The Geography of Grocery Demand in the UK: An Evaluation of the 2003 Morrisons-Safeway Merger

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Abstract

In 2003, the UK Competition Commission (CC) approved the acquisition of Safeway plc by Wm. Morrisons plc, respectively the fourth and sixth largest firms in the industry. Because Morrisons focused on the North and Safeway on the South, this merger had the potential to create a fourth national champion to rival Asda, Sainsbury's, and Tesco, hopefully improving competition, lowering prices, and improving quality for consumers. But, the merger could also have had an adverse affect on competition by creating pockets of local market power which the merged firm could exploit. To evaluate the CC's decision, I construct a geographic distribution of demand which models the local interactions between consumer demographics and store locations. My model has several parts. I estimate a Discrete/Continuous structural model of demand from a high quality panel of consumer micro-data (the TNS Worldpanel) to explain both store choice and conditional demand for groceries. After combining this demand system with disaggregate census data, I recover marginal costs and then predict store-level

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sales and profits as well as willingness-to-pay. I use these tools to evaluate the welfare implications of the merger and of a counter-factual merger between Safeway and Tesco. I find that the changes in prices, profits, and consumer welfare under either merger are quite small – although larger for a Tesco-Safeway merger. Although consumers are slightly worse off under these mergers, the results support the UK Competition Commission's approval of the merger.

1 Introduction

On 9 January 2003, William Morrisons plc, a UK supermarket chain, made an unsolicited offer for its larger rival Safeway plc, prompting a flurry of takeover proposals from other firms seeking to purchase Safeway. Safeway's suitors included Asda, Sainsbury's, and Tesco as well as Kohlberg Kravis & Roberts (KKR), a private equity firm, and Trackdean Investments Ltd., a family investment vehicle. As the takeover battle escalated, the UK Secretary of State for Trade and Industry referred the acquisition proposals of the four supermarket firms to the UK Competition Commission under the 1973 Fair Trading Act: the Secretary believed that acquisition by Asda, Sainsbury's, or Tesco would cause a substantial lessening of competition and that a Morrisons-Safeway merger might also be anti-competitive. Ultimately the CC approved the merger with Morrisons subject to the divestment of 52 stores where the CC thought the merger would have an adverse impact on local competition. After the CC's decision, on 15 December 2003, Morrisons made a revised offer to acquire Safeway which received the approval of both firms' shareholders on 11 February 2004.

In theory, the merger appeared to make good business sense because Morrisons was concentrated in the North, Yorkshire, and Midlands whereas Safeway was strong in London, the South East, and Scotland. Furthermore, Safeway, although not a failed company, lacked a consistent pricing strategy and had struggled to differentiate itself vis-a-vis Asda, Sainsbury's, and Tesco whereas Morrisons had profitably differentiated itself and grown in a financially sound manner [Seth and Randall, 2001]. Consequently, a combined firm under Morrisons' management could become a strong national competitor through increased scale, greater purchasing power, and better coverage of regional markets. The concomitant increase in competition in the groceries industry should have improved consumer welfare through lower prices and/or higher quality. In practice, the firm struggled for the next several years to integrate Safeway's operations with its own, despite divesting 72 additional stores as well as 114

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Safeway Compact convenience stores to further focus its positioning on larger format stores.

In addition to the 2003 merger investigation [UK Competition Commission, 2003], the UK supermarket industry has been the subject of several other investigations by the Competition Commission. In 2000, prior to the merger inquiry, the CC investigated the conduct of multiples towards suppliers [UK Competition Commission, 2000][1] as well as their pricing practices, leading to the adoption of a Supermarket Code of Practice (SCOP) between multiples and suppliers. In addition, most supermarkets voluntarily adopted a national pricing policy to allay concerns about 'price flexing', the exploitation of local market power to set higher prices. In addition, the report considered requiring planning approval for the dominant firms, Asda, Morrisons, Safeway, Sainsbury's, and Tesco, prior to opening large stores or performing large extensions of existing stores within fifteen minutes of another one of their stores. A subsequent investigation in 2006 resulted in a strengthened version of SCOP, called Groceries Supply Code of Practice (GSCOP), and a market test to determine whether the largest firms could open new stores or undertake renovations of existing stores [UK Competition Commission, 2006].[2]

Given this background, I evaluate the CC's approval of the Morrisons-Safeway merger by constructing a structural model of the geographic distribution of demand for groceries to explain how consumers' physical locations and preferences interact with stores' locations, pricing, and profitability. Understanding this interaction is central to developing good policy because the geographic distribution of consumers and their preferences determines the profitability of a store at a specific physical location. In addition, stores of the same fascia[3] or parent firm increase local market power because the owning firm will capture part of the demand lost from a price increase when consumers switch to the firm's other stores [Smith, 2004]. Furthermore, the locations of nearby stores as well as their prices and qualities, affect the number of consumers who choose a store and their expenditure. This strategic interaction between stores may also propagate pricing pressures over larger distances through chaining. Con-

[1] 'Multiples' were defined as firms operating at least ten stores having sales areas greater than 600 square meters.

[2] Because the Competition Appeal Tribunal upheld Tesco's challenge to the lawfulness of the market test, the CC undertook an additional inquiry to address concerns about the economic costs of the test as well as its effectiveness [UK Competition Commission, 2009].

[3] *Fascia* refers to the brand on the front of a firm's stores such as *Tesco Express*, *Tesco Metro*, or *Tesco Extra* each of which is a different fascia, although all are owned by the same corporation, Tesco plc.

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sequently, I combine a discrete/continuous model of demand with UK census data to calculate the expected demand each fascia's stores face at different locations. The discrete/continuous demand system [Dubin and McFadden, 1984, Hanemann, 1984] explains both store choice and conditional demand. By aggregating over the distribution of consumer types and locations, as specified in the census data, I can compute the expected demand at each store, given prices. I then use this aggregate, geographic distribution of demand for several other calculations. After recovering marginal costs by inverting the first order equations for profit, I solve for Bertrand-Nash equilibrium prices, and use these prices to calculate firms' profits and bounds on consumers' compensating variation. Throughout these calculations, I assume that stores can set the optimal price for each household type's basket, which greatly simplifies estimation and computation of prices, profits, and consumer welfare. Finally, I use these tools to compare three different policy scenarios: the counter-factual state before the observed merger, the observed state after Morrisons acquired Safeway, and a counter-factual merger between Tesco and Safeway. Given Tesco's dominant position in the industry, the Tesco-Safeway counter-factual should put an upper bound on the adverse effects of the acquisition of Safeway by any of its suitors. Because the census data is disaggregate at the output area (OA) level,[4] I can compute welfare effects at this level as well as the change in profits at individual stores.

My approach to estimating demand is most similar to Smith [2004], who develops a discrete/continuous choice model to measure market power, both by computing elasticities and considering the welfare implications of a series of mergers and demergers. Like Smith, I use store characteristics and locations from the IGD data.[5] My estimates benefit from access to the Taylor Nelson Sofres (TNS) Worldpanel,[6] a high quality homescan panel of consumer microdata containing actual consumer choices, prices, and expenditure whereas Smith only observed price-cost margins and had to rely on survey data about consumers' stated store choice and expenditure. Consequently, I can estimate the demand parameters more precisely via Maximum Likelihood Estimation (MLE) instead of his two-step method. I also avoid the estimation and identi-

[4] An OA or *Output Area* is the smallest geographical area for which the UK census provides data. OAs roughly correspond to a ward. On average they contain 125 households and about 300 residents. See http://www.statistics.gov.uk/census2001/glossary.asp#oa.

[5] IGD was formerly known as the *Institute of Grocery Distribution* and was formed from the merger of the Institute of Certified Grocers and Institute of Food Distribution.

[6] Note: the TNS Worldpanel was recently rebranded as the Kantar Worldpanel.

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fication problems he encountered because of the limitations of his data. Lastly, I use aggregate units of groceries and price indexes for each fascia, region, and household type which Beckert et al. [2009] constructed from a combined TNS-IGD dataset in order to study the composition of consumers' shopping baskets. Although Beckert et al. [2009] use quadratic utility, I choose a specification with non-linear demand curves which is more appropriate for merger analysis.

There is a long literature on estimating consumer demand for groceries. Deaton and Muellbauer [1980b] provides a survey of 'classic' functional forms, demonstrating the advantages of their Almost Ideal Demand System (AIDS) [Deaton and Muellbauer, 1980a]. These studies were limited by the aggregate data and computational resources available at the time. There is a growing literature on the supermarket industry which builds on advances in modeling discrete choices. Beckert et al. [2009], which uses the same data as this chapter, examines how consumers choose baskets of goods and finds that often a large fraction of a given household type never purchases certain categories such as alcohol or pet food. Briesch et al. [2010] find that not only do about 20% of US consumers stop at multiple stores per shopping trip, but that they purchase different baskets from different stores and that destination categories determine store choice as well as complementarities between different fascia. Also, the pricing strategy of a fascia affects whether consumers prefer to purchase a large or a small basket: EDLP (Every Day Low Pricing) favors large baskets whereas a Hi-Lo strategy makes opportunistic purchases of small baskets of whatever is on promotion preferable [Bell and Lattin, 1998]. Pakes et al. [2006] develop an alternative approach to these estimation strategies using moment inequalities which may be more robust to identifying assumptions and specification.

This chapter continues as follows: first, I describe the model (Section 2) and discuss several datasets which I use for estimation and geographic aggregation (Section 3). Next, I explain the estimation methodology in Section 4 and the results in Section 5. Then, I usethe geographic distribution of demand to recover firms' marginal costs and to compute price equilibria in Section 6. Finally in Section 7 I use these results to evaluate how the Morrisons-Safeway and counterfactual Tesco-Safeway mergers affect welfare. Section 8 concludes.

2 The Model of Consumer Demand

The geographic distribution of demand for groceries consists of a structural model of demand integrated over the empirical distribution of consumers to compute the expected demand for a store at a specific location. Several factors affect store choice and expenditure conditional on that choice: store and consumer characteristics, spatial locations of both stores and households, and consumer preferences. This section explains the model of consumer preferences at the core of the computations to evaluate welfare effects of the Morrisons-Safeway merger. These calculations – estimating demand, recovering marginal costs, and solving for pre- and post-merger Bertrand-Nash price equilibria – all depend on integrating predicted demand over the distribution of consumers.

Because firm behavior depends on the aggregate demand that each of store faces, I use a static, discrete/continuous model of demand based on Smith [2004] to estimate demand for each Government Official Region (GOR) and household composition – e.g., students, pensioners, couple with children, etc. (See Section 3 for more discussion of the data.). This model predicts both store choice and conditional expenditure for representative consumers. For the TNS data, described in 3.1, the empirical distribution of expenditure at chosen stores falls off exponentially for all levels above the lowest 10%.[7] Consequently, primary shopping constitutes the majority of expenditure so I model just one trip per period instead of a primary and 'top-up' trip as in Smith [2004]. By emphasizing aggregate purchases, I avoid unnecessary difficulties from estimating a more complex model of how consumers choose baskets of goods. In addition, the model is easy to estimate using maximum likelihood. If behavior is actually driven significantly by different shopping modes, the model will be misspecified. I also consider only one trip per household to avoid dealing with dynamic demand issues, such as correlations between trips, inventory keeping, search, and habit formation [Hendel and Nevo, 2004, Seiler, 2010].

2.1 Indirect Utility

In the data I observe both consumer and store characteristics, some of which – such as the size of the car park[8] and the distance between the store and the consumer – affect only store choice and others which affect both store choice and grocery expenditure. I specify an indirect utility function, $U_{hj}\left(x_h, z_j, \xi_h, \epsilon_{hj}; \theta\right) = V_{hj}\left(x_h, z_j, \xi_h; \theta\right) + \epsilon_{hj}$, where ϵ_{hj} is an unobserved household-store shock. I split $V_{hj}\left(x_h, z_j, \xi_h; \theta\right)$ into V^{Loc} and V^{Exp} because some covariates affect only store choice but not conditional expenditure. Thus, V^{Loc} captures the utility derived

[7] When I fit a line to log (expenditure), adjusted R^2 is 0.97, indicating that an exponential fits the distribution well.

[8] I.e., 'parking lot' in American English.

solely from a the attributes of a store's location[9] whereas V^{Exp} is the utility from the location and expenditure at a specific store:

$$V_{hj}\left(x_h, z_j, \xi_h; \theta\right) \quad = \quad V_{hj}^{Loc}\left(x_h, z_j; \theta\right) + V_{hj}^{Exp}\left(x_h, z_j, \xi_h; \theta\right).$$

x_h is household h's attributes, z_j store j's characteristics, θ the parameters to be estimated, and ξ_h a household-specific random effect. The shocks ϵ_{hj} and ξ_h are observed by the household but neither the econometrician nor the firm: firms know the distribution of household types but not the type of a specific consumer.

Both V^{Loc} and V^{Exp} are based on the specification in Smith [2004],which is derived from Hanemann [1984]. Thus, V_{hj}^{Loc}, the utility consumer h receives from just store j's location, is

$$V_{hj}^{Loc} \quad = \quad \beta_{carpark} carpark_j + \beta_{dist} dist_{hj}$$

and $V_{hj}^{Exp}(\cdot)$, the utility household h receives from both location and shopping (i.e., their conditional expenditure), is

$$\begin{aligned} V_{hj}^{Exp} \quad &= \quad \mu\left[\delta + \alpha_{out}\log p_{out} + \alpha_{price}\log p_j + \alpha_{inc}\log y_h + \alpha_{area} area_j + \xi_h\right] \\ &\times \quad \left(\frac{p_j}{p_{out}}\right)^{-\gamma_{price}}. \end{aligned}$$

This functional form leads to expenditure shares which are log-linear in price and income. Here, y_h is household h's income, p_j the aggregate index of hedonic prices for a unit of groceries at store j, p_{out} the price of an outside good, $area_j$ the sales area, $carpark_j$ the size of the car park, and $dist_{hj}$ the Cartesian distance between the household and the store.[10] μ is the relative contribution of the utility from purchasing groceries versus the utility from just the store's

[9] Orhun [2005] shows in an extension of Seim [2006]'s model of entry under incomplete information, that location-specific unobservables play a crucial role in determining the spatial positioning of supermarkets in the US. I ignore this type of shock, though unobserved factors such as the accessibility of a store, unobserved store qualities, or local complementarities with other destinations could be important.

[10] Phibbs and Luft [1995] show that Cartesian distance is a good approximation for travel time and that the longer the trip, the higher the correlation between travel time and Cartesian distance.

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location. The outside good consists of goods purchased on the trip other than groceries, such as stopping at the chemist, or for a take-away meal. The outside good is necessary to ensure that the utility function is homogeneous of degree zero. Because I do not observe purchases of the outside good, I normalize the price p_{out} to 1, so the term drops out of the utility specification.[11] For practical estimation purposes, I work with

$$V_{hj}^{Exp} = \mu\left[\delta + \alpha_{price}\log p_j + \alpha_{inc}\log y_h + \alpha_{area} area_j + \xi_h\right] p_j^{-\gamma_{price}}.$$

As in Dubin and McFadden [1984], heterogeneity enters the model in two ways, as the unobserved shock ϵ_{hj}, due to unobserved store characteristics, and the household fixed effect ξ_h, due to unobserved household characteristics. Note that ϵ_{hj} affects only store choice whereas ξ_h affects store choice and conditional expenditure. ϵ_{hj} captures unobserved utility which a household gains from a store's characteristics: for example, the store could stock some key good which the consumer values, be conveniently located on the consumer's regular commute, or be near other stores where the consumer shops. I assume that ϵ_{hj} follows a Type I Extreme Value distribution, yielding a multinomial logit specification which is tractable but often suffers from problems such as independence of irrelevant alternatives (IIA) and unrealistic substitution patterns [McFadden, 1981]. In particular, this assumption requires stores to be substitutes. Briesch et al. [2010] show that certain product categories affect fascia choice, that roughly 20% of trips involve stops at two different fascia, and that some fascia are complements with others. However, these facts have not been reproduced with UK data: i.e., UK shopping habits may be different because, among other reasons, US culture is much more car-centric and US houses typically have much more storage space, facilitating both more stops per shopping trip and larger purchases (or purchases of larger pack-sizes) because of reduced inventory costs. Many researchers now use random coefficients to rectify the problems from IIA. To some extent, I mitigate the problems of IIA by estimating demand separately for different types of consumers, as described below. I do not specify an outside option for store choice where $U_{h0} = 0 + \epsilon_{h0}$, as in most studies such as Smith [2004], because I actually observe all of a household's choices in the IGD data.

The random effect, ξ_h, captures unobserved household characteristics such as household size, variation in the outside option, and preferences for atypical

[11] Beckert et al. [2009] also assume that the price of the outside good is constant.

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items, all of which produce departures from the reference basket and may cause measurement error. Measurement error occurs from unobserved variations in quality, i.e. when the actual price and assortment in a store differ from the reference offer. For example, variations in price and other promotions cause the consumer to substitute from goods in the reference basket to similar products. In the data, I do not observe sales or promotions, so unobserved variations in price will distort the basket's composition from the reference unit of groceries. Furthermore, a store may not stock certain products in the reference basket either because of outages or local variations in the assortment of goods offered. For example, most fascia tend to stock more organic and luxury items in affluent neighborhoods. This variation is an important source of non-price competition and may be a significant, especially given the lack of price variation seen in UK data.[12] Consequently, the true price and quality of the basket actually purchased will differ from the price index for units of groceries and corresponding reference basket. ξ_h attempts to control for these unobserved variations in the quality and price. I assume that ξ_h is the same for all stores in a consumer's choice set to simplify estimation. This assumption depends on the correlation between non-price competition and geographic location. Finally, the actual home scan process used to collect the TNS data provides another source of measurement error (See 3.1 and Leicester and Oldfield [2009b]) because of fatigue, attrition, and reporting errors which vary by both product characteristics and household type. The differential reporting of different product types will also distort the observed basket from the baseline. However, these errors are typically about 5% of expenditure or less so I assume I can ignore them.

Bias will occur when a significant component of the household random effect is measurement error and not exogenous variation in the composition of a household's basket. For example, richer households (higher y_h) will tend to purchase higher quality baskets so the price index will understate the true price paid. Similarly, a higher price for the reference basket may cause substitution to lower cost items of lower quality so that purchased quality is lower than the quality used for generic 'units of groceries'. Thus, I expect that in the presence of measurement error (or endogeneity), ξ_h will be correlated with both household expenditure, y_h, and the price index, p_j. In this case, the parameter estimates will be biased.

Following Smith [2004], I assume that the store and household shocks are

[12] I am indebted to Jerry Hausman for pointing this out to me.

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independent to facilitate estimation via full information maximum likelihood. If ϵ_{hj} and ξ_h are correlated then the model is misspecified and will suffer from selection bias [Heckman, 1979]. These shocks could be correlated if characteristics which affect store choice also affect expenditure, such as advertising or product promotions. To correct this bias, I would need to use one of the estimation strategies in Dubin and McFadden [1984].

I do not specify time, fascia, or regional dummies because they are highly collinear with those included in the price index and the solver failed to converge when I specified them. Similarly, I was unable to estimate δ. Also following Griffith and Nesheim [2010] and Griffith et al. [2010], given the incredible richness of product characteristics in the data, I assume that I observe all product characteristics and that there is no need to control for a (potentially endogenous) unobserved product characteristic, unlike the BLP model [Berry et al., 1995] of differentiated products.

Following Beckert et al. [2009], I use household composition to categorize households by type and then estimate the model separately for each group. When the variation in each group is low, this method controls for some of the unobserved heterogeneity.[13] This assumption simplifies computation and is supported by the low estimated variance for ξ_h (See 5.).

To avoid infeasible expenditure shares, I assume that ξ_h is distributed as a truncated normal where the bounds are chosen to ensure that $w_{hj} \in [0, 1]$. This, unfortunately, causes the support of ξ_h to depend on the data potentially making ML estimation inconsistent.[14] In the data I observe that the size of the tails which need to be truncated have extremely small probability mass. In addition, some households violate these expenditure share bounds, but they are only 59 out of 16897 observations (0.34%). These violations are spread evenly across household types. Consequently, in order to facilitate computation, I assume that $\xi \sim \mathrm{N}\left(0, \sigma^2\right)$.

Lastly, I set $\alpha_{inc} = 1$ in order to identify the scale parameter, μ. I do not impose the restriction that $\alpha_{inc} = \gamma_{price}$ as in Smith [2004], so γ_{price} is free. See 4.2 for further discussion.

After applying all of these considerations, the indirect utility from expenditure is

[13] Random coefficients would probably improve the fit of the model.

[14] ξ_h is a function of the parameters because the shock is obtained by solving the relationship for the observed and calculated conditional demand, which is computed below using Roy's Identity.

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$$V_{hj}^{Exp} = \mu \left[\delta + \alpha_{price} \log p_j + \log y_h + \alpha_{area} area_j + \xi_h\right] p_j^{-\gamma_{price}}.$$

2.2 Conditional Demand

According to classical microeconomic theory, Roy's Identity can be used to derive the conditional demand. Because the indirect utility depends on an aggregate price index, not the prices of the individual goods, I assume that I can treat the price index as a 'price' and apply Roy's Identity. If this is not true, then the aggregate conditional demand for groceries must be derived by applying Roy's Identity to each individual good and then aggregating. For the case where utility depends only on the total price of the basket via an index restriction, the true derived aggregate conditional demand, $q_{hj}^{true} \propto q_{hj}$, and the constant of proportionality depends on the expenditure share weights, as shown in Appendix A.

Under this assumption, the conditional demand is

$$q_{hj} = -\frac{\partial V_{hj}/\partial p_j}{\partial V_{hj}/\partial y_h}$$

$$q_{hj} = \frac{y_h}{p_j} \left\{\gamma_{price} \left[\delta + \alpha_{price} \log p_j + \log y_h + \alpha_{area} area_j + \xi_h\right] - \alpha_{price}\right\}$$

and the expenditure share is

$$w_{hj} = \gamma_{price} \left[\delta + \alpha_{price} \log p_j + \log y_h + \alpha_{area} area_j + \xi_h\right] - \alpha_{price}.$$

Because $\alpha_{price} < 0$ for the price term, the expenditure share has a simple interpretation: the constant term, $-\alpha_{price}$, captures the subsistence expenditure required by a household and the bracketed term represents expenditure on goods which are not necessities.

3 Data

Evaluating the Morrisons-Safeway merger requires predicting the demand a store faces and then computing the equilibrium prices under different policy scenarios and the changes in consumer welfare. I estimate the structural model of demand from data on household shopping trips, household attributes, and store characteristics. I use a dataset which Beckert et al. [2009] (BGN, hereafter) assembled by merging the TNS Worldpanel, which includes data on household consumption and characteristics, with the IGD database of store characteristics.[15] In addition, BGN construct a price index for units of a reference basket of groceries.

Recovering marginal costs, solving for Bertrand-Nash equilibrium prices, and calculating changes in welfare all utilize the same method: compute the expectation of the appropriate equation, such as the profit first order equations, and then solve for the appropriate factor, such as marginal costs or equilibrium prices. The expectation is formed by integrating predicted demand at each store over the empirical distribution of consumers as specified in Table KS020 of the UK 2001 Census, which contains OA-level data on household composition.

I now discuss the main features of the TNS and IGD datasets furth.

3.1 TNS Worldpanel

I use the TNS data from November 2003 to November 2004 to estimate demand for units of groceries by household type and region.[16] This data is a homescan panel of consumer purchases from the UK Worldpanel for Fast-Moving Consumer Goods (FMCG) sector. Households use a scanner to record information about their purchases at the SKU level, including the date, price, quantity, and location of purchase. In addition, they can enter items without a barcode, such as raw fruit and vegetables. The scanning system transmits results electronically to TNS who periodically verify the information using the consumer's receipts. In addition, TNS provides further data on household characteristics from which I determined each household's composition type. The only store characteristics in the data are the address and fascia.

The data which I use was prepared by BGN. They divide the data by GOR and household type. The household types are similar to those in the UK 2001 Census's Table KS020. Because marital status should not affect consumption behavior, BGN aggregate household types which differ only by marital status: e.g., a married couple with dependent children is treated the same as an un-

[15] I only work with data for England and Wales because too many stores are missing from the data for Northern Ireland, Scotland, and the various Isles.

[16] Because I observe data only after the Morrisons-Safeway merger, I estimate the post-merger demand system and then use the structural model to compute the unobserved pre-merger state, which provides a basis for welfare comparisons. See 7.

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married couple with dependent children. In addition, BGN construct a price index for a unit of groceries from an aggregate of hedonic price indexes for each fascia by region and household type. I use this aggregate index as the price when estimating demand. This index varies by year, month, GOR, and fascia which complicates estimation by decreasing the amount of variation in price. In addition, as explained in 2.1, the price index assumes that each household type purchases the same reference basket and could introduce measurement error to the extent that a household's basket differs from the reference basket. See C.3 in the Appendix for further discussion of the price index.

Although, the TNS data includes all shopping trips which a household reports during a period, BGN draw a single trip at random for each household. This facilitates estimation by avoiding dynamic issues such as correlation, inventories, and habit formation, but ignores much of the information in the data. For merger evaluation, this may not matter because the analysis depends on the expected demand a store faces, which is formed by aggregating over all representative consumers who shop at a store. Because of regional pricing, aggregate demand at all of a fascia's stores determines each fascia's regional pricing behavior; consequently, dynamics are less important for accurate assessment of the welfare consequences than predicting the consumption of individual consumers. In addition, BGN assume each household's choice set consists of the 30 stores closest to their home. For most households, this is a reasonable assumption because of consumers' aversion to traveling more than 10 to 15 minutes to shop [Smith, 2004]. However, BGN find that a small fraction of households shop at more distant stores so they exclude these consumers from the dataset. These distant purchases may be determined by the shoppers' commute paths, as Houde [2011] found for gasoline purchases.

Appendix C provides more information on the issues associated with using TNS data.

3.2 IGD Data

Because the TNS data lacks store characteristics, BGN supplement it with the IGD data, which contain the store characteristics for all of the stores of the major supermarket firms as well as many smaller regional and local companies. The data include the date of opening, closing, and the last renovation as well as the store's address, post code, sales area, gross area, and car park size. The IGD data span 1900-2004 which enables me to determine which stores operated under

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the Safeway fascia prior to their acquisition by Morrisons. After data cleaning and allowing for store acquisitions, conversions, and closures, my dataset has $10,883$ stores for England and Wales.

Following BGN, I group the data into the following fascia: Aldi, Asda, Budgens, Coop, Iceland, Kwik Save, Lidl, Marks & Spencer, Morrisons, Netto, Other, Safeway, Sainsbury's, Somerfield, Tesco, and Waitrose as well as SainS and TescS, for Sainsbury's and Tesco's convenience stores. Coop consists of the different regional Cooperative movement stores whereas Other contains the fringe of regional and smaller grocery retailers. This simplification facilitates estimation but overstates these firms' market power because they lack the centralization, logistics, and focused strategies of the other fascia.

4 Demand Estimation

I estimate the demand system via maximum likelihood. Because of its efficiency, MLE is an good choice when endogeneity and unobserved product characteristics are not important. However, the estimator will be inconsistent if the assumptions in Section 2 fail.

The likelihood for a household, $L_h(x;\theta)$, is composed of two pieces: the likelihood of choosing a location (i.e. a specific store) and the conditional likelihood of expenditure:

$$\begin{aligned} L_h(x;\theta) &= \Pr[h \text{ chooses } j, \text{buys } q_{hj}] \\ L_h(x;\theta) &= \Pr[h \,\text{chooses}\, j] \times \Pr[q_{hj} \,| h \,\text{chooses}\, j] \end{aligned}$$

where q_{hj} is the units of groceries household h purchases at store j. Consequently,

$$\log L_h(x;\theta) = \ell^{choice} + \ell^{q}$$

where ℓ^{choice} is the log-likelihood computed from the probability of household h choosing store j and ℓ^q is the log-likelihood of purchasing q_{hj} units of groceries conditional on shopping at j. These two components of the log-likelihood are easily calculated using the shocks, ϵ_{hj} and ξ_h, because they follow Type I Extreme value and normal distributions, respectively.

4.1 Computation of the Log-likelihood

Give the distributional assumptions, I estimate the full model using maximum likelihood in a single step as follows:

1. Compute a set of initial guesses by drawing points about the OLS point estimates of conditional expenditure on the covariates. I use multiple, randomly-drawn, starting points in a region about the OLS estimates.

2. Maximize the full log-likelihood:

   (a) Compute the household-specific shock, $\xi_h(\theta)$, by inverting the equation for conditional demand

   (b) Compute the log-likelihood for store choice, $\ell_h^{choice}(x_h, z_j, \xi_h(\theta); \theta)$

   (c) Compute the log-likelihood for conditional expenditure, $\ell_h^q(x_h, z_j, \xi_h(\theta); \theta)$

Because $\epsilon_{hj} \sim$ Type I Extreme Value, the probability of choosing a store (the *discrete* part of the discrete/continuous choice model) is the convenient multinomial logit form [McFadden, 1981], which facilitates computation of the log-likelihood for the consumer's store choice:

$$\Pr[h\, chooses\, j] = \frac{\exp[V_{hj}(x_h, z_j, \xi_h; \theta)]}{\sum\limits_{k \in J_h} \exp[V_{hk}(x_h, z_k, \xi_h; \theta)]}$$

where, J_h is household h's choice set and j the chosen store. Consequently, the log-likelihood, ℓ_h^{Store}, is

$$\ell_h^{choice}(x_h, z, \xi_h; \theta) = -\log \sum_{k \in J_h} \exp[V_{hk} - V_{hj}]$$

where I have rewritten the fraction in the choice probability to be more stable numerically.

ℓ^{choice} is a function of the indirect utility, V_{hk}, which in turn depends on the shock, ξ_h. I obtain ξ_h by inverting the equation for expenditure share

$$\xi_h = \frac{1}{\gamma_{price}} w_{hj} + \frac{\alpha_{price}}{\gamma_{price}} - [\delta + \alpha_{price} \log p_j + \log y_h + \alpha_{area} area_j].$$

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I also use the shock ξ_h to compute ℓ^q, the log-likelihood from consumer expenditure conditional on store choice. Because ξ_h is a truncated normal, the likelihood is

$$\begin{aligned}\ell_h^q\left(x_h, z_j, \xi_h; \theta\right) &= -\frac{1}{2}\log\sigma^2 - \frac{1}{2}\log 2\pi - \frac{1}{2\sigma^2}\xi_h\left(w_{hj}, x_h, z_j; \theta\right)^2 \\ &- \log\left[\Phi\left(b_h\right) - \Phi\left(a_h\right)\right].\end{aligned}$$

Φ is the normal cumulative distribution function, a_h and b_h are the truncation bounds which ensure that $w_{hj} \in [0,1]$, and σ^2 is the variance of the shock. I have written ξ_h as a function of covariates and parameters to emphasize that the support of ξ_h depends on the data and parameter estimates. Under these conditions, MLE is still consistent but may converge faster than $\sqrt{N}$ [Donald and Paarsch, 1996]. I dropped the term $\log\left[\Phi\left(b_h\right) - \Phi\left(a_h\right)\right]$ from the estimation procedure because in practice the bounds are so far apart that this normalization term is nearly constant.

4.2 Identification

Variation in household and store characteristics affects the indirect utility and, thus, likelihood in two ways. Some characteristics – such as the size of the car park and household-store distance – only affect store choice whereas others – such as price, income, and sales area – affect both store choice and conditional expenditure. Consequently, variation in the data leads to the identification through one or both of these channels. In addition, identification depends on the restrictions imposed on the model as well as the distributional assumptions for the errors. These restrictions include the standard logit normalization of the variance of ϵ_{hj} to $\pi^2/6$ [Train, 2009] and the normalization $\alpha_{inc} = 1$ in order to identify the scale parameter, μ.[17] Identification of α_{price}, α_{area}, γ_{price}, and σ^2 follows from the identification of μ, the log-linear functional form of the conditional expenditure equation, and the variation of the covariates income, y_h, price, p_j, and sales area, $area_j$. $\beta_{carpark}$ and β_{dist} are identified through variation in the size of car park and household-store distance when otherwise similar households choose different stores.

In theory, δ should be identified from the conditional expenditure and vari-

[17]This normalization is reminiscent of the restriction that $\alpha_{inc} = 1$ in the AIDS model, as required by economic theory.

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ation of the covariates, but the solver diverges when I include δ in the model. Lack of variation in the price index could contribute to this problem because the standard deviation of the price index for each GOR, household type, and month is usually less than 20% and often closer to 10% of the mean price. Firms' national pricing policies further reduce price variation. Ellis [2009] finds that although UK grocery prices fluctuate by up to 40% per week, monthly observations understate the amount of variation. In addition, UK consumers are extremely price sensitive so weekly fluctuations in price and promotions influence expenditures and lead to departures from the reference basket of groceries, i.e. measurement error. Both effects decrease the correlation between expenditure and the monthly price index. Diagnostic OLS regressions for the expenditure share equation have R^2 less than 0.2. Consequently, a model with a higher-frequency price index[18] or which focuses on aggregate expenditure may produce more reliable results. I control for the measurement error in the basket of groceries by estimating the model by household composition using price indexes which are computed for each region, household type, fascia, and month. ξ_h captures the remaining unobserved variation in consumer preferences. Adding random coefficients to the model might reduce this error further.

In regions of the parameter space where γ_{price} is close to zero, the utility reduces to an expression which is nearly linear in covariates, making identification of μ impossible because the interaction between household and store characteristics disappears. [Train, 2009]. This problem complicates estimation because the price index is normalized so that $p_j \approx 1$ and point estimates for $\hat{\gamma}_{price}$ range from 0.26 to 0.4 (See 1.), making $p_j^{-\gamma_{price}}$ quite flat and close to 1.

The model could also be misspecified because of the failure of Roy's Identity, endogeneity, or incorrect treatment of shocks. Assuming Roy's Identity holds for the price index, the parameter estimates should be consistent and unbiased after controlling for selection via the model for store choice. But, when Roy's Identity is not valid, the parameters will not be identified. For example, if prices enter the indirect utility via an index restriction, then conditional expenditure is really

$$\begin{aligned} w_{hj} &= \Psi\left\{\gamma_{price}\left[\delta + \alpha_{price}\log p_j + \log y_h + \alpha_{area} area_j + \xi_h\right]\right. \\ &- \left.\alpha_{price}\right\}, \end{aligned}$$

[18] A household-specific price index is another option, especially because some consumers never purchase certain goods such as alcohol.

for some constant of proportionality Ψ, which is a function of the expenditure shares (See Section A for the derivation.). Then δ and γ_{price} are not identified from conditional expenditure alone because only $\Psi\gamma_{price}$ can be identified from variation in y_h (α_{price} and α_{area} are still identified). Thus, δ and γ_{price} must be identified from variation in store choice. Assuming Roy's Identity holds for the price index is equivalent to the restriction that $\Psi = 1$.

Endogeneity potentially affects the estimation results through simultaneity and measurement error. Price endogeneity is a problem, particularly if firms observe ξ_h and incorporate it into their price setting mechanism. If households which spend more also prefer more expensive, higher quality goods, then the coefficient on price will be biased. In addition, income could be correlated with ξ_h if more affluent households spend more because they purchase higher priced, higher quality goods, such as organic produce, which deviate from the reference basket. But, the correlation between ξ_h and income is likely small because, ceteris paribus, the different fascia position themselves to appeal to certain consumer groups. By controlling for fascia in the price indexes, I attempt to control for these sources of endogeneity.

The discrete/continuous choice specification should control for selection bias by explicitly modeling store choice as long as the sample of households in the dataset is representative. However, if $\mathbb{E}\left[\epsilon_{hj}\xi_h\right] \neq 0$ then selection bias is possible: for example, households which prefer certain fascia spend more at those fascia. Or, an advertising campaign could affect both store choice and expenditure. Then the parameter estimates will be biased.

The unobserved quality of store locations – such as ease of access, proximity to other stores, or exceptional staff – may matter, as Orhun [2005] found for US supermarkets. Such a shock is similar to unobserved product-market characteristic, ξ_{jt}, in models like Berry et al. [1995] and often correlated with price. But fascia pursue a national pricing strategy so local characteristics only affect price through the resulting equilibrium price for a region. Consequently, local fixed effects should not be significant.

4.2.1 Estimation and Numerical Issues

I discuss computational and numerical issues in B of the Appendix.

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5 Demand Estimation Results

Table 1 displays the point estimates for the model of household demand for groceries by household type.[19] The structural parameters consist of the β coefficients, which only affect the utility a consumer obtains from a store's location, and the other coefficients, which affect the utility from a store's location and from consumption. The coefficient σ_{ξ}^2 is the variance of the household-specific shock, ξ_h. All point estimates cannot be rejected at the 5% level (or better) and have the expected signs: i.e., the results show that consumers prefer lower prices, shorter travel times, easier parking, and more variety (i.e. more sales area). In addition, estimates are similar in sign and magnitude across household types.[20]

Although the estimates for the variance of the household shock, ξ_h, appear small, they have the same order of magnitude as the variation in price. Small $\widehat{\sigma_{\xi}^2}$ may be caused by estimating by household type to control for heterogeneity in household composition. This result supports the assumption that households purchase a type-specific reference basket of units of groceries and that departures from this basket, in terms of quality, assortment, and price are small: i.e., the price index captures consumer behavior well and there is little measurement error. The bounds on the expenditure share, w_{jh}, further limit the variation in the household-specific shock.

The largest parameter in magnitude is $\hat{\beta}_{dist}$ for all household types, indicating that consumers dislike traveling, which agrees with other studies [Smith, 2004]. Single households – young, pensioners, and single parents – have by far the greatest distaste for distance, reflecting either higher values of time or lack of a partner to share the work of running a household. The coefficient for the size of $\beta_{carpark}$ is also large and significant. Both of these point estimates reflect the importance of convenience to consumers.

Because the conditional own-price elasticity of a household for a store is $\eta_{hj} = -1 + \gamma_{price}\alpha_{price}w_{hj}^{-1}$, the product of γ_{price} and α_{price} affects a household's elasticity: price sensitive household types have more negative values for $\gamma_{price}\alpha_{price}$. The estimates show, then, that single pensioners and single parents

[19] When comparing the scale of the point estimates for location and conditional expenditure, it is important to multiply coefficients of V_{hj}^{Exp} by the scale parameter, μ. E.g., to compare β_{dist} to $\mu\alpha_{price}$, instead of α_{price}.

[20] I performed likelihood ratio tests to check if I could aggregate similar household types. In all cases, the test rejected the hypothesis that any of these household types could be combined at the 1% level. Consequently, I do not consider aggregation of household types further.

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with children are the most price sensitive whereas single non-pensioners are the least price sensitive, possibly because single pensioners and single parents tend to have lower incomes. When I examined the mean and medium expenditure vs. household type, this story only holds for single pensioners. Perhaps, single parents effectively have lower incomes vis-a-vis other household compositions because they lack the scale economies of couples and, consequently, have less time for 'home production' activities such as shopping and housekeeping. Also, total expenditure on groceries in the TNS data may not be a reliable measure of income for households receiving welfare benefits.

To recast these results in more economically meaningful terms, I compute elasticities and profits and compare them with the perceived ranking of firms in the marketing literature and popular press (See Section 6.). These metrics confirm that Asda, Morrisons, Sainsbury's, and Tesco dominate the UK supermarket industry and exert significant pressures on their rivals while being constrained primarily by each other.

5.1 Elasticities

To understand the extent of firms' market power, I compute own- and cross-price elasticities as well as elasticities for income, area, and distance. First, I calculate the elasticities observed for each store in an OA's choice set. Using these store-level elasticities, I can evaluate the local market power at a highly disaggregate level. Next, I average elasticities over all fascia and OA in a GOR, weighting by the population in OAs whose choice sets include the relevant fascia. Consequently, the reported elasticities represent the market power a typical consumer encounters when a fascia is in their choice set.[21] The averaged elasticities measure the regional market power of the different fascia. This approach handles the differentiation of stores, both by location and quality. To obtain the national average elasticities, I average the elasticities over GOR, weighted by the population in each GOR.

More formally, I compute the elasticities for each OA's choice set from the expected demand, q_{ja}, each store j faces in OA a:

[21] To some extent, this is an artifact of only defining a store's choice set as the 30 closest stores. However, most consumers visit more distant stores infrequently because of their strong distaste for travel and propensity to shop near their homes.

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$$q_{ja} = \sum_{h \in H_a} \int \int n_{ha} s_{jha} q_{jha} dF(y, \xi),$$

where H_a is the set of household types in OA a, n_{ha} is the number of households of type h in a, and s_{jha} is the probability of someone in a choosing store j from the stores in a's choice set. In addition, I integrate over the distribution for income and ξ, assumed to be log-normal and normal, respectively. Then, I compute the price-elasticities for store j with respect to price for fascia k for each OA's choice set:

$$\begin{aligned}
\eta_{j,k} &= \frac{p_k}{q_{ja}} \frac{\partial q_{ja}}{\partial p_k} \\
\eta_{j,k} &= \frac{p_k}{q_{ja}} \sum_{h \in H_a} \int \int n_{ha} \left(\frac{\partial s_{jha}}{\partial p_k} q_{jha} + s_{jha} \frac{\partial q_{jha}}{\partial p_k} \right) dF(y, \xi) \\
\eta_{j,k} &= \frac{p_k}{q_{ja}} \sum_{h \in H_a} n_{ha} \int \int s_{jha} \left(q_{jha} \left(\frac{\partial V_{hja}}{\partial p_j} \mathbb{I}[j \cap k] - \sum_{i \in C_a} s_{iha} \frac{\partial V_{iha}}{\partial p_k} \right) \right. \\
&- \left. \mathbb{I}[j \cap k] \left(\frac{q_{hja}}{p_j} + \gamma_{price} \alpha_{price} \frac{y_{ha}}{p_j^2} \right) \right) dF(y, \xi).
\end{aligned}$$

Here, C_a is the set of stores in the choice set for OA a and $\mathbb{I}[j \cap k]$ is 1 iff stores j and k have the same fascia and 0 otherwise. This formula shows that a price increase affects demand at a store at both the extensive margin through the choice probability, s_{jha}, and the intensive margin through the conditional demand, q_{jha}. Competition from rival stores, on the other hand, only operates through the choice probability via the term $-\frac{p_k}{q_{ja}} \sum_{h \in H_a} \int \int s_{jha} q_{jha} \sum_{i \in C_a} s_{iha} \frac{\partial V_{iha}}{\partial p_k}$, which explains why some fascia devote considerable resources to non-price competition to capture consumers at the extensive margin. When several stores with the same fascia are in an OA's choice set, their local own-price elasticities increase because the fascia's other stores capture some of the customers who would substitute away on a price increase. This multi-store effect increases local market power for major firms by making demand less elastic. If firms were free to pursue price flexing to exploit their local market power, then most elasticities would increase in magnitude because the term $\sum_{i \in C_a} s_{iha} \partial V_{iha} / \partial p_k$ reduces to $s_{kha} \partial V_{kha} / \partial p_k$. Consequently, regional (or national) pricing may be an effective strategy to make demand less elastic, increasing both market power and profits. Regional pricing may also facilitate tacit collusion because it is easier to monitor and coordinate on price.

Table 2 presents population-weighted own- and cross-price elasticities. Each row represents a fascia's set of elasticities with respect to the prices of the fascia listed in the column. All own-price elasticities are negative, ranging from -4.22 to -5.54 which correspond to a price-cost margin of about 18-24%, using the Lerner formula. This markup is higher than the low margins typically reported for the supermarket industry because I can only recover marginal costs and do not observe the fixed costs involved in distribution, logistics, and other infrastructure.

Cross-price elasticities are significantly smaller and show considerable variation in the market power of the different fascia, ranging from 0.00 to 0.52. These surprisingly low values show that firms wield considerable local power, driven by consumers' distaste for travel and multi-store effects. Most second tier firms have relatively larger cross-price elasticities with respect to the Asda, Morrison, Sainsbury's, and Tesco (AMST) fascia than the AMST fascia have with them, except for a few fascia such as Iceland. These results show that the AMST fascia exert more competitive pressure on smaller firms than vice-versa. Cross-price elasticities are also larger between fascia which pursue similar formats and strategies, such as Aldi vs. Kwik Save or Netto vs. Kwik Save which compete for similar market segments. Tesco's dominance is clear: almost every fascia's largest cross-price elasticity is with respect to Tesco. These results are similar to those found in the CC's 2006 supermarket investigation [UK Competition Commission, 2006].

The elasticities for the LAD (Aldi, Lidl, and Netto) are surprising because these stores pursue similar strategies so their cross-price elasticities should be symmetric. However, the elasticities with respect to changes in Lidl's price are extremely small because the price index for Lidl is 35% larger than Aldi's and Netto's prices on average, making Lidl a particularly unappealing substitute for price-sensitive consumers. In addition, cross-price elasticities for Aldi and Lidl with respect to Netto are about half of Netto's because Aldi and Lidl have twice as many stores as Netto and the geographic averaging involved in the calculations.

Elasticities also show some limitations to my model. The model overstates the market power of the Coop and Other fascias. Coop stores are part of a larger buyer co-operative and lack the central coordination and economies of scale and

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scope of AMST. The Other fascia contains many independent, fringe firms which operated a limited number of stores on a regional or smaller basis. Classifying them as a single fascia engaged in regional price setting considerably overstates their market power and influence on the computed equilibrium or aggregated elasticities. Also, fascia which consistently operate smaller formats have smaller elasticities. Finally, the logit functional form assumption requires that rival fascias are substitutes.

Another possible source of low cross-price elasticities is missing data. If many stores are missing, then the choice sets constructed from the IGD data will understate the density of stores, increasing the distance between stores and, hence, decrease cross-price elasticities. Because most of the missing stores are independent operators and small convenience stores, this should not have a significant impact on results.[22]

As a check, I compared my results to Smith [2004], who computes elasticities using a similar model. He finds own-price elasticities which are roughly a factor of two larger in magnitude than mine and cross-price elasticities which are a factor of 10 to 100 larger. These differences arise for several reasons: he does not construct elasticities at the choice set level; he estimates demand using data on fascias' price-cost margins and from consumer surveys about shopping habits; and, he performs sensitivity analysis to determine α_{price} and α_{inc} (β_1 and β_2 in his notation) because he cannot identify them separately.

6 Geography of Competition

By combining the parameter estimates with census and postcode data, I constructed a geographic distribution of demand to understand how store locations and the distribution of consumers affect competition and consumer welfare. These spatial locations help determine how much local market power a fascia can exploit and how pricing pressures propagate via chaining (where a store's price affects more distant stores through its impact on intervening stores). I use this method of aggregating demand over the empirical distribution of consumers in order to calculate marginal costs, price equilibria, fascia profits, and consumer welfare. This section of the chapter focuses on how the method works and the recovery of marginal costs. In Section 7, I use this technique to evaluate the welfare consequences of the Morrisons-Safeway merger and a counter-factual merger between Tesco and Safeway.

[22] I am grateful to Patrick Mitchell-Fox, an analyst at IGD, for clarifying this issue.

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Supermarkets make a complex offer to consumers by varying price, quality, range, and service (PQRS), all of which firms choose to maximize their profits. UK Competition Commission [2006] found that supermarkets, with the exception of Coop and Somerfield, set national prices, based on Tesco's argument that prices propagate through the chain of substitution, producing a national price. I assume that firms sets prices for their fascia regionally to capture the strategic effect of regional variation in the assortment (range) of products: in practice, assortment varies on an even smaller scale.[23] Unfortunately, this variation is difficult to observe. This model of competition is incorrect if either variation in assortment is large and local or it is small. In the former case, firms essentially choose a store-specific price for a unit of groceries and pursue price flexing; in the latter case, they choose a national price. The regional pricing assumption overstates (understates) firms' market power if pricing is at the national (store) level. However, if Tesco's argument is valid and there is sufficient density of stores and consumers, then the chain of substitution produces national prices.[24] It is not clear how these different models of competition would affect the welfare change under a merger.

For all of these calculations, I assume that a static model captures the relevant economics for this policy analysis. The IGD data show that during the 1980s and 1990s, firms' built primarily mid-sized (280 m^2 to 1,400 m^2) and large-sized ($>$ 1,400 m^2) stores. Since 2000, however, competition has focused on convenience stores ($<$ 280 m^2), because of legal restrictions on building larger formats.[25] The market test proposed by the CC in 2006 strengthened these planning constraints [UK Competition Commission, 2006].

6.1 Geographic Aggregation

I recover each fascia's marginal cost for each region and household type by inverting the first order conditions (FOCs) for expected profit, assuming Bertrand-Nash competition in prices. I assume that each firm functions as a product in a multi-product, oligopoly and sets prices for its fascia regionally.

To calculate marginal costs, I calculate the geographic expectation of the FOCs as follows:

[23] Controlling for fascia should capture most of the variation in quality and service because firms try to provide a uniform shopping experience across stores.

[24] Using the machinery of this chapter, it should be possible to test Tesco's national pricing argument.

[25] Firms may also have been constrained by a lack of suitable sites for larger stores.

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1. For each GOR, compute pair-wise distances between all stores and OAs using the UK Office of National Statistics (ONS) 2006 All Fields Postcode Directory (AFPD), which maps post codes and OAs into 'northings' and 'eastings', a standard X-Y coordinate system for UK geographical data. Given the high precision of UK postcodes this introduces little error compared to a household's true location.

2. Form choice sets for each OA from the 30 closest stores.

3. Calculate the expected FOCs for profit at each store by integrating demand over household types, income, and OAs using the KS020 Table of the UK 2001 Census. The demand is the product of the probability that a household chooses a specific store and the conditional demand. Then, aggregate across stores by fascia.

4. Invert the first order equations and recover marginal costs for each fascia, household type, and region, allowing for strategic interactions for the firms (Sainsbury's and Tesco) which control multiple fascia.

After recovering marginal costs, I use a similar method to compute expected firm profits and price equilibria.

I assume that marginal cost is the same for all of a fascia's stores and that scale economies and network effects do not affect marginal costs; i.e., that a linear specification is sufficient. To the extent that these factors matter, my model will be misspecified. Both Jia [2008] and Holmes [2011] show that both of these forces affect competition among US discounters, but the smaller scale of the UK may decrease the importance of these factors.

Before discussing the results in 6.2, I first explain the equilibrium assumption, profit function, and derivation of the first order equations.

6.1.1 Equilibrium Assumption

Marginal cost recovery is based on computing profits and FOCs at equilibrium prices. But, solving for equilibrium prices when there are multiple consumer types and hundreds of products is technically challenging, even if competition is limited to just several hundred key value items (KVI) [UK Competition Commission, 2006]. Consequently, I assume that the fascia compete via Bertrand-Nash competition in each region and they choose an optimal price for the reference basket of each household type. This assumption simplifies the problem of solving for the price equilibrium and marginal costs.

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Because there are many more goods than household types and households purchase a type-specific reference basket, this assumption is equivalent to each firm choosing the vector of prices of individual goods, p, such that they satisfy

$$\begin{pmatrix} \tilde{p}_1 \\ \cdots \\ \tilde{p}_H \end{pmatrix} = \begin{bmatrix} \omega_1^T \\ \cdots \\ \omega_H^T \end{bmatrix} p$$

for some optimal price indexes, $\tilde{p}_h$, and vectors of expenditure shares, ω_h. Thus, firms can adjust prices in a way that generates the profit-maximizing price for each type's basket. Clearly, this equation mapping prices to basket prices only has a solution if the matrix of expenditure shares is full rank.[26] Appendix 7 in UK Competition Commission [2000] provides further support: Sainsbury's, Somerfield/Kwik Step, Tesco, and Waitrose all report that they focus pricing strategy on the basket price consumers face as part of their offer. Furthermore, Tesco buying managers set prices to target certain subgroups, consistent with central Tesco pricing policy.

6.1.2 Profits Under Multi-Product Oligopoly

Given the equilibrium optimization assumption, the geographic profit function aggregates each household's expected conditional demand over household types and OAs. Thus, π_{jha}, the profit at store j from household type h in OA a, is

$$\pi_{jha} = n_{ha} \left(p_j - c_j\right) q_{jha} s_{jha}.$$

Aggregating over all OAs in a region, conditional on household type, yields a store's conditional profits:

$$\pi_{jh} = \sum_{a \in \mathcal{OA}} n_{ha} \left(p_j - c_j\right) q_{jha} s_{jha}.$$

Then, total profit per store is just the sum over consumer types:

[26] When the matrix is full rank there will also be multiple solutions because of the non-trivial null space of the expenditure share matrix.

$$\pi_j = \sum_{h\in\mathcal{H}}\sum_{a\in\mathcal{OA}} n_{ha}\left(p_j - c_j\right) q_{jha}s_{jha} + F_j,$$

where F_j is the fixed cost of opening and operating store j. To obtain a fascia's profits, I aggregate over the set of all stores the fascia operates, $\mathcal{F}_f$:

$$\pi_f = \left(p_f - c_f\right)\sum_{j\in\mathcal{F}_f}\sum_{h\in\mathcal{H}}\sum_{a\in\mathcal{OA}} n_{ha}q_{jha}s_{jha} + \left|\mathcal{F}_f\right| F_f.$$

Because I observe neither a household's income nor shock, ξ_h, I integrate over their distributions, assumed to be normal and log normal, respectively. The moments for income are computed from the TNS data.[27]

Sainsbury's and Tesco operate multiple fascias which increases their market power, according to the theory of multi-product firms. Consequently, the FOCs must include these effects. Let firm f operate T different fascia. A firm's individual stores are enumerated in sets $\mathcal{F}_f^1, \ldots, \mathcal{F}_f^T$ for each fascia type t. Then, the firm f's set of stores $\mathcal{F}_f = \underset{t\in T}{\cup}\mathcal{F}_f^t$ is the union of the set of stores for each fascia type. Now, each firm's profit is the sum of the profits of each its fascia:

$$\begin{aligned}\pi_f &= \sum_{t\in T}\sum_{j\in\mathcal{F}_f^t}\sum_{h\in\mathcal{H}}\sum_{a\in\mathcal{OA}}\int\int n_{ha}\left(p_f^t - c_f^t\right) q_{jha}s_{jha}dF\left(y\right)dF\left(\xi_h\right)\\ &+ \left|\mathcal{F}_f^t\right| F_f^t.\end{aligned}$$

In most firms, this reduces to the profits from a single fascia.

6.1.3 FOCs Under Multi-Product Oligopoly

Recovering marginal costs or solving for a new price equilibrium under different market structures requires computing the multi-product profit FOCs. Consequently, cross-price effects are important when firms set prices if the markets served by the different fascia overlap sufficiently. E.g., if the markets for Tesco and Tesco Metro have have large cross-price elasticities – i.e. are good

[27] I perform the integration via a Gaussian-Hermite product rule with three nodes in each dimension because using more nodes had negligible impact on the results. I tried using sieve estimation [Chen, 2007] to approximate the income distribution but there was not enough data to use a non-parametric method.

substitutes – then assuming that competition is single-product oligopoly will understate Tesco's true market power.

Let the multi-product firm f choose prices $p_f^1, \ldots, p_f^T$. Because firms choose the optimal price for each household type's basket, this complex optimization problem reduces to a set of separate optimization problems for each household type. Thus, firms solve a non-linear system of Bertrand-Nash FOCs where each fascia's FOC conditional on household type is:

$$\begin{aligned}
0 &= \frac{\partial \pi_f}{\partial p_f^v} \\
0 &= \sum_{j \in \mathcal{F}_f^v} \sum_{h \in \mathcal{H}} \sum_{a \in \mathcal{OA}} n_{ha} q_{jha} s_{jha} \\
&+ \sum_{t \in T \setminus \{v\}} \left(p_f^t - c_f^t\right) \sum_{j \in \mathcal{F}_f^t} \sum_{h \in \mathcal{H}} \sum_{a \in \mathcal{OA}} n_{ha} \left\{ q_{jha} \frac{\partial s_{jha}}{\partial p_f^v} \right\} \\
&+ \left(p_f^v - c_f^v\right) \sum_{j \in \mathcal{F}_f^v} \sum_{h \in \mathcal{H}} \sum_{a \in \mathcal{OA}} n_{ha} \left\{ q_{jha} \frac{\partial s_{jha}}{\partial p_f^v} + s_{jha} \frac{\partial q_{jha}}{\partial p_f^v} \right\}.
\end{aligned}$$

This equation shows that prices affect profits through the price charged, the relative desirability of other stores, and the change in demand at each store. To recover marginal costs, rewrite the equations in matrix notation:[28]

$$\begin{aligned}
0 &= D_f + G_f \left(p_f - c_f\right) \\
D_{f,(v)} &= \sum_{j \in \mathcal{F}_f^v} \sum_{h \in \mathcal{H}} \sum_{a \in \mathcal{OA}} n_{ha} q_{jha} s_{jha} \\
G_{f,(v,t)} &= \sum_{j \in \mathcal{F}_f^t} \sum_{h \in \mathcal{H}} \sum_{a \in \mathcal{OA}} n_{ha} \left\{ q_{jha} \frac{\partial s_{jha}}{\partial p_f^v} + s_{jha} \frac{\partial q_{jha}}{\partial p_f^v} \mathbb{I}\left[t = v\right] \right\}.
\end{aligned}$$

The subscripts denote the element in the vector or matrix. The vector D_f is the total demand at each fascia. G_f is a matrix of changes in demand at the margin. The cross-partial for market share in these terms is:

[28] $\mathbb{I}\left[b\right]$ is the indicator function which is 0 if b is false and 1 if b is true.

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$$\frac{\partial s_{jha}}{\partial p_f^v} = \begin{cases} s_{jha}\left(\dfrac{\partial V_{jha}}{\partial p_f^v} - \sum\limits_{m\in\mathcal{F}_f^v} s_{mha}\dfrac{\partial V_{mha}}{\partial p_f^v}\right) & j\in\mathcal{F}_f^v \\ -s_{jha}\sum\limits_{m\in\mathcal{F}_f^v} s_{mha}\dfrac{\partial V_{mha}}{\partial p_f^v} & j\in\mathcal{F}_f^t, t\neq v \\ 0 & \text{otherwise} \end{cases}$$

After inverting the FOCs, the marginal costs are

$$c_f = p_f + G_f^{-1}D_f.$$

Conversely, given a set of marginal costs, FOCs can be solved for a new equilibrium price vector under different market structures.

6.2 Results

I now discuss the results on marginal costs, price-cost margins, and profits. I focus on how results vary by either GOR or household composition, depending on which is more important economically.[29]

6.2.1 Marginal Costs

According to Smith [2004], the UK supermarket industry has a simple cost structure which consists of purchasing goods, distribution, labor, and store operations. He argues that the first three are marginal costs, based on research by the UK Competition Commission [2000]. Like Smith, I do not observe advertising, headquarters overhead, and other firm-level costs so I assume they are fixed.

Because the price index varies by month, region, and fascia, I recover marginal costs for each month, region, and fascia from the FOCs, as explained in 6.1.3. The discussion of results focuses on May 2004 because the same patterns persist across periods, although results for other months show some small variation in costs. Marginal costs can only be recovered in GOR where a fascia operates: for example, I do not observe any Budgens or Waitrose stores in the North East

[29] Most results in this paper can be viewed by fascia, household composition, or GOR. To facilitate comprehension, I aggregated or averaged along one of these dimensions. A detailed appendix with results along all three of these dimensions is available upon request.

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and, consequently, cannot recover their marginal costs in this region. In these cases, the marginal cost is coded as NaN or 'Missing' to ensure that these cases are handled correctly in subsequent computations.

Cost recovery depends on the assumption that firms play a Bertrand-Nash pricing game for multi-product firms, where each fascia functions as a product because of the regional pricing assumption.[30] I assume that Sainsbury's and Tesco are the only firms which operate multiple fascia (brands), which is a reasonable approximation of actual behavior because most firms focus on a specific market segment.[31]

Table 3 reports population-weighted marginal costs with multi-fascia effects averaged across household type. Allowing for the multi-fascia effect lowered marginal costs by 0.7 to 7 percent for Sainsbury's and Tesco's fascias, depending on household type and region. Rival fascias have the same marginal costs in either case. Operating multiple fascias increases Sainsbury's and Tesco's market power because some of the demand lost from a price increase at one fascia is captured at their other fascia. Ignoring this strategic effect overstates Sainsbury's and Tesco's true costs.

Smith [2004] also found that failure to consider multi-fascia effects leads to incorrect marginal costs. My recovered marginal costs also agree with the marketing literature [Seth and Randall, 2001]: Aldi and Netto pursue a deep discount strategy and are the low cost leaders; Iceland and Kwik Save also offer low costs and target working and lower-middle class households; Asda, Tesco, Morrissons-Safeway, and Sainsbury's – listed in order of increasing marginal costs – occupy the middle ground; Tesco's convenience store fascia enjoys a cost advantage over Sainsbury's; and, lastly, Marks & Spencer and Waitrose have significantly higher costs than all other fascia, reflecting their emphasis on higher quality. Surprisingly, Lidl's marginal costs are much higher than Aldi's and Netto's, driven by Lidl's much higher prices. In addition, fascia with higher marginal costs charge higher prices. Each fascia also has the same ordering for the costs of serving different household types. These trends persist when viewed across either household types or region.[32] Marginal costs vary by household

[30] In the most general sense, each individual store is a product. Because firms pursue a regional pricing strategy, they set one price per fascia-household type in each GOR. When price flexing occurs, each store functions as a product.

[31] For example, Tesco's fascias include Tesco Express, Tesco Metro, Tesco, and Tesco Extra. The assignment of other firms' stores to one fascia is based on the fact that only Sainsbury's and Tesco focus on both the supermarket and convenience store formats.

[32] I examined the standard deviation of both marginal cost and the price cost margin for each fascia-household type pair across GOR. Both quantiles and histograms indicate that

type because the baskets for different types vary in size and composition. Geographical differences, such as distance to distribution centers, density, wages, or congestion, also cause regional variations in marginal costs. For example, average marginal costs are consistently higher for the East Midlands, London, the South East, and Wales for all fascia.

6.2.2 Price-Cost Margin

From the marginal costs and price indexes, I calculate the price-cost margin, $PCM = (p - c)/p$, for each fascia by household composition (See Table 4.). Price-cost margins vary primarily by household type and not by region. These margins also agree with the marketing literature. Of the big four, Asda, Morrisons-Safeway, and Tesco all have margins ranging from 22% to 23% , which are slightly lower than Sainsbury's (PCM from 23% to 24%). Sainsbury's margin for its convenience store format is also higher than Tesco's, though both firms have higher markups for this format than for the standard format. Similarly, Aldi and Netto – the deep discounters – and Iceland and Kwik Save – which target lower income households – have lower PCM. Lastly, Marks & Spencer also has comparably low margins, driven by their extremely high costs.

Margins vary by household composition in a similar way for each fascia: single pensioners, single parents, and pensioner couples are more profitable whereas couples with children, other without children, and other with children are less profitable. Although total marginal costs are lower for serving the former, per capita marginal costs usually are not. Consequently, more profitable household types purchase items with higher margins, such as prepared food.

The margins I calculated agree with those in Smith [2004]'s Table 3, column (i), which computes the revenue minus the cost of purchasing goods divided by revenue. His value for the margin is based on all marginal costs (purchase of goods, distribution and labour) and is smaller. The CC estimated a multinomial choice model and also finds that margins are 20% in concentrated markets and 15% in non-concentrated markets [UK Competition Commission, 2006]. These margins are much higher than the market literature's value of roughly 5%. As discussed at the beginning of this section, there are several fixed costs, such as advertising, store-level overhead, and headquarters costs, which I do not

$\widehat{\sigma_{MC}}/MC$ and $\widehat{\sigma_{PCM}}/PCM$ are less than 10% at the 75th (90th) quantile: the distribution is clumped near 0 with a sharply declining right tail. Fascia-household pairs with higher variation are those which are poorly represented in the TNS data, such as the young and pensioners, and fascia with few observations in a GOR, such as Sainsbury's convenience store format.

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observe and assume are fixed costs. If I could observe these costs and recompute the margins, I would expect to find margins that were closer to those in the marketing literature.

6.2.3 Geographic Distribution of Profits

Using the geographic distribution of demand, I predict both fascia and store-level profits by region and household composition. I summarize the different fascias' share of profits by GOR in Table 5. Asda, Morrisons, Sainsbury's, and Tesco (AMST) have the largest shares other than Coop and Other, whose apparently large market shares result from aggregation, as discussed in 3.2. These fascia lack the coordination and integration of AMST. AMST also have particularly large market shares among the most profitable household types (couples, couples with children, others, and others with children) which tend to be larger, both in numbers of adults and children. In addition, Tesco occupies a dominant position followed by Sainsbury's and Asda, who have comparable market shares. Tesco's lead is even stronger when combined with its convenience store fascia: Tesco's small format stores have much more market share, lower costs, and higher margins than Sainsbury's. The combined Morrison-Safeway fascia is a more effective national competitor than these fascia were individually when compared with the counter-factual pre-merger state in Section 7: Safeway and Morrisons are often strong where the other is weak. These results also show that Iceland is a strong niche competitor.

Table 5 also shows which fascia have the largest share of profits in each region. Of the big four, Asda is clearly strongest in the North and weaker further South; Morrison-Safeway favors the North East and Yorkshire; Sainsbury's has significant market share across the country, but is concentrated in London and the South; and, Tesco is strong everywhere, but quite dominant in the East, South East, and Wales with market shares there of 19-26%. Other patterns are visible, such as the deep discounters' focus on the North and Midlands, and Waitrose's concentration on the more affluent areas in London and the South East.

There is considerable variation in the profitability of individual stores, as shown in Table 6 which reports summary statistics for total profit by store and by sales area.[33] These statistics show that fascia which operate larger

[33] A store whose sales area was miscoded in the TNS data causes the anomalously large maximum profit for Marks & Spencer in Tab.Stats.Profit.Store.Both.All.

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format stores, as expected, have larger total sales per store but that convenience stores and smaller format stores, such as Budgens and Iceland, are much more profitable per sales area. The deep discounters, Aldi and Netto are also quite profitable per sales area: Lidl, however, is not as profitable because of its much higher marginal cost. The profitability of AMST's stores has considerably more variance than most other fascia, probably because AMST operate more extremely large format stores (hypermarkets). For all fascias, there is a long upper tail: some stores are extremely profitable, either because they are well located or have huge sales areas. Also, firms may operate less profitable stores to foreclose entry to rivals, preventing a situation which would be even less profitable.

7 Merger Evaluation and Policy Experiment

In 2003 the UK Competition Commission approved the acquisition of Safeway by Morrisons instead of Tesco or a handful of other suitors. To evaluate the merger, I compare the pre-merger state with both the actual merger and a counter-factual Tesco-Safeway merger. This comparison uses firm profits, prices, market shares, and compensating variation to quantify changes in consumer welfare and firm profits. The counter-factual Tesco-Safeway merger provides an upper bound on the adverse welfare consequences of the acquisition of Safeway because Tesco has the most market power and is strong in every region.

My method is similar to the method used in 6.1 to recover marginal costs and compute firm profits. In contrast to other merger evaluations, I only observe consumer shopping decisions after the Morrisons-Safway merger has occurred. Consequently, I must reconstruct firm behavior prior to the merger. Fortunately, the IGD data starts considerably earlier than 2003 and includes observations on which stores operated under the Safeway fascia. I use this data to construct two counter-factual datasets, one for the state before the observed merger and another for after a hypothetical Tesco-Safeway merger. For both datasets, I solve for the Bertrand-Nash equilibrium prices and use them to compare firm and consumer welfare under each scenario.

In each scenario, I assume that marginal costs remain constant for each fascia regardless of the industry structure. The only exception is Safeway whose pre-merger marginal costs are assumed to be the same as Morrisons's and whose post-merger costs are the same as the firm which acquired Safeway (i.e. Morrisons or Tesco).[34] Because Safeway's strategy lacked focus [Seth and Randall, 2001], any suitor would expect to improve the performance of Safeway stores by replacing Safeway's purchasing, distribution, and operations with their own business processes. Consequently, Safeway's pre-merger costs are probably higher than Morrisons's, and this assumption understates the welfare gains from the merger.

7.1 Computation of Welfare

Unfortunately, the standard, analytic expression for the change in compensating variation does not apply to my model of utility because the marginal utility of income is non-linear in income [Train, 2009, Anderson et al., 1992]. Consequently, I cannot easily compute the expected maximum utility and solve for the compensating variation. However, it is possible to compute bounds on the compensating variation [McFadden, 1999]:

$$\sum_{j \in C_a} s^0_{hja} C_{jj} \leq \mathbb{E}\left[CV_{ha}\right] \leq \sum_{j \in C_a} s^1_{hja} C_{jj},$$

where C_a is the choice set for OA a, C_{jj} is the compensating variation if the consumer chooses store j in both the pre- and post-merger scenarios, $i = 0$ ($i = 1$) indicates the pre-merger (post-merger) scenario, and s^i_{hja} is the probability household h chooses store j under scenario i. The intuition for this formula is that the consumer would need more (less) compensation if he were unable to change his choice of store before (after) the policy change. Let p^0_j and p^1_j be the prices at store j before and after the merger. Then C_{jj} can be calculated by solving for C_{jj} from the definition of compensating variation

$$V_{hja}\left(y_h, p^0_j\right) \quad = \quad V_{hja}\left(y_h - C_{jj}, p^1_j\right)$$

which yields

$$\begin{aligned} C_{jj} \quad &= \quad y_h - \exp\left\{\left(\frac{p^1_j}{p^0_j}\right)^{\gamma}\left(\log y_h - \alpha_p \log p^0_j + \alpha_{area} area_j + \xi_h\right)\right. \\ &+ \quad \left. \alpha_p \log p^1_j - \alpha_{area} area_j - \xi_h\right\}. \end{aligned}$$

[34]In theory, I should be able to recover Safeway's actual marginal costs if I had access to TNS data prior to the merger.

Note that $C_{jj} = 0$ if the price does not change. Furthermore, only the utility of consumption affects the willingness-to-pay because utility from location does not change. $C_{jj} < 0$ means that the consumer needs compensation for his lower post-merger utility. Finally, I compute the total lower and upper bounds on compensating variation for each GOR and household type by integrating over the distribution of consumers, income, and the shock ξ_h. For this problem, this method yields tight bounds and eliminates the need for a more complex procedure to calculate the change in consumer welfare.

7.2 Results

The observed Morrisons-Safeway merger and counter-factual Tesco-Safeway merger cause little change in consumer welfare and firm profits vis-a-vis the pre-merger state. Both mergers caused small changes in prices, profits, market shares, and compensating variation, although these effects are larger for the Tesco-Safeway merger which is also worse for consumers.

Table 7 compares the changes in market shares, Δs, profits, $\Delta\pi$, and prices, $\Delta price$, where the subscripts refer to whether Morrisons or Tesco acquired Safeway. The first column, s_{pre}, provides pre-merger market shares for comparison. The changes in profits and prices are computed via population-weighted averages across GOR and household composition. I compare the total pre-merger market share and profits of the acquiring firm and Safeway with the post-merger values for the combined firm. The change in market shares for both mergers was small – less than 0.02% for Morrisons and 0.35% for Tesco. The lack of geographic overlap between Morrisons and Safeway explains the small magnitude of the change, especially given the assumption that Safeway's per-merger marginal costs were the same as Morrisons. If Safeway's true costs were larger, then the change in market share should be larger because the true pre-merger price would be higher. The merger should also produce a larger increase in consumer welfare from the lower prices associated with the combined firm's cost savings.

When Safeway merges with either Morrisons or Tesco the change in profits is also small: 0.07% and 0.67% of pre-merger profits, respectively. Almost all firms increase their profits after either merger, although by less than 1%. Most firms can increase their profits and prices much more under the Tesco-Safeway merger because Tesco's market power enables it to raise prices more than Morrisons and prices are strategic complements under Bertrand-Nash competition.

The main exception is Waitrose, whose profits decrease by about 1% because Waitrose decreases its price by 0.25% or more in response to these mergers, probably because of increased competition in the South and London where the majority of Waitrose's customers live. In addition, the multi-fascia strategic effect propagates the changes in Sainsbury's and Tesco's prices from their supermarket fascia to their convenience store fascia, causing price increases of about 1%.

The bounds on consumer-willingness-to-pay are summarized by region and household type in Tables 8 and 9. These tables show the upper and lower bounds on compensating variation, CV_{low} and CV_{upper}, for three scenarios. The labels 'Pre', 'Morr', and 'Tesco' in the column headings indicate which scenarios are being compared: pre-merger, after the Morrisons-Safeway merger, and after the counter-factual Tesco-Safeway merger.[35] These bounds are usually quite tight – i.e. less than 10% – and, consequently, provide a good estimate of consumer welfare.

When aggregated to the national level or by household composition, these mergers appear to decrease consumer welfare. The largest negative welfare changes appear to be for couples, couples with children, and others with children. However, these categories tend to be relatively more numerous. There is considerable regional variation and both mergers improve welfare in some regions. For example, the Morrisons-Safeway merger reduces consumer welfare by at most -0.12% of pre-merger profits, but improves welfare in the East Midlands, London, and the South West by providing stronger competition with Sainsbury's and Tesco. Similarly, the Tesco-Safeway merger causes at most a -0.54% decrease in consumer welfare, but produces positive compensating variation in Yorkshire and the East Midlands. The small magnitude of these changes could be caused either by an extremely competitive market where there is sufficient competition to prevent higher prices or by a situation where each store is effectively a local monopolist. Furthermore, regional pricing may be an effective strategy for tacit collusion to sustain higher prices. Any of these causes could prevent a merger in the supermarket industry from significantly changing the nature of competition.

I also computed the compensating variation for the welfare change between Morrisons and Tesco acquiring Safeway. The results show that acquisition by Tesco would be worse for consumer types when aggregated at the national level,

[35] The change in compensating variation for Morr vs. Tesco is not just the difference between Pre vs. Tesco and Pre vs. Morr because the marginal utility is non-linear in income.

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though consumers in the Northwest, Yorkshire, and the West Midlands would be slightly better off. These regions correspond to areas where Morrisons has traditionally been stronger and Tesco relatively weaker.

Overall, my results support the UK Competition Commission's decision to approve Morrisons's acquisition of Safeway because it has little effect on firm profits and consumer welfare – certainly significantly less than a counter-factual merger between Tesco and Safeway. In the long run, Morrisons-Safeway could have developed into another strong national competitor to Asda, Sainsbury's, and Tesco if Morrisons had not had such difficulty integrating Safeway's operations. Moreover, the CC's requirement that Morrisons divest itself of some stores where local competitiveness could be affected further minimized potential adverse consequences of this merger.

8 Conclusion

This chapter evaluates the impact of Morrisons's acquisition of Safeway on consumer welfare and firm profits. By combining estimates for the demand system with census data, I compute changes in prices, expected profits, and consumer-willingness-to-pay for both the observed merger and a counter-factual Tesco-Safeway merger. Because the data is highly disaggregate these calculations provide information about the nature of demand and competition at even the OA and store-level. The results show that the Morrisons-Safeway merger, which the CC approved in 2003, had little impact on consumer welfare. A counter-factual merger with Tesco would have been an order of magnitude worse for consumers, though still have had a small impact.

These results depend on several assumptions, but especially that locations are fixed exogenously. Adding a stage to the model where fascia choose locations could affect results. In addition, the unobserved quality of locations [Orhun, 2005], scale economies, and network effects might also influence the results [Holmes, 2011, Jia, 2008].

Unfortunately, the current model cannot distinguish between a competitive equilibrium and tacit collusion, both of which could cause small changes in welfare. Using the method developed in this paper, I can, in theory, compute the price equilibrium if firms pursue price flexing instead of regional pricing and how these pricing strategies affect welfare. From a policy point of view, it is also worth investigating whether regional pricing facilitates collusion.

Future work could use this geographical distribution of demand to investigate

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market definition, whether chaining effects propagate pricing pressure across catchment areas, the local market power of different stores, and whether regional pricing facilitates collusion.

This appendix contains supplementary information about using Roy's identity with a price index, numerical issues involved in estimating the model, and the data and how it was cleaned.

A Roy's Identity and Price Indexes

Because Roy's identity holds for true prices but not necessarily a price index, treating the price index as the true price can produce an incorrect result when deriving demand. Let the indirect utility be $V_{hj} = V_{hj}(p_j, y_h)$, where p_j is the price index for a unit of groceries at store j and y_h is household h's expenditure. The true specification of the indirect utility is $V_{hj}^{true} = V_{hj}(\breve{p}_j, y_h)$ where $\breve{p}_j$ is the vector of all prices of goods at the store. The price index is a function of this vector of prices, $p_j = f(\breve{p}_j)$. Assume that prices enter the indirect utility via an index restriction. I.e., the price index $p_j = \omega \cdot \breve{p}_j$, where ω is a vector of expenditure shares. Then, $V_{hj}^{true} = V_{hj}(\omega \cdot \breve{p}_j, y_y)$. If $\breve{p}_{jk}$ is the k-th component of the vector $\breve{p}_j$ and $\breve{q}_{jk}$ k-th component of demand, then Roy's identity implies that

$$\begin{aligned}
\breve{q}_{jk} &= -\frac{\partial V_{hj}^{true}}{\partial \breve{p}_{jk}} / \frac{\partial V_{hj}^{true}}{\partial y_h} \\
&= -\left[\frac{\partial V_{hj}}{\partial p_j}\frac{\partial p_j}{\partial \breve{p}_{jk}}\right] / \frac{\partial V_{hj}}{\partial y_h} \\
&= -\omega_k \frac{\partial V_{hj}}{\partial p_j} / \frac{\partial V_{hj}}{\partial y_h}.
\end{aligned}$$

Aggregating individual expenditures to compute the total units of groceries demanded by a household shopping at store j yields

$$\begin{aligned}
q_j &= \omega \cdot \breve{q}_j \\
&= -\left(\sum_k \omega_k^2\right) \frac{\partial V_{hj}}{\partial p_j} / \frac{\partial V_{hj}}{\partial y_h},
\end{aligned}$$

assuming that the aggregation of demand uses the same weights as the price index. Consequently, the result from Roy's Identity must be scaled by the sum of the squares of the weights on the individual goods (or categories) if the price index is used instead of individual price. If the weights $\omega_k \approx 1/n$ then $\sum_{k=1}^{n} \omega_k^2 \approx 1/n$ which is small because the index is composed of thousands of products. If this factor is not accounted for, the reported parameter estimates will be too small. The scaling factor, μ, in the indirect utility helps account for this scaling difference between the discrete and continuous choice parts of the model so the model provides reasonable predictions of both store choice and expenditure.

B Estimation and Numerical Issues

To calculate reliable point estimates, I use SNOPT 7.0 [Gill et al., 2002], one of the best solvers currently available to maximize the log-likelihood. SNOPT solves sparse, large-scale, constrained optimization problems using a sequential quadratic programming (SQP) algorithm. The SQP algorithm determines the search direction by minimizing a sequence of quadratic sub-problems which approximate the Lagrangian locally, subject to linearized constraints. Although other algorithms, such as the interior point method used in KNITRO [Byrd et al., 2006], are sometimes faster, interior point methods only work well on convex problems. For this problem SNOPT is much more reliable, especially for starting values in some regions of parameter space where the estimated variance of ξ_h is extremely small. SNOPT, KNITRO, and IPOPT [Wachter and Biegler, 2006], a free interior point solver which is similar to KNITRO, produce similar solutions and reliably outperform MATLAB's fmincon.

In addition, I used multiple starting values and computed accurate gradients using complex-step differentiation (CSD) [Al-Mohy and Higham, 2009] (See B.1.). In theory, CSD is more accurate than finite difference methods and often as accurate as analytic derivatives if you take a very small step size. In practice, I suspect that the solver will perform better with analytic gradients.

B.1 Complex Step Differentiation

CSD uses imaginary numbers to compute derivatives numerically which are more accurate than finite difference methods and often as good as automatic differentiation [Martins et al., 2001], a compiler-like tool which analyzes source code

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and computes efficient analytic derivatives. CSD calculates gradients numerically by taking a very small step[36] in the complex direction and approximating the gradient as $\dfrac{\partial f(x)}{\partial x_i} \approx \texttt{Imag}\left[\dfrac{f(x+ih\cdot e_i)}{h}\right]$ where e_i is a unit vector in the i-th direction. From the Taylor series expansion of $f(x)$, it is easy to show that the error is $O\left(h^2\right)$ but with a much smaller h than for (two-sided) finite difference [Al-Mohy and Higham, 2009].

B.2 Verification of Optimum

Because the log-likelihood of a discrete choice model may have multiple local maxima, it is important to ensure that the solver has converged to a local maximum and that it is the global maximum [McFadden, 1984].

To verify that the solver converged to a local optimum, I try multiple starting values, use several solvers (SNOPT, KNITRO, Ipopt), and test my code on a Monte Carlo data set. For all households, the solver's exit codes indicate that it found locally optimal solutions, although not always within the desired tolerance. Numerical difficulties occur when the variance of the household-specific shock, σ_ξ^2, is small, which causes numerical truncation in the calculation of ℓ_h^q.[37] I also compared the results from SNOPT 7.0 to those from Ipopt 3.5.5, a modern Interior Point solver [Wachter and Biegler, 2006]. For all households, the two solvers found the same optima to at least four decimal places. In addition, I confirmed that the gradients and Lagrange multipliers were close to 0, that the condition number was small, and that all eigenvalues of the Hessian were positive, indicating that the solver's solutions were local optima.[38]

To examine the properties of the solution on a larger scale, I compare the solver's optimum to the value of the log-likelihood at 500 quasi-Monte Carlo Niederreiter points in a hypercube of $\pm\hat{\sigma}$ about the solver's solution.[39] For every household type, the solver's solution was larger than at any of the Niederreiter points, indicating that the solver had probably found the global maximum.

Proving that the local maximum is the global maximum is more difficult. McFadden [1984] discusses functional form restrictions that ensure that a lo-

[36] CSD's superior accuracy depends on taking a smaller step size than finite difference methods.

[37] I am grateful to Todd Munson in the MCS division of Argonne National Laboratory for explaining this point to me.

[38] I computed the Hessian using CSDbecause BFGS approximations to the Hessian often differ considerably from the true value, particularly when the solver converges quickly.

[39] Niederreiter points are superior to standard Monte Carlo draws because they do a better job of covering the hypercube than pseudo-Monte Carlo draws [Judd, 1998].

cal maximum of a logit model is the global solution. One practical option is to compare the values of the log-likelihood and a quadratic approximation – analogous to that used by most solvers – about the solver's solution on a set of quasi-Monte Carlo points to examine if the quadratic approximation is accurate, if there is consistent bias in one direction, and if the objective function has multiple peaks.[40]

C TNS Worldpanel

The TNS Worldpanel is a complex, high quality home scan panel of consumer shopping behavior which was designed for marketing purposes and contains rich detail about both household demographics and product characteristics. Participants scan every grocery item which they purchase and bring into the home using a scanner provided by TNS.[41] The data is sent to TNS electronically and periodically verified using till receipts. If an item lacks an SKU – such as raw fruit and vegetables – then the household enters the price and other details manually. Households typically participate in the panel for about two years and in return receive modest compensation which is designed to avoid influencing consumer spending on groceries [Leicester and Oldfield, 2009a].

Despite the precision of the measurement, there are several potential sources of bias: sampling bias, learning how to scan, attrition, and fatigue. Sampling bias occurs because a disproportionate number of participating households are those in their prime consuming years (couples with and without children). The young (students) and the old (pensioners) are under-represented and often missing completely in some regions. TNS reweights the data to correct for this bias. To avoid learning effects, TNS discards the first two weeks of data from new participants. Also, scanning behavior changes over time because of fatigue or scanning causing households to modify their consumption habits [Leicester and Oldfield, 2009b]. In addition, household types attrit at different rates. Nevertheless, TNS selects households and locations to maintain a representative distribution of consumer types. Leicester and Oldfield [2009b] discusses these issues in more detail as part of a comparison with the benchmark Expenditure and Food Survey (EFS). They conclude that scanner data matches the general trends of the EFS although with about 25% lower recorded expenditures.

[40] Ken Judd suggested this technique to me.

[41] E.g., if they purchase lunch at Marks & Spencer and eat it at the office the transaction is not recorded in the TNS data.

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Following Beckert et al. [2009], I simplify the complexity of the data by grouping similar fascia together, constructing household types which are based on the census categories for household composition, and constructing a price index for units of a reference basket of groceries. The following subsections examine these decisions in more detail.

C.1 Household Type

I assign each household in the TNS data a type based on the KS020 Household Composition Table in the UK 2001 Census (See Table 11 on page 57.).[42] Then, I combine types which differ by only marital status, which should not affect consumption. I assume that each household purchases units of groceries of its type-specific reference basket of groceries at the price specified by the price index as discussed further in C.3.

C.2 Aggregation of Fascia

The TNS and IGD data provide much more detailed fascia than can be feasibly used for estimation. Consequently, similar 'sub-fascia' are grouped into 18 broader categories with one fascia for each of the major firms except Sainsbury's and Tesco, which each have an additional fascia type for their convenience store format. In addition, I coalesce the various regional Cooperative movement stores into one Coop fascia and assign the fringe of regional and independent grocery retailers to the Other fascia.

The firms which are represented by Other typically have only a local presence. In all GOR, 75% or more of Other stores are the size of convenience stores. In some regions, several firms under the Other fascia have have a comparable number of stores to the national players. However, given their consistently small sales areas and regional presence, these stores probably have little market power and lack the cost advantages of the fascia which have more national presence, more efficient supply chains, and economies of scale and scope. Consequently, treating all these fringe stores as one fascia overstates their market power.

Similarly, using a single Coop fascia overstates the market power of the Cooperative movement stores because they lack the focus and centralized coordination of the major fascia.

[42] Household type 11 (KS0200015 Other, all pensioner) is not included because there are no observations of this type in the TNS data.

C.3 Price Index for Aggregate Consumption

I use the aggregate hedonic price indexes which Beckert et al., 2009 construct by performing hedonic regressions within product categories and then aggregating with category expenditure weights. The hedonic regressions control for regional, fascia, and monthly fixed effects. The price index aggregates bar-code level hedonic price indexes to produce an aggregate index for the price of a unit of groceries. This unit of groceries represents the price of the reference basket of goods which each household type faces in a specific fascia-region-month. The hedonic weights from the index can also be used to impute prices for stores in the consumer's choice set where I do not observe prices because the consumer shops elsewhere.

This aggregation assumes that, conditional on household type, households behavior roughly satisfies the Gorman Polar form – i.e., their preferences are homothetic across different goods, perhaps with some satiation level of spending. The assumption that household expenditure is split across goods in constant fractions, regardless of income, has important implications for the price equilibrium and cost recovery, as discussed in Section 6.

The price data consists of prices, goods, product characteristics, quantities, and pack sizes for over 16 million purchases. The variation occurs both in the choice of basket – which is across household type and region – and prices – which is across fascia, regions, and months. Using this data, the price index is constructed as follows:

1. Group similar barcode-level purchase data into specific categories (shampoo, milk, mineral water, etc.) and then compute a hedonic regression

$$\log p_{bst} = \alpha_f^r + t_t + \alpha^r t_{ft} + r_r + z_b^{'} \beta^r + \epsilon_{bst}$$

   for each category, using the observations at store s, fascia f, barcode (product) b, geographic region g, time t and product category group r. I suppress the subscripts for individual i of household-type h who actually purchased the item on some trip.

2. From the category regression, compute predicted prices for counter factual purchases at all fascia, dates, and regions:

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$$\hat{p}_{bst} \quad = \quad \exp\left[\hat{\alpha}^r_f + \hat{t}_t + \hat{\alpha}^r t_{ft} + \hat{r}_r + z_b^{'}\hat{\beta}^r + \hat{\epsilon}_{bst}\right].$$

$\hat{\epsilon}_{bst}$ is the residual for the price which was observed for the item b at a specific fascia-region-date. I assume that this shock is an unobserved product characteristic which would be the same for any household purchasing the same item at a different fascia and date, regardless of household type.

3. Compute the predicted price for fascia-product category-month-region-household type by taking the mean over these factors:

$$\hat{p}_{rfhgt} \quad = \quad \frac{1}{N_{rfhgt}} \sum_{\left(\tilde{b},\tilde{s},\tilde{t}\right)\in A_{rfhgt}} \hat{p}_{\tilde{b}\tilde{s}\tilde{t}}$$

   where N_{rfhgt} is the number of predicted prices for a fascia-product category-household type in a given month and region and A_{rfhgt} is the set of the indices for a given fascia-product category-household type, (b, s, t).

4. Compute the product category expenditure weights for each individual household type by region:

$$w_{rhg} \quad = \quad \sum_{i\in h\cap g}\sum_{b\in r} e_{ib} / \sum_{i\in h\cap g}\sum_{b} e_{ib}$$

   where e_{ib} is household i's annual expenditure on product b, $h\cap g$ is the set of households of type h in region g. Thus, w_{rhg} is the observed expenditure weight for all households of type h in region g on product category r. Annual expenditure is either the total expenditure observed per year or the observed expenditure scaled by 12/ (Months of Data) if there is less than a year of data for a household i. Note: these expenditure weights are assumed to be constant over time.

5. Finally, calculate the expenditure-weighted aggregate hedonic price index (hereafter, the 'price index') for each household type-fascia-region-month

$$P_{fhgt} \quad = \quad \sum_r w_{rhg}\hat{p}_{rfhgt}.$$

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Constructing a universal 'unit of groceries' remains a challenge because quality is not the same across fascia or even within fascia. In addition, (unobserved) price tiers for different locations and formats, promotions, stock outages, and seasonal effects further complicate these measurements. Also, non-price competition is important in the UK supermarket industry, especially the variation of the assortment of goods based on local market demographics, such as stocking more organic products in more affluent neighborhoods. As shown below, households do not purchase the same baskets, e.g. some households never purchase alcohol or pet food. Also, the fraction of the basket spent on different kinds of goods changes with income. The price index averages over these different factors. To minimize the impact of measurement error, I include a household shock, ξ_h.

The use of this price index and units of a reference basket of groceries to estimate demand depends on the validity of assumption that consumers, conditional on household type, purchase the same basket of goods at each fascia. The mean, median, and standard deviation of expenditure by household type and fascia on fresh food, prepared food, alcohol and non-food at supermarkets show considerable variation: for example, the standard deviation is often the same order of magnitude as the mean (See, for example, the mean and standard deviation for alcohol in Tables 12 and 13.).[43] Furthermore, median alcohol expenditure is zero for all household type-fascia pairs and median non-food expenditure is almost always zero. In addition, research for US consumers indicates that they purchase different baskets from different stores, that different fascia are even complementary, and consumers often make more than one stop on a trip [Briesch et al., 2010]. Because consumers often deviate from the reference basket both in quality and composition, consumer expenditure is observed with measurement error. If the shock ξ_h fails to control for this heterogeneity, the model will suffer from endogeneity.

In addition, expenditure and basket composition are correlated with fascia because different fascia target different demographic segments. This correlation could also be caused by TNS's sampling mechanism if household type is correlated with other demographics which predispose a household to choose a specific fascia or basket as well as the location where they live. This endogeneity would be even more important to handle in a dynamic model where firms (and households) choose locations.

[43] Tables for the other expenditure categories are available upon request.

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C.4 Computation of Choice Sets and Distance

To simplify estimation and welfare calculations, I assume that the choice set of each household or OA consists of the 30 nearest stores. This assumption seems reasonable, based on the statistics in Table 14 which show mean, median, and 75-th percentile distances for the 30 stores closest to each OA by region. Because consumers have high disutility from travel [Smith, 2004], most households are unlike to consider stores outside this choice set unless a particular store is conveniently located or stocks a good which the consumer values highly.

A small fraction of households actually shops at more distant stores; Beckert et al. [2009] drop these observations from the data which could bias the results. The choice set may also overstate demand for convenience stores if consumers are less willing to travel to smaller stores than larger formats. Constructing choices sets of a uniform size does, however, facilitate implementation of the estimation code, and captures the majority of the stores that each household considers.

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	1 Young	1 Pen	1 Parent	Couple	Pen Couple	Coup child	Other no	Other with
β_{dist}	-23.186	-23.6066	-23.5437	-20.7668	-21.2056	-21.7874	-22.1953	-22.2463
s.e.	(0.5452)	(0.5335)	(0.7623)	(0.4082)	(0.4433)	(0.3423)	(0.365)	(0.477)
$\beta_{carpark}$	8.1156	5.6679	10.4491	8.8168	8.4139	8.3756	7.4687	5.8252
s.e.	(0.7079)	(0.6385)	(0.9534)	(0.7159)	(0.5463)	(0.447)	(0.46)	(0.6318)
α_{price}	-1.2631	-1.2524	-1.2716	-1.3631	-1.1699	-1.5193	-1.4123	-1.4281
s.e.	(0.0508)	(0.0547)	(0.065)	(0.0487)	(0.0509)	(0.0467)	(0.0469)	(0.0582)
α_{area}	3.9843	4.2313	4.0631	3.2774	2.8035	4.621	4.4084	5.509
s.e.	(0.4316)	(0.4749)	(0.6907)	(0.2593)	(0.3406)	(0.3017)	(0.3117)	(0.4575)
γ_{price}	0.2624	0.2711	0.2899	0.3343	0.2902	0.3982	0.3586	0.3814
s.e.	(0.0108)	(0.0122)	(0.0157)	(0.0123)	(0.0131)	(0.0132)	(0.0126)	(0.0171)
σ^2_ξ	0.4132	0.3421	0.3622	0.3021	0.2455	0.3364	0.348	0.3685
s.e.	(0.0144)	(0.0118)	(0.0181)	(0.0091)	(0.0081)	(0.0081)	(0.0087)	(0.012)
μ	5.3991	4.0861	3.4768	6.2805	4.1435	5.0852	5.5838	5.0072
s.e.	(0.6514)	(0.5439)	(0.6675)	(0.6096)	(0.5463)	(0.3787)	(0.4402)	(0.4737)

Tab. 1: Point Estimates

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	Aldi	Asda	Budg	Coop	Icel	Kwik	Lidl	MandS	Netto	Other	Morr	Sain	SainS	Some	Tesc	TescS	Wait
Aldi	-5.25	0.38	0.02	0.15	0.24	0.35	0.04	0.02	0.12	0.24	0.23	0.19	0.00	0.09	0.36	0.06	0.03
Asda	0.20	-4.73	0.03	0.15	0.23	0.26	0.04	0.02	0.09	0.22	0.20	0.22	0.01	0.09	0.37	0.06	0.04
Budg	0.07	0.19	-4.91	0.13	0.26	0.06	0.02	0.03	0.03	0.31	0.14	0.30	0.02	0.11	0.52	0.09	0.13
Coop	0.14	0.22	0.03	-4.33	0.19	0.21	0.03	0.03	0.07	0.15	0.18	0.19	0.00	0.10	0.32	0.05	0.03
Icel	0.17	0.30	0.04	0.14	-5.00	0.23	0.05	0.03	0.09	0.27	0.19	0.26	0.02	0.13	0.40	0.07	0.06
Kwik	0.27	0.34	0.02	0.19	0.24	-4.81	0.04	0.01	0.12	0.23	0.23	0.16	0.00	0.09	0.30	0.05	0.01
Lidl	0.14	0.26	0.02	0.13	0.24	0.19	-4.65	0.03	0.06	0.23	0.18	0.19	0.01	0.15	0.33	0.06	0.07
MandS	0.13	0.25	0.04	0.13	0.24	0.15	0.04	-5.54	0.06	0.26	0.19	0.24	0.02	0.10	0.36	0.07	0.08
Netto	0.23	0.29	0.01	0.16	0.20	0.30	0.03	0.01	-5.04	0.23	0.25	0.18	0.01	0.09	0.31	0.05	0.01
Other	0.12	0.21	0.04	0.09	0.21	0.17	0.04	0.03	0.07	-4.22	0.18	0.20	0.02	0.11	0.34	0.06	0.03
Morr	0.18	0.28	0.03	0.15	0.23	0.21	0.04	0.03	0.11	0.26	-4.68	0.21	0.01	0.12	0.36	0.06	0.04
Sain	0.12	0.27	0.05	0.12	0.25	0.14	0.04	0.04	0.06	0.28	0.17	-4.62	0.02	0.13	0.43	0.08	0.07
SainS	0.04	0.15	0.05	0.07	0.34	0.05	0.03	0.06	0.08	0.45	0.19	0.32	-4.79	0.14	0.32	0.12	0.05
Some	0.13	0.24	0.04	0.15	0.27	0.16	0.05	0.03	0.07	0.29	0.20	0.25	0.02	-4.76	0.41	0.07	0.04
Tesc	0.14	0.27	0.05	0.16	0.24	0.17	0.04	0.03	0.07	0.26	0.19	0.25	0.01	0.13	-4.50	0.05	0.05
TescS	0.12	0.25	0.05	0.13	0.28	0.14	0.05	0.05	0.07	0.31	0.18	0.29	0.03	0.15	0.40	-4.90	0.06
Wait	0.06	0.20	0.06	0.11	0.24	0.04	0.04	0.07	0.03	0.29	0.17	0.29	0.02	0.12	0.44	0.08	-4.84

Tab. 2: Population-Weighted Average Price Elasticities

	NE	NW	York	E Mid	W Mid	E Eng	Lon	SE	SW	Wales
Aldi	0.59	0.59	0.59	0.64	0.59	0.60	0.63	0.62	0.60	0.63
Asda	0.71	0.72	0.71	0.76	0.70	0.70	0.75	0.76	0.70	0.76
Budg	−−	−−	0.70	0.71	0.69	0.69	0.72	0.71	0.69	−−
Coop	0.79	0.82	0.79	0.85	0.78	0.75	0.82	0.84	0.73	0.83
Icel	0.64	0.64	0.64	0.65	0.62	0.63	0.66	0.65	0.62	0.66
Kwik	0.63	0.63	0.63	0.68	0.63	0.64	0.68	0.66	0.63	0.68
Lidl	0.79	0.80	0.79	0.80	0.77	0.77	0.79	0.79	0.76	0.86
MandS	1.07	1.08	1.10	1.09	1.02	1.01	1.06	1.05	1.12	1.14
Netto	0.58	0.60	0.60	0.62	0.57	0.57	0.60	0.64	−−	0.63
Other	0.67	0.74	0.72	0.79	0.69	0.69	0.74	0.77	0.69	0.75
Morr	0.75	0.78	0.76	0.82	0.75	0.74	0.80	0.83	0.74	0.82
Sain	0.79	0.80	0.79	0.85	0.78	0.77	0.82	0.86	0.77	0.83
SainS	−−	0.79	0.77	−−	0.74	0.70	0.80	0.83	0.71	0.73
Some	0.74	0.74	0.73	0.79	0.73	0.72	0.77	0.76	0.72	0.78
Tesc	0.74	0.75	0.75	0.80	0.73	0.73	0.78	0.80	0.73	0.78
TescS	0.70	0.71	0.70	0.76	0.70	0.69	0.73	0.72	0.70	0.75
Wait	−−	0.95	0.94	1.01	0.91	0.90	0.96	1.01	0.90	1.03

Tab. 3: Average Marginal Costs with Multi-Fascia Effects by GOR

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	1 Young	1 Pen	1 Parent	Couple	Pen Couple	Coup child	Other no	Other with
Aldi	0.23	0.26	0.27	0.18	0.26	0.17	0.17	0.17
Asda	0.24	0.27	0.28	0.20	0.27	0.18	0.19	0.19
Budg	0.24	0.27	0.28	0.20	0.28	0.19	0.19	0.20
Coop	0.27	0.30	0.29	0.22	0.30	0.21	0.22	0.22
Icel	0.23	0.27	0.28	0.19	0.27	0.18	0.19	0.19
Kwik	0.23	0.27	0.28	0.19	0.27	0.18	0.18	0.19
Lidl	0.25	0.28	0.28	0.21	0.28	0.20	0.21	0.20
MandS	0.22	0.25	0.25	0.18	0.26	0.14	0.17	0.16
Netto	0.22	0.26	0.27	0.18	0.26	0.17	0.17	0.17
Other	0.27	0.30	0.30	0.23	0.30	0.21	0.22	0.22
Morr	0.25	0.28	0.28	0.21	0.28	0.20	0.20	0.20
Sain	0.25	0.28	0.29	0.21	0.28	0.20	0.21	0.20
SainS	0.28	0.31	0.31	0.24	0.31	0.23	0.24	0.23
Some	0.25	0.28	0.29	0.21	0.28	0.20	0.20	0.20
Tesc	0.25	0.28	0.29	0.20	0.28	0.19	0.20	0.20
TescS	0.26	0.29	0.30	0.22	0.29	0.21	0.21	0.22
Wait	0.24	0.27	0.28	0.21	0.27	0.19	0.20	0.20

Tab. 4: Average Price-Cost Margins with Multi-Fascia Effects by Household Composition

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	NE	NW	York	E Mid	W Mid	E Eng	Lon	SE	SW	Wales	Total
Aldi	9.51	9.95	4.81	5.49	6.64	2.96	1.02	1.33	2.96	6.50	4.41
Asda	14.49	14.68	11.31	8.38	9.48	9.11	4.80	7.51	9.86	8.43	9.33
Budg	0.00	0.00	0.20	1.31	0.18	3.34	1.57	2.20	0.46	0.00	1.15
Coop	9.39	8.43	10.48	15.51	8.05	7.64	5.98	9.05	8.99	8.67	8.85
Icel	7.30	7.11	4.15	7.09	6.27	6.71	10.89	8.40	7.28	9.37	7.64
Kwik	13.34	14.75	10.50	9.90	12.32	0.24	1.22	0.52	2.14	16.90	6.56
Lidl	1.85	1.15	1.30	2.54	1.00	1.49	1.88	1.65	3.31	3.65	1.87
MandS	0.55	0.53	0.54	0.42	0.59	0.77	2.15	0.99	6.02	0.55	1.45
Morr	15.84	6.95	15.17	7.81	9.51	4.39	6.25	6.12	7.17	5.50	7.79
Netto	5.83	2.71	8.60	3.30	1.66	1.37	1.60	0.60	0.00	0.19	2.23
Other	3.96	12.10	14.09	12.95	19.22	15.11	20.19	14.53	16.31	10.90	14.96
Sain	6.13	6.57	5.21	5.97	7.98	11.50	14.94	13.13	8.61	2.62	9.38
SainS	0.00	0.12	0.09	0.00	0.25	0.05	2.40	0.55	0.21	0.08	0.52
Some	2.03	2.03	2.42	4.32	4.74	5.07	4.21	5.47	10.05	6.02	4.77
Tesc	8.84	10.59	9.77	12.76	9.89	25.64	12.22	19.58	12.80	18.75	14.62
TescS	0.94	2.27	1.27	1.92	1.96	2.94	3.94	3.43	2.65	1.58	2.58
Wait	0.00	0.06	0.10	0.32	0.25	1.68	4.73	4.93	1.19	0.30	1.89
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

Tab. 5: Share of profits by GOR (Percentage): Morrisons-Safeway Merger

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	Profit per Store				Profit per Sales Area				
	Mean	Median	Std.Dev	Max	Mean	Median	Std.Dev	Max	N
Aldi	8.78	8.22	3.34	42.22	0.0011	0.0011	0.0005	0.0070	303
Asda	23.24	19.06	16.46	142.62	0.0005	0.0004	0.0002	0.0015	242
Budg	5.01	4.89	2.15	12.26	0.0013	0.0008	0.0013	0.0074	138
Coop	2.82	2.56	1.73	11.64	0.0005	0.0003	0.0005	0.0036	1891
Icel	6.41	5.99	2.35	16.70	0.0014	0.0012	0.0006	0.0049	719
Kwik	6.49	6.11	2.45	24.07	0.0009	0.0009	0.0005	0.0061	610
Lidl	3.24	3.06	1.10	6.18	0.0003	0.0003	0.0001	0.0009	349
MandS	2.69	1.20	19.62	354.27	0.0001	0.0001	0.0001	0.0005	325
Morr	8.52	7.59	5.11	43.37	0.0004	0.0003	0.0004	0.0037	551
Netto	8.10	7.42	3.03	18.61	0.0013	0.0012	0.0005	0.0036	166
Other	3.60	3.26	2.11	16.09	0.0011	0.0009	0.0008	0.0060	2502
Sain	13.31	10.11	13.70	124.73	0.0003	0.0003	0.0002	0.0035	425
SainS	4.37	3.98	2.54	15.04	0.0012	0.0013	0.0007	0.0033	72
Some	5.05	4.50	2.52	24.47	0.0006	0.0005	0.0005	0.0039	570
Tesc	17.85	12.96	16.82	155.75	0.0004	0.0004	0.0002	0.0016	494
TescS	5.83	4.76	5.68	63.82	0.0014	0.0012	0.0010	0.0045	267
Wait	7.08	2.98	26.40	276.00	0.0004	0.0002	0.0013	0.0133	161

Tab. 6: Store profits: England + Wales

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	s_{pre}	Δs_{Morr}	Δs_{Tesco}	$\Delta \pi_{Morr}$	$\Delta \pi_{Tesco}$	$\Delta price_{Morr}$	$\Delta price_{Tesco}$
Aldi	4.41	0.00	−0.02	0.17	0.26	0.02	0.10
Asda	9.32	0.01	−0.03	0.13	0.37	0.04	0.14
Budg	1.15	−0.00	−0.00	0.06	0.42	0.02	0.14
Coop	8.85	0.00	−0.04	0.09	0.23	0.02	0.10
Icel	7.64	0.00	−0.03	0.07	0.30	0.03	0.14
Kwik	6.55	0.01	−0.03	0.20	0.18	0.02	0.18
Lidl	1.87	−0.00	−0.01	0.06	0.28	0.01	0.10
MandS	1.45	−0.00	−0.01	0.00	0.19	0.03	0.13
Morr	2.49	0.01	−0.01	0.13	0.10	0.26	0.10
Netto	2.23	0.00	−0.01	0.14	0.13	−0.16	0.08
Other	14.96	−0.00	−0.06	0.04	0.25	−0.00	0.11
Safe	5.29	−−	−−	−−	−−	−−	−−
Sain	9.38	−0.00	−0.03	0.04	0.39	−0.01	0.14
SainS	0.52	−0.00	−0.00	−0.06	0.09	0.30	0.85
Some	4.78	−0.00	−0.02	0.02	0.35	−0.01	0.14
Tesc	14.62	0.00	0.35	0.08	2.44	0.09	0.59
TescS	2.58	−0.00	−0.03	0.06	−0.36	−0.02	1.20
Wait	1.91	−0.02	−0.02	−0.96	−0.64	−0.37	−0.25

Tab. 7: Percent change in market shares, profits, and price post-merger.

	Pre vs. Morr		Pre vs. Tesco		Morr vs. Tesco	
	CV_{low}	CV_{upper}	CV_{low}	CV_{upper}	CV_{low}	CV_{upper}
NE	−22.21	−21.90	−24.68	−23.37	−2.66	−1.45
NW	−8.20	−8.08	−2.13	−0.16	6.04	7.93
York	−21.75	−21.36	8.29	10.47	29.94	31.85
E Mid	14.17	14.41	9.20	11.58	−5.34	−2.66
W Mid	−40.53	−39.88	−30.57	−28.33	9.07	11.89
E Eng	−29.45	−28.93	−79.60	−77.08	−50.11	−48.18
Lon	43.46	44.83	−10.16	−4.50	−53.36	−49.53
SE	−11.33	−11.24	−91.19	−85.74	−79.92	−74.45
SW	15.34	15.99	−74.71	−72.53	−90.83	−88.28
Wales	−8.96	−8.26	−28.14	−26.89	−19.85	−18.38
Total	−69.47	−64.42	−323.70	−296.55	−257.00	−231.25

Tab. 8: Bounds on expected compensating variation by GOR

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	Pre vs. Morr		Pre vs. Tesco		Morr vs. Tesco	
	CV_{low}	CV_{upper}	CV_{low}	CV_{upper}	CV_{low}	CV_{upper}
1 Young	−9.04	−8.63	−11.49	−8.44	−2.72	0.29
1 Pen	−6.99	−6.72	−18.06	−16.42	−11.21	−9.69
1 Parent	−0.79	−0.53	−20.15	−18.80	−19.49	−18.24
Couple	−12.26	−11.29	−44.69	−37.69	−33.00	−26.19
Pen Couple	−4.68	−4.36	−14.27	−11.92	−9.76	−7.53
Coup child	−22.33	−20.76	−141.97	−136.37	−120.41	−115.38
Other no	−10.23	−9.21	−57.03	−51.61	−47.39	−42.19
Other with	−3.14	−2.93	−16.05	−15.29	−13.02	−12.32
Total	−69.47	−64.42	−323.70	−296.55	−257.00	−231.25

Tab. 9: Bounds on expected compensating variation by household composition

TNS Household	TNS HH Type(s)	KS020 Household
1 Single Young	2	KS0200003 Single non-pensioner
2 Single Pensioner	1	KS0200002 Single Pensioner
3 Single Parent	7	KS0200011 Single parent, dependent children
4 Childless couple	4	KS0200005 + KS0200008 Couple, no children
5 Pensioner couple	3	KS0200004 Pensioner couple
6 Couple with children	5	KS0200006 + KS0200009 Couple dependent children
7 Others – no children	6, 8,10, 11, 12	KS0200007 + KS0200010 Couple, with non-dependent children ; KS0200012 Single parent non-dependent children ; KS0200013 Other, dependent children ; KS0200014 Other, all student ; KS0200016 Other, other
8 Others – with children	9	KS0200013 Other, with dependent children

Tab. 11: Conversion of Census KS020 to TNS Household Type

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	1 Young	1 Pen	1 Parent	Couple	Pen Couple	Coup child	Other no	Other with
Aldi	0.0512	0.1296	0.0716	0.0855	0.0936	0.0452	0.1045	0.0207
Asda	0.0658	0.0429	0.0505	0.0801	0.0891	0.0496	0.0660	0.0532
Budg	0.0717	0.0000	0.0000	0.0432	0.0699	0.0511	0.0000	0.2391
Coop	0.0335	0.0437	0.0603	0.0714	0.0574	0.0781	0.0806	0.0519
Icel	0.0258	0.0103	0.0442	0.0588	0.0018	0.0279	0.0153	0.0068
Kwik	0.0993	0.0792	0.0577	0.1074	0.0270	0.0678	0.0804	0.0695
Lidl	0.0564	0.0473	0.0742	0.0422	0.0933	0.0503	0.0604	0.0616
MandS	0.0251	0.0340	0.0155	0.0228	0.0198	0.0243	0.0264	0.0169
Morr	0.0495	0.0592	0.0437	0.0959	0.0756	0.0445	0.0639	0.0461
Netto	0.0524	0.1312	0.0209	0.1131	0.0424	0.0315	0.0721	0.1486
Other	0.0428	0.0000	0.0000	0.0043	0.0182	0.0096	0.0173	0.0008
Sain	0.0630	0.0665	0.0340	0.0921	0.0629	0.0500	0.0708	0.0604
SainS	0.1782	0.0000	0.0000	0.0000	0.0000	0.0413	0.0520	0.0000
Some	0.0446	0.0379	0.0638	0.0662	0.0827	0.0441	0.0445	0.0339
Tesc	0.0617	0.0731	0.0375	0.0921	0.0729	0.0539	0.0610	0.0505
TescS	0.0562	0.0506	0.0257	0.0037	0.0189	0.0346	0.0682	0.0145
Wait	0.0540	0.0642	0.0262	0.0852	0.0336	0.0269	0.0572	0.0719

Tab. 12: Mean Expenditure on Alcohol by Household Composition

	1 Young	1 Pen	1 Parent	Couple	Pen Couple	Coup child	Other no	Other with
Aldi	0.1169	0.2566	0.1187	0.1690	0.2050	0.1067	0.1768	0.0617
Asda	0.1496	0.1517	0.1181	0.1734	0.1877	0.1300	0.1442	0.1370
Budg	0.1353	0.0000	0.0000	0.1365	0.2614	0.1694	0.0000	0.3112
Coop	0.1105	0.1712	0.1878	0.2049	0.1779	0.2230	0.2101	0.1662
Icel	0.1229	0.0570	0.1140	0.1562	0.0126	0.1140	0.0766	0.0313
Kwik	0.2541	0.2227	0.2010	0.1948	0.1297	0.1902	0.2098	0.1635
Lidl	0.1918	0.1635	0.1669	0.1140	0.2188	0.1374	0.1489	0.1776
MandS	0.1088	0.1669	0.0536	0.0840	0.0773	0.0874	0.1285	0.0533
Morr	0.1424	0.1757	0.1439	0.2116	0.1724	0.1280	0.1509	0.1268
Netto	0.1217	0.2827	0.0437	0.2278	0.0942	0.0815	0.1449	0.2618
Other	0.1940	0.0000	0.0000	0.0473	0.1304	0.0918	0.1276	0.0061
Sain	0.1604	0.1655	0.0799	0.1970	0.1655	0.1246	0.1558	0.1611
SainS	0.3648	0.0000	0.0000	0.0000	0.0000	0.0819	0.1274	
Some	0.1566	0.1434	0.1438	0.1734	0.2289	0.1337	0.1553	0.1102
Tesc	0.1454	0.1762	0.0985	0.1954	0.1693	0.1304	0.1552	0.1264
TescS	0.1606	0.1446	0.0852	0.0200	0.0700	0.0826	0.1980	0.0768
Wait	0.1369	0.1736	0.0787	0.1966	0.1042	0.0888	0.1370	0.1210

Tab. 13: Std. Dev. of Expenditure on Alcohol by Household Composition

	Mean (km)	Median (km)	Q75 (km)	Std Dev	% > 20 km	N
NE	6.38	5.00	7.63	5.79	3.16	8599
NW	5.06	3.85	5.72	4.04	1.67	22712
York	6.51	4.67	7.32	5.89	3.48	16793
E Mid	7.31	5.16	10.22	5.42	2.82	14107
W Mid	5.94	3.92	7.84	4.92	2.89	17458
E Eng	8.44	7.72	10.49	4.46	2.47	18199
Lon	2.40	2.33	2.87	1.23	0.00	24149
SE	7.17	6.30	9.85	4.12	0.40	26642
SW	9.57	8.17	13.67	6.57	6.95	17013
Wales	10.92	7.58	13.06	9.52	13.98	9766

Tab. 14: Statistics for Store-OA Distance by GOR