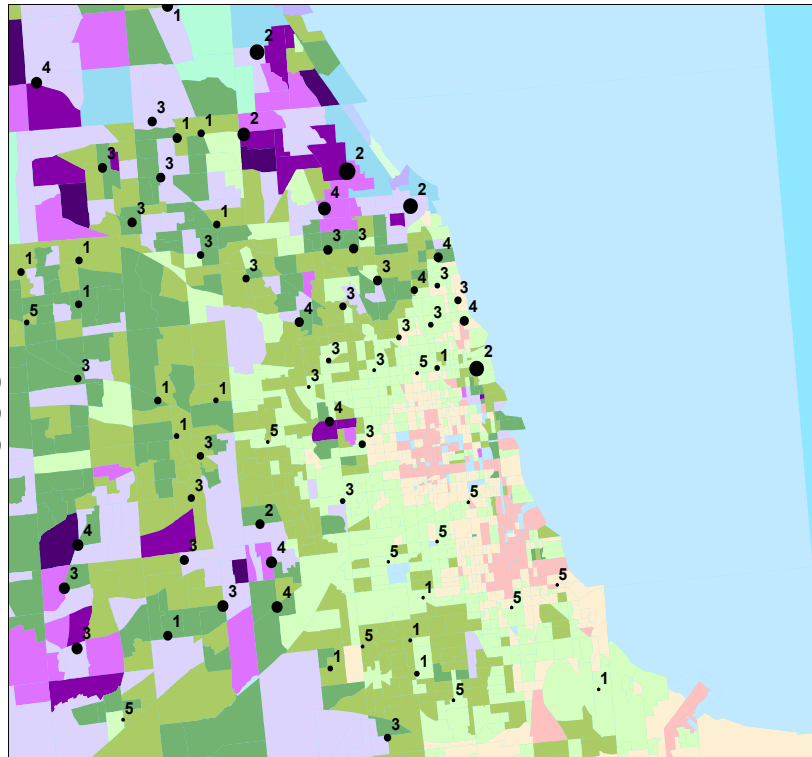
Figure 11: 5-zone Configuration using clustering of the store-specific prices (note dots are proportional to mean household values in a store's trading area)

		param	s.e.	t-stat
	holiday	-0.38	0.09	-4.09
demographics	income	-1.69	0.36	-4.73
	hvalmean	0.02	0.00	8.91
	age60	-1.11	0.68	-1.63
	ethnic	0.23	0.46	0.51
	shopindx	2.09	0.37	5.62
	jewel	0.31	0.03	8.90
	edlp	-0.04	0.01	-4.07
Log Price Index	Analgesics	1.95	0.33	5.93
	Bath soap	0.58	0.13	4.30
	Beer	-5.12	0.79	-6.45
	Bottled juices	-3.57	0.86	-4.13
	Canned cooking soups	2.26	0.55	4.10
	Cereals	0.62	0.42	1.47
	Cigarettes	-1.66	0.80	-2.09
	Cookies	-1.92	0.54	-3.55
	Crackers	-0.13	0.77	-0.17
	Dish detergent (liq)	0.48	0.72	0.66
	Canned eating soups	-1.87	0.50	-3.76
	Front-end candies	0.50	0.52	0.97
	Frozen dinners	1.51	0.39	3.91
	Frozen entrees	1.73	0.34	5.06
	Frozen juices	-0.74	0.34	-2.14
	Fabric softeners	-1.24	0.96	-1.29
	Grooming products	-1.15	0.42	-2.73
	Laundry detergents	-1.10	0.82	-1.34
	Non-sliced cheeses	1.50	0.49	3.05
	Dish detegent (powder)	-0.92	0.50	-1.82
	Canned salmon, crabs, etc	1.06	0.36	2.98
	Oatmeal	-2.83	0.66	-4.30
	Paper towels	-3.11	1.24	-2.51
	Refrigerated juices	-0.20	0.16	-1.21
	Sliced cheeses	3.09	0.66	4.70
	Soft drinks	2.05	0.64	3.24
	Shampoos	0.70	0.79	0.88
	Snack crackers	1.65	0.59	2.81
	Soaps	1.38	1.39	0.99
	Toothbrushes	-4.60	1.09	-4.22
	Canned tuna	-0.43	0.26	-1.64
	Toothpastes	-0.83	0.50	-1.64
	Bathroom tissues	-3.89	0.85	-4.59
	constant	44.14	5.15	8.57
	observations	1486.00		
	R-square	0.37		

Table 16: Store-Choice Regression based on share of market for store trips