# The Rise of Discounters and its Impact on Concentration, Market Power and Welfare

Martin O'Connell, Howard Smith and Øyvind Thomassen*

May, 2026

**Abstract**

We quantify changes in concentration, market power, and welfare in the UK grocery retail sector from 2002 to 2021. We document that the expansion of discounter-format retailers coincided with declining retail and manufacturer concentration across narrowly defined product categories. We develop an equilibrium model of consumer choice over retailers and products, retailer pricing, and Nash-in-Nash bargaining between manufacturers and retailers. Applying the model to breakfast cereals, we find that discounter expansion—through store entry, efficiency gains, and changes in product offerings—reduced concentration and prices, increased consumer and total surplus, and especially benefited households near newly opened stores.

**Keywords:** discounters, concentration, market power, distributional effects

**JEL classification:** D12, L11, L13, L81

**Acknowledgments:** The authors gratefully acknowledge financial support from the Economic and Social Research Council (ESRC) under the Centre for the Microeconomic Analysis of Public Policy (CPP; grant number ES/T014334/1). We are grateful to Pierre Dubois, Rachel Griffith, Rob Mitchell, Ariel Pakes, Áureo de Paulo and Joel Stiebale, for their comments and insightful suggestions. We also thank seminar participants at various institutions and conferences. The contents of this publication are authors' own analysis and findings. The analysis has been carried out by the authors using data from Worldpanel by Numerator's Take Home data (all use is subject to Worldpanel by Numerator's terms and conditions). Worldpanel by Numerator does not endorse, and is not responsible for, the efficacy or accuracy of the analysis and findings. The use of Worldpanel by Numerator's data does not imply any endorsement by Worldpanel by Numerator's data of the interpretation or analysis of the data. Worldpanel by Numerator cannot independently verify the findings, nor can it endorse the views or conclusions set out in this article. All errors and omissions remain the responsibility of the authors of this publication.

*O'Connell is at the University of Wisconsin-Madison and the Institute for Fiscal Studies, Smith is at Oxford University and the Institute for Fiscal Studies and Thomassen is at NHH Norwegian School of Economics. **Correspondence:** moconnell9@wisc.edu, howard.smith@economics.ox.ac.uk and oyvind.thomassen@gmail.com.

# 1 Introduction

The grocery retail sector is of substantial economic importance, accounting for a significant share of household expenditure. Competition authorities in many countries have expressed concerns over rising market concentration, growing retailer market power, and barriers to entry—particularly those stemming from zoning and planning regulations. These concerns have shaped decisions to block further consolidation in the sector, such as the rejection of the 2024 Kroger–Albertsons merger in the US and the 2019 ASDA–Sainsbury's merger in the UK.[1]

In recent years, a retail format often referred to as *discounters*—or *limited assortment stores*—has grown rapidly in both store count and revenue share. This trend has occurred in parallel in the UK, the US, and across much of the EU. Discounters follow a no-frills business model centered on a limited product range composed primarily of private-label goods, i.e., products exclusive to a single retailer and sold without manufacturer branding. In contrast to traditional retailers, discounters make relatively limited use of branded goods, i.e., products that carry manufacturer branding and are sold across multiple retailers. Firms in this format—such as Aldi and Lidl—operate smaller stores than traditional supermarket chains, enabling them to largely circumvent government planning restrictions that constrain rivals using large-store formats. Since discounters combine a distinct retail format with heavy reliance on private-label goods, their expansion has potentially important implications not only for retail concentration and prices, but also for manufacturer concentration, vertical relations, and the division of surplus between consumers, retailers, and manufacturers.

In this paper, we quantify changes in concentration, market power, and welfare in the UK grocery retail sector from 2002 to 2021 and provide evidence on the impact of the rise of discounters. We combine longitudinal microdata, a structural model of surplus division among retailers, manufacturers, and consumers, and spatial and temporal variation in discounter store expansion shaped in part by changes in planning and land-access conditions.

First, we provide evidence from the UK grocery sector on changes in retailer and manufacturer concentration across a large number of narrowly defined product categories. We exploit microdata that track purchases of disaggregate products (UPCs) brought into the home by over 100,000 households from 2002 to 2021, covering all major grocery retailers, including discounters and traditional retailers. These products are grouped into more than 100 narrowly defined categories, each

[1] See, respectively, Federal Trade Commission (Feb. 26, 2024) complaint and Competition and Markets Authority (2019).

designed to represent a distinct product market. We document substantial changes in market structure over this period, with broadly similar patterns across categories. At the retail level, concentration—measured using a Herfindahl–Hirschman Index (HHI) of retail market shares within each category—initially rose and then declined. The average category-level HHI increased from 1,551 in 2002 to 1,851 in 2011, before falling back to 1,560 by 2021. At the manufacturer level, concentration remained stable from 2002 to 2011, then declined as the market share of branded manufacturers fell. The reduction in concentration at both levels coincided with the rapid expansion of the discounters. This expansion was facilitated by a planning regime that was relatively favorable to the discounters, and further supported by the Controlled Land Order (2010), which prohibited incumbent traditional retailers from restricting nearby discounter entry through restrictive land-control practices.

Second, we estimate a model of retail market power and retailer–manufacturer relations, and use it to quantify the evolution of market power and the distribution of economic surplus between consumers, retailers, and manufacturers. To enable a disaggregated analysis of the supply chain that accommodates the rise of discounters and their private-label suppliers, we focus on a single category: breakfast cereals. This category exhibits concentration patterns that are broadly representative of those in other categories.

We develop an equilibrium model that captures the differences between branded and private-label suppliers in their vertical relations with retailers. Retail prices are determined by Bertrand–Nash competition among retailers, who optimize against product- and retailer-specific marginal costs that depend on wholesale prices. Private-label suppliers have limited bargaining power, so we model their wholesale prices as equal to marginal cost. Branded-goods suppliers negotiate wholesale prices, which we model using a Nash-in-Nash bargaining framework.[2] Bargaining outcomes depend on each party's gains from trade relative to breakdown; firms with larger portfolios outside the negotiation have stronger bargaining positions. Conditional on product–retailer demands, the bargaining-power and marginal-cost parameters can be estimated using a linear instrumental-variable strategy. Our main quantitative takeaways are robust to alternative supply models, and the model can account for cross-category demand and pricing effects (Thomassen et al., 2017).

We model product–retailer demand using a discrete-choice framework in which consumers choose among the breakfast cereals available at each retailer. A key determinant of retailer choice is travel distance to the nearest store, which we incorporate using store-location data spanning 2002 to 2021. Our model allows for

[2] Empirical applications of this framework include Draganska et al. (2010), Ho and Lee (2017), Crawford et al. (2018), and Noton and Elberg (2018).

heterogeneous preferences over product and retailer attributes, including price sensitivity, the taste for breakfast cereal relative to the outside option, preferences across cereal brands and types (e.g., wheat, rice), and persistent tastes for retailers. We identify the parameters governing this heterogeneity using the panel structure of our microdata, constructing moments based on the persistence of household choices over time and variation in household-specific choice sets.

Our estimates indicate that the distribution of price–cost margins (i.e., additive markups) across breakfast cereal products exhibits a modest inverted U-shape from 2002 to 2021, peaking in 2008 and mirroring the changes in retailer concentration described above. This pattern is primarily driven by traditional retailers, whose margins initially rose but then declined as competitive pressure from discounters intensified. In contrast, margins on products sold by discounters increased over the period, narrowing much of the initial gap with traditional retailers. We show that this reflects strengthening portfolio effects among discounters: the diversion ratio from an average discounter product to other products sold by the same discounter rose by approximately 50% between 2002 and 2021. This increase in within-firm substitutability, combined with the expansion of discounter store networks, enabled discounters to raise margins while continuing to exert downward pressure on traditional-retailer prices and expand market share, ultimately increasing their share of total industry profits by more than 8 percentage points.

To quantify the impact of the rise of discounters, we simulate what the market would have looked like had Aldi and Lidl not expanded beyond their 2002 position. One counterfactual holds their store network fixed at 2002 levels, isolating the role of store entry and local access. Another additionally eliminates post-2002 efficiency gains, product-quality growth, and portfolio changes, isolating changes to the in-store business model. Comparing observed and counterfactual outcomes allows us to quantify the importance of these margins for market performance.

We show that the rise of discounters reduced retailer- and manufacturer-level HHIs by 262 and 236 points, respectively—equivalent to more than a 10% decline. This expansion also reduced average prices by 5%. The decline reflects both discounter efficiency gains, through lower marginal costs partially passed through to prices, and reduced margins on products sold by traditional retailers. Thus, discounters contributed not only to greater product variety but also to lower prices—through their own cost advantages and by intensifying competition. Overall, total market surplus increased by 3.4% of total revenue, while consumer surplus rose by 5.2% of total revenue. Discounter profits grew, but these gains were more than offset by losses incurred by traditional retailers and manufacturers.

We also implement a policy-motivated counterfactual that captures the acceleration in discounter expansion following the Controlled Land Order (2010) by restricting store growth to its previous trend. This exercise suggests that the increase in store openings following the Controlled Land Order accounts for roughly half of the welfare gains from the store-entry counterfactual, highlighting the importance of entry and land-access conditions. This is consistent with previous work showing that the removal of entry barriers can generate substantial welfare gains (e.g., Bourreau et al., 2021).

Our model generates counterfactual predictions at the consumer level, enabling us to quantify the distributional effects of the discounters' rise. We find substantial heterogeneity in consumer welfare gains: in 2021, the interquartile range of gains, as a share of total cereal spending, spans 2% to 5%. These gains are broadly distributed across the income distribution, but exhibit systematic spatial variation. Households that saw the opening of a nearby discounter—where previously none existed—experienced the largest gains. Nevertheless, even households without a new nearby store benefited substantially, reflecting the competitive pressure that discounters exerted on traditional retailers.

**Related literature** We contribute to a literature measuring the evolution of market power (see Miller, 2025 for a recent survey). One strand of this literature estimates markups using production-function approaches across industries (e.g., De Loecker et al., 2020). A complementary approach uses structural demand models in specific sectors to infer markups and their distribution. Work in this literature typically either abstracts from the role of retailers (e.g., Grieco et al., 2024) or relies on simplifying assumptions that limit the role of retailers (e.g., Döpper et al., 2025 and Atalay et al., 2023, which assume constant and zero retail margins, respectively). De Loecker and Scott (2022) compare these approaches using demand- and production-based markup estimates in the beer industry and find support for a highly competitive retail sector in which retailers fully pass through wholesale-price changes, while emphasizing the importance of accounting for downstream costs.

We extend this literature by treating retailers as strategic intermediaries with market power both downstream and in their negotiations with manufacturers. We model retailer choice directly: consumers choose among retailer–product options, and the estimated demand system implies economically important differentiation driven by travel distance to stores and persistent retailer preferences.

Our results also contribute to a growing literature documenting trends in market concentration. Several recent studies show that conclusions about trends in national-level concentration are sensitive to market definition (e.g., Rossi-Hansberg et al., 2020; Affeldt et al., 2021; Benkard et al., 2021; Smith and Ocampo, 2025; see also Peltzman, 2014; Shapiro, 2018). We contribute new evidence for the UK by tracking changes in concentration across a wide set of narrowly defined fast-moving consumer goods markets, documenting trends at both retail and manufacturer levels of the supply chain.

We also contribute to the literature on the impact of new retail formats. Prior work has linked the entry of non-traditional retailers to productivity growth and consumer gains (e.g., Foster et al., 2006; Hausman and Leibtag, 2007; Atkin et al., 2018). Other research focuses on Walmart's expansion (see Basker, 2007 for a survey), emphasizing effects on rival retailers and the role of economies of density (Jia, 2008; Holmes, 2011). Cleeren et al. (2010) document rising competitive pressure from discounter entry. A more recent literature studies the effects of dollar store entry on food consumption and welfare (Cao et al., 2024; Caoui et al., 2026; Schneier, 2025b). We extend this literature by quantifying the effects of discounter entry on market power, surplus, and its distribution across consumers, retailers, and manufacturers. To do so, we estimate a structural model of demand and supply at the retailer–product level.

The model captures the role played by private-label products using a vertical bargaining framework, building on the Nash-in-Nash approach in Draganska et al. (2010) and Ho and Lee (2017). More broadly, the paper relates to the literature on vertical relations in retailing (e.g., Villas-Boas, 2007; Bonnet and Dubois, 2010; Bonnet et al., 2025) and work on private-label products and retail competition (e.g., Meza and Sudhir, 2010; Dubois and Jodar-Rosell, 2010; Griffith et al., 2018). We also contribute to the literature modeling market power in the breakfast cereal market (e.g., Nevo, 2000, 2001; Backus et al., 2021; Barahona et al., 2023) by allowing both retailers and manufacturers to exert pricing power.

The rest of the paper is structured as follows. Section 2 introduces the microdata and documents the evolution of concentration across grocery markets. Section 3 presents the equilibrium model of the breakfast cereal market, and Section 4 discusses identification and estimation. Section 5 presents estimates and documents the evolution of markups. Section 6 quantifies the effect of the discounters' rise on market performance. A final section concludes.

## 2 Data, Market, and Trends in Concentration

**Consumer data** We use longitudinal microdata from Worldpanel by Numerator's Take Home Purchase Panel (henceforth Numerator data), which covers households residing in Great Britain over 2002–2021. The sample includes approximately 15,000 households in 2002, rising to 30,000 from 2011 onward. Households typically remain in the panel for several years and record all fast-moving consumer-goods purchases, including food, beverages, toiletries, pet food, and cleaning products. They record purchases by scanning UPCs using a handheld scanner or mobile app, and by submitting receipts electronically or by post.[3] For each transaction, we observe quantity, expenditure, retailer and UPC characteristics, including product category and manufacturer. For panel members, we observe annual household income, household size, the age of household members, and residential postal sector, one of approximately 1,500 sectors in Great Britain.

**Store location and input price data** We use a dataset compiled from multiple sources that records retailer store locations over 2002–2021. For 2014–2021, we use data from Geolytix Retail Points; for 2002–2007, we use data from the Institute for Grocery Distribution; and for intervening years, we use Glenigan data on new supermarket construction projects. We combine store locations with household locations to construct household-specific, time-varying distances to the nearest store of each retailer (see Appendix A). We also use official input-price data for cereal grains and sugar (see Appendix B).

**Retail formats** We refer collectively to Asda, Morrisons, Safeway, Sainsbury's, and Tesco as *traditional retailers.* Safeway operated separately until its acquisition by Morrisons in 2005. These retailers have long had a significant presence in UK grocery retailing and typically operate large stores carrying a wide range of products. We refer to Aldi and Lidl as *discounters.* They follow an everyday-low-pricing strategy, sell a limited product range, and rely heavily on private-label products (also known as own-label products): on average, private-label products account for 90% of Aldi's sales and 80% of Lidl's, compared with about 50% for traditional retailers. Like the traditional retailers, discounters operate stores throughout the UK, and both groups follow *national pricing* policies.[4]

[3] For non-barcoded items, such as loose fruit and vegetables, households scan a code in a book provided by Numerator.

[4] "Most retailers set their prices uniformly, or mostly uniformly, across their store network [...]. Various other facets of the retail offer, such as promotions, may also be applied uniformly, or mostly uniformly, across a retailer's store network" (CC 2008, paragraph 4.98, pp. 498–501).

**Private labels** For private-label goods, the retailer controls quality, marketing, pricing, and quantity decisions (see CMA, 2023, para. 3.8), so that in practice the vertical structure comes close to vertical integration. This allows retailers to switch between private-label manufacturers without consumers noticing, weakening manufacturers' bargaining positions. The Competition and Markets Authority (CMA)—the UK's antitrust regulator, which succeeded the Competition Commission—investigated ten representative food categories and found that retailers generally secure competitive prices from private-label suppliers.

> Own-label food and drink manufacturers compete with each other to win and retain contracts from retailers. ... competition to win and retain supply contracts appears to be strong, switching does occur, and retailers generally appear to obtain competitive prices, assisted by the transparency of the costs of their own-label suppliers. (CMA 2023, para. 10)

This cost transparency is often facilitated by "Open Book Accounting", under which suppliers share their costs with retailers (para. 4.39). The CMA also reports that "very few of the manufacturers we spoke to make own-label as well as branded products" (CMA, 2023, para. 4.28).

Even where a branded manufacturer supplies private-label products, it faces competition from specialist private-label firms, and the CMA finds that "for most products, own-label margins are low and have generally fallen in the most recent financial year" (CMA, 2023, para. 11). Figure 1 in CMA (2023) shows that net margins average around 2% for private-label manufacturers, compared with about 14% for branded producers.[5]

**Planning policy and controlled land use** Two features of the planning system favored discounters. First, the Competition Commission (CC, 2000, 2008) found the system highly restrictive for retailers seeking to open large stores, defined as having sales areas above 1400 square meters. Traditional retailers primarily use this format, whereas discounters typically operate mid-sized stores, with sales areas between 280 and 1400 square meters, which face fewer planning restrictions. Second, before 2010, traditional retailers limited discounter expansion through land controls, such as restrictive covenants and exclusivity clauses. The Controlled Land Order (2010),

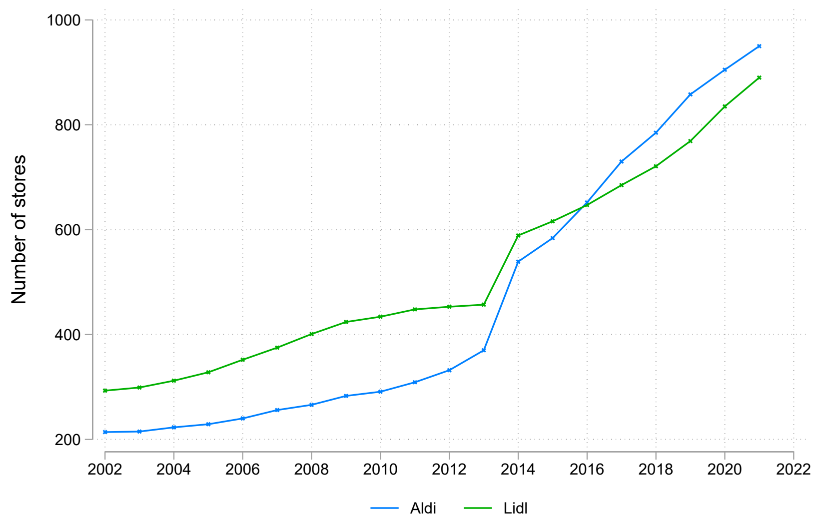
[5] Pasirayi and Richards (2023) provide evidence from emerging markets that branded-goods manufacturers can exert market power when they supply private-label goods, but distinguish these settings from Western economies like the UK, where private-label products have a large market share and a developed manufacturing base.

however, prohibited traditional retailers from using these practices, releasing many mid-sized sites well suited to discounters. The Order exempted discounters, allowing them to continue using such controls against rivals and thereby strengthening their incentives to expand store coverage.[6] See Appendix C for further discussion.

**Market trends** A major change in the UK grocery market over the first two decades of the 21$^{st}$ century was the growing popularity of discounters relative to traditional retailers, with important consequences for both downstream and upstream concentration.

A key element of this growth was expanding store coverage. Figure 2.1 shows the sharp rise in Aldi and Lidl stores, from 507 stores in 2002 (214 Aldi and 293 Lidl) to 757 in 2011, and 1840 in 2021. The acceleration after 2010 coincides with the Controlled Land Order. More than 90% of discounter stores opened between 2002 and 2021 were in postal sectors already served by an incumbent traditional retailer. Over the same period, traditional-retailer store counts grew by only 40%,[7] reflecting continued planning restrictions.

Figure 2.1: *Discounter store coverage growth over time*




*Notes: Authors' calculations using a store coverage dataset based on Geolytix Retail Point, Institute for Grocery Distribution, and Glenigan data.*

The expansion in store coverage was accompanied by a substantial rise in Aldi and Lidl's average market share across the 226 fast-moving consumer goods categories, from about 3% in 2002 to about 14% in 2021 (Figure 2.2, panels (a) and

[6]Schneier (2025a) shows that land-use restrictions of the type banned by the Order are also widespread in the US and have substantial effects on entry, reducing entry by firms subject to them and promoting entry by firms able to use them against others.

[7]This figure excludes stores some of these firms operate in the "convenience store" format, which have very low floorspace (less than 280 square meters).

(e)).[8] This growth in market share had important implications for retail concentration. Panel (b) plots the Herfindahl–Hirschman Indexes (HHIs), calculated using retailer revenue shares within each product category. Retail concentration rose between 2002 and 2006, coinciding with Morrisons' acquisition of Safeway and several smaller mergers, and remained relatively stable until 2011. It then declined substantially as discounters expanded. Panel (e) shows that average retail HHIs rose from 1551 in 2002 to 1851 in 2011, before falling to 1560 by 2021.

The rise of Aldi and Lidl also affected manufacturer concentration, calculated using manufacturer revenue shares within each category. For private-label goods, we treat the manufacturer as a distinct firm for each retailer, because, as discussed above, the private-label supply chains are effectively retailer-controlled and the identities of private-label manufacturers are often unobserved. Panels (c) and (d) of Figure 2.2 summarize the manufacturer-level patterns. Since private-label products account for a high share of discounter sales, discounter private-label shares follow a similar pattern as discounter retail shares, rising sharply after 2011. The mean share increases from around 4% in 2011 to over 12% in 2021. This contributes to a decline in manufacturer concentration, with the mean HHI falling from 1676 to 1437 between 2011 and 2021.

**Breakfast cereals**

In our analysis of market power and surplus, we focus on the market for multi-portion breakfast cereals. As shown in Figure 2.2, where breakfast cereal trends are highlighted in red, this category exhibits changes in retailer and manufacturer concentration that are broadly representative of other product categories.

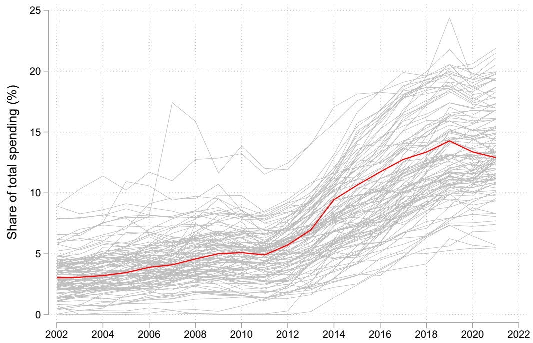
We exclude single-portion cereal products and cereal bars from the market definition. We also exclude products and manufacturers with very small market shares. Specifically, we require that a manufacturer accounts for at least 1% of breakfast cereal spending in any single year over 2002–2021; that a brand accounts for at least 0.1% of spending in any year; and that a brand–pack-size combination either accounts for at least 0.1% of spending in any year or is the most popular available pack size for that brand in any year. These conditions leave us with approximately 90% of total breakfast cereal spending.

We define products at the barcode level, capturing differences in brand and pack size. For instance, "Kellogg's Cornflakes 750g" is a specific product within the Kellogg's Cornflakes brand.

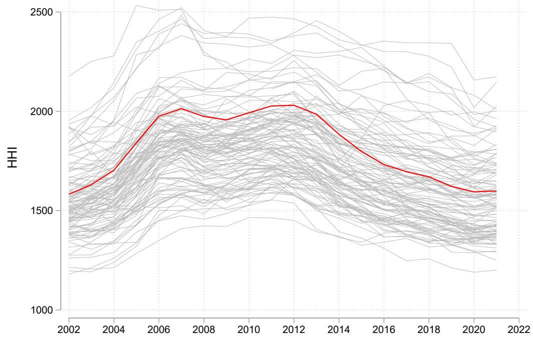
[8] These categories are based on a classification developed by Numerator and designed to reflect distinct consumer markets, with slight adjustments for consistency over time. We report them in Appendix R.

Figure 2.2: *Evolution of market concentration*

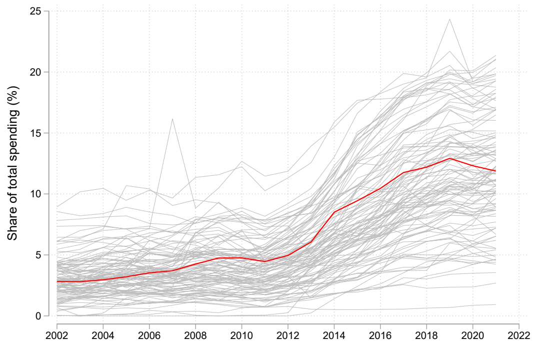
(a) Discounter retail market shares



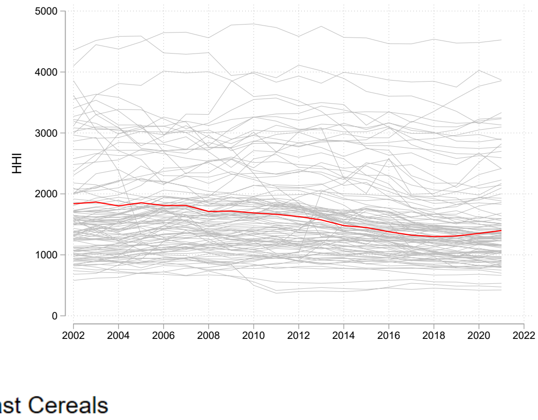

(b) Retail HHIs




(c) Discounter private-label market shares




(d) Manufacturer HHIs




(e) Across category mean shares and HHIs

| | Discounter share: | | HHI | |
|---|---|---|---|---|
| | Retail | Manufacturer | Retail | Manufacturer |
| 2002 | 3.23 | 3.04 | 1551 | 1636 |
| 2011 | 4.81 | 4.03 | 1851 | 1676 |
| 2021 | 14.05 | 12.44 | 1560 | 1437 |

*Notes: Authors' calculations using Numerator's Take Home Purchase Panel, 2002–2021. Panel (a) shows the share of spending made in discounters, and panel (c) shows the share of spending on discounter private-label products. Panels (b) and (d) show the evolution of retail and manufacturer HHIs. The red line corresponds to breakfast cereal; the gray lines represent all other product categories with average spending shares greater than 0.25% over 2002–2021 (they collectively account for 88% of fast-moving consumer goods spending). Panel (e) reports the mean discounter shares and HHIs across categories in 2002, 2011, and 2021, weighted by each category's mean revenue-share over 2002–21.*

**Market structure** Table 2.1 summarizes the structure of the breakfast cereal market. Panel A focuses on retailers, and panel B on manufacturers of branded products. Retailers stock both branded products and their own private-label products, which are exclusive to a single retailer.

Column (1) reports the average number of branded products sold by each retailer or produced by each manufacturer. Column (2) shows the average number of private-label products sold by each retailer, and column (3) shows the average number of vertical links per firm—for instance, in a typical year, Asda stocks products from all six branded manufacturers, and Kellogg's sells its products through six retailers. The remaining columns report average prices and firm-level spending shares.

Table 2.1: *Breakfast cereal retailers and manufacturers*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Number of: | | | Price (£/kg) | | Spending share (%) | | |
| | branded products | private-label products | vertical links | branded products | private-label products | Mean | 2002 | 2021 |
| **Panel A: Retailers** | | | | | | | | |
| *Traditional retailers* | | | | | | | | |
| Asda | 97 | 37 | 5 | 5.01 | 2.87 | 16.57 | 16.34 | 14.57 |
| Morrisons | 83 | 22 | 5 | 5.16 | 3.14 | 9.93 | 5.80 | 9.94 |
| Safeway | 70 | 9 | 5 | 5.03 | 3.17 | 6.05 | 8.55 | - |
| Sainsbury's | 92 | 31 | 5 | 5.20 | 3.09 | 15.60 | 16.29 | 14.02 |
| Tesco | 114 | 46 | 6 | 5.11 | 3.05 | 32.88 | 29.04 | 29.53 |
| *Discounters* | | | | | | | | |
| Aldi | 3 | 28 | 1 | 3.86 | 2.80 | 4.68 | 1.83 | 8.06 |
| Lidl | 4 | 23 | 1 | 3.95 | 2.50 | 3.09 | 0.98 | 5.30 |
| *Small retailers* | | | | | | | | |
| Other | 86 | - | 5 | 4.81 | - | 16.04 | 21.16 | 18.59 |
| **Panel B: Branded manufacturers** | | | | | | | | |
| Dorset | 5 | - | 4 | 4.35 | - | 0.52 | 0.16 | - |
| Halo | 4 | - | 5 | 4.78 | - | 1.58 | 3.14 | 0.20 |
| Kelloggs | 60 | - | 6 | 5.47 | - | 34.52 | 40.57 | 32.11 |
| Nestle | 39 | - | 6 | 4.96 | - | 17.60 | 21.01 | 13.65 |
| Jordans | 10 | - | 5 | 4.27 | - | 2.89 | 2.51 | 3.56 |
| Whitworths | 28 | - | 6 | 4.53 | - | 14.36 | 13.17 | 15.65 |

*Notes: Authors' calculations using Numerator's Take Home Purchase Panel, 2002–2021. Numbers describe the sample we use to estimate our model and cover 90% of total breakfast cereal spending (see text for details). Columns (1)–(6) are means across years firms were in operation. All firms were in operation over 2002–2021 except Safeway, which ceased operation as an independent firm in 2005, and Dorset, which was acquired by Jordans in 2012. Prices are deflated by the all-items CPI and expressed in 2021 £.*

On average, 76% of annual breakfast cereal spending takes place at traditional retailers. These retailers typically stock products produced by all six branded manufacturers and offer broad private-label ranges. The discounters' share of breakfast cereal retailing rose from under 3% in 2002 to 13% in 2021, mirroring their broader expansion. Over this period, Aldi and Lidl increased their links with branded manufacturers, from zero to two for Aldi and from one to three for Lidl. We aggregate smaller national retailers with relatively small market shares into a composite "Other" retailer.[9]

Each branded cereal product is produced by one of six manufacturers. The largest is Kellogg's, followed by Nestle, Whitworths, and three smaller manufacturers, Dorset, Halo, and Jordans. All manufacturers sell through several retailers, with the mean annual number ranging from four for Dorset to six for Kellogg's, Nestle, and Whitworths. The largest two manufacturers have seen a decline in their market share from 2002 to 2021, in part due to the rise in private-label sales.

It is typically not observable which manufacturers supply a given supermarket's private-label breakfast cereal products, although some public information exists on private-label supply. Two points emerge: some branded manufacturers supply private-label goods to UK supermarkets, while others do not; and multiple firms produce private-label cereals but not branded products (see Appendix D).

**Local effects of discounter entry** Using the store–location and household data, we present event studies around local discounter entry. We construct an area–year panel at the postal-sector level and define entry as the first year in which Aldi or Lidl opens within 5 km of the sector centroid. For each area–year, we compute a local cereal price index using cereal products available within 5 km and national market-share weights, and the share of breakfast cereal purchases made at discounters.

Figure 2.3 plots event-time coefficients from regressions including area and year fixed effects. Discounter entry is associated with a decline of about 0.06 log points in the local cereal price index and an increase of around 3 percentage points in the discounter share of cereal purchases, with little evidence of differential pre-trends. These patterns are consistent with the mechanisms in our structural analysis: discounter entry expands access to lower-priced options, attracts consumers, and increases competitive pressure on incumbent retailers.

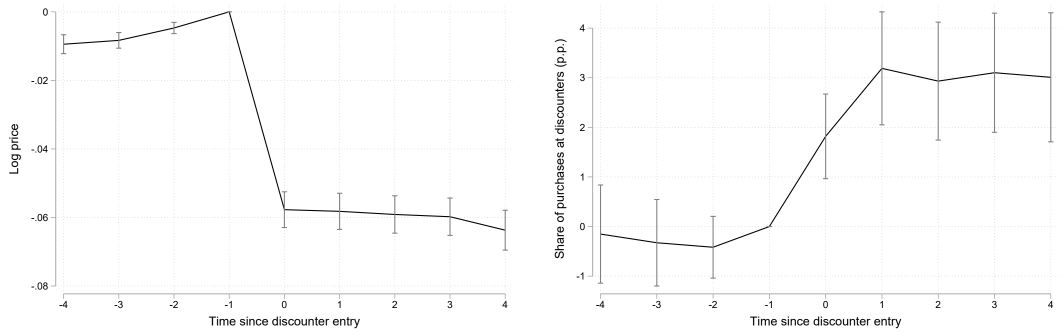
In summary, the growing market penetration of the discounters coincided with substantial declines in both retail and manufacturer concentration in the breakfast cereal market, a pattern typical of other fast-moving consumer goods categories. At the local level, discounter entry is associated with lower effective cereal prices and a higher share of cereal purchases made at discounters. To evaluate how the rise

[9] These include retailers focused on convenience store formats (Co-op, Kwik Save, Somerfield), high-quality products (Waitrose and Marks & Spencer), and internet-only shopping (Ocado). We exclude minor outlets, including independent stores, which collectively account for 6% of breakfast cereal spending.

of discounters affected market power and economic surplus, we turn to a structural model of demand and supply.

Figure 2.3: *Local effects of discounter entry*

(a) Local breakfast cereal prices (b) Local discounter breakfast cereal share




*Notes: Authors' calculations using Numerator's Take Home Purchase Panel, 2002–2021. The figure plots event–study coefficients around the year in which Aldi or Lidl opens within 5 km of a postal-sector centroid; event time* $-1$ *is the omitted category. The sample comprises* 39,278 *area–year observations for* 2,140 *postal sectors, of which* 653 *experience discounter entry within 5 km. The local cereal price index in panel (a) is a weighted average price of breakfast cereal products available within 5 km, using national market shares as weights. Panel (b) shows the share of breakfast cereal purchases in that area–year made at discounters. All regressions include area and year fixed effects, with standard errors clustered by area; vertical lines are 95% confidence intervals.*

# 3 A Model of the Breakfast Cereal Market

## 3.1 Overview

We develop a model of pricing in the breakfast cereal market that allows us to recover retail and manufacturer markups and simulate counterfactual market outcomes absent the rise of discounters. The supply side captures horizontal competition among retailers and manufacturers, as well as vertical bargaining between retailers and branded-good manufacturers. On the demand side, households choose both a product and a retailer. The timing is as follows: in each year-quarter market $t$, manufacturers and retailers negotiate wholesale markups, and, simultaneously, retailers set retail prices. On each household-week choice occasion $i$ in market $t$, the household selects either a product–retailer pair or the outside good.

## 3.2 Supply

In this subsection, we condition on a given market and suppress the market subscript $t$. Consumer choice options are indexed by $j$, where $j = [k(j), r(j)]$ denotes a combination of product $k$ and retailer $r$. The manufacturer of product $j$ is $f(j)$.

Let $q_j(\boldsymbol{p}, \mathcal{J})$ denote market demand (measured in kilograms) for option $j$, given the $|\mathcal{J}| \times 1$ vector of retail prices $\boldsymbol{p}$ and choice set $\mathcal{J}$.

Define the retailer and manufacturer additive markups (or margins) as $\Gamma_j^R = p_j - w_j - c_j^R$ and $\Gamma_j^F = w_j - c_j^F$, respectively, where $w_j$ is the wholesale price and $(c_j^R, c_j^F)$ denote retailer and manufacturer marginal costs. At retail prices $\boldsymbol{p}$ and manufacturer margins $\boldsymbol{\Gamma}^F$, the profits of retailer $r$ and manufacturer $f$ are

$$\pi_r(\boldsymbol{p}, \boldsymbol{\Gamma}^F) = \textstyle\sum_{j \in \mathcal{J}_r} (p_j - \Gamma_j^F - c_j) q_j(\boldsymbol{p}, \mathcal{J}), \text{ and} \tag{3.1}$$

$$\pi_f(\boldsymbol{p}, \boldsymbol{\Gamma}^F) = \textstyle\sum_{j \in \mathcal{J}_f} \Gamma_j^F q_j(\boldsymbol{p}, \mathcal{J}), \tag{3.2}$$

respectively, where $\mathcal{J}_r$ denotes the set of options sold by retailer $r$, $\mathcal{J}_f$ is the set of options supplied by manufacturer $f$ (i.e., product–retailer pairs for products it produces), and $c_j = c_j^R + c_j^F$ is total marginal cost.

Retailer $r$ sets prices to maximize profits in equation (3.1) treating manufacturer markups and rival retailers' prices as given. The first-order conditions for retail prices are

$$\boldsymbol{\Gamma}^R(\boldsymbol{p}) = \boldsymbol{\Delta}(\boldsymbol{p})^{-1} \boldsymbol{q}(\boldsymbol{p}, \mathcal{J}), \tag{3.3}$$

where $\boldsymbol{\Delta}$ is a $|\mathcal{J}| \times |\mathcal{J}|$ matrix of (negative) demand own- and cross-price derivatives, with off-diagonal elements equal to zero for pairs of options not sold by the same retailer.

We assume static Bertrand–Nash pricing by retailers. The UK's competition authorities conducted several in-depth investigations into the supermarket industry over our sample period, including two market investigations (CC, 2000, 2008) and two merger inquiries (CC, 2003; CMA, 2019). None of these investigations concluded that the grocery retailers were engaged in market-wide coordination, providing support for our Bertrand–Nash pricing assumption.[10]

Manufacturer markups are determined through bilateral negotiations between the retailer–manufacturer pairs $n = (r, f) \in \mathcal{N}$, where $\mathcal{N}$ is the set of trading pairs, treating retail prices as given.[11] The disagreement point for pair $n$ is that

[10]For example, CC (2008, para. 8.40) conclude that "we did not find that grocery retailers were engaged in tacit coordination." More recently, CMA (2019, para. 9.36) state that "overall, we considered the evidence to be more consistent with competition and we therefore find that there is no pre-existing coordination in the markets for in-store groceries." During our sample period, we are only aware of investigations involving collusion in two grocery categories: dairy (OFT case number CE/3094-03, 2011) and cigarettes (OFT case number CE/2596-03, 2010).

[11]The simultaneous approach to retail prices and manufacturer markups is used in Draganska et al. (2010), Ho and Lee (2017), Crawford et al. (2018) and Noton and Elberg (2018). An alternative assumption, with greater computational cost, is that wholesale and retail prices are determined sequentially (see Bonnet et al., 2025); to make the sequential model computationally feasible it is necessary to focus on a small number of options. See Lee et al. (2021a) for a discussion.

retailer $r$ no longer stocks manufacturer $f$'s products, implying quantity gains from trade for each $j \in \mathcal{J}$ given by $\Delta_n q_j(\boldsymbol{p}, \mathcal{J}) = q_j(\boldsymbol{p}, \mathcal{J}) - q_j(\boldsymbol{p}, \mathcal{J} \setminus \mathcal{J}_n)$ where $\mathcal{J}_n$ is the set of options covered in negotiation $n$.[12] Holding retail prices $\boldsymbol{p}$ fixed, a change in wholesale markups redistributes but does not change the total gain from trade. Consequently, the parties in negotiation $n$ have a single objective (splitting the surplus) and require only a single negotiating instrument. We assume they negotiate over the per-unit manufacturer markup $\Gamma_n^F$ which is common across all $j \in \mathcal{J}_n$.[13]

The Nash Bargaining problem for pair $n$ is

$$\max_{\Gamma_n^F \geq 0} \left[ \sum_{j' \in \mathcal{J}_r} (p_{j'} - \Gamma_{n(j')}^F - c_{j'}) \Delta_n q_{j'}(\boldsymbol{p}, \mathcal{J}) \right]^{(1-b_n)} \left[ \sum_{n' \in \mathcal{N}_f} \sum_{j' \in \mathcal{J}_{n'}} \Gamma_{j'}^F \Delta_n q_{j'}(\boldsymbol{p}, \mathcal{J}) \right]^{b_n} \quad (3.4)$$

where $\mathcal{N}_f$ denotes the set of bilateral negotiations involving manufacturer $f$ and $b_n$ and $(1 - b_n)$ represent the bargaining power of the manufacturer and retailer respectively. The solution to equation (3.4) is

$$\rho_n \textstyle\sum_{j' \in \mathcal{J}_r} (p_{j'} - \Gamma_{n(j')}^F - c_{j'}) \Delta_n q_{j'}(\boldsymbol{p}, \mathcal{J}) = \sum_{n' \in \mathcal{N}_f} \Gamma_{n'}^F \sum_{j' \in \mathcal{J}_{n'}} \Delta_n q_{j'}(\boldsymbol{p}, \mathcal{J}), \quad (3.5)$$

where $\rho_n = b_n/(1 - b_n)$ is the manufacturer's relative bargaining power. This condition equates the two parties' gains from trade, weighted by bargaining power. It implies that a manufacturer's markups are increasing in its *leverage*: the extent to which the gain from trade is high for the retailer relative to the manufacturer. For private-label products, we set $b_n = 0$, which implies $\Gamma_n^F = 0$, so retailers set prices optimizing against marginal cost, $c_j$. We use the Nash-in-Nash solution concept: in equilibrium the vector $\boldsymbol{\Gamma}^F$ solves the system of Nash bargaining problems defined in equation (3.4) for all $n \in \mathcal{N}$.[14] To express the bargaining problem compactly, let

[12] An alternative assumption for the disagreement point is that the retailer no longer stocks product $j$, while continuing to stock all other products sold by the manufacturer. Since disagreement points are out-of-equilibrium behavior there is no direct evidence for this assumption. However, we note that CC and CMA investigations detail cases where retailers threaten to delist a range of a manufacturer's products wider than just a single product. See also Bonnet et al. (2025), who find their results are robust to alternative disagreement point specifications.

[13] As these are per-unit, the manufacturer's per-pack markups for $j \in \mathcal{J}_n$ are proportional to pack quantity, $(\text{kg})_j$.

[14] We use the standard Nash-in-Nash solution in which each bargaining problem is based on gains from trade relative to the disagreement point of not trading. An alternative specification would include an "outside option" in the sense of Binmore et al. (1989), where the retailer can threaten to replace a supplier with an alternative supplier that is not one of its trading partners in equilibrium; see, for example, Ho and Lee (2019). For traditional retailers, this alternative specification is unlikely to be important because they typically stock products from the full set of major branded manufacturers. For discounters, outside replacement options may be more relevant, since they stock fewer branded products and could in principle replace one branded supplier with another. We do not model such replacement options because only a small set

$\boldsymbol{A}(\boldsymbol{p})$ be the $|\mathcal{N}| \times |\mathcal{J}|$ matrix where row $n$ gives quantity gains from trade for all options sold by retailer $r(n)$ in the negotiation (with zeroes for other options), i.e., the element in row $n$ and column $j$ is

$$A_{nj}(\boldsymbol{p}) = 1[j \in \mathcal{J}_{r(n)}] \times \Delta_n q_j(\boldsymbol{p}, \mathcal{J}).$$

Let $\boldsymbol{B}(\boldsymbol{p})$ denote the $|\mathcal{N}| \times |\mathcal{N}|$ matrix giving the manufacturer's quantity gain for products in the column negotiation if the row negotiation $n$ is agreed, i.e., the element in row $n$ and column $n'$ is

$$B_{nn'}(\boldsymbol{p}) = 1[f(n) = f(n')] \times \textstyle\sum_{j' \in \mathcal{J}_{n'}} \Delta_n q_{j'}(\boldsymbol{p}, \mathcal{J}).$$

The system of $|\mathcal{N}|$ Nash bargaining solutions (3.5) is

$$\boldsymbol{\Gamma}^F = \boldsymbol{\rho}\boldsymbol{B}(\boldsymbol{p})^{-1}\boldsymbol{A}(\boldsymbol{p})(\boldsymbol{p} - \boldsymbol{\Gamma}^F - \boldsymbol{c}), \tag{3.6}$$

where $\boldsymbol{\rho}$ is a diagonal matrix of $\rho_n$ terms. Equilibrium retail prices and manufacturer markups are obtained when (i) the $|\mathcal{J}|$ retail pricing first-order conditions in (3.3) and (ii) the $|\mathcal{N}|$ bargaining solutions in (3.6) are jointly satisfied.

We assume that private-label manufacturers have zero bargaining power. This is motivated by the fact that, for any private-label product, a retailer can switch producers without the customer noticing, which is not the case for a branded good. Assuming there are multiple private-label producers, with identical marginal costs, the Nash Bargaining negotiation with a private-label supplier can be viewed as constrained by an "outside option" (in the sense of Binmore et al. (1989)) of sourcing the product from an alternative private-label supplier at marginal cost. This delivers the same outcome as setting $b = 0$ for private-label manufacturers. This logic also applies to branded manufacturers when they supply private-label goods. Hence, their private-label lines are in a different bargaining position from their branded goods. As a result, these private-label contracts do not increase the manufacturer's bargaining leverage vis-à-vis the retailer and should not be included when calculating the disagreement point in negotiations over branded goods. In practice it would also be difficult to do so, since we do not observe which manufacturers produce each retailer's private-label cereals.

Retailers may take cross-category effects (i.e., substitution to non-cereals) into account when pricing breakfast cereals (Thomassen et al., 2017). Our model accommodates this (see Appendix E). Under this interpretation of the model, breakfast cereal retail markups equal the difference between price and the retailer's marginal

of discounter negotiations involve branded manufacturers, and branded products sold through discounters account for a small share of the overall breakfast cereal market.

cost, net of the marginal benefit—through increased profits in other categories—of generating an additional unit of breakfast cereal demand. We return to this point when discussing our counterfactual analysis in Section 6. The simultaneous timing assumption in our model facilitates the incorporation of cross-category effects. This is because it does not require us to keep track of the impact of changes in wholesale prices (or the effect of bargaining breakdowns) on prices in other categories.

Some branded manufacturers in the breakfast cereal category sell products in other product categories to supermarkets. We assume that these manufacturers do not link negotiations across categories.

**Alternative supply models** When $b_n > 0$, the bargaining model implies double marginalization and negotiations are not bilaterally efficient. There is empirical evidence of double marginalization—for example, Luco and Marshall (2020) find support for it in the US branded soft drink market, and Noton and Elberg (2018) document wholesale prices above marginal costs in the Chilean branded retail coffee market—but vertical contracts can also be designed to avoid it. We therefore also present results under two bilaterally efficient benchmarks: retailer pricing and manufacturer pricing.

Under *retailer pricing*, manufacturer margins are zero ($\Gamma_j^F = 0$ for all $j$), and total margins are determined by the retailers' pricing condition (3.3). This case is nested in our model when $b_n = 0$ for all $n$. It is also consistent with a two-stage model of negotiated two-part tariffs in which manufacturers and retailers simultaneously negotiate wholesale prices $w_j$ and transfers, and retailers subsequently set retail prices. Wholesale prices are set equal to the manufacturer marginal cost to ensure that bilateral efficiency, while transfers determines the division of surplus. See Rey and Verge (2019) and Appendix F. Although our model assumes simultaneous timing for wholesale and retail prices, it is thus consistent with a sequential model of two-part tariffs in the special case when $b_n = 0$. For $b_n > 0$, however, simultaneous timing does not readily accommodate two-part tariffs, as noted in Panhans, 2024.

Under *manufacturer pricing*, manufacturers set retail prices directly. Each manufacturer simultaneously sets the retail price of its options to maximize total variable profits, optimizing against marginal costs, $c_j$. Manufacturers may share some of this rent with retailers through fixed transfers, which we do not model. This benchmark is not nested within our bargaining model: $b_n = 1$ does not correspond to manufacturer pricing.[15]

## 3.3 Demand

We now reintroduce market subscripts $t$. Let $i$ index a household-week, let $h = h(i)$ denote the household and let $t = t(i)$ denote the (year-quarter) market. In each household-week, the household shops for groceries and chooses among the set of available breakfast cereal options, $\mathcal{J}_t$, and the outside option, $j = 0$, of shopping without purchasing breakfast cereal.

The utility that household-week $i$ in market $t$ derives from option $j \in \mathcal{J}_t$, with per-pack price $\tilde{p}_{jt}$,[16] option characteristics $\mathbf{x}_j = [x_j^l]_{l\in\mathcal{L}}$, and distance $\text{dist}_{ir}$ to the nearest store of retailer $r = r(j)$, is

$$U_{ij} = \underbrace{\boldsymbol{\theta}_2 \mathbf{x}_{jt} + \Delta\xi_{jt}}_{\delta_{jt}} + \underbrace{\sigma^\phi \nu_i^\phi + \textstyle\sum_{l\in\mathcal{L}} \sigma^l \nu_h^l x_j^l - \alpha_i \tilde{p}_{jt} - (\tau_0 + \tau_1 u_h) \log \text{dist}_{ir} + \boldsymbol{\lambda}' \mathbf{r}_{hj}}_{\mu_{ij}(\boldsymbol{\theta}_1)} + \epsilon_{ij} \tag{3.7}$$

where $\Delta\xi_{jt}$ is an option–market level unobservable, $u_h$ is an indicator for whether the household resides in an urban area, and $\mathbf{r}_{hj}$ collects interactions between option characteristics and household demographics.[17] The price coefficient is

$$\alpha_i = \exp(\bar{\alpha} + \alpha^y y_{ht} + \sigma^\alpha \nu_h^\alpha).$$

The taste shocks $\boldsymbol{\nu}_h = ([\nu_h^l]_{l\in\mathcal{L}}, \nu_i^\phi, \nu_h^\alpha)$ are independent draws from a standard normal distribution, $\boldsymbol{\sigma} = ([\sigma^l]_{l\in\mathcal{L}}, \sigma^\phi, \sigma^\alpha)$ are scaling terms, and $y_{ht}$ is annual equivalized household income.[18] The parameters of the model are $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)$ where $\boldsymbol{\theta}_1 = (\boldsymbol{\sigma}, \bar{\alpha}, \alpha^y, \tau_0, \tau_1, \boldsymbol{\lambda})$ denotes parameters in the household-week specific term $\mu_{ij}$ and $\boldsymbol{\theta}_2$ denotes parameters in mean utility $\delta_{jt}$.

For all inside goods, utility includes both a household-level shock ($\nu_h^1$) capturing persistent tastes and a household-week shock ($\nu_i^\phi$) capturing short-run variation in whether the household wishes to buy breakfast cereal.

[15] Note that, when $b_n = 1$ for all $n$, manufacturers make take-it-or-leave-it offers, but no equilibrium exists because retailers have an incentive to deviate from zero retail markups whenever demand is positive (see Lee et al., 2021b).

[16] The pack price $\tilde{p}_{jt} \equiv p_{jt} \times (\text{kg})_j$ where $p_{jt}$ is the price per kilogram as defined in the previous subsection and $(\text{kg})_j$ is the weight of $j$ in kilograms.

[17] We use official data to construct the urban indicator. See Appendix A.

[18] Equivalized household income is a per-capita measure given by dividing income by the number of adult-equivalent persons in the household.

We interpret the outside good as grocery shopping without purchasing breakfast cereal. The outside good is a composite option encompassing the same set of retailers as the inside options. We normalize the mean utility of the outside option so that $U_{i0} = \epsilon_{i0}$, implying that $\delta_{jt}$ is interpreted as the mean utility difference between option $j$ and the outside good.

The mean utility $\delta_{jt}$ also captures non-cereal factors that influence the choice of retailer $r$ for cereal, such as utility from other services or product categories co-purchased with cereal. In Section 6, we outline the assumptions under which it is possible to separately identify changes over time in cereal-specific and non-cereal components of mean utility for each retailer.

We assume the idiosyncratic term $\epsilon_{ij}$ follows a Type I Extreme Value distribution. The choice probability for household-week $i$ in market $t$ for option $j \in \mathcal{J}_t$ is

$$s_{ij} = s_j(\boldsymbol{\delta}_t, \boldsymbol{\mu}_i(\boldsymbol{\theta}_1)) = \frac{\exp(\delta_{jt} + \mu_{ij}(\boldsymbol{\theta}_1))}{1 + \sum_{j' \in \mathcal{J}_t} \exp(\delta_{j't} + \mu_{ij'}(\boldsymbol{\theta}_1))}.$$

Integrating over the distribution $F_t(\boldsymbol{\mu}|\boldsymbol{\theta}_1)$ gives the market share: $s_{jt} = s_j(\boldsymbol{\delta}_t, \boldsymbol{\theta}_1) = \int_{\mu} s_j(\boldsymbol{\delta}_t, \boldsymbol{\mu}) \mathrm{d}F_t(\boldsymbol{\mu}|\boldsymbol{\theta}_1)$. We approximate the integral by simulation, using the household data as described in Section 4.1 (see Appendix H.1). To obtain demand $q_{jt}$ in units of weight, as in Section 3.2, we multiply the market share of $j$ by its weight: $q_{jt} = M \times (\mathrm{kg})_j \times s_{jt}$, where $M$ is the market size in terms of number of consumers.[19]

# 4 Identification and Estimation

We estimate demand in the first stage, without imposing any supply-side restrictions. In the second stage, we use the estimated demand system to recover the supply-side parameters. We discuss our identification strategy for each stage in turn.

## 4.1 Demand Parameters

We estimate demand parameters using a method-of-moments estimator that combines market-level moments with household-level micro moments. The estimator matches market shares, while exploiting the panel structure of the data to identify

[19] We define the potential market as household-weeks with a grocery shopping trip. In each year-quarter, market size equals the number of households multiplied by ten, the average number of weeks per quarter in which a household undertakes a grocery shopping trip in our sample. Since $M$ enters demand and its derivatives multiplicatively, and marginal costs are constant in quantity, it cancels from the markup equations and can be normalized to one for this purpose.

preference heterogeneity. This delivers the market-level substitution patterns and elasticities required for the supply-side pricing and bargaining model.

**Market-level moments** We assume that product attributes and assortment decisions are determined prior to the realization of demand shocks, but allow prices to be correlated with the unobserved component.[20] We follow Berry (1994) and Berry et al. (1995). Given a parameter vector $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)$, we solve for the mean utilities $\boldsymbol{\delta}(\boldsymbol{\theta}_1)$ by equating observed market shares, $S_{jt}$, with model-predicted shares: $S_{jt} = s_j(\boldsymbol{\delta}_t(\boldsymbol{\theta}_1), \boldsymbol{\theta}_1)$ for all $(j,t)$. We then recover the structural errors as $\Delta\xi_{jt}(\boldsymbol{\theta}) = \delta_{jt}(\boldsymbol{\theta}_1) - \boldsymbol{x}_{jt}\boldsymbol{\theta}_2$. We assume that the unobserved utility component satisfies $\mathbb{E}(\Delta\xi_{jt}(\boldsymbol{\theta})|\mathbf{z}_{jt}) = 0$. This yields the market-level moments $\mathbf{g}_A(\boldsymbol{\theta}) = |N_A|^{-1}\sum_{jt}\mathbf{z}'_{jt}\Delta\xi_{jt}(\boldsymbol{\theta})$, where $|N_A|$ is the number of option-market observations. The instrument vector $\mathbf{z}_{jt}$ includes observed characteristics $\boldsymbol{x}_{jt}$ (indicators for year-quarters, retailers, and products; used as their own instruments), eight cost-shifter instruments,[21] and a set of BLP-style instruments constructed from observable characteristics of rival options to capture the intensity of competition (see Berry et al. (1995), Gandhi and Houde (2019), and Appendix G for details). The distance variable does not enter $\mathbf{z}_{jt}$ and therefore plays no role in identifying $\boldsymbol{\theta}_2$. Instead, the coefficient on distance is identified from household-level micro moments.

**Micro moments** The micro moment conditions are particularly informative about taste heterogeneity, governed by $\boldsymbol{\theta}_1$. For micro moment condition $m$ and household $h$, let $Y_h^m$ denote the observed moment and $y_h^m(\boldsymbol{\theta})$ the corresponding model prediction. The population moment condition is

$$\mathbb{E}(Y_h^m) - \mathbb{E}(y_h^m(\boldsymbol{\theta})) = 0, \quad \forall m$$

where expectations are taken over households.

We compute observed micro moments using the full consumer dataset. As evaluating predicted moments on the full sample is computationally costly, we follow O'Connell et al. (2025) and use the full dataset for the observed moments and a subsample for predicted moments. Let $N_H$ denote the full set of households. We draw $N_H^*$, a random subset of 2000 households, and, for each household, draw three household-weeks from different markets, yielding 6000 household-weeks. For

[20] Observed breakfast cereal attributes are fixed over time, so the first assumption is automatically satisfied. We assume assortment decisions are made prior to pricing decisions. For recent work that explicitly addresses demand estimation with endogenous product assortment, see Aguirregabiria et al. (2023).

[21] These are the eight input prices in $\mathbf{x}^{\mathbf{s}}_{\mathbf{jt}}$ which are given in Table 5.1(c), (i.e., maize price × corn base, through to sugar price).

each sampled household-week, we observe demographics and location, and simulate draws of unobserved taste shocks entering $\boldsymbol{\mu}_i$.

The sample analog of the $m$th micro moment is

$$\mathrm{g}_M^m(\boldsymbol{\theta}) = \frac{1}{|N_H|} \sum_{h \in N_H} Y_h^m - \frac{1}{|N_H^*|} \sum_{h \in N_H^*} y_h^m(\boldsymbol{\theta}). \tag{4.1}$$

We use three sets of micro moments; Appendix G gives details.

The first set exploits persistence in household choices across choice occasions to identify the spread parameters of random coefficients. These moments measure whether a household persistently chooses options with high or low values of characteristics. We construct one moment for each characteristic with persistent taste heterogeneity: price, the inside-good indicator, retailer, brand, and cereal base.[22] These panel moments use repeated household choices to identify preference heterogeneity, playing a role similar in spirit to second-choice data when such data are unavailable (Thomassen and Zhang, 2026).

The second set matches the relationship between choices and household characteristics. These moments include the interaction between option price and household income; distance between the household and the retailer, separately for households in major urban areas and other households; the interaction between the inside-good indicator and urban residence; and the interaction between a chocolate-cereal indicator and the presence of children in the household.

The coefficient on distance is identified from variation in households' distances to stores and their retailer and product choices. We treat distances as predetermined with respect to idiosyncratic taste shocks, conditional on the market, retailer, and the realized store network. In particular, we assume that variation in distance to the nearest discounter is not driven by cereal-specific demand shocks at the household level. Supporting evidence is provided in Section 2, which shows no pre-trend in local discounter cereal purchases prior to nearby discounter entry.

The third set of micro moments is informative about the household-week-specific shock to the utility of the inside good, governed by $\sigma^\phi$. These moments relate the probability of choosing any breakfast cereal to household-specific measures of the local choice set. We use four such measures: the number of available options within 2 kilometers; an indicator for whether this number is positive; the distance to the 50th nearest option; and the distance to the 200th nearest option. As with the distance moments, we treat these choice-set measures as predetermined with

[22]For retailers, brands, and cereal bases, we constrain the spread parameters $\sigma^l$ to be identical within each group. We aggregate separately over retailers, brands, and cereal bases to construct a single moment for each.

respect to idiosyncratic taste shocks, conditional on the market, retailer, and the realized store network.

**Estimation** We estimate utility parameters by solving $\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \mathbf{g}(\boldsymbol{\theta})'\mathbf{W}\mathbf{g}(\boldsymbol{\theta})$ where $\mathbf{g}(\boldsymbol{\theta}) = [\mathbf{g}_A(\boldsymbol{\theta}), \mathbf{g}_M(\boldsymbol{\theta})]$ is the vector of stacked moment conditions: $\mathbf{g}_A(\boldsymbol{\theta})$ denotes the market-level moments and $\mathbf{g}_M(\boldsymbol{\theta}) = [\mathbf{g}_M^m(\boldsymbol{\theta})]_{\forall m}$ collects the micro moments. The weighting matrix $\mathbf{W}$ is block diagonal, $\boldsymbol{W} = \text{diag}(\boldsymbol{W}_A, \boldsymbol{W}_M)$. For the market-level moments, $\boldsymbol{W}_A$ is the standard 2SLS weighting matrix. For the micro moments, $\boldsymbol{W}_M$ is diagonal, with each entry equal to the inverse squared observed component of the corresponding moment. This weighting normalizes the micro moments to yield unit-free percentage deviation between predicted and observed contributions (see Low and Meghir, 2017). See Appendix H for further details of the estimator and Appendix I for details on how we compute standard errors.

## 4.2 Supply-Side Parameters

The supply-side parameters consist of cost and bargaining parameters. To identify these, we combine the model's equilibrium pricing conditions (3.3) and (3.6) to obtain

$$\boldsymbol{\Gamma}_t^F = \boldsymbol{\rho}\boldsymbol{\ell}_t \quad \text{where} \quad \boldsymbol{\ell}_t \equiv \boldsymbol{B}_t^{-1}\boldsymbol{A}_t\boldsymbol{\Gamma}_t^R(\boldsymbol{p}_t). \tag{4.2}$$

The leverage term $\boldsymbol{\ell}_t$ is known given the estimated demand system and observed prices. It depends on retailer margins, $\boldsymbol{\Gamma}_t^R$, which we recover using equation (3.3).

We specify total marginal cost for option $j$ in market $t$ as

$$c_{jt} = \boldsymbol{\gamma}\boldsymbol{x}_{jt}^s + \omega_{jt}, \tag{4.3}$$

where $\boldsymbol{\gamma}$ are cost parameters, $\boldsymbol{x}_{jt}^s$ is a vector of observed cost shifters, and $\omega_{jt}$ is an unobserved cost shock. The cost-shifter vector $\boldsymbol{x}_{jt}^s$ includes eight cereal input prices, quarter effects, year effects interacted with retailer dummies, year effects interacted with indicators for whether the product is private label or branded, and product effects. The inclusion of these controls allows for broad cost changes at the retailer–year level, as well as common time variation that differs between branded and private-label products, so that $\omega_{jt}$ captures the residual option-market cost shock after conditioning on these components.

By definition $\Gamma_{jt}^R + \Gamma_{f(j)t}^F = p_{jt} - c_{jt}$, so we can write

$$[p_{jt} - \Gamma_{jt}^R] = \rho_{n(j)}\ell_{n(j)t} + \boldsymbol{\gamma}\boldsymbol{x}_{jt}^s + \omega_{jt}, \tag{4.4}$$

where $\ell_{n(j)t}$ is the element of $\boldsymbol{\ell}_t$ corresponding to bargaining pair $n(j)$. We allow the coefficient on leverage to vary by retailer type. In addition, we set this coefficient to zero for private-label products, consistent with pricing under a vertically integrated structure. Specifically, $\rho_{n(j)} = \chi_j \times (\rho_0 + \rho_1 \chi_n)$, where $\chi_j$ is an indicator for whether option $j$ is branded (as opposed to private-label), and $\chi_n$ is an indicator for whether bargaining pair $n$ involves a traditional (non-discounter) retailer.

We identify the parameters $(\boldsymbol{\rho}, \boldsymbol{\gamma})$ from the condition that the residual cost shock is mean independent of supply-side instruments $\mathbf{z}^s_{jt}$, conditional on the controls included in $\boldsymbol{x}^s_{jt}$, i.e., $\mathbb{E}[\omega_{jt}|\mathbf{z}^s_{jt}, \boldsymbol{x}^s_{jt}] = 0$, where $\mathbf{z}^s_{jt}$ collects the excluded portfolio instruments. These instruments are required because the leverage term depends on retail markups. For a bargaining pair $(r, f)$, let the negotiated set be the set of product–retailer options sold by retailer $r$ and supplied by manufacturer $f$, i.e., the options whose terms are determined in that bilateral negotiation. Our instruments measure the size of this set relative to each party's overall portfolio. Specifically, we use: the number of options offered by the retailer and by the manufacturer; the number of options in the negotiated set; the share of the retailer's portfolio accounted for by the negotiated set; the share of the manufacturer's portfolio accounted for by this set; and the share of the manufacturer's options outside the negotiated set that belong to brands represented within the negotiated set. We also interact these variables with an indicator for traditional retailers. Because $\boldsymbol{x}^s_{jt}$ includes retailer–year effects and year effects interacted with whether the product is private label or branded, identification of the leverage coefficient relies on variation in these portfolio variables after netting out common retailer–year cost components and common time variation by product ownership type. The maintained exclusion restriction is that the portfolio instruments are orthogonal to the remaining option–market cost shock.[23]

In principle, the parameter $\rho$ is identified for private-label goods, given an observed leverage variable for these products and a suitable instrument. In our data, however, we cannot estimate $\rho$ for private-label goods because we do not observe which manufacturer produces each product and therefore cannot construct the corresponding leverage term. We instead set the private-label bargaining weight to

[23]When we allow for cross-category pricing effects (see Appendix E), equation (4.4) identifies an *effective* marginal cost, equal to technological marginal cost net of the marginal benefit—through increased profits in other categories—of generating an additional unit of breakfast cereal demand. Retailer–year effects absorb any retailer-time component of this term, while the private-label/branded year effects absorb common time variation by product ownership type. The maintained exclusion restriction is therefore that the portfolio instruments are orthogonal to its remaining option-level component. Economically, this requires that, conditional on these controls, the portfolio instruments are not systematically related to option-level heterogeneity in cross-category diversion incentives.

zero, an assumption justified both by the theoretical arguments in Section 3.2 and by the evidence from the UK's competition authority discussed in Section 2.

# 5 Model Estimates

## 5.1 Parameters

Table 5.1(a) reports estimates of the demand parameters. Households prefer geographically closer retailers, and the disutility of distance is 14% higher, on average, for those residing in major urban areas. Households with children have stronger preferences for breakfast cereals containing chocolate. We allow for unobserved preference heterogeneity in price sensitivity and tastes for breakfast cereal (i.e., inside options), brand, retailer, and cereal base. For each of these, the spread parameter is large and statistically significant. We do not report mean taste parameters, as these are absorbed by the product and retailer effects. Additionally, we allow for a household-time-varying shock to preferences for breakfast cereals, which also has a substantial spread parameter ($\sigma^{\phi}$).[24]

We estimate these parameters in part by targeting a set of micro moments. Table 5.1(b) reports the observed moments alongside their model-predicted counterparts. The model closely matches the persistence moments, which primarily inform the spread parameters governing preference heterogeneity; the demographic moments, which capture cross-sectional covariances; and the inside-option moments, which use local choice-set measures to help identify the household-time-varying inside-option shock. The model also reproduces the relationship between purchase probabilities and travel distance to the nearest store selling an option, indicating that it captures spatial variation in household choices (see Appendix J.2).

We report supply estimates using equation (4.4) in Table 5.1(c). Column (1) presents OLS results, while column (2) reports our main estimates, which use a set of retailer and manufacturer portfolio variables to instrument for leverage. In our main specification, the estimated bargaining parameter—computed from the leverage coefficient as $\hat{b} = \hat{\rho}/(1 + \hat{\rho})$—is 0.59 for discounters and 0.61 for larger retailers, with the difference between the two statistically insignificant. The coefficients on the cost shifters are generally consistent with input prices feeding into marginal costs. In particular, input prices interacted with closely related cereal bases, such as maize for corn-based products, wheat for wheat- and bran-based products, and

[24] As a diagnostic for time variation in price sensitivity, we also estimated a specification allowing the baseline price-sensitivity parameter to shift before and after 2010; the shift is economically small and statistically insignificant, and the implied elasticities are essentially unchanged.

Table 5.1: *Parameter estimates and model fit*

(a) Demand parameters

| | Estimate | Standard error |
|---|---|---|
| Price | | |
| Baseline ($\bar{\alpha}$) | 1.63 | 0.10 |
| $\times$ income ($\alpha^y$) | -0.72 | 0.22 |
| Spread ($\sigma^\alpha$) | 0.32 | 0.03 |
| Inside option | | |
| $h$ spread ($\sigma^1$) | 6.92 | 1.50 |
| $i$ spread ($\sigma^\phi$) | 12.28 | 2.13 |
| Option attributes | | |
| Brand ($\sigma^2$) | 1.16 | 0.04 |
| Retailer ($\sigma^2$) | 3.35 | 0.10 |
| Cereal base ($\sigma^3$) | 2.73 | 0.08 |
| Log distance | | |
| $\times$ non-urban ($\tau_0$) | 1.82 | 0.15 |
| $\times$ urban ($\tau_1$) | 2.30 | 0.26 |
| Option–household interactions | | |
| Inside $\times$ urban ($\lambda_2$) | 0.46 | 0.64 |
| Chocolate $\times$ children ($\lambda_1$) | 1.66 | 0.18 |
| Product effects | Yes | |
| Retailer effects | Yes | |
| Market effects | Yes | |

(b) Demand model fit: Micro moments

| | Data | Model |
|---|---|---|
| Panel moments | | |
| Price | 0.169 | 0.168 |
| Inside good | 0.036 | 0.036 |
| Brand | 0.168 | 0.162 |
| Retailer | 0.370 | 0.350 |
| Cereal base | 0.131 | 0.131 |
| Demographic moments | | |
| Price $\times$ income | 0.759 | 0.761 |
| Log distance $\times$ non-urban | 0.470 | 0.501 |
| Log distance $\times$ urban | 0.213 | 0.226 |
| Inside $\times$ urban | 0.165 | 0.163 |
| Chocolate $\times$ children | 0.093 | 0.093 |
| Inside option nest moments | | |
| # opt. in 2km | 53.7 | 56.2 |
| 1[# opt. in 2km$>$ 0] | 0.243 | 0.249 |
| km to $50^{th}$ nearest opt. | 0.696 | 0.655 |
| km to $200^{th}$ nearest opt. | 1.32 | 1.21 |

(c) Supply parameters

| | (OLS) | | (IV) | |
|---|---|---|---|---|
| | Estimate | Standard error | Estimate | Standard error |
| Bargaining parameter (b) | | | | |
| Discounters | -0.042 | 0.071 | 0.590 | 0.033 |
| Traditional retailers | -0.097 | 0.060 | 0.612 | 0.035 |
| Leverage ($\rho_0$) | -0.040 | 0.066 | 1.442 | 0.197 |
| Leverage x traditional retailers ($\rho_1$) | -0.048 | 0.072 | 0.139 | 0.088 |
| Maize price x corn base | 0.123 | 0.047 | 0.109 | 0.014 |
| Wheat price x wheat base | 0.128 | 0.042 | 0.103 | 0.016 |
| Rice price x rice base | 0.035 | 0.071 | 0.019 | 0.025 |
| Oats price x oats base | -0.020 | 0.029 | -0.038 | 0.015 |
| Wheat price x bran base | 0.130 | 0.058 | 0.121 | 0.023 |
| Maize price x multi base | 0.060 | 0.102 | 0.008 | 0.049 |
| Oats price x granola base | 0.094 | 0.031 | 0.109 | 0.015 |
| Sugar price | 0.002 | 0.020 | -0.033 | 0.010 |
| Product effects | Yes | | Yes | |
| Retailer–year effects | Yes | | Yes | |
| Private-label–year effects | Yes | | Yes | |
| Quarter effects | Yes | | Yes | |

*Notes: Panel (a) reports demand parameter estimates. Panel (b) reports the observed moments and corresponding model-prediction values for the micro moment conditions used in demand estimation. Panel (c) reports supply parameter estimates. The bargaining parameters is reported separately for traditional retailers and discounters. In the estimation, the latter group includes Aldi, Lidl, and the residual "Other" retailer category. Standard errors in panel (a) are clustered at the household level, and those in panel (c) are heteroskedasticity-robust. Weak-instrument diagnostics for demand estimation are reported in Appendix J.1. For the supply equation, the Lewis–Mertens robust weak-IV diagnostic (local-to-zero, absolute-bias version) is 39.49.*

oats for granola, are positive and statistically significant. Some coefficients are less precisely estimated or have unexpected signs, which may reflect imperfect mapping between inputs and products.

## 5.2 Markups and the Division of Vertical Margins

We estimate that the sales-weighted average own-price elasticity for breakfast cereal options (i.e., product–retailer options) is -6.64, while the average elasticity at the breakfast cereal category level is -0.57. To facilitate comparison with the literature, we also construct brand-level elasticities by aggregating the option-level elasticities over all retailer-product options belonging to a brand. The average brand-level elasticity is -5.08.

Our option-level elasticities are larger in magnitude than the brand-level elasticities reported for the US in Nevo (2001) and Backus et al. (2021). Aggregating to the brand level narrows this gap, indicating that part of the difference reflects our more disaggregate product–retailer definition of the choice object. At the same time, our brand-level elasticities remain somewhat larger in magnitude than those reported in these US studies, suggesting that differences in country, period, retailer structure, and product coverage may also play a role. By contrast, our category-level elasticity is closer in magnitude to that reported in Backus et al. (2021), although it is somewhat more elastic.

Table 5.2 reports average option-level and brand-level elasticities for branded and private-label options, separately for traditional retailers and discounters, in 2002, 2011, and 2021.[25] Using equations (3.3), (4.2), and (4.4), we recover retailer and manufacturer price–cost margins, $\boldsymbol{\Gamma}_t^R$ and $\boldsymbol{\Gamma}_t^F$, respectively, and thus total marginal costs, defined as $\boldsymbol{c}_t \equiv \boldsymbol{p}_t - \left(\boldsymbol{\Gamma}_t^R + \boldsymbol{\Gamma}_t^F\right)$. The table reports these alongside price–cost margins, Lerner indexes, and the share of total margins accruing to retailers.

Several notable patterns emerge. First, in all product–retailer groups, own-price elasticities decline in magnitude over time. The average option-level elasticity across all options moves from about $-8.3$ in 2002 to $-6.9$ in 2021, with similar patterns for branded and private-label and across traditional retailers and discounters. Brand-level elasticities also decline in magnitude over time, though they remain smaller in absolute value than the corresponding option-level elasticities throughout.

[25] Option-level elasticities depend not only on the price sensitivity of the households choosing a given option, but also on the option's price level and the substitution patterns it faces across products and retailers. In the estimated model, households with higher price sensitivity are more likely to choose private-label and discounter options (see Appendix K).

Table 5.2: *Average elasticities, costs and markups*

| | | Traditional retailers | | Discounters | | All options |
|---|---|---|---|---|---|---|
| | | Branded | Private-label | Branded | Private-label | |
| 2002 | Own-price elasticity (option) | -8.68 | -7.38 | -10.44 | -5.19 | -8.27 |
| | Own-price elasticity (brand) | -6.08 | -6.25 | -5.61 | -4.73 | -6.29 |
| | Marginal cost c (£/kg) | 2.07 | 2.08 | 2.86 | 1.80 | 2.03 |
| | Total margin $\Gamma^R + \Gamma^F$ (£/kg) | 2.91 | 1.20 | 1.23 | 0.94 | 2.50 |
| | Lerner index ($\frac{\Gamma^R+\Gamma^F}{p}$) | 0.61 | 0.38 | 0.30 | 0.35 | 0.56 |
| | Retailer share (%) | 48% | 100% | 48% | 100% | 61% |
| 2011 | Own-price elasticity (option) | -8.59 | -6.64 | -7.71 | -5.32 | -7.95 |
| | Own-price elasticity (brand) | -5.97 | -5.73 | -4.77 | -4.36 | -5.87 |
| | Marginal cost c (£/kg) | 2.04 | 1.67 | 1.34 | 1.64 | 1.95 |
| | Total margin $\Gamma^R + \Gamma^F$ (£/kg) | 3.24 | 1.40 | 2.24 | 1.12 | 2.70 |
| | Lerner index ($\frac{\Gamma^R+\Gamma^F}{p}$) | 0.64 | 0.47 | 0.64 | 0.42 | 0.59 |
| | Retailer share (%) | 52% | 100% | 41% | 100% | 64% |
| 2021 | Own-price elasticity (option) | -7.94 | -5.09 | -6.76 | -4.22 | -6.92 |
| | Own-price elasticity (brand) | -5.57 | -4.29 | -5.14 | -3.40 | -4.62 |
| | Marginal cost c (£/kg) | 1.76 | 1.18 | 1.37 | 1.08 | 1.54 |
| | Total margin $\Gamma^R + \Gamma^F$ (£/kg) | 2.93 | 1.29 | 2.49 | 1.08 | 2.39 |
| | Lerner index ($\frac{\Gamma^R+\Gamma^F}{p}$) | 0.64 | 0.55 | 0.65 | 0.54 | 0.62 |
| | Retailer share (%) | 49% | 100% | 45% | 100% | 64% |

*Notes: The table reports average own-price elasticities (option and brand level), total marginal costs, total margins, Lerner indexes, and retailer shares of total margins in 2002, 2011 and 2021. For private-label products, the retailer share is 100%. Marginal costs and margins are expressed in 2021 £ per kg.*

Second, marginal costs decline, especially after 2011 and particularly for private-label cereals and for branded cereals sold by discounters. For discounter private-label options, for example, average marginal costs fall from around £1.8/kg in 2002 to £1.1/kg in 2021. This pattern is consistent with economies of density associated with discounter store expansion (see Figure 2.1 and Holmes 2011), as well as improvements in supply-chain efficiency over time. Branded products typically have higher marginal costs than private-label products, especially at traditional retailers and in the later years of the sample. This pattern is broadly consistent with evidence from CC (2000), which suggests that private-label cereal have lower production or sourcing costs.[26]

Third, average Lerner indexes rise from 2011 to 2021, driven by increases in private-labels products and in branded products sold by discounters.

These patterns—declining marginal costs, less elastic demand, and rising Lerner indexes—are broadly consistent with recent evidence from US consumer product markets based on scalable demand estimation and manufacturer pricing (Döpper

[26]CC (2000, para. 7.206) report that "most [retail] companies agreed that higher margins could be obtained from own-label products because of lower costs."

et al., 2025; Atalay et al., 2023). Our focus on a single category allows us to trace these mechanisms in detail and, in particular, to show how vertical relationships and retailer conduct shape the evolution of markups over time.

Finally, for branded products, retailers account for approximately 50% of total vertical margins, with manufacturers accounting for the remainder. This suggests that retailers obtain a substantial share of markups, consistent with significant market power in both pricing and negotiations with manufacturers. Our findings are broadly consistent with direct evidence in Alvarez-Blaser et al. (2025), who use cost, wholesale, and retail price data for a large global manufacturer of non-durable household products and show that, in the UK, retailers capture a large share of vertical margins, with average retail markups exceeding manufacturer markups.

In Figure 5.1, we summarize the evolution of the markup distribution (measured by total vertical price–cost margins) from 2002 to 2021. Panel (a) shows the interquartile range and median of markups over time. Markups follow a shallow inverted U-shape, peaking in 2008. The subsequent decline coincides with the main phase of discounter expansion. Panel (b) separates options by whether they are sold by traditional retailers or discounters. The distribution for the traditional retailers closely mirrors that in panel (a). In contrast, markups for discounter products display a clear upward trend beginning around 2010. In that year, the $25^{th}$, $50^{th}$ and $75^{th}$ percentiles of the discounter margin distribution (per kilogram) were £0.74, £0.94 and £1.37, respectively—similar to their levels in 2002. By 2021, these had risen to £0.88, £1.20 and £1.51, reflecting a substantial increase in discounter margins over the period. Thus, discounter expansion is associated with both lower average local prices (see Section 2) and rising markups on the products they sell, alongside declining markups at rival retailers. This pattern underscores the role of retail conduct in shaping the evolution of market power.

Each option's (i.e., product–retailer's) price–cost margin can be decomposed as:

$$p - c = \tfrac{1}{\varepsilon} + \left(\Gamma^R - \tfrac{1}{\varepsilon}\right) + \Gamma^M,$$

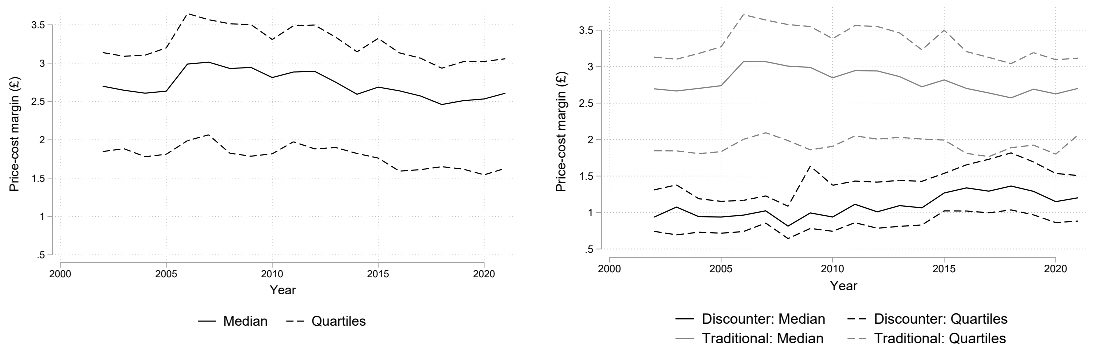
where $\varepsilon$ is the (absolute value of the) option's own-price semi-elasticity. The first component, $\frac{1}{\varepsilon}$, is the markup that would arise under single-product pricing. The term $\Gamma^R - \frac{1}{\varepsilon}$ captures the additional markup due to multi-product pricing by retailers, reflecting the strength of within-retailer diversion effects. Finally, $\Gamma^M$ represents the markup accruing to manufacturers due to their bargaining power in negotiations with retailers. This decomposition is useful for distinguishing active multi-product retailer pricing from passive pass-through by retailers. If retailers simply passed through wholesale prices, the incremental portfolio component $\Gamma^R - \frac{1}{\varepsilon}$

would be absent, even though final retail prices could still reflect upstream pricing power. Deviations of this term from zero therefore measure the contribution of within-retailer diversion to downstream pricing power, separate from both the single-product benchmark and upstream bargaining power.

Figure 5.1: *Markups over time*

(a) Across all retailers

(b) By retailer type



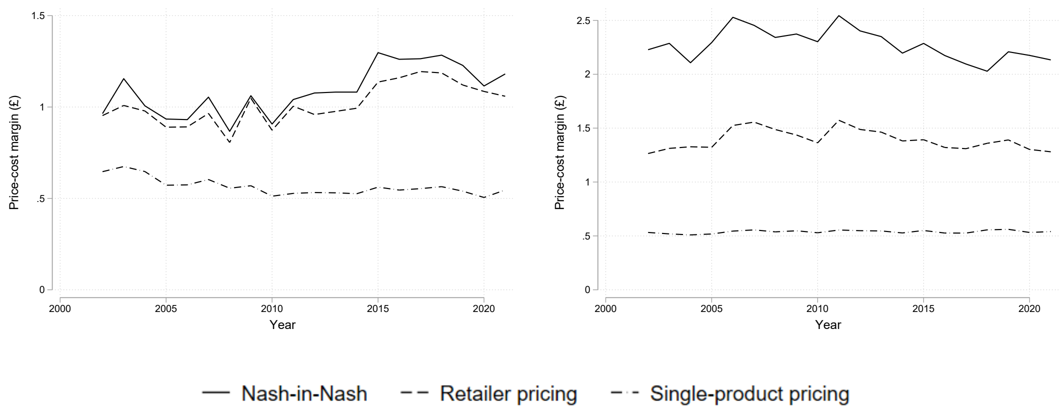

*Notes: Graphs show the $25^{th}$, $50^{th}$ and $75^{th}$ percentiles of total vertical price–cost margins across all options (panel (a)) and separately across options sold by discounters and traditional retailers (panel (b)). Margins are expressed in 2021 £ per kg.*

Figure 5.2 presents the decomposition for the sales-weighted average price–cost margin for discounters (panel (a)) and traditional retailers (panel (b)). Total margins exhibit different patterns across retailer types. Discounter margins increase from 2010, while margins for traditional retailer first rise and then fall, with the decline coinciding with the expansion of discounters. These changes are driven almost entirely by retailer portfolio effects (i.e., the difference between retailer and single-product firm pricing). Manufacturer market power plays a minor role in discounters, as discounters primarily stock private-label products. In contrast, manufacturers account for a larger share of margins for traditional retailers, reflecting the importance of branded products in their assortments.

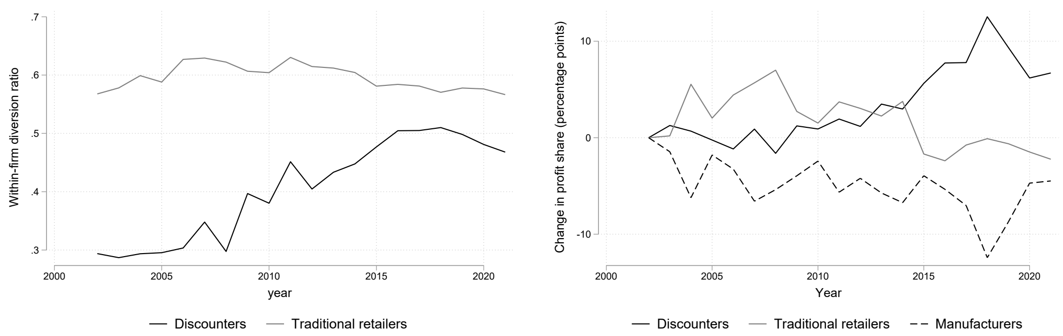
Panel (c) further illustrates the role of within-retailer portfolio effects using only the demand estimates. It reports within-firm diversion ratios over time, separately for options sold by discounters and traditional retailers. For each option, we compute the share of lost demand following a price increase that is diverted to other options sold by the same retailer, and we plot the revenue-weighted average across options. The diversion ratio for traditional retailers initially rises and then gradually declines, reflecting increasing competitive pressure from discounters as consumers become more likely to substitute to discounters. The corresponding diversion ratio for discounters rises strongly over time, indicating that, as discounters expand their assortments and store networks, a larger share of demand stays within the retailer when one of its products becomes more expensive. Together with panels (a) and (b), this pattern shows that substantial within-firm diversion translates into significant downstream pricing power.

Figure 5.2: *Markup decomposition, within-firm diversion ratios and profits*

(a) Discounter markups (b) Traditional retailer markups




(c) Within-firm diversion ratios (d) Discounter profit share




*Notes: The top two panels show sales-weighted averages of price–cost margins across options under alternative supply models sold by discounters (panel (a)) and traditional retailers (panel (b)). Panel (c) shows revenue-weighted average within-firm diversion-ratios for options sold by discounters and traditional retailers. Panel (d) shows the profit share accruing to discounters, traditional retailers and manufacturers of branded products, expressed as differences from their 2002 shares. Margins are expressed in 2021 £ per kg.*

Panel (d) shows that these trends translate into discounters capturing an increasing share of total breakfast cereal profits at the expense of traditional retailers and branded manufacturers. Prior to 2008, discounters accounted for 3.9% of total profits, with the remainder split between non-discounter retailers (56.3%) and manufacturers of branded products (39.8%). By 2017–2021, the discounter share had risen by 8.3 percentage points to 12.1%, with other retailers' share falling by 4.0 percentage points and manufacturers' share declining by 4.3 percentage points. This shift in the division of vertical margins underlines the key role played by retailers in driving the evolution of market power over our sample period.

Our approach is related to De Loecker and Scott (2022), who emphasize the importance of accounting for downstream costs, and combine demand- and production-based markup estimates in the beer industry to assess retail conduct. Their exercise summarizes retail competition with a single parameter and finds support for a highly competitive retail sector. In our setting, we observe household panel choices and store locations directly, allowing us to estimate retailer choice using consumer–store distances. The estimated demand system implies imperfect substitutability between retailers, driven by spatial frictions and persistent retailer-specific preferences. These substitution patterns generate economically meaningful downstream retail margins. The role of spatial frictions is consistent with prior store-choice estimates for the UK and US (CC, 2008; Ellickson et al., 2020), while the implied retail margins are consistent with direct evidence on the division of vertical margins in UK consumer goods markets (Alvarez-Blaser et al., 2025).

# 6 Counterfactual Analysis

The goal of the counterfactual analysis is to measure the impact of discounter expansion between 2002 and 2021 on equilibrium outcomes. We do this by replacing discounter primitives with their 2002 counterparts, simulating market outcomes, and comparing them to the corresponding observed equilibrium outcomes. This approach isolates the impact of the discounters' expansion on market performance and avoids extrapolation beyond the observed range of the data.

## 6.1 Counterfactual Specification

We consider three main counterfactual scenarios to assess the role of factors associated with the rise of the discounters. These three scenarios provide partial decompositions of the forces behind the rise of discounters. First, the store-entry counterfactual (CF1) varies the number of discounter stores, $\mathcal{S}_t$. This changes only the spatial availability of discounter stores while holding their in-store primitives fixed at observed levels, and is informative about changes in entry and planning constraints that affected discounter presence. Second, the in-store counterfactual (CF2) varies in-store offerings—captured by the set of available options, marginal costs, and mean utilities $(\mathcal{J}_t, \mathbf{c}_t, \boldsymbol{\delta}_t)$. This keeps the observed store network but imposes a "traditional retailer" path on discounter assortments, costs, and relative mean utilities, and is informative about changes in discounters' business models, supply-chain efficiency, and vertical relationships *conditional on* their network. The third combines both changes. In each case, we solve for the resulting equilibrium wholesale and retail prices and compute outcomes for each year-quarter market in 2021. Since these channels co-evolved and were shaped by the same policy environment, the counterfactuals are partial-equilibrium exercises that isolate different dimensions of the observed evolution.[27] We outline the three sets of counterfactual assumptions below. Further details of the counterfactual specification are given in Appendix M.

**Store-entry counterfactual** This counterfactual (CF1) measures the impact of the expansion of discounter stores, holding in-store offerings fixed at their observed levels. In this scenario, distances from households to discounter stores are fixed at their initial 2002 values.

**In-store counterfactual** This counterfactual (CF2) measures the impact of changes in discounters' in-store offerings since 2002, holding the store network $\mathcal{S}_t$ at observed levels. We modify three primitives: the set of breakfast cereal options $\mathcal{J}_t$, marginal costs $\mathbf{c}_t$, and mean utilities $\boldsymbol{\delta}_t$.

1. *Product–retailer options.* We replace the set $\mathcal{J}_t^D$ of product–retailer options available at discounters with the set $\mathcal{J}_1^D$ available in $t = 1$, corresponding to 2002.[28]

2. *Marginal costs.* The marginal cost of option $j$, where $(r, k)$ denote retailer and product, in market $t$, where $(y, q)$ are year and quarter, is

$$c_{jt} = \gamma_w \mathbf{w}_{kt} + \gamma_{\mathrm{q}(t)} + \gamma_k + \gamma_{ry(t)} + \gamma_{fy(t)} + \omega_{jt}, \tag{6.1}$$

   where $\mathbf{w}_{kt}$ is a vector of input prices, and $\gamma_{ry}$ and $\gamma_{fy}$ are retailer–year and branded/private-label year effects, respectively.[29] In the counterfactual, we replace the discounter retailer–year effects $\gamma_{ry}$ with the average time path estimated for traditional retailers.

3. *Mean utility.* The mean utility of option $j = (k, r)$—i.e., product $k$ at retailer $r$—in market $t$ is the sum of a fixed product effect, a fixed retailer effect, and a time-varying product–retailer effect: $\delta_{jt} = \theta_k + \theta_r + \xi_{jt}$.[30] We fur-

[27] We recover counterfactual manufacturer and retailer margins in each market by jointly solving the retailers' first-order conditions (equation (3.3)) and the Nash bargaining solution (equation (3.6)). Details of the solution algorithm are provided in Appendix L.

[28] Differentiated-product demand models can overstate welfare gains from product introduction by mechanically increasing the inclusive value that drives consumer surplus as the number of products grows; see Ackerberg and Rysman (2005). While the in-store-offering counterfactual changes discounter assortments, it compares observed product sets and characteristics from 2002 and 2021 rather than extrapolating to products outside the data.

[29] Equation (6.1) rewrites equation (4.3) by expanding $\mathbf{x}_{jt}^s$ into its components.

[30] In Section 3.3, equation (3.7), we write $\delta_{jt} = \boldsymbol{\theta}_2 \mathbf{x}_{jt} + \Delta\xi_{jt}$. $\mathbf{x}_{jt}$ comprises product, retailer and market fixed effects, meaning we can rewrite $\delta_{jt} = \theta_k + \theta_r + \theta_t + \Delta\xi_{jt}$. Defining $\xi_{jt} \equiv \theta_t + \Delta\xi_{jt}$ leads to the equation in the text.

ther decompose $\xi_{jt}$ as $\xi_{jt} = \xi_{rt} + \Delta\xi^*_{jt}$, where $\xi_{rt}$ is a retailer–market-specific effect and $\Delta\xi^*_{jt}$ is a mean-zero product–retailer deviation. Substituting this decomposition yields

$$\delta_{jt} = \theta_k + \theta_r + \xi_{rt} + \Delta\xi^*_{jt}. \tag{6.2}$$

For discounters, we set the retailer–market effects $\xi_{rt}$ to follow the average path observed for the traditional retailers, rather than their discounter-specific trajectories.

**Full counterfactual** This counterfactual (CF3) combines the changes from both the store-entry and in-store-offering counterfactuals to measure the overall effect of the rise of the discounters. Comparing this counterfactual with CF1 and CF2 helps assess the importance of store entry and in-store offerings in shaping market power and economic surplus.

After presenting the main counterfactuals, we also report a policy-motivated variant of the store-entry counterfactual that isolates the role of post-2012 changes in planning and land-access conditions.

**Discussion** The full counterfactual summarizes the combined effect of changes in discounter entry conditions, including planning rules and the prohibition of restrictive land practices, and changes in their in-store business model on equilibrium pricing and surplus. It captures pricing responses by retailers and manufacturers, taking traditional retailers' product assortments and store networks as given at their observed configurations. It therefore does not incorporate potential strategic responses by traditional retailers along these margins. In practice, the scope for such responses is limited. Traditional retailers already offer broad assortments of breakfast cereals, including branded products and an extensive range of private-label options, which span the product characteristic space and leave little scope for further assortment expansion in response to discounter entry. In addition, traditional retailers faced significant constraints on opening new stores due to planning regulations (see Section 2). Moreover, the expansion of discounter store networks accelerated after the 2010 prohibition of restrictive land practices previously used by traditional retailers, which enabled discounters to enter previously inaccessible sites near incumbent traditional retailers. Given these constraints, and the fact that discounters primarily opened stores in areas already served by traditional retailers, we view large offsetting changes in traditional retailers' geographic footprints as unlikely.

## 6.2 Results

Table 6.1 summarizes counterfactual analysis results by comparing observed and counterfactual equilibrium outcomes in the final year of our sample, 2021.

**Primitives** Panel (A) reports changes in the primitives underlying the counterfactuals. The store-entry counterfactual increases the distance of the average household from an Aldi or Lidl store from 4 km to 11 km. The in-store counterfactual reduces the average number of discounter cereal options from 80 to 26 and lowers their average mean utility. It reduces average marginal costs when all products are included, reflecting composition changes, but increases them for overlapping options, consistent with discounter efficiency gains over time for a given set of products.

**Market equilibrium** Panel (B) summarizes the impact of discounter expansion on concentration, prices and margins. In 2021, the retail HHI for breakfast cereals was 1822. Had discounters remained at their 2002 market positions, the retail HHI would have been 262 points higher at 2084. The rise of discounters therefore accounts for most of the decline in breakfast cereal retail concentration from 2013 onward (see Figure 2.2(b)).[31] Discounter expansion leads to a similar fall of 236 points in manufacturer concentration. Both store entry and improvements in discounters' in-store offerings contributed to these declines.

The changes are reflected in prices. In 2021, the average cereal price was £3.93/kg; without the rise of discounters, it would have been £4.12/kg. This decline reflects changes in discounters' marginal costs and product portfolios, as well as the exercise of market power by discounters, competing retailers, and manufacturers. The aggregate vertical price–cost margin is similar in the store-entry counterfactual, but is higher in the counterfactuals that hold discounter product offerings at their 2002 positions; in 2021 it was £2.39/kg, whereas it is £2.54/kg in the full counterfactual. This 15p difference is close to the 19p difference in average prices, with the remaining gap reflecting offsetting changes in marginal costs and product composition.

The total vertical price–cost margin for products sold by discounters was £1.31/kg in 2021, compared with £0.98/kg had they remained at their 2002 market position.

[31] The red lines in Figure 2.2(b) and (d) show the path of breakfast cereal HHIs in the data. The model-based HHIs follow similar paths, albeit with slightly lower levels because our structural analysis groups together smaller retailers and omits some niche manufacturers.

This increase reflects both compositional shifts in discounters' product portfolios and higher margins on products available in both observed and counterfactual equilibria.[32] To isolate the latter effect, we also report margins for "overlapping" discounter options—products available in 2021 and in all three counterfactuals. For these products, discounter expansion raises margins for both branded and private-label products. For branded products, both retail and manufacturer margins increase, with the manufacturer component rising more, consistent with the discounters' expanded branded product ranges strengthening manufacturers' bargaining positions. Overall, the increase in margins more than offsets the reduction in marginal costs, implying higher prices for cereals sold by discounters.

Panel (B) also reports margins for products sold by traditional retailers. Competitive pressure from discounters lowers margins for both branded and private-label products. For branded products, the decline is driven by the retail component, with manufacturer margins remaining largely unchanged. The intermediate counterfactuals show that both store-network expansion and improvements in discounters' in-store offerings contributed to the erosion of traditional retailers' market power.

**Market surplus** Panel (C) reports changes in consumer, producer, and total surplus under each counterfactual relative to the 2021 observed equilibrium. Discounter expansion increased consumer surplus in the breakfast cereal market by £75.0 million, equivalent to 5.2% of total breakfast cereal spending in 2021. The intermediate counterfactuals show that both store-networks expansion and discounters' in-store improvements contributed to these gains.

Discounters' profits were £56.2 million higher than they would have been had their market position remained at 2002 levels, equal to 58.7% of their 2021 profits. These gains were more than offset by declines in profits for traditional retailers and manufacturers, amounting to 12.8% and 5.6% of their respective 2021 profits. Overall, consumer gains and discounter profit gains exceed these losses by £49.7 million, or 3.4% of total cereal spending, with both store-network expansion and in-store improvements contributing to this gain.

[32] The set of discounter products differs across counterfactuals: the observed equilibrium and CF1 include a different set of products than CF2 and CF3. Comparisons across these scenarios therefore involve different product sets.

Table 6.1: *Counterfactual analysis*

| | Observed equilibrium | Counterfactual equilibrium: Store (CF1) | In-store (CF2) | Full (CF3) |
|---|---|---|---|---|
| A) Discounter primitives | | | | |
| Distance (km) | 3.99 | 10.99 | - | 10.99 |
| Portfolio size | 80 | - | 26 | 26 |
| Mean utility ($\delta$) | | | | |
| All options | -2.80 | - | -3.33 | -3.33 |
| Overlapping options | -2.05 | - | -3.05 | -3.05 |
| Marginal cost (£/kg) | | | | |
| All options | 1.13 | - | 0.93 | 0.93 |
| Overlapping options | 0.56 | - | 0.62 | 0.62 |
| B) Market equilibrium | | | | |
| Concentration (HHI) | | | | |
| Retail | 1822 | 1957 | 1979 | 2084 |
| Manufacturer | 2074 | 2221 | 2223 | 2310 |
| Average market price (£/kg) | | | | |
| Unweighted | 3.93 | 3.94 | 4.08 | 4.12 |
| Sales-weighted | 3.29 | 3.39 | 3.10 | 3.26 |
| Margins (£/kg) | 2.39 | 2.39 | 2.51 | 2.54 |
| Discounter margins (£/kg) | | | | |
| All options | 1.31 | 1.18 | 1.10 | 0.98 |
| Overlapping options | | | | |
| Branded | | | | |
| Retail component | 0.65 | 0.53 | 0.53 | 0.40 |
| Manufacturer component | 1.39 | 1.17 | 1.12 | 0.86 |
| Private-label | 1.02 | 0.89 | 1.00 | 0.92 |
| Traditional retailer margins (£/kg) | | | | |
| Branded | | | | |
| Retail component | 1.45 | 1.47 | 1.48 | 1.50 |
| Manufacturer component | 1.47 | 1.47 | 1.46 | 1.47 |
| Private-label | 1.29 | 1.32 | 1.33 | 1.36 |
| C) $\Delta$ annual market surplus (£m) | | | | |
| Consumer surplus | - | -49.7 | -32.3 | -75.0 |
| *% of spending* | | *(-3.44%)* | *(-2.24%)* | *(-5.19%)* |
| Producer surplus | | | | |
| Traditional retailers | - | 42.1 | 26.4 | 60.8 |
| *% change* | | *(8.86%)* | *(5.56%)* | *(12.79%)* |
| Discounters | - | -42.7 | -24.3 | -56.2 |
| *% change* | | *(-44.54%)* | *(-25.39%)* | *(-58.67%)* |
| Manufacturers | - | 21.1 | 5.1 | 20.8 |
| *% change* | | *(5.88%)* | *(1.43%)* | *(5.82%)* |
| Total surplus | - | -29.2 | -25.1 | -49.7 |
| *% of spending* | | *(-2.02%)* | *(-1.74%)* | *(-3.44%)* |

*Notes: The table compares average outcomes in the 2021 observed and counterfactual equilibrium. Unless otherwise stated the averages are unweighted. Panel (A) summarizes the change to market primitives in each counterfactual scenario. Panels (B) and (C) summarize the change in endogenous market outcomes. Marginal costs, prices, margins and surplus are expressed in 2021 £ per kg.*

**Planning-policy counterfactual** We also consider a policy-motivated variant of CF1 aimed at capturing the role of post-2012 changes in planning and land-access conditions. Rather than returning discounter store locations to their 2002 configuration, we allow store networks in each region to evolve along their observed path through 2012 and then impose a counterfactual path in which the number of discounter stores grows only at its pre-2012 linear trend (see Appendix M). This exercise provides an illustrative benchmark for the extent to which the welfare gains from discounter expansion are associated with the acceleration in store growth after 2012. A broader comparison of alternative planning or land-use policies would require modeling entry decisions by both discounters and traditional retailers, which is beyond the scope of the paper.

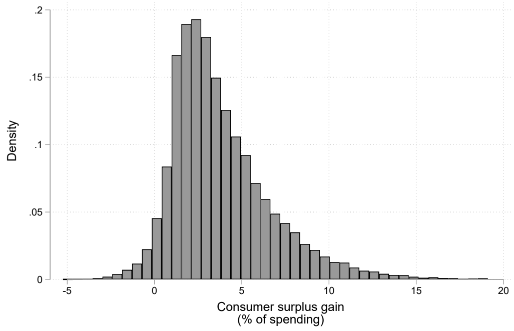
Relative to the observed 2021 equilibrium, this counterfactual implies that the post-2012 increase in store openings raised consumer and total surplus by £25.2 million and £15.3 million, respectively (see Appendix P). These gains amount to around half of those from post-2002 store openings (CF1), indicating that the post-2012 acceleration in discounter store growth played an important role.

**Distributional effects** Figure 6.1 shows how the consumer-surplus gains are distributed across households. We report the difference between consumer surplus in the observed and full counterfactual (CF3) equilibria in 2021, expressed as a fraction of household-level breakfast cereal spending. Panel (a) shows substantial heterogeneity: the interquartile range is 2%–5%, and the 95th percentile household gains around 9%. Panel (b) shows little systematic relationship with equivalized household income, indicating that the benefits were broadly shared across the income distribution.

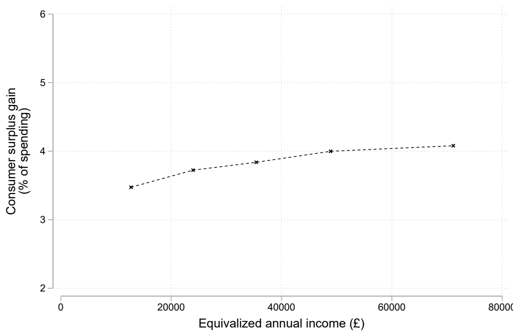
Panel (c) relates consumer gains to changes in proximity to discounter stores. Households with no reduction in distance to the nearest discounter—shown by the red cross—gain around 2.2%, reflecting improvements in discounters' in-store offerings and indirect gains from increased competitive pressure on traditional retailers. The black crosses show average gains by the size of the reduction in distance. Households with distance reductions gain more, highlighting the importance of the geography of store expansion.

Figure 6.1: *Distributional impact*

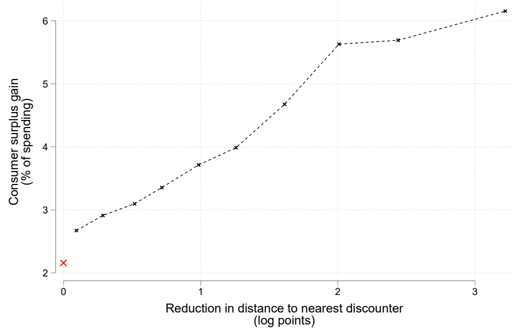
(a) Distribution across households




(b) Impact by income quintiles




(c) Impact by travel distance reduction




*Notes: Figures show the difference in consumer surplus, expressed as a fraction of total expenditure, between the observed and full counterfactual equilibria for the year 2021. Panel (a) reports the distribution of consumer changes across households. Panel (b) shows the average change for each household income quintile. Panel (c) presents the average change by the reduction in travel distance to the nearest discounter store.*

**Cross-category effects** Consumers often purchase multiple categories during a store visit (see Smith and Thomassen, 2012), and improvements in discounters' non-cereal offerings may affect cereal demand. We allow the retailer-time component of mean utility to include both cereal-specific factors and non-cereal shopping effects. Using an auxiliary moment based on continuing cereal products, we separate these components and use the decomposition when scaling the cereal estimates to aggregate consumer gains; details are in Appendix N.

Retailers may also account for cross-category effects when setting cereal prices. In that case, recovered markups should be interpreted relative to an effective marginal cost, equal to technological marginal cost net of the marginal benefit from additional demand in other categories. Our cost specification includes retailer-year effects, which accommodate such retailer-time variation; Appendix E gives the formal derivation.

**Aggregate implications** The descriptive analysis in Section 2 shows that concentration trends in breakfast cereals mirror broader patterns across fast-moving consumer goods. To gauge the aggregate magnitude of the consumer gains, we scale our breakfast-cereal estimates to the set of categories sold by discounters.

We decompose the estimated consumer-surplus gain into gains from reduced travel costs and gains arising from cereal-specific factors, including product availability, prices, and mean utilities, after removing gains attributable to non-cereal retailer utility effects, which we do not scale to other categories (see Appendix O). The remaining gain is split 45% from reduced travel costs and 55% from cereal-specific factors. We scale up the breakfast cereal component using the reciprocal of breakfast cereals' share of total fast-moving consumer good spending (1.3%), and the travel cost component by the reciprocal of the share of weekly shopping trips that include breakfast cereals (31.3%). This back-of-the-envelope calculation implies a 2021 consumer-surplus gain of approximately £2 billion. While the precise magnitude is uncertain, the exercise suggests that discounter expansion delivered substantial consumers benefits beyond the breakfast cereal market.

**Retail conduct and the evolution of market power** The counterfactual results show that the rise of discounters reduced concentration, lowered prices, and raised consumer surplus. The model also allows us to document where changes in market power arise within the vertical chain, by capturing both downstream pricing incentives and upstream negotiations between retailers and manufacturers.

Our estimates indicate that retailers account for a substantial share of total vertical margins for branded products: retailers are not merely passive intermediaries, but are themselves important strategic actors. Discounter expansion reshaped this downstream component of market power. Markups on products sold by discounters rose as their store networks and assortments expanded, while markups at traditional retailers fell, reflecting increased competitive pressure.

Downstream retail market power arises from differentiation across retailers, which we infer from consumer shopping patterns. The demand model uses observed travel distances to capture the spatial component of retailer choice and exploits the panel dimension of the household data to infer persistent heterogeneity in retailer preferences. These estimated substitution patterns imply substantial within-retailer diversion, especially for discounters as they expand, which translates into economically meaningful changes in downstream markups.

To assess which conclusions depend on the vertical bargaining structure, we compare the baseline model to two benchmarks: retailer pricing, in which manufacturers earn no wholesale markups, and manufacturer pricing, in which manufacturers set retail prices directly. Retailer pricing is nested in the bargaining model as the special case in which manufacturers have no bargaining power (see Section 3.2; our estimates instead imply positive manufacturer margins. The main qualitative effects of discounter expansion on prices, concentration, and consumer surplus are similar across these alternatives (Appendix Q), indicating that the headline welfare conclusions are not driven by the particular bargaining specification. We nevertheless view the bargaining model as the appropriate baseline because it reflects the institutional role of retailers as price setters and buyers from branded manufacturers and allows both downstream pricing power and upstream bargaining power. This choice is also supported by direct evidence on positive margins at both the retailer and manufacturer levels, e.g., in Alvarez-Blaser et al., 2025. This structure is central to the paper's question: how the rise of discounters shaped the evolution of market power and the division of surplus between retailers and manufacturers.

# 7 Conclusion

The rise of the discounter format has been a common feature of grocery retailing across many countries in recent decades, with potentially significant implications for market structure and performance. Using rich microdata from the UK, we document that discounter expansion coincided with substantial declines in retail and manufacturing concentration across most narrowly defined product categories. Focusing on the breakfast cereal market, we estimate a structural model of consumer demand and vertical relationships and find that discounter growth led to lower prices, reduced concentration, and increases in both consumer and total surplus. These effects arise directly from an increase in the number of stores, efficiency gains, and changes in product offerings, and indirectly from heightened competitive pressure on traditional retailers and branded manufacturers. While discounters increased their own market power over time, the net effect of their expansion was pro-competitive. Our findings highlight the importance of retail format innovation in shaping market outcomes and underscore the value of analyzing narrowly defined product markets to understand broader trends in concentration and market power.

# References


Ackerberg, D. A. and M. Rysman (2005). Unobserved product differentiation in discrete-choice models: Estimating price elasticities and welfare effects. *RAND Journal of Economics 36*(4), 771–788.

Affeldt, P., T. Duso, K. Gugler, and J. Piechucka (2021). Market concentration in Europe: Evidence from antitrust markets. Technical report, London, Centre for Economic Policy Research.

Aguirregabiria, V., A. Iaria, and S. Sokullu (2023). Identification and estimation of demand models with endogenous product entry and exit. *arXiv preprint arXiv:2308.14196*.

Alvarez-Blaser, S., A. Cavallo, A. MacKay, and P. Mengano (2025). Markups and cost pass-through along the supply chain. *NBER Working Paper 34110.*

Atalay, E., E. Frost, A. T. Sorensen, C. J. Sullivan, and W. Zhu (2023). Scalable Demand and Markups. *NBER Working Paper 31230.*

Atkin, D., B. Faber, and M. Gonzalez-Navarro (2018). Retail Globalization and Household Welfare: Evidence from Mexico. *Journal of Political Economy 126*(1), 1–73.

Backus, M., C. Conlon, and M. Sinkinson (2021). Common Ownership and Competition in the Ready-To-Eat Cereal Industry. *NBER WP 28350*.

Barahona, N., C. Otero, and S. Otero (2023). Equilibrium Effects of Food Labeling Policiesa. *Econometrica 91*(3).

Basker, E. (2007). The causes and consequences of Wal-Mart's growth. *Journal of Economic Perspectives 21*(3), 177–198.

Benkard, C. L., A. Yurukoglu, and A. L. Zhang (2021). Concentration in Product Markets. *NBER Working Paper 28745.*

Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–90.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics 25*(2), 242–262.

Binmore, K., A. Shaked, and J. Sutton (1989). An outside option experiment. *The Quarterly Journal of Economics 104*(4), 753–770.

Bonnet, C., Z. Bouamra-Mechemache, and H. Molina (2025). The buyer power effect of retail mergers: An empirical model of bargaining with equilibrium of fear. *RAND Journal of Economics 56*(2), 194–215.

Bonnet, C. and P. Dubois (2010). Inference on vertical contracts between manufacturers and retailers allowing for nonlinear pricing and resale price maintenance. *RAND Journal of Economics 41*(1), 139–164.

Bourreau, M., Y. Sun, and F. Verboven (2021, November). Market entry, fighting brands, and tacit collusion: Evidence from the french mobile telecommunications market. *American Economic Review 111*(11), 3459–99.

Cao, Y., J. A. Chevalier, J. Handbury, H. Parsley, and K. R. Williams (2024). Willingness to travel with endogenous distance: Evidence from the changing retail landscape. NBER Working Papers 33307, National Bureau of Economic Research, Inc.

Caoui, E. H., B. Hollenbeck, M. Osborne, and E. Page (2026). The impact of dollar store expansion on local market structure and food access. *Quantitative Marketing and Economics 24*, 7.

CC (2000). *Supermarkets: A Report on the Supply of Groceries from Multiple Stores in the United Kingdom.* Competition Commission, The Stationery Office, London, U.K.

CC (2003). *Safeway plc and Asda Group Limited (owned by Wal-Mart Stores Inc.); Wm Morrison Supermarkets PLC; J Sainsbury plc; and Tesco plc: A Report on the Mergers in Contemplation.* The Stationery Office, London, U.K.

CC (2008). The supply of groceries in the uk market investigation. Technical report, Competition Commission, The Stationery Office, London, U.K.

Cleeren, K., F. Verboven, M. G. Dekimpe, and K. Gielens (2010). Intra- and interformat competition among discounters and supermarkets. *Marketing Science 29*(3), 456–473.

CMA (2019). *Anticipated merger between J Sainsbury PLC and Asda Group Ltd.* Competition and Markets Authority, London, U.K.

CMA (2023). *Price inflation and competition in food and grocery manufacturing and supply.* Competition and Markets Authority, London, U.K.

Crawford, G. S., R. S. Lee, M. D. Whinston, and A. Yurukoglu (2018). The welfare effects of vertical integration in multichannel television markets. *Econometrica 86*(3), 891–954.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The Rise of Market Power and the Macroeconomic Implications. *Quarterly Journal of Economics 135*(2), 561–644.

De Loecker, J. and P. T. Scott (2022). Markup estimation using production and demand data. an application to the us brewing industry. Unpublished manuscript.

Döpper, H., A. MacKay, N. H. Miller, and J. Stiebale (2025). Rising markups and the role of consumer preferences. *Journal of Political Economy 133*(8), 000–000.

Draganska, M., D. Klapper, and S. B. Villas-Boas (2010). A larger slice or a larger pie? An empirical investigation of bargaining power in the distribution channel. *Marketing Science 29*(1), 57–74.

Dubois, P. and S. Jodar-Rosell (2010). Price and Brand Competition between Differentiated Retailers: A Structural Econometric Model. TSE Working Papers 10-159, Toulouse School of Economics.

Ellickson, P. B., P. L. Grieco, and O. Khvastunov (2020). Measuring competition in spatial retail. *The RAND Journal of Economics 51*(1), 189–232.

Foster, L., J. Haltiwanger, and C. Krizan (2006). Market selection, reallocation, and restructuring in the u.s. retail trade sector in the 1990s. *Review of Economics and Statistics 88*(4), 748–758.

Gandhi, A. and J.-F. Houde (2019). Measuring Substitution Patterns in Differentiated-Products Industries. Technical Report w26375, National Bureau of Economic Research, Cambridge, MA.

Grieco, P. L., C. Murry, and A. Yurukoglu (2024). The evolution of market power in the us automobile industry. *Quarterly Journal of Economics 139*(2), 1201–1253.

Griffith, R., M. Krol, and K. Smith (2018). Why do retailers advertise store brands differently across product categories? *Journal of Industrial Economics 66*(3), 519–569.

Hausman, J. and E. Leibtag (2007). Consumer benefits from increased competition in shopping outlets: Measuring the effect of Wal-Mart. *Journal of Applied Econometrics 22*(7), 1157–1177.

Ho, K. and R. S. Lee (2017). Insurer competition in health care markets. *Econometrica 85*(2), 379–417.

Ho, K. and R. S. Lee (2019). Equilibrium provider networks: Bargaining and exclusion in health care markets. *American Economic Review 109*(2), 473–522.

Holmes, T. J. (2011). The Diffusion of Wal-Mart and Economies of Density. *Econometrica 79*(1), 253–302.

Jia, P. (2008). What happens when wal-mart comes to town: An empirical analysis of the discount retailing industry. *Econometrica 76*(6), 1263–1316.

Lee, R. S., M. D. Whinston, and A. Yurukoglu (2021a). Structural empirical analysis of contracting in vertical markets. In *Handbook of Industrial Organization*, Volume 4, pp. 673–742. Elsevier.

Lee, R. S., M. D. Whinston, and A. Yurukoglu (2021b, September). Structural empirical analysis of contracting in vertical markets. Working Paper 29282, National Bureau of Economic Research.

Low, H. and C. Meghir (2017). The use of structural models in econometrics. *Journal of Economic Perspectives 31*(2), 33–58.

Luco, F. and G. Marshall (2020). The competitive impact of vertical integration by multiproduct firms. *American Economic Review 110*(7), 2041–64.

Meza, S. and K. Sudhir (2010). Do private labels increase retailer bargaining power? *Quantitative Marketing and Economics 8*(3), 333–363.

Miller, N. H. (2025). Industrial organization and the rise of market power. *International Journal of Industrial Organization 98*, 103131.

Nevo, A. (2000). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *RAND Journal of Economics 31*(3), 395–421.

Nevo, A. (2001). Measuring Market Power in the Ready-to-Eat Cereal Industry. *Econometrica 69*(2), 307–342.

Noton, C. and A. Elberg (2018). Are supermarkets squeezing small suppliers? evidence from negotiated wholesale prices. *Economic Journal 128*(610), 1304–1330.

O'Connell, M., H. Smith, and Ø. Thomassen (2025). A two sample size estimator for large data sets. *Econometrics Journal*, utaf002.

Panhans, M. T. (2024). Vertical integration in a sequential model of a supply chain with bargaining. Working Paper 349, Federal Trade Commission, Bureau of Economics. Accessed: 2026-01-14.

Pasirayi, S. and T. J. Richards (2023). Assessing the impact of manufacturer power on private label market share in an equilibrium framework. *Journal of Business Research 154*, 113302.

Peltzman, S. (2014). Industrial concentration under the rule of reason. *Journal of Law and Economics 57*(S3), S101–S120.

Rey, P. and T. Verge (2019). Secret contracting in multilateral relations. TSE Working Papers 16-744, Toulouse School of Economics (TSE).

Rossi-Hansberg, E., P.-D. Sarte, and N. Trachter (2020). Diverging Trends in National and Local Concentration. In *NBER Macroeconomics Annual 2020, volume 35*, NBER Chapters, pp. 115–150. National Bureau of Economic Research, Inc.

Schneier, C. (2025a). Distributional effects of exclusive dealing in retail real estate. PDF available at: https://camillaschneier.github.io/schneier_chicago_exclusive_dealing.pdf.

Schneier, C. (2025b). The impact of the dollar store on households and local retail competition. *mimeo*. PDF available at: https://camillaschneier.github.io/schneier_chicago_dollar_stores.pdf.

Shapiro, C. (2018). Antitrust in a time of populism. *International Journal of Industrial Organization 61*, 714–748.

Smith, D. A. and S. Ocampo (2025). The evolution of US retail concentration. *American Economic Journal: Macroeconomics 17*(1), 71–101.

Smith, H. and Ø. Thomassen (2012). Multi-category demand and supermarket pricing. *International Journal of Industrial Organization 30*(3), 309–314.

Thomassen, Ø., H. Smith, S. Seiler, and P. Schiraldi (2017). Multi-category competition and market power: A model of supermarket pricing. *American Economic Review 107*(8), 2308–51.

Thomassen, Ø. and L. Zhang (2026). Identification of differentiated products demand with micro moments: Consumer panel data. *Economics Letters*, 112905.

Villas-Boas, S. (2007). Vertical relationships between manufacturers and retailers: Inference with limited data. *Review of Economic Studies 74*(2), 625.

# Appendix:
# For online publication

## The Rise of Discounters and its Impact on Concentration, Market Power and Welfare

Martin O'Connell, Howard Smith and Øyvind Thomassen

May, 2026

## A Store and Household Locations

No single data source covers store locations over the full sample period. We therefore combine three sources to construct retailer-year store-location data. The Institute of Grocery Distribution (IGD) store dataset provides store locations for each retailer over 2002–2006. Geolytix Retail Points provides the same information for 2014–2021. For the intervening years, 2007–2013, we use data from Glenigan on new building projects, which records new supermarket store completion dates, retailer identities, and postcodes.

We construct store locations for 2007–2013 by starting from the set of 2014 Geolitix stores and working backward, removing stores completed in each preceding year according to Glenigan. This approach uses store openings but provides an accurate count of open stores because store closures are rare. As an external validation, we compare the resulting store counts with information from company annual reports and find that they closely match the total number of stores operated by each retailer in each year.

To calculate the household-retailer distances, we randomly draw a residential postcode, and its exact grid reference, from each household's postal sector and compute the distance to the nearest store of each retailer.

To define whether the household is in an urban area, we match the postal sector of the household with the Office for National Statistics Rural Urban Classification, and define the binary variable 'urban' as indicating that the postal sector is in either a major or minor urban conurbation.

## B Cereal Input Prices: Data Description

We use three data sources for crop prices:

1. *UK Agricultural Price Index (API).* Price index of agricultural outputs in GBP, 2015=100.

2. *EU official import prices.* Price index of EU imports in Euro per 100kg.

3. *UN Food and Agriculture Organization (FAO) market data.* International export prices in USD per tonne.

We use these data sources to construct the eight cost variables in Table 5.1(c). The first seven of these consist of a crop input price interacted with a cereal base dummy, for each of the seven cereal bases. The eighth is a sugar price index interacted with a dummy which takes the value 1 for some of the cereal bases. There are multiple candidate crop input prices to interact with each cereal base, e.g., for the cereal base corn there are different types of maize product, etc. To select a series for each cereal base we run a regression of retail prices on alternative input prices for each of seven cereal bases and select the input price with the highest statistical significance. This results in the following input price for each cereal base:

1. Corn: UN FAO market data, USA (Gulf), maize (US no. 2, yellow).
2. Wheat: EU Import prices, common wheat.
3. Rice: UN FAO market data, Pakistan, Rice (25
4. Oats: UK API, oats.
5. Bran: as wheat.
6. Multi: EU Import price, maize.
7. Granola: UK API, oats.

The eighth cost variable is a sugar price index. We use the following sugar price series: UN FAO market data, ICE futures USA sugar. We find this is significant only for cereal bases 1, 3, 5, 6 and 7 so we interact it with a single dummy which indicates whether the cereal is from one of these bases.

We convert all series in Euros or US dollars to GBP using the exchange rate where they are in another currency. Since input prices are monthly, we average to the quarterly level. We also normalize by dividing all series by its price in market 1 (year 2001, quarter 1). So, input prices in the first period are all equal to 1.

# C Planning Policy and Controlled Land

**Competition Commission's store and retailer classifications** Two market inquiries by the Competition Commission (CC)—CC, 2000, 2008—considered planning and controlled land from a competition perspective. To define terms, CC (2008) classified *mid-sized* stores as those with a sales area of 280–1,400 square meters, and *larger* stores as those with a sales areas greater than 1,400 square meters respectively (paragraph 4.63). It also classified grocery retailers into *discounters* and *large grocery retailers* (paragraphs 3.3-3.7). In this paper, we refer to the latter as traditional retailers. The CC found that nearly all of the larger grocery stores were operated by traditional retailers, while discounters exclusively used mid-sized stores.

**Restrictive planning policy in the 2000s** Before the mid-1990s, planning policy had been relatively liberal and had resulted in traditional retailers opening many larger stores (CC 2000, paragraph 2.165). In the mid-1990s, however, the government changed planning policy by adding two tests that made it harder to open larger stores, primarily affecting traditional retailers. The first was the *sequential* test, which required authorities to favor town-center and retail-park developments, which tend to be mid-sized, over out-of-town developments, which tend to involve larger stores. The second was the *need* test, which required evidence of local need for an additional store. As larger stores were the preferred format of the traditional retailers, these changes greatly inhibited their expansion. This was less true for discounters, because they used mid-sized stores that were less adversely affected by these tests.

These changes constituted a barrier to entry that "had a major impact on store development plans" (CC 2008, paragraph 2.168), "locked in" (CC 2008, paragraph 2.175) the market structure for traditional retailers, and "made entry into and expansion within multiple grocery retailing more difficult for parties wanting to acquire large sites in out of town locations" (CC 2008, paragraph 2.202). Discounters were less seriously affected by these policies (CC 2008, paragraph 2.205). For example, Aldi claimed that because its stores were smaller and not out of town, and could be accommodated in town centers, retail parks, and edge-of-town locations, it was not inhibited by them (CC 2008, paragraph 5.150). The CC concluded that the planning system after these changes "constrains new entry by larger grocery stores" but that "these constraints are less significant for mid-sized grocery stores" given that "for these stores suitable locations that are not subject to planning restrictions are more easily found" (CC 2008, paragraph 7.44).

**Proposed changes to planning policy** The CC proposed reforms to the operation of the sequential and need tests in the planning system. These proposals were not adopted by the government. As a result, the planning regime did not change, and traditional retailers continued to be constrained throughout 2002–2021.

**Controlled land** The CC also investigated land-control practices that it viewed as capable of restricting competition by preventing land from being used by rival grocery firms. These included restrictive covenants on land sales, exclusivity arrangements in shopping centers and retail park, and the leasing or sub-leasing of land sites to third parties not involved in grocery retailing. These practices were viewed particularly problematic when combined with a restrictive planning regime. The combination of a restrictive planning system and controlled landsides frustrated new entry that would otherwise strengthen competition (see paragraph 7.121). Controlled land sites restricted the opening both of mid-sized and larger stores.

**The Controlled Land Order** CC (2008) proposed remedies to address controlled land, which resulted in the Controlled Land Order 2010. The aim of the Order was to limit large grocery retailers' ability to use land-site control to prevent land from being used by competing grocers. It designated a list of retailers to be restricted by the Order; this list included the traditional retailers but not the discounters. The Order banned restrictive covenants and exclusivity clauses in land deals that prohibited rivals from opening stores. Traditional retailers were required to release existing restrictive covenants and were prohibited from entering new ones. After the Order, discounters could enter some sites that landlords previously could not have leased to them. Because discounters were not restricted by the Order, they retained the ability to use land controls to prevent competitors from opening stores nearby.

# D Breakfast Cereal Manufacturers

This appendix provides additional evidence on the manufacturers that supply private-label breakfast cereals to UK supermarkets. We do not observe the supplier of each retailer's private-label cereal product in our transaction data. Public information nevertheless indicates two relevant facts. First, there are multiple specialist manufacturers that supply private-label breakfast cereals but do not sell major branded cereals in our data. Second, some branded manufacturers also appear to have supplied private-label cereals, although the extent of this activity is not observed.

*Specialist private-label manufacturers* Several firms manufacture private-label breakfast cereals for UK supermarkets without supplying branded cereals, either from UK plants or by exporting from other European countries. The following list is not exhaustive, but provides examples, together with quotes from their websites.

- Cereal Products (production mainly in Portugal) “From breakfast cereals to snacks, we manufacture a wide range of products with various packaging options to meet your specific needs.”
- Deeside Cereals (production in the UK) “Deeside Cereals manufactures breakfast cereals for the major supermarket chains.”
- Mulder Natural Foods (production in Belgium) “Looking for an expert in breakfast cereals for your private label? Crunchy/granola, muesli, extrusion/co-extrusion or flakes... your wish is our command.”
- MPRUK (production in the UK) “we provide an almost full range of Breakfast Cereal under private label.”
- LHF (production in the UK) "Welcome to Life Health Foods! We produce breakfast cereals and healthy fruit snacks. We have four fantastic brands, and provide own-label and branded manufacture and packaging services for many of the leading retailers and brands in the UK.”
- H J Brueggen KG (production in Germany, Poland and France) “We produce private labels for the leading European and international retail chains. Whether premium, discount or entry-level price quality, whether conventional or organic: We master all segments thanks to an excellent, graduated price-quality ratio.”

*Discounter brands* Aldi and Lidl sell breakfast cereals under their own brands, including 'Harvest Morn' and 'Crownfield', respectively. These are retailer-owned brands: the trademarks are registered in the UK to Aldi and Lidl, while production is outsourced to private-label manufacturers rather than carried out by the retailers themselves.

*Branded manufacturers and private-label production* There is also some public information on whether branded breakfast cereal manufacturers produce private-label goods. In some cases they do, although we do not observe details of which products.

- Kelloggs, the largest branded cereal manufacturer, states that it does not make private-label goods for UK supermarkets. For example, during our sample period, Kelloggs says: "We don't make cereal for anyone else so Special K has always had a unique, premium quality but many own brands have attempted to copy both the look, taste and packaging within IP limits," (Louise Thompson-Davies, brand communications manager at Kellogg UK, in (Food and Drink Business Europe, May 24, 2013).

- A small number of the products under the Sugar Puffs and later Monster Puffs brand were made by Halo and later Brecks Foods, which acquired the rights in 2016. We found no evidence that these companies made private-label products in the breakfast cereal category.

- Jordans and Dorset came under common ownership in 2014 when a Competition Commission investigation approved their merger. The CMA materials describing these firms' activities do not indicate that Jordans or Dorset produced private-label breakfast cereals.

- Whitworths (initially known as Weetabix Limited) is the firm that makes Weetabix. In 2004 a competition report by the UK's Office of Fair Trading suggested that Weetabix produced private labels, according to the Office of Fair Trading's report on the Latimer Acquisitions Ltd / Weetabix Ltd acquisition, which states that "Weetabix is active in the manufacture and sale of cereal products, mainly breakfast cereals and cereal bars. Its products are sold under the Weetabix, Alpen, Ready Brek and Weetos brands, as well as retailer brands."

- Nestlé's UK breakfast cereal business is operated through Cereal Partners UK (CPUK&I). CPUK&I do make private labels according to the following quote from the news story "Cereal Partners set to close site as sales drop" in *The Grocer* magazine. "Under the proposals, production of Cheerios will transfer to Staverton in Wiltshire, and CPUK&I will cease its supermarket branded cereal business at the end of its current contracts." (Mar 29, 2025).

# E Cross-Category Effects in Pricing

Let $q_{ort}$ be the aggregate quantity of other categories sold at retailer $r$ and let $\Gamma_{ort} = (p_{ort} - c_{ort})$ be the retailer's markup. We discuss cross-category pricing effects using the baseline bargaining model, which nests the retailer pricing model. In the manufacturer-pricing model we assume the manufacturer does not sell products in other categories, so that cross-category effects are not relevant.

The objective function of retailer $r$ in period $t$ in the bargaining model is

$$\Pi_{rt} = \textstyle\sum_{j' \in \mathcal{J}_{rt}} q_{j't}(p_{j't} - \Gamma^F_{j't} - c_{j't}) + \chi q_{ort} \Gamma_{ort}$$

where $\chi \in \{0, 1\}$ indicates whether the retailer internalizes cross-category effects. The first-order condition with respect to price $p_{jt}$ is given by

$$\frac{\partial \Pi_{rt}}{\partial p_{jt}} = q_{jt} + \textstyle\sum_{j' \in \mathcal{J}_{rt}} \frac{\partial q_{j't}}{\partial p_{jt}}(p_{j't} - \Gamma^F_{j't} - c_{j't}) + \chi \frac{\partial q_{ort}}{\partial p_{jt}} \Gamma_{ort} = 0.$$

Dividing by the derivative of demand for product $j$ with respect to its price, this can be rewritten:

$$\underbrace{p_{jt} + \frac{q_{jt}}{\frac{\partial q_{jt}}{\partial p_{jt}}}}_{\text{marginal revenue, } j} + \underbrace{\sum_{j' \in \mathcal{J}_{rt} \setminus \{j\}} \frac{\frac{\partial q_{j't}}{\partial q_{jt}}}{\frac{\partial q_{jt}}{\partial p_{jt}}}(p_{j't} - \Gamma^F_{j't} - c_{j't})}_{\text{marginal profit, other cereals at } r} = \underbrace{c_{jt} + \Gamma^F_{jt}}_{\substack{\text{perceived} \\ \text{marginal cost, } j}} - \underbrace{\chi \frac{\frac{\partial q_{ort}}{\partial p_{jt}}}{\frac{\partial q_{jt}}{\partial p_{jt}}} \Gamma_{ort}}_{\substack{\text{marginal} \\ \text{externality}}}.$$

The first term on the right-hand side is the retailer's perceived marginal cost: it includes the retailer component of marginal cost $c^R_j$ and the wholesale price. The second term on the right-hand side is the product of a diversion ratio and markup. The diversion ratio is the marginal change in quantity of other categories purchased from retailer $r$ $q_{or}$ relative to the marginal change in cereal quantity $q_{kr}$ following a price increase. Its sign is theoretically ambiguous: it is negative when cereals and other categories are substitutes and positive when they are complements. Complementarity may arise due to shopping costs, for example, if some of those who stop purchasing a unit of $j$ at retailer $r$ also switch to alternative retailers for other categories (see Thomassen et al. 2017). The size of this effect may vary over time as the quantity of other goods $q_{or}$ purchased jointly with cereals changes.

To capture these cross-category effects in retailer incentives, we define

$$e_{jt} = \frac{\frac{\partial q_{ort}}{\partial p_{jt}}}{\frac{\partial q_{jt}}{\partial p_{jt}}} \Gamma_{ort},$$

and define *effective marginal costs* as:

$$\bar{c}_{jt} = c_{jt} - \chi e_{jt}.$$

This reflects the retailer's marginal opportunity cost of supplying an additional unit of breakfast cereal $j$, accounting for potential gains (or losses) in other categories.

Retailer adjusted markups are then $\tilde{\boldsymbol{\Gamma}}^R_t = \boldsymbol{p}_t - \boldsymbol{\Gamma}^F_t - \bar{\boldsymbol{c}}_t$. In matrix form this becomes

$$\bar{\boldsymbol{c}}_t + \boldsymbol{\Gamma}^F_t = \boldsymbol{p}_t - \boldsymbol{\Delta}_t(\boldsymbol{p}_t)^{-1}\boldsymbol{q}_t.$$

Under the bargaining model, we have $\mathbf{\Gamma}_t^F = \rho_{n(j)}\tilde{\ell}_{jt}$ where $\tilde{\ell}_{jt}$ is defined in equation (4.2), except that the gains from trade to the retailers use adjusted markups $\tilde{\mathbf{\Gamma}}_t^R = \boldsymbol{p}_t - \mathbf{\Gamma}_t^F - \bar{\boldsymbol{c}}_t$ and therefore account for cross-category externalities of stocking a product. With estimates of $\boldsymbol{\Delta}_t(\boldsymbol{p}_t)$ from the demand estimation, the second-stage regression is:

$$[p_{jt} - \tilde{\Gamma}_{jt}^R] = \rho_{n(j)}\tilde{\ell}_{jt} + \underbrace{\boldsymbol{\gamma}\boldsymbol{x}_{jt}^s + \omega_{jt}}_{\bar{c}_{jt}}$$

While this specification identifies the effective marginal cost $\bar{c}_{jt}$, separate identification of $c_{jt}$ and $e_{jt}$ requires further assumptions beyond the scope of the paper.

# F Efficient Bargaining Case

Our supply model nests, as a special case, the retail-pricing outcome of a two-stage model of negotiated two-part tariffs with bilateral efficiency. This occurs when $b_n = 0$ for all negotiations.

We follow the setup in Rey and Verge (2019). In the first stage, each manufacturer–retailer pair bilaterally and simultaneously negotiates a wholesale price and transfer $(w_j, T_j)$ for each product–retailer option $j$. Firms' payoffs are profits net of transfers, $\Pi_r = \pi_r - \sum_{j\in J_r} T_j$ and $\Pi_f = \pi_f + \sum_{j\in J_f} T_j$. The terms are private to the negotiating pair. In the second stage, wholesale prices remain private and retailers simultaneously set prices, optimizing against their own wholesale prices.

Let $\pi_f(\boldsymbol{w}, J)$ and $\pi_r(\boldsymbol{w}, J)$ denote the payoffs to manufacturer $f$ and retailer $r$ at the Nash equilibrium in retail prices, before transfers. Unlike our main model, this two-part tariff framework assumes sequential price setting: manufacturers anticipate how changes in wholesale prices will affect downstream retail prices, yielding a subgame-perfect equilibrium.

Negotiations are bilateral and take place between individual manufacturer–retailer pairs. Let $g = (f, r)$ denote a negotiating pair, let $\boldsymbol{w}_a$ denote the vector of wholesale prices negotiated by this pair, and let $\boldsymbol{w}_{-g}$ denote the vector of wholesale prices for all other pairs. The vector $\boldsymbol{w}_a$ is *bilaterally efficient* (or *pairwise stable*) if it maximizes the joint surplus of the negotiating pair, taking all other wholesale prices as given:[33]

$$\boldsymbol{w}_a = \arg\max_{\boldsymbol{w}'_a} \pi_f(\boldsymbol{w}'_a, \boldsymbol{w}_{-g}, J) + \pi_r(\boldsymbol{w}'_a, \boldsymbol{w}_{-g}, J). \tag{F.1}$$

Under the conditions in Rey and Verge (2019), bilateral efficiency is achieved when wholesale prices are set equal to the manufacturer's marginal costs, with

[33] Rey and Verge (2019) show that wholesale prices satisfying pairwise stability may not survive *multilateral* deviations—i.e., coordinated renegotiation across multiple retailer–manufacturer pairs—under certain patterns of own- and cross-price elasticities. To address this concern, one can either verify that profitable multilateral deviations do not exist under the estimated model, or adopt a delegated-agent framework in which each manufacturer negotiates independently with different retailers through agents who do not coordinate, preventing such multilateral deviations from arising.

transfers allocating the resulting joint surplus between the parties. This eliminates vertical externalities within each negotiating pair. Externalities across different negotiating pairs may remain, so the outcome need not maximize total vertical surplus.

Rey and Verge (2019) show that, in the unique Nash-in-Nash equilibrium with private contracts, the wholesale price $w_j$ is set to the manufacturer's marginal cost, while the transfer $T_j$ allocates the joint surplus. They also show that this outcome can be supported as the equilibrium of a non-cooperative game under the delegated agent assumption, in which there is no information flow across firm's negotiating pairs.

The model features transfers and assumes sequential rather than simultaneous price setting, but it yields the same wholesale and retail prices as our model when $b_n = 0$. In that case, total markups coincide with those from a Bertrand–Nash equilibrium in which retailers optimize retail prices against total marginal cost, see conditions (3.3). A key assumption behind this equivalence is that each negotiating pair takes as given the contracts agreed by all other pairs.[34] A related paper, de Fontenay and Gans (2014), obtains the same outcome in terms of retail prices and quantities, but with quantity-forcing in the negotiations.

**Retailer pricing** The retailer pricing model is nested in the bargaining model for the case where $\rho_n = 0$ for all $n$, which implies $\mathbf{\Gamma}_t^F = 0$. Therefore it is given by the derivation for the bargaining model setting $\rho_n = 0$ and $\mathbf{\Gamma}_t^F = 0$ throughout.

**Counterfactuals** The in-store counterfactual and the full counterfactual restore adjusted marginal costs to their values in the corresponding quarter of 2002 (see Appendix M). This is equivalent to returning the estimated cross-category component of effective marginal costs to its 2002 level, so the counterfactual captures consumer gains from changes in discounter cross-category pricing incentives to the extent that these are reflected in cereal effective marginal costs. This is an approximation: cross-category effects depend on equilibrium outcomes that may change in the counterfactual, while prices and margins in other categories are held fixed. A full calculation of counterfactual cross-category effects would require modeling demand and price across categories, which is beyond the scope of the paper.

# G Moments

In this appendix, we detail the market-level BLP instruments and the three sets of micro moments used in demand estimation.

## G.1 BLP Instruments

We construct BLP instruments using the following observed product characteristics: indicators for private-label budget, private-label not budget, wheat, rice, oats, bran,

[34] This assumption, often referred to as "passive beliefs," implies that if an agent receives a non-equilibrium offer, the terms of other contracts remain unchanged—i.e., deviations are unilateral.

multigrain, granola, contains chocolate, nuts, fruit and honey, as well as pack size, and pack size squared. The instruments are based on two alternative ways of summing the observed characteristics; for the $l$th characteristic these sums are

$$|\mathcal{J}_{rt}|^{-1}\left(\textstyle\sum_{j'\in\mathcal{J}_{rt}} x^l_{j't}\right) - x^l_{jt} \qquad \text{and} \qquad |\mathcal{J}_t \setminus \mathcal{J}_{rt}|^{-1}\left(\textstyle\sum_{j'\in\mathcal{J}_t\setminus\mathcal{J}_{rt}} x^l_{j't}\right) - x^l_{jt},$$

for observation $(j,t)$, where $r$ is the retailer for option $j$. Intuitively, these instruments measure how close option $j$ is to the average of other options sold, (i) in the same retailer and (ii) in competitor retailers, across each dimension of characteristic space, and therefore capture the intensity of competition for the option and are likely to drive to what extent the retailer can set price above marginal cost (see Berry et al. (1995) and Gandhi and Houde (2019) for a discussion).

## G.2 Micro Moments

For each moment $m$, the estimator matches an observed household-level moment $Y^m_h$, computed using the full set of households $N_H$, to a predicted counterpart $y^m_h(\boldsymbol{\theta})$, computed using the subsample $N^*_H$ as described in equation (4.1). We use three sets of micro moments.

### G.2.1 Cross-Period Persistence Moments

The first set of moments use persistence in household choices across choice occasions. Let $I_h$ denote the set of household-weeks in the full sample for household $h$, and let $I^*_h$ denote the corresponding set in the subsample used to compute predicted moments. For each characteristic $l$, let $m(l)$ denote the corresponding moment, let $\mathcal{J}^l_t$ denote the set of options for which characteristic $l$ is defined, and let $\mathcal{P}_2(I'_h)$ denote the set of unordered pairs of household-weeks $i$ from $I'_h \in \{I_h, I^*_h\}$ in which $h$ chooses an option in $\mathcal{J}^l_{t(i)}$. For household-week $i$, define

$$x^l_i(\boldsymbol{\theta}) = \frac{\sum_{j\in J^l_{t(i)}} s_{ij}(\boldsymbol{\theta}) x^l_{jt(i)}}{\sum_{j\in J^l_{t(i)}} s_{ij}(\boldsymbol{\theta})}, \qquad x^l_i = \frac{\sum_{j\in J^l_{t(i)}} 1[i \text{ chooses } j] x^l_{jt(i)}}{\sum_{j\in J^l_{t(i)}} 1[i \text{ chooses } j]}.$$

Let $\bar{x}^l$ and $\bar{x}^l(\boldsymbol{\theta})$ denote the corresponding sample means, computed with equal weighting across households.

The observed and predicted household-level moments are

$$Y^{m(l)}_h = \frac{1}{|\mathcal{P}_2(I_h)|} \sum_{(i,i')\in\mathcal{P}_2(I_h)} (x^l_i - \bar{x}^l)(x^l_{i'} - \bar{x}^l),$$

and

$$y^{m(l)}_h(\boldsymbol{\theta}) = \frac{1}{|\mathcal{P}_2(I^*_h)|} \sum_{(i,i')\in\mathcal{P}_2(I^*_h)} (x^l_i(\boldsymbol{\theta}) - \bar{x}(\boldsymbol{\theta})^l)(x^l_{i'}(\boldsymbol{\theta}) - \bar{x}^l(\boldsymbol{\theta})).$$

These are centered moments. Centering removes changes in the average level of the characteristic and focuses the moment on whether households persistently choose options with above- or below-average values.

There are five cross-period persistence moments.

1. *Price*: $x^l_{jt} = \tilde{p}_{jt}$ and $\mathcal{J}^l_t = \mathcal{J}_t$.
2. *Inside good*: $x^l_{jt} = 1[j > 0]$ and $\mathcal{J}^l_t = \mathcal{J}_t \cup \{0\}$.
3. *Retailer*: $x^l_{jt} = 1[r(j) = r]$ and $\mathcal{J}^l_t = \mathcal{J}_t$. This gives a retailer-specific moment for each retailer $r$, which we aggregate to a single retailer-persistence moment by summing over retailers.
4. *Brand*: $x^l_{jt} = 1[\text{brand}(j) = a]$ and $\mathcal{J}^l_t = \mathcal{J}_t$. This gives a brand-specific moment for each brand $a$, which we aggregate to a single brand-persistence moment by summing over brands.
5. *Cereal base*: $x^l_{jt} = 1[c(j) = c]$ and $\mathcal{J}^l_t = \mathcal{J}_t$. This gives a cereal-base-specific moment for each base $c$, which we aggregate to a single cereal-base-persistence moment by summing over cereal bases.

### G.2.2 Household-Option Interaction Moments

The second set of moments uses variables that vary across household-option pairs. Let $d^l_{ij}$ denote such a variable and let $m(l)$ denote the corresponding moment. The observed and predicted moment are

$$Y_h^{m(l)} = \frac{1}{|I_h^l|} \sum_{i \in I_h^l} \frac{\sum_{j \in \mathcal{J}^l_{t(i)}} 1[i \text{ chooses } j] d^l_{ij}}{\sum_{j \in \mathcal{J}^l_{t(i)}} 1[i \text{ chooses } j]},$$

and

$$y_h^{m(l)}(\boldsymbol{\theta}) = \frac{1}{|I_h^{*l}|} \sum_{i \in I_h^{*l}} \frac{\sum_{j \in \mathcal{J}^l_{t(i)}} s_{ij}(\boldsymbol{\theta}) d^l_{ij}}{\sum_{j \in \mathcal{J}^l_{t(i)}} s_{ij}(\boldsymbol{\theta})},$$

where $I^l_h = \{i \in I_h : \sum_{j \in \mathcal{J}^l_{t(i)}} 1[i \text{ chooses } j] > 0\}$ and $I^{*l}_h = \{i \in I^*_h : \sum_{j \in \mathcal{J}^l_{t(i)}} s_{ij}(\boldsymbol{\theta}) > 0\}$.

We use five household-option interaction moments:

1. *Price-income interaction*: $d^l_{ij} = \tilde{p}_{jt} \times y_{h(i)t(i)}$ and $\mathcal{J}^l_t = \mathcal{J}_t$.
2. *Distance, major urban areas*: $d^l_{ij} = 1[u_h = 1] \log(\text{dist}_{ir(j)})$ and $\mathcal{J}^l_t = \{j \in \mathcal{J}_t : r(j) \neq \text{Other}\}$.
3. *Distance, other areas*: $d^l_{ij} = 1[u_h = 0] \log(\text{dist}_{ir(j)})$ and $\mathcal{J}^l_t = \{j \in \mathcal{J}_t : r(j) \neq \text{Other}\}$.
4. *Inside good and urban residence*: $d^l_{ij} = 1[u_h = 1] 1[j > 0]$ and $\mathcal{J}^l_t = \{0\} \cup \{j \in \mathcal{J}_t : r(j) \neq \text{Other}\}$.

5. *Children and chocolate cereals*: $d^l_{ij} = 1[\text{children}_{h(i)} = 1]1[\text{chocolate}_j = 1]$ and $\mathcal{J}^l_t = \mathcal{J}_t$.

### G.2.3 Choice-Set and Inside-Good Moments

The third set of moments helps identify the variance parameter $\sigma^\phi$ governing the household-week-specific shock to the utility of buying breakfast cereal. These moments relate household-specific choice-set measures to whether the household chooses any inside good.

Let $z^l_i$ denote a household-week-level measure of the local choice set. The observed and predicted household-level moments are

$$Y^{m(l)}_h = \frac{1}{|I_h|} \sum_{i \in I_h} z^l_i \, 1[i \text{ chooses } j > 0],$$

and

$$y^{m(l)}_h(\boldsymbol{\theta}) = \frac{1}{|I^*_h|} \sum_{i \in I^*_h} z^l_i \, s_{i,j>0}(\boldsymbol{\theta}),$$

where $s_{i,j>0}(\boldsymbol{\theta}) = \sum_{j \in \mathcal{J}_{t(i)}} s_{ij}(\boldsymbol{\theta})$ is the predicted probability that household-week $i$ chooses any breakfast cereal option.

We use four choice-set measures:

1. the number of available options within 2 kilometers;
2. an indicator for whether this number is positive;
3. the distance to the 50th nearest option; and
4. the distance to the 200th nearest option.

# H Details of Estimator

The estimator for the demand model is

$$\hat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \begin{bmatrix} \mathbf{g}_A(\boldsymbol{\theta}) \\ \mathbf{g}_M(\boldsymbol{\theta}) \end{bmatrix}' \begin{bmatrix} \boldsymbol{W}_A & \mathbf{0} \\ \mathbf{0} & \boldsymbol{W}_M \end{bmatrix} \begin{bmatrix} \mathbf{g}_A(\boldsymbol{\theta}) \\ \mathbf{g}_M(\boldsymbol{\theta}) \end{bmatrix}$$

The micro moments $\mathbf{g}_M(\boldsymbol{\theta})$ is a $14 \times 1$ vector that stacks the moments given by (4.1), and described in Appendix G.2. The BLP moments $\mathbf{g}_A(\boldsymbol{\theta})$ are

$$\mathbf{g}_A(\boldsymbol{\theta}) = |N_A|^{-1} \boldsymbol{Z}' \boldsymbol{\Delta\xi}(\boldsymbol{\theta})$$

where $N_A$ is the set of $jt$ observations and $|N_A|$ the number of observations, $\boldsymbol{Z}$ is a matrix of instruments, and

$$\boldsymbol{\Delta\xi}(\boldsymbol{\theta}) = \boldsymbol{\delta}(\boldsymbol{\theta}_1) - \boldsymbol{X}\boldsymbol{\theta}_2$$

where the vector $\boldsymbol{\delta}(\boldsymbol{\theta}_1)$ is the value of $\boldsymbol{\delta}$ that, given $\boldsymbol{\theta}_1$, matches observed and predicted market shares, and is found by iterating on the BLP contraction. Here $\boldsymbol{\theta}_1$ are the nonlinear parameters and $\boldsymbol{\theta}_2$ are the linear parameters.

The matrix $\boldsymbol{X}$'s columns are a constant, dummies for all except one market, dummies for all except one retailer, dummies for all except one product. The matrix $\boldsymbol{Z}$ consists of the columns of $\boldsymbol{X}$, plus a set of instruments for price (cost-shifter and BLP instruments).

The vectors $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ represent a decomposition of the parameter vector $\boldsymbol{\theta}$ into its nonlinear ($\boldsymbol{\theta}_1$) and linear ($\boldsymbol{\theta}_2$) components. For each trial value $\boldsymbol{\theta}_1$ during numerical minimization, we concentrate out the linear parameters as

$$\hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1) = (\boldsymbol{X}'\boldsymbol{Z}\boldsymbol{W}_A\boldsymbol{Z}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{Z}\boldsymbol{W}_A\boldsymbol{Z}'\boldsymbol{\delta}(\boldsymbol{\theta}_1). \tag{H.1}$$

Rewriting the parameters as $\boldsymbol{\theta} = (\boldsymbol{\theta}_1, \hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1))$, where $\hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1)$ is given by equation (H.1), the estimator is

$$\hat{\boldsymbol{\theta}}_1 = \arg\min_{\theta_1} \begin{bmatrix} \mathbf{g}_A(\boldsymbol{\theta}_1, \hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1)) \\ \mathbf{g}_M(\boldsymbol{\theta}_1, \hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1)) \end{bmatrix}' \begin{bmatrix} \boldsymbol{W}_A & \mathbf{0} \\ \mathbf{0} & \boldsymbol{W}_M \end{bmatrix} \begin{bmatrix} \mathbf{g}_A(\boldsymbol{\theta}_1, \hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1)) \\ \mathbf{g}_M(\boldsymbol{\theta}_1, \hat{\boldsymbol{\theta}}_2(\boldsymbol{\theta}_1)) \end{bmatrix}$$

$$\hat{\boldsymbol{\theta}}_2 = \hat{\boldsymbol{\theta}}_2(\hat{\boldsymbol{\theta}}_1).$$

The matrix $\boldsymbol{W}_A$, corresponding to the BLP moments, is given by $(\mathbf{Z}'\mathbf{Z}/|N_A|)^{-1}$, where $|N_A|$ is the total number of market-option observations, and $\mathbf{Z}$ is the matrix of instruments. The matrix $\mathbf{W}_M$, corresponding to the micro moments, is diagonal, with the entry for moment $m$ equal to the reciprocal of the square of the observed component of that moment: $1/(\bar{Y}^m)^2$, where $\bar{Y}^m$ is defined in equation (4.1). This normalization puts the micro moments—which are not measured in the same units—on a common (units-free) scale as percentage deviation between predicted and observed contributions (see Low and Meghir 2017).

## H.1 Simulation of Market Shares

For given $(\boldsymbol{\delta}_t, \boldsymbol{\theta}_1)$, the model-implied market share of option $j$ in market $t$ is

$$s_{jt}(\boldsymbol{\delta}_t, \boldsymbol{\theta}_1) = \int s_{ij}(\boldsymbol{\delta}_t, \boldsymbol{\mu}_i(\boldsymbol{\theta}_1))\, dF_t(\boldsymbol{\mu}|\boldsymbol{\theta}_1),$$

where $s_{ij}(\cdot)$ is the choice probability for household–week $i$ and $F_t(\cdot)$ is the distribution of household attributes (observed and unobserved) in market $t$ (see Section 3.3).

We approximate this integral by simulation using the household panel as the empirical distribution of observables. As described in Section 4.1, we draw a random subset $N_H^*$ of 2,000 households from the full panel and, for each selected household $h \in N_H^*$, we select three household–week observations from different quarter–year markets. This yields a set $I^* \subset I$ of 6,000 household–weeks, which we treat as simulation draws from the distribution of observed household characteristics across markets.

For each $i \in I^*$, we then take $S$ independent draws from the unobserved taste shocks,

$$\boldsymbol{\nu}_{is} = \big([\nu^l_{h(i)s}]_{l\in\mathcal{L}_1}, \nu^\phi_{is}, \nu^\alpha_{h(i)s}\big) \sim \mathcal{N}(0, I), \qquad s = 1, \ldots, S,$$

and keep these draws fixed across all iterations of the GMM algorithm. In estimation, we use one simulated taste-shock draw per household–week ($S = 1$) Given $(\boldsymbol{\nu}_{is}, y_{h(i)t}, \text{dist}_{ir})$ and the parameter vector $\boldsymbol{\theta}_1$, we compute the individual choice probabilities

$$s_{ij}\big(\boldsymbol{\delta}_t, \boldsymbol{\mu}_{is}(\boldsymbol{\theta}_1)\big)$$

for all options $j \in \mathcal{J}_t$ in each market $t$ where $i$ is observed.

The simulated market share for option $j$ in market $t$ is then

$$\hat{s}_{jt}(\boldsymbol{\delta}_t, \boldsymbol{\theta}_1) = \frac{1}{S|I^*_t|}\sum_{i\in I^*_t}\sum_{s=1}^{S} s_{ij}\big(\boldsymbol{\delta}_t, \boldsymbol{\mu}_{is}(\boldsymbol{\theta}_1)\big),$$

where $I^*_t \subset I^*$ is the set of simulated household–weeks belonging to market $t$. These simulated shares $\hat{s}_{jt}(\boldsymbol{\delta}_t, \boldsymbol{\theta}_1)$ enter the BLP contraction used to recover $\boldsymbol{\delta}_t(\boldsymbol{\theta}_1)$ and hence the product-level moments $\boldsymbol{g}_A(\boldsymbol{\theta})$.

For post-estimation objects, including elasticities, markups, and counterfactual outcomes, we use the same household–week sampling procedure but increase the number of simulated taste-shock draws to $S = 20$ per household–week.

# I Standard Errors

There are three relevant sample sizes: $|N_A|$ for the BLP-style aggregate moments, $|N^*_H|$ for the small household sample, and $|N_H|$ for the large household sample. For the asymptotic analysis, we assume that the ratios $k_0 = |N_A|/|N^*_H|$ and $k = |N^*_H|/|N_H|$ remain fixed as $|N_A| \to \infty$. Equivalently, since we hold $k_0$ and $k$ constant, we could take $|N^*_H| \to \infty$ as the starting point.

The asymptotic covariance matrix of the estimator depends on the asymptotic distribution of the two sets of moments. By the central limit theorem,

$$\sqrt{|N_A|}g_A(\boldsymbol{\theta}) \to N(\mathbf{0}, \boldsymbol{\Omega}_A) \tag{I.1}$$

$$\sqrt{|N^*_H|}g_M(\boldsymbol{\theta}) \to N(\mathbf{0}, \boldsymbol{\Omega}_M). \tag{I.2}$$

where estimators for the asymptotic covariances of the moments, $\boldsymbol{\Omega}_A$ and $\boldsymbol{\Omega}_M$, are given below. Multiplying by $\sqrt{k_0}$, (I.2) yields

$$\sqrt{|N_A|}g_M(\boldsymbol{\theta}) = \sqrt{|N_A|/|N^*_H|}\sqrt{|N^*_H|}g_M(\boldsymbol{\theta}) \to N(\mathbf{0}, k_0\boldsymbol{\Omega}_M). \tag{I.3}$$

We treat the product-level moments and household-level moments as independent for purposes of inference, and briefly discuss this assumption here. Each predicted micro moment $y_h(\boldsymbol{\theta})$ is constructed as a function of the aggregate data, i.e., the observed shares and the implied mean utilities $\delta$. The household-level micro-moment contribution $Y_h - y_h(\boldsymbol{\theta})$ is sampling noise orthogonal to the aggregate shocks, and therefore has expectation zero conditional on that aggregate data. The product-level moments are themselves functions of the aggregate data, so this conditional-mean-zero property yields zero asymptotic cross-covariance between the two sets of moments. Treating observed shares as population shares would make the cross-covariance exactly zero even though the same panel underlies both sets of moments. In reality, observed shares are not strictly speaking population shares, but the sample is so large (15,000–30,000 households, and more than 72,000 cereal purchases in the median quarter) that each household has a negligible impact on these shares. Moreover, the market shares $S_{jt}$ that go into the BLP contraction are computed using the full dataset, so that the relevant sample size is $|N_H|$, which is assumed to grow with $|N_A|$ since $k_0$ and $k$ are fixed. These shares therefore converge to the population shares as $|N_A| \to \infty$.

Proceeding with the assumption of independence and stacking (I.1) and (I.3) we get

$$\sqrt{|N_A|}\begin{bmatrix} g_A(\boldsymbol{\theta}) \\ g_M(\boldsymbol{\theta}) \end{bmatrix} \to N\left(\mathbf{0}, \begin{bmatrix} \boldsymbol{\Omega}_A & \mathbf{0} \\ \mathbf{0} & k_0\boldsymbol{\Omega}_M \end{bmatrix}\right)$$

Standard errors are then obtained in the usual way, as the square root of the diagonal of the matrix

$$(\mathbf{G}'\mathbf{W}\mathbf{G})^{-1}\mathbf{G}'\mathbf{W}\boldsymbol{\Omega}\mathbf{W}\mathbf{G}(\mathbf{G}'\mathbf{W}\mathbf{G})^{-1}/|N_A|$$

where

$$\begin{aligned} \mathbf{W} &= \begin{bmatrix} \mathbf{W}_A & \mathbf{0} \\ \mathbf{0} & \mathbf{W}_M \end{bmatrix} \\ \mathbf{G} &= \begin{bmatrix} \nabla \mathbf{g}_A(\boldsymbol{\theta}) \\ \nabla \mathbf{g}_M(\boldsymbol{\theta}) \end{bmatrix} \\ \boldsymbol{\Omega} &= \begin{bmatrix} \boldsymbol{\Omega}_A & \mathbf{0} \\ \mathbf{0} & k_0\boldsymbol{\Omega}_M \end{bmatrix}. \end{aligned}$$

The covariance of the market level moments is

$$\boldsymbol{\Omega}_A = \frac{1}{|N_A|}\sum_{(j,t)\in N_A}\left[\boldsymbol{Z}_{jt}'\boldsymbol{\Delta}\boldsymbol{\xi}_{jt}(\hat{\boldsymbol{\theta}})\right]\left[\boldsymbol{Z}_{jt}'\boldsymbol{\Delta}\boldsymbol{\xi}_{jt}(\hat{\boldsymbol{\theta}})\right]'.$$

The covariance of the micro moments (see O'Connell et al. (2025) for a derivation), is given by

$$\begin{aligned}
\boldsymbol{\Omega}_M &= k\hat{\boldsymbol{\Sigma}}_Y + \hat{\boldsymbol{\Sigma}}_y - k(\hat{\boldsymbol{\Sigma}}_{Yy} + \hat{\boldsymbol{\Sigma}}'_{Yy}) \\
\hat{\boldsymbol{\Sigma}}_Y &= \frac{1}{|N_H|} \sum_{h \in N_H} [\mathbf{Y}_h - \bar{\mathbf{Y}}][\mathbf{Y}_h - \bar{\mathbf{Y}}]' \\
\hat{\boldsymbol{\Sigma}}_y &= \frac{1}{|N_H^*|} \sum_{h \in N_H^*} [\mathbf{y}_h(\hat{\boldsymbol{\theta}}) - \bar{\mathbf{y}}(\hat{\boldsymbol{\theta}})][\mathbf{y}_h(\hat{\boldsymbol{\theta}}) - \bar{\mathbf{y}}(\hat{\boldsymbol{\theta}})]' \\
\hat{\boldsymbol{\Sigma}}_{Yy} &= \frac{1}{|N_H^*|} \sum_{h \in N_H^*} [\mathbf{Y}_h - \bar{\mathbf{Y}}][\mathbf{y}_h(\hat{\boldsymbol{\theta}}) - \bar{\mathbf{y}}(\hat{\boldsymbol{\theta}})]'.
\end{aligned}$$

The vectors $\mathbf{Y}_h$ and $\mathbf{y}_h(\boldsymbol{\theta})$ represent the observed and predicted components of the moment for household $h$. The vector $\bar{\mathbf{Y}}$ contains the sample means of $\mathbf{Y}_h$ across households in the large sample, while $\bar{\mathbf{y}}(\hat{\boldsymbol{\theta}})$ is the vector of means of $\mathbf{y}_h(\boldsymbol{\theta})$ across households in the small sample. This covariance structure allows for arbitrary within-household correlation across household-weeks $i$, i.e., standard errors are clustered at the household level $h$.

## I.1 Sampling Variation in Market Shares

The empirical inside shares are constructed from the consumer panel as follows. First, we compute the total share of grocery-shopping occasions in market $t$ that include a breakfast-cereal purchase, which determines the aggregate inside share and hence the outside-good share. Second, conditional on a breakfast-cereal purchase, we compute the fraction of purchases accounted for by each retailer–product option $j$. The model share $S_{jt}$ is the product of these two objects: the aggregate inside share times option $j$'s conditional share among cereal purchases.

The purchase counts discussed below refer to the conditional distribution of cereal purchases across inside options. The panel contains between 15,000 and 30,000 households, and the median quarter has more than 72,000 cereal purchases. The average market has 637 options, so on average we observe well over 100 purchases per option–market cell. For less popular products we observe fewer purchases: across option–quarter cells, the distribution of purchase counts has a 5–95 percentile range of 17–241 and a median of 49. These low-count cells account for a small fraction of total quantity and surplus, and options in this tail are disproportionately associated with the residual "other retailers" category rather than the main discounters.

In the estimation we treat the resulting empirical shares, $S_{jt}$, including the outside-good share, as population shares when forming the product-level moments $\boldsymbol{g}_A(\boldsymbol{\theta})$. We do not implement the small-sample bias corrections for share measurement error proposed by Berry et al. (2004) or Freyberger (2015). Given the purchase counts described above, and the fact that our main objects of interest (elasticities, markups, and counterfactuals) are driven by higher-share options and the major retailers, we do not expect remaining sampling error in the smallest cells to materially affect the results.

# J Demand-Side Diagnostics

## J.1 Demand-Side Instrument Relevance

The BLP product-level moments $\boldsymbol{g}_A(\boldsymbol{\theta})$ treat option prices $p_{jt}$ as endogenous and use cost-shifter and BLP-style instruments in $\boldsymbol{Z}$ (see Section 4.1). To assess instrument relevance, we run a reduced-form first-stage regression of prices on the full set of exogenous characteristics $\boldsymbol{x}_{jt}$ and excluded instruments $\boldsymbol{z}_{jt}$,

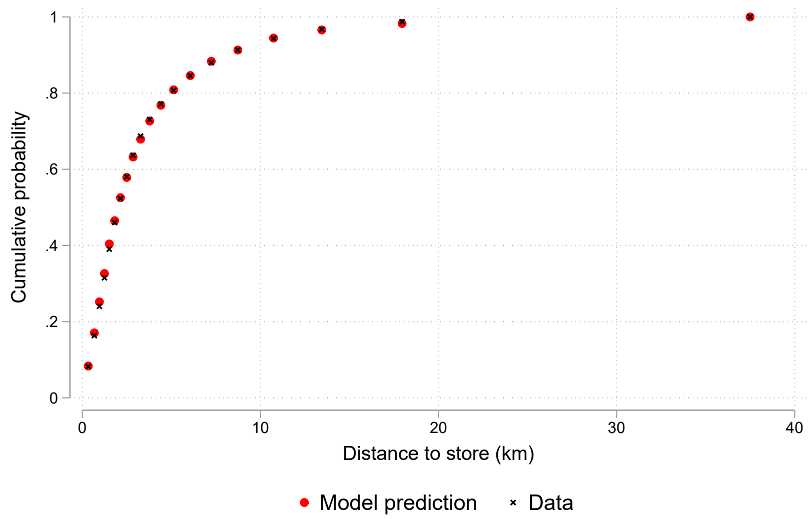
$$p_{jt} = \boldsymbol{x}_{jt}'\pi_x + \boldsymbol{z}_{jt}'\pi_z + \eta_{jt},$$

using the same sample and fixed effects as in the structural estimation. We report the Montiel Olea–Pflueger effective $F$ statistic, which is robust to heteroskedasticity. With our preferred instrument set, the effective $F$ statistic is 16.79. At the 5% significance level, this exceeds the critical value for a 10% worst-case bias threshold (13.09), though not the more stringent 5% threshold (23.77). We therefore view the excluded demand instruments as sufficiently relevant by the conventional 10% benchmark.

## J.2 Model Fit

In Section 4.1, we report the fit of the micro moments. In Figure J.1 we show that model-predicted relationship between the average cumulative probability of a household choosing an option and the travel distance to the nearest store selling that option closely matches the corresponding pattern in the data. In other words, the model successfully recovers the how purchase probabilities vary spatial with travel distances.

Figure J.1: *Impact of distance on choice probabilities*



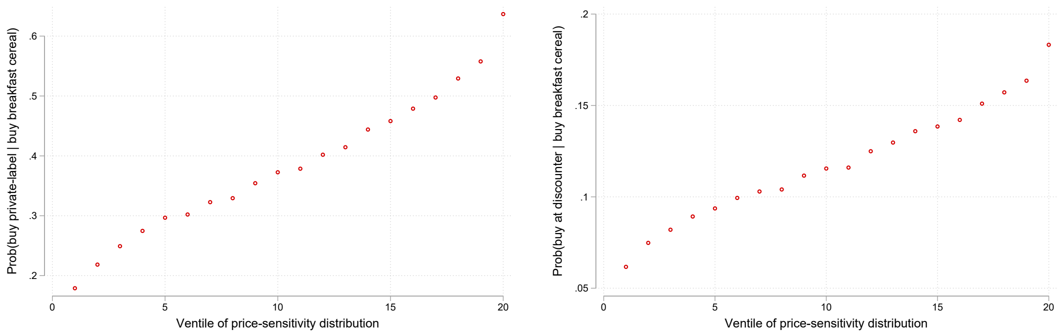

*Notes: Each marker shows the cumulative probability of a household choosing an option within the distance indicated on the horizontal axis from their home. Probabilities are conditional on choosing an inside option. Red markers show predictions from our model and black markers are probabilities computed with the data.*

# K Price Sensitivity and Household Sorting

To illustrate how household sorting varies with estimated price sensitivity, Figure K.1 plots the predicted probability of choosing a private-label option and the predicted probability of choosing a discounter option across ventiles of the estimated price-sensitivity distribution. In each case, we condition on purchasing breakfast cereal. The figure shows that households with higher estimated price sensitivity are systematically more likely to choose both private-label and discounter options.

Figure K.1: *Purchase incidence by price sensitivity*

(a) Private-label options (b) Discounter options




*Notes: The figure plots how the average predicted probability of choosing private-label options (panel (a)) and discounter options (panel (b)) varies across ventiles of the estimated price-sensitivity distribution. In each case, we condition on purchasing breakfast cereal. We pool observations across all markets.*

# L Counterfactual Algorithm

We perform counterfactuals market-by-market. Here, we suppress market subscripts $t$. Morrow and Skerlos (2011) propose reformulating the standard BLP supply side (equation (3.3)) as

$$\mathbf{p} - \tilde{\mathbf{c}} = \boldsymbol{\zeta}(\mathbf{p}),$$

where $\tilde{\mathbf{c}}$ is the marginal cost that the retailer optimizes against,

$$\boldsymbol{\zeta}(\mathbf{p}) = \boldsymbol{\Lambda}(\mathbf{p})^{-1}\boldsymbol{\Gamma}(\mathbf{p})'(\mathbf{p} - \tilde{\mathbf{c}}) - \boldsymbol{\Lambda}(\mathbf{p})^{-1}\mathbf{s}(\mathbf{p}),$$

$\boldsymbol{\Lambda}$ is a $J \times J$ diagonal matrix with entries

$$\Lambda_{jj} = \textstyle\sum_{i \in I^*} s_{ij} \frac{\partial U_{ij}}{\partial p_j}$$

and $\boldsymbol{\Gamma}$ is a $J \times J$ matrix with entries

$$\boldsymbol{\Gamma}_{jj'} = \begin{cases} \sum_{i \in I^*} s_{ij} s_{ij'} \frac{\partial U_{ij'}}{\partial p_{j'}} & \text{if } j \text{ and } j' \text{ are co-owned} \\ 0 & \text{otherwise.} \end{cases}$$

Morrow and Skerlos (2011) show that the mapping $p \leftarrow \tilde{\mathbf{c}} + \boldsymbol{\zeta}(\mathbf{p})$ is a contraction.

Let $\boldsymbol{\gamma}^R$ be the per-pack (i.e. not per-kilogram) retailer markup and $\tilde{\mathbf{c}}$ the (wholesale price inclusive) retail marginal costs (also per pack), so that $\mathbf{p} \equiv \boldsymbol{\gamma}^R + \tilde{\mathbf{c}}$. We can write the contraction with $\boldsymbol{\gamma}^R$ as an argument instead:

$$\boldsymbol{\gamma}^R \leftarrow \boldsymbol{\zeta}(\boldsymbol{\gamma}^R + \tilde{\boldsymbol{c}}). \tag{L.1}$$

Let $\mathrm{kg}_j$ be the pack size in kilograms for option $j$. Then the per-pack retailer markup $\boldsymbol{\gamma}^R$ relates to the per-kilo retailer markup $\boldsymbol{\Gamma}^R$ as $\Gamma_j^R = \gamma_j^R/\mathrm{kg}_j$, and similarly for prices and costs.

In per-kilogram terms, the manufacturer markup $\boldsymbol{\Gamma}^F$ (see equation (4.2)) can be written as

$$\begin{aligned} \boldsymbol{\Gamma}^F &= \rho \boldsymbol{\chi} \boldsymbol{B}(\boldsymbol{p})^{-1} \boldsymbol{A}(\boldsymbol{p}) \boldsymbol{\Gamma}^R && \text{(L.2)} \\ &= \boldsymbol{\varphi}(\boldsymbol{\Gamma}^R). && \text{(L.3)} \end{aligned}$$

To solve for counterfactual prices we take the following steps.

1. (Step 0). Start with guesses of per-pack retail prices $\mathbf{p}_s$ and per-pack manufacturer markup $\boldsymbol{\gamma}_s^F$, for iteration counter $s = 0$, as well as known total vertical per-pack marginal costs $\boldsymbol{c}$ (which remain fixed throughout this exercise).

2. (Step 1). With $\tilde{\boldsymbol{c}}_s = \boldsymbol{\gamma}_s^F + \boldsymbol{c}$, update retailer markup as $\boldsymbol{\gamma}_{s+1}^R = \boldsymbol{\zeta}(\boldsymbol{p}_s)$, using equation (L.1).

3. (Step 2). Transform $\boldsymbol{\gamma}_{s+1}^R$ to per-kilogram terms, $\boldsymbol{\Gamma}_{s+1}^R$. Use the updated matrices $\boldsymbol{A}(\boldsymbol{p}_s)$ and $\boldsymbol{B}(\boldsymbol{p}_s)$ and equation (L.3), with $\boldsymbol{\Gamma}^R = \boldsymbol{\Gamma}_{s+1}^R$ to calculate $\boldsymbol{\Gamma}_{s+1}^F$, and transform to per-pack terms: $\boldsymbol{\gamma}_{s+1}^F$ (by multiplying each element $j$ of $\boldsymbol{\Gamma}_{s+1}^F$ by the corresponding pack size $\mathrm{kg}_j$).

4. (Step 3). Update retail prices (in per-pack terms) as $\boldsymbol{p}_{s+1} = \boldsymbol{c} + \boldsymbol{\gamma}_{s+1}^R + \boldsymbol{\gamma}_{s+1}^F$.

5. Iterate on steps 1-3 until convergence defined as $\|\boldsymbol{p}_{s+1} - \boldsymbol{p}_s\| < 10^{-8}$.

The foregoing discussion is for the baseline bargaining model. For the alternative two-part tariff (or retailer pricing) model the algorithm is identical except that we fix $\boldsymbol{\Gamma}^F = \boldsymbol{\varphi}(\boldsymbol{\Gamma}^R) = 0$ in equation (L.3). We can then skip Step 2. In Step 1, $\tilde{\boldsymbol{c}} = \boldsymbol{c}$, and in Step 3, $\boldsymbol{p}_{s+1} = \boldsymbol{c} + \boldsymbol{\gamma}_{s+1}^R$.

# M Counterfactual Specification

Throughout this appendix, $\Delta_{CF} Y_t$ denotes the effect of the observed evolution of discounters, defined as the observed equilibrium outcome minus the corresponding counterfactual outcome. In the results tables, counterfactual changes are reported relative to the observed equilibrium and therefore use the opposite sign.

**Store-entry counterfactual (CF1)** This counterfactual measures the impact of the expansion in the number of discounter stores, holding the in-store offering as observed in each period. Let $\mathcal{S}_t^D \subset \mathcal{S}_t$ denote the set of discounter stores in period $t$. In the counterfactual, we fix the set of discounter stores at its initial value $\mathcal{S}_t^D = \mathcal{S}_1^D$, so that the counterfactual set of stores in period $t$ is given by $\mathcal{S}_t' = \mathcal{S}_1^D \cup (\mathcal{S}_t \setminus \mathcal{S}_t^D)$. The change in the endogenous outcome $\mathrm{Y}_t$ resulting from this counterfactual (CF1) is:

$$\Delta_{CF1}\mathrm{Y}_t = \mathrm{Y}(\mathcal{S}_t, \mathcal{J}_t, \mathbf{c}_t, \boldsymbol{\delta}_t) - \mathrm{Y}(\mathcal{S}_t', \mathcal{J}_t, \mathbf{c}_t, \boldsymbol{\delta}_t).$$

In this scenario, the distances from consumer $i$ to discounter stores in period $t$ are fixed at their initial values, $\mathrm{dist}_{ir1}$, while distances to all other retailers remain unchanged.

**In-store counterfactual (CF2)** This counterfactual measures the impact of changes to the in-store offering at discounter stores since 2002, keeping the set of stores $\mathcal{S}_t$ as observed in each period. We modify three primitives: the set of breakfast cereal options $\mathcal{J}_t$, marginal costs $\mathbf{c}_t$, and mean utilities $\boldsymbol{\delta}_t$. The change in the outcome $\mathrm{Y}_t$ in period $t$ from this counterfactual (CF2) is:

$$\Delta_{CF2}\mathrm{Y}_t = \mathrm{Y}(\mathcal{S}_t, \mathcal{J}_t, \mathbf{c}_t, \boldsymbol{\delta}_t) - \mathrm{Y}(\mathcal{S}_t, \mathcal{J}_t', \mathbf{c}_t', \boldsymbol{\delta}_t')$$

where counterfactual primitives (denoted with primes) are defined as follows.

1. *Product–retailer options.* In the counterfactual, we replace the set $\mathcal{J}_t^D$ of product–retailer options available at discounters in period $t$ with the set $\mathcal{J}_1^D$ available in period $t = 1$.[35] The resulting counterfactual set of options in period $t$ is $\mathcal{J}_t' = \mathcal{J}_1^D \cup (\mathcal{J}_t \setminus \mathcal{J}_t^D)$.

2. *Marginal costs* Let option $j$ correspond to retailer $r$, product $k$, and manufacturer or ownership type $f$, and let market $t$ correspond to year $y$ and quarter $q$. Marginal cost is specified as

$$c_{jt} = \gamma_w \mathbf{w}_{kt} + \gamma_{\mathrm{q}(t)} + \gamma_k + \gamma_{ry(t)} + \gamma_{fy(t)} + \omega_{jt}, \tag{M.1}$$

   where $\mathbf{w}_{kt}$ is a vector of input prices, and $\gamma_{ry}$ and $\gamma_{fy}$ are retailer–year and branded/private-label year effects, respectively. In the counterfactual, we assume that, for discounters, retailer-year effects $\gamma_{ry}$ follow the corresponding values for traditional retailers. Formally, for $y > 2002$, we replace these terms with the average across traditional retailer options:

$$\gamma_{r(j)y}' = |\mathcal{J}_y^{Tr}|^{-1} \textstyle\sum_{j' \in \mathcal{J}_y^{Tr}} \gamma_{r(j')y} \quad \text{for all } j \in \mathcal{J}_y^D$$

[35] More precisely, for each period $t$, we use the same quarter in the year 2002—represented as $t = 1$ for notational simplicity. In post-2002 markets, this entails removing products from Aldi and Lidl introduced after 2002 and reinstating the smaller number of products available in the same quarter of 2002 but subsequently discontinued.

where $\mathcal{J}_y^{Tr}$ and $\mathcal{J}_y^D$ are the sets of options in traditional retailers and discounters, respectively, in year $y$.[36] Substituting these values into equation (M.1) yields counterfactual costs $c'_{jt}$.

3. *Mean utility.* The mean utility of option $j = (k, r)$—i.e., product $k$ at retailer $r$—in market $t$ is the sum of a fixed product effect, a fixed retailer effect, and a time-varying product–retailer effect: $\delta_{jt} = \theta_k + \theta_r + \xi_{jt}$.[37] We further decompose $\xi_{jt}$ as $\xi_{jt} = \xi_{rt} + \Delta\xi^*_{jt}$, where $\xi_{rt}$ is a retailer–market–specific effect and $\Delta\xi^*_{jt}$ is a mean-zero product–retailer deviation. Substituting this decomposition, mean utility can be expressed as

$$\delta_{jt} = \theta_k + \theta_r + \xi_{rt} + \Delta\xi^*_{jt}. \tag{M.2}$$

In the counterfactual, we adjust the retailer–market effects for discounters so that they follow the path observed for the traditional retailers, rather than their discounter-specific trajectories. Specifically, for each period $t$, we replace $\xi_{r(j)t}$ for discounter products with the average across traditional retailer options:

$$\xi'_{r(j)t} = |\mathcal{J}_t^{Tr}|^{-1} \textstyle\sum_{j' \in \mathcal{J}_t^{Tr}} \xi_{r(j')t} \quad \text{for all } j \in \mathcal{J}_t^D$$

where $\mathcal{J}_t^{Tr}$ is the set of options in traditional retailers in market $t$. Substituting these values into equation $(M.2)$ yields counterfactual mean utility $\delta'_{jt}$.[38]

**Full counterfactual (CF3)** This counterfactual (CF3) combines the changes from both the store-entry and in-store-offering counterfactuals, to measure the overall effect of the rise of the discounters. The change in outcome $\mathrm{Y}_t$ in period $t$ is given by:

$$\Delta_{CF3}\mathrm{Y}_t = \mathrm{Y}(\mathcal{S}_t, \mathcal{J}_t, \mathbf{c}_t, \boldsymbol{\delta}_t) - \mathrm{Y}(\mathcal{S}'_t, \mathcal{J}'_t, \mathbf{c}'_t, \boldsymbol{\delta}'_t).$$

By comparing the results of this counterfactual with those of CF1 and CF2, we can assess the relative importance of store entry versus changes to the in-store offering in shaping changes to market power and economic surplus.

**Planning-policy counterfactual** This counterfactual is a policy-motivated variant of the store-entry counterfactual. Rather than fixing the set of discounter stores at its 2002 level, we allow the Aldi and Lidl store networks to evolve along their observed paths through 2012 and then impose a counterfactual path in which, within each region of Great Britain, store numbers continue to grow at the average annual rate observed between 2002 and 2012.

[36] Options in different markets $t$ in the same year are treated as distinct in these sets.

[37] In Section 3.3, equation (3.7), we write $\delta_{jt} = \boldsymbol{\theta}_2 \mathbf{x}_{jt} + \Delta\xi_{jt}$. $\mathbf{x}_{jt}$ comprises product, retailer and market fixed effects, meaning we can rewrite $\delta_{jt} = \theta_k + \theta_r + \theta_t + \Delta\xi_{jt}$. Defining $\xi_{jt} \equiv \theta_t + \Delta\xi_{jt}$ leads to the equation in the text.

[38] For discounter options in the counterfactual assortment, we also assume that the counterfactual deviations $\Delta\xi^*_{jt}$ and cost shocks $\omega_{jt}$ take the values from the corresponding quarter of the first year, denoted $t'$. That is, we set $\Delta\xi^*_{jt} = \Delta\xi^*_{jt'}$ and $\omega_{jt} = \omega_{jt'}$.

Formally, let $g \in \mathcal{G}$ index the nine regions of Great Britain, and let $N_{cgy}$ denote the number of stores operated by chain $c \in \{\text{Aldi}, \text{Lidl}\}$ in region $g$ in year $y$. For each chain-region pair $(c, g)$, we compute the average annual growth in store numbers over the period 2002–2012 as

$$\bar{m}_{cg} = \frac{N_{cg,2012} - N_{cg,2002}}{10}.$$

By 2021, the counterfactual number of stores is then given by

$$N'_{cg,2021} = N_{cg,2012} + 9\bar{m}_{cg},$$

rounded to the nearest integer.

To implement this counterfactual, we retain all discounter stores observed up to 2012. For post-2012 openings, we then randomly keep only the number of stores required for each chain-region pair to match the implied 2021 counterfactual total $N'_{cg,2021}$. Let $\mathcal{S}_{2021}^{D,\leq 2012}$ denote the set of discounter stores opened by year 2012 and active in 2021, and let $\mathcal{S}_{cg,2021}^{D,>2012}$ denote the set of post-2012 stores for chain $c$ in region $g$ that are active in 2021. For each $(c, g)$, we draw without replacement a subset $\tilde{\mathcal{S}}_{cg,2021}^{D,>2012} \subseteq \mathcal{S}_{cg,2021}^{D,>2012}$ such that the total number of active stores matches the target implied by $N'_{cg,2021}$. The counterfactual store network for 2021 is then

$$\mathcal{S}_{2021}^{PP} = \mathcal{S}_{2021}^{D,\leq 2012} \cup \bigcup_{c \in \{\text{Aldi},\text{Lidl}\}} \bigcup_{g \in \mathcal{G}} \tilde{\mathcal{S}}_{cg,2021}^{D,>2012} \cup (\mathcal{S}_{2021} \setminus \mathcal{S}_{2021}^{D}),$$

where $\mathcal{S}_{2021}^{D} \subset \mathcal{S}_{2021}$ is the set of discounter stores in 2021.

The change in the endogenous outcome under this planning-policy counterfactual is therefore

$$\Delta_{PP}\Upsilon_{2021} = \Upsilon(\mathcal{S}_{2021}, \mathcal{J}_{2021}, \mathbf{c}_{2021}, \boldsymbol{\delta}_{2021}) - \Upsilon(\mathcal{S}_{2021}^{PP}, \mathcal{J}_{2021}, \mathbf{c}_{2021}, \boldsymbol{\delta}_{2021}).$$

This exercise is intended as an illustrative benchmark for the role of the post-2012 acceleration in discounter store growth, rather than as a fully structural estimate of the effect of any single policy change.

# N Decomposition of Cereal and Non-cereal Utility Effects

The mean utility of option $j = (k, r)$—i.e., product $k$ at retailer $r$—in market $t$ is given by:

$$\delta_{jt} = \theta_k + \theta_r + \xi_{jt}.$$

We decompose the time-varying component as $\xi_{jt} = \xi_{jt}^{*} + \psi_{rt}$, where $\xi_{jt}^{*}$ captures factors intrinsic to the breakfast cereal product, and $\psi_{rt}$ reflects retailer-level effects not specific to breakfast cereals (e.g., changes in the quality of the shopping experience or improvements in other product categories purchased alongside cereals).

To separately identify $\xi^*_{jt}$ and $\psi_{rt}$, we exploit continuing options—specific cereals $k$ sold by retailer $r$ in consecutive periods. Let $\mathcal{J}^{\text{cont}}_{rt}$ be the set of such options for retailer $r$ in period $t$. We assume the change over time in the intrinsic cereal-specific utility component is mean zero:

$$\mathbb{E}(\xi^*_{jt} - \xi^*_{j,t-1}) = \mathbb{E}([\xi_{jt} - \xi_{j,t-1}] - [\psi_{rt} - \psi_{r,t-1}]) = 0, \quad \forall j \in \mathcal{J}^{\text{cont}}_{rt},$$

for each $(r, t)$. This assumption is motivated by the fact that the characteristics of continuing options do not change, so that average shifts in their option-level mean utilities identify changes in retailer-level non-cereal effects.

The sample analog implies, for all $(r, t)$,

$$\psi_{rt} - \psi_{r,t-1} = |\mathcal{J}^{\text{cont}}_{rt}|^{-1} \textstyle\sum_{j \in \mathcal{J}^{\text{cont}}_{rt}} [\xi_{jt} - \xi_{j,t-1}].$$

Normalizing $\psi_{r1} = 0$ yields $\psi_{rt}$ for all $t > 1$.

In equation (M.2), we re-write mean utility:

$$\delta_{jt} = \theta_k + \theta_r + \xi_{rt} + \Delta\xi^*_{jt},$$

where

$$\xi_{rt} \equiv |\mathcal{J}_{rt}|^{-1} \sum_{j \in \mathcal{J}_{rt}} \xi_{jt}, \quad \Delta\xi^*_{jt} \equiv \xi_{jt} - \xi_{rt}$$

Noting that:

$$\xi_{rt} = |\mathcal{J}_{rt}|^{-1} \sum_{j \in \mathcal{J}_{rt}} \xi^*_{jt} + \psi_{rt} \equiv \xi^*_{rt} + \psi_{rt}$$

we obtain:

$$\delta_{jt} = \theta_k + \theta_r + \psi_{rt} + \xi^*_{rt} + \Delta\xi^*_{jt},$$

where $\xi^*_{rt}$ and $\Delta\xi^*_{jt}$ capture retailer–market-level and idiosyncratic intrinsic cereal effects, respectively, and $\psi_{rt}$ captures retailer–market-level non-cereal effects.

# O Consumer Surplus

We write the utility of option $j > 0$ for household–week $i$ as $U_{ijt} = \delta_{jt} + \mu_{ij} + \epsilon_{ij}$, which includes the heterogeneous taste term $\mu_{ij}$, as specified in equation (3.7). We write $\mu_{ij} = \mu_j(\tilde{p}_{jt}, \boldsymbol{\nu}_i, \text{dist}_{ir(j)})$ to make explicit its dependence on equilibrium price $\tilde{p}_{jt}$, the random taste shock vector $\boldsymbol{\nu}_i$, and distance $\text{dist}_{ir(j)}$. Note that distances in year-quarter $t$ depend on the set $\mathcal{S}_t$ of store locations. Let $F(\mu_i|\tilde{\mathbf{p}}_t, \mathcal{S}_t)$ be the distribution function of the vector $\mu_i = (\mu_{ij})_{j \in J}$. For a given realization $(\boldsymbol{\epsilon}_i, \mu_i)$, let the optimal choice be denoted

$$j(\boldsymbol{\epsilon}_i, \mu_i, \mathcal{J}_t) \quad \equiv \quad \underset{j \in \mathcal{J}_t \cup \{0\}}{\arg\max} \{\delta_{jt} + \mu_{ij} + \epsilon_{ij}\}$$

where $\delta_{0t} = \mu_{i0} = 0$. The compensating variation of a consumer in market $t$ being offered options $\mathcal{J}_t$ with mean utilities $\boldsymbol{\delta}_t = \{\delta_{jt}\}_{j\in\mathcal{J}_t}$, is

$$\begin{aligned}\mathrm{CS}_t &= \int_{\mu_i} \frac{1}{\alpha_i}\left[\mathbb{E}_{\boldsymbol{\epsilon}_i}\left(\max_{j\in\mathcal{J}_t\cup\{0\}}\{\delta_{jt}+\mu_{ij}+\epsilon_{ij}\}\right)\right] dF(\mu_i|\tilde{\mathbf{p}}_t,\mathcal{S}_t)\\ &= \int_{\mu_i} \frac{1}{\alpha_i}\left[\ln\left(1+\sum_{j\in\mathcal{J}_t}\exp(\delta_{jt}+\mu_{ij})\right)\right] dF(\mu_i|\tilde{\mathbf{p}}_t,\mathcal{S}_t).\end{aligned}$$

The consumer's expected travel cost $T_t$ and the expected contribution $Z_t$ from time-varying non-cereal utility effects $\psi_{r(j)t}$ are respectively given by

$$\begin{aligned}T_t &= -\int_{\mu_i}(\tau_0+\tau_1 u_i)\frac{1}{\alpha_i}\textstyle\sum_{j\in\mathcal{J}_t}\Big\{\log \mathrm{dist}_{ij} s_{ijt}(\mu_i)\Big\} dF(\mu_i|\tilde{\mathbf{p}}_t,\mathcal{S}_t), \text{ and}\\ Z_t &= \int_{\mu_i}\frac{1}{\alpha_i}\textstyle\sum_{j\in\mathcal{J}_t}\Big\{\psi_{r(j)t}s_{ijt}(\mu_i)\Big\} dF(\mu_i|\tilde{\mathbf{p}}_t,\mathcal{S}_t).\end{aligned}$$

See below for the steps in this derivation. Since these effects are additive in utility, the utility component attributable to breakfast cereal products, excluding transport costs and non-cereal retailer choice effects, is

$$B_t = \mathrm{CS}_t - T_t - Z_t.$$

**Aggregate surplus** To compute aggregate consumer surplus we use the full counterfactual consumer surplus change $\Delta_{CF3}\mathrm{CS}$. In addition, we compute corresponding changes for transport costs and other category effects, i.e.,

$$\Delta_{CF3}\mathrm{T}_t = \mathrm{T}(\mathcal{S}_t,\mathcal{J}_t,\mathbf{c}_t,\boldsymbol{\delta}_t) - \mathrm{T}(\mathcal{S}'_t,\mathcal{J}'_t,\mathbf{c}'_t,\boldsymbol{\delta}'_t)$$

and

$$\Delta_{CF3}\mathrm{Z}_t = \mathrm{Z}(\mathcal{S}_t,\mathcal{J}_t,\mathbf{c}_t,\boldsymbol{\delta}_t) - \mathrm{Z}(\mathcal{S}'_t,\mathcal{J}'_t,\mathbf{c}'_t,\boldsymbol{\delta}'_t),$$

giving

$$\Delta_{CF3}\mathrm{B}_t = \Delta_{CF3}\mathrm{CS}_t - \Delta_{CF3}\mathrm{T}_t - \Delta_{CF3}\mathrm{Z}_t.$$

The implied aggregate consumer surplus change is $\Delta_{CF3}\mathrm{B}_t \times SC_B + \Delta_{CF3}\mathrm{T}_t \times SC_T$ where $SC_B$ is the scale-up factor for the breakfast cereal component (1/revenue share of breakfast cereals) and $SC_T$ is the scale-up factor for transport costs (1/trip share of breakfast cereals).

**Derivation of expected surplus components.**

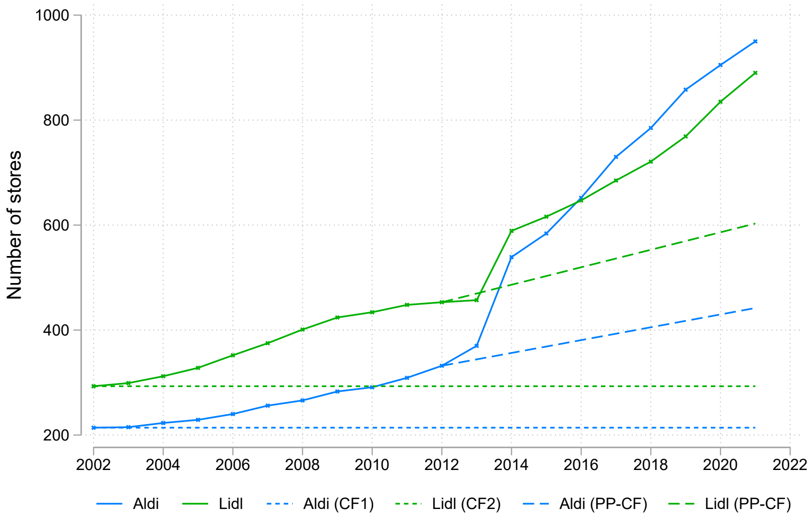
$$
\begin{aligned}
T_t &= -\int_{\mu_i} (\tau_0 + \tau_1 u_i)\frac{1}{\alpha_i}\mathbb{E}_{\boldsymbol{\epsilon_i}}\big[\log \text{dist}_{ij(\boldsymbol{\epsilon_i},\mu_i)}\big]dF(\mu_i|\tilde{\mathbf{p}}_t, \mathcal{S}_t)\\
&= -\int_{\mu_i} (\tau_0 + \tau_1 u_i)\frac{1}{\alpha_i}\int_{\boldsymbol{\epsilon_i}} \log \text{dist}_{ij(\boldsymbol{\epsilon_i},\mu_i)} dF_{\epsilon}(\boldsymbol{\epsilon_i})dF(\mu_i|\tilde{\mathbf{p}}_t, \mathcal{S}_t)\\
&= -\int_{\mu_i} (\tau_0 + \tau_1 u_i)\frac{1}{\alpha_i}\int_{\boldsymbol{\epsilon_i}} \textstyle\sum_{j\in J_t}\Big\{\log \text{dist}_{ij} 1\big[j = j(\boldsymbol{\epsilon_i}, \mu_i)\big]\Big\}dF_{\epsilon}(\boldsymbol{\epsilon_i})dF(\mu_i|\tilde{\mathbf{p}}_t, \mathcal{S}_t)\\
&= -\int_{\mu_i} (\tau_0 + \tau_1 u_i)\frac{1}{\alpha_i}\textstyle\sum_{j\in J_t}\Big\{\log \text{dist}_{ij} \displaystyle\int_{\boldsymbol{\epsilon_i}} 1\big[j = j(\boldsymbol{\epsilon_i}, \mu_i)\big]dF_{\epsilon}(\boldsymbol{\epsilon_i})\Big\}dF(\mu_i|\tilde{\mathbf{p}}_t, \mathcal{S}_t)\\
&= -\int_{\mu_i} (\tau_0 + \tau_1 u_i)\frac{1}{\alpha_i}\textstyle\sum_{j\in J_t}\Big\{\log \text{dist}_{ij} s_{ijt}(\mu_i)\Big\}dF(\mu_i|\tilde{\mathbf{p}}_t, \mathcal{S}_t)
\end{aligned}
$$

The $Z_t$ term can be derived analogously.

# P Planning-Policy Counterfactual

Figure P.1 reports the evolution of the number of Aldi and Lidl stores over time, in the data and under both the full store counterfactual (CF1) and the planning-policy counterfactual (see Appendix M). Table P.1 summarizes the results of CF1 and the planning-policy counterfactual for equilibrium outcomes. The final column reports the percentage of the full store counterfactual effect (CF1) that is realized under the planning-policy counterfactual. For example, the difference in retail HHI between the observed equilibrium (1822) and the full store counterfactual (1957) is 135, while the corresponding difference under the planning-policy counterfactual (1895) is 73. Thus, the planning-policy counterfactual accounts for 53.9% (=73/135) of the total CF1 effect.

Figure P.1: *Discounter store coverage growth over time*




*Notes: The figure shows the evolution of the number of Aldi and Lidl stores over time in the data, under the full store counterfactual (CF1), and under the planning-policy counterfactual. The planning-policy counterfactual allows store networks to evolve as observed through 2012 and then imposes a continuation of the pre-2012 linear growth trend.*

Table P.1: *Counterfactual analysis*

| | Observed equilibrium | Counterfactual equilibrium: Store (CF1) | Counterfactual equilibrium: Planning-policy | % of CF1-Δ realized under planning-policy CF |
|---|---|---|---|---|
| A) Discounter primitives | | | | |
| Distance (km) | 3.99 | 10.99 | 6.53 | *36.3%* |
| B) Market equilibrium | | | | |
| Concentration (HHI) | | | | |
| Retail | 1822 | 1957 | 1895 | *53.9%* |
| Manufacturer | 2074 | 2221 | 2144 | *47.3%* |
| Average market price (£/kg) | | | | |
| Unweighted | 3.93 | 3.94 | 3.94 | *153.7%* |
| Sales-weighted | 3.29 | 3.39 | 3.34 | *45.6%* |
| Margins (£/kg) | 2.39 | 2.39 | 2.40 | 153.7 |
| Discounter margins (£/kg) | | | | |
| All options | 1.31 | 1.18 | 1.25 | *42.9%* |
| Overlapping options | | | | |
| Branded | | | | |
| Retail component | 0.65 | 0.53 | 0.60 | *44.2%* |
| Manufacturer component | 1.39 | 1.17 | 1.26 | *61.4%* |
| Private-label | 1.02 | 0.89 | 0.98 | *35.4%* |
| Traditional retailer margins (£/kg) | | | | |
| Branded | | | | |
| Retail component | 1.45 | 1.47 | 1.46 | *65.4%* |
| Manufacturer component | 1.47 | 1.47 | 1.47 | *117.1%* |
| Private-label | 1.29 | 1.32 | 1.32 | *84.6%* |
| C) Δ annual market surplus (£m) | | | | |
| Consumer surplus | - | -49.7 | -25.2 | *50.7%* |
| Producer surplus | | | | |
| Traditional retailers | - | 42.1 | 21.6 | *51.3%* |
| Discounters | - | -42.7 | -21.3 | *49.8%* |
| Manufacturers | - | 21.1 | 9.6 | *45.4%* |
| Total surplus | - | -29.2 | -15.3 | *52.3%* |

*Notes: The table compares outcomes in the observed 2021 equilibrium with those under the full store counterfactual (CF1) and the planning-policy counterfactual. Unless otherwise stated the averages are unweighted. Panel (A) reports changes in market primitives, while Panels (B) and (C) report the resulting changes in endogenous outcomes. The planning-policy counterfactual allows discounter store networks to evolve as observed through 2012 and then imposes growth at the pre-2012 linear trend. The final column reports the percentage of the total CF1 effect (relative to the observed equilibrium) that is realized under the planning-policy counterfactual. Prices, margins, and surplus are expressed in 2021 £ per kg.*

# Q Results under Alternative Supply Models

## Q.1 Retailer pricing

Table Q.1: *Average elasticities, cost and markups*

| | | Traditional retailers | | Discounters | | All options |
|---|---|---|---|---|---|---|
| | | Branded | Private-label | Branded | Private-label | |
| 2002 | Marginal cost c (£/kg) | 3.56 | 2.08 | 3.47 | 1.80 | 3.16 |
| | Total margin $\Gamma$ (£/kg) | 1.43 | 1.20 | 0.62 | 0.94 | 1.37 |
| | Lerner index ($\frac{\Gamma}{p}$) | 0.29 | 0.38 | 0.14 | 0.35 | 0.31 |
| 2011 | Marginal cost c (£/kg) | 3.57 | 1.67 | 2.62 | 1.64 | 3.08 |
| | Total margin $\Gamma$ (£/kg) | 1.71 | 1.40 | 0.96 | 1.12 | 1.57 |
| | Lerner index ($\frac{\Gamma}{p}$) | 0.33 | 0.47 | 0.27 | 0.42 | 0.36 |
| 2021 | Marginal cost c (£/kg) | 3.23 | 1.18 | 2.70 | 1.08 | 2.56 |
| | Total margin $\Gamma$ (£/kg) | 1.45 | 1.29 | 1.15 | 1.08 | 1.37 |
| | Lerner index ($\frac{\Gamma}{p}$) | 0.31 | 0.55 | 0.30 | 0.54 | 0.38 |

*Notes: Table reports average own-price elasticities, total vertical marginal costs and Lerner indexes in 2002, 2012 and 2021. Retailer share is average share of total margins accruing to retailers. For private-label products this is 100%. Marginal costs and margins are expressed in 2021 £ per kg.*

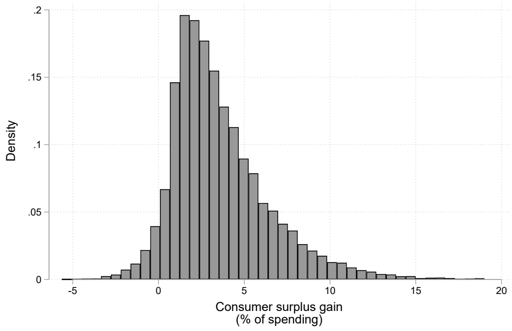
Table Q.2: *Counterfactual analysis*

| | Observed equilibrium | Counterfactual equilibrium: Store (CF1) | In-store (CF2) | Full (CF3) |
|---|---|---|---|---|
| A) Discounter primitives | | | | |
| Marginal cost (£/kg) | | | | |
| All options | 1.34 | - | 0.95 | 0.95 |
| Overlapping options | 0.75 | - | 0.67 | 0.67 |
| B) Market equilibrium | | | | |
| Concentration (HHI) | | | | |
| Retail | 1822 | 1964 | 1968 | 2079 |
| Manufacturer | 2074 | 2253 | 2252 | 2382 |
| Average market price (£/kg) | | | | |
| Unweighted | 3.93 | 3.94 | 4.09 | 4.11 |
| Sales-weighted | 3.29 | 3.40 | 3.07 | 3.23 |
| Margins (£/kg) | 1.37 | 1.38 | 1.43 | 1.44 |
| Discounter margins (£/kg) | | | | |
| All options | 1.10 | 0.98 | 1.02 | 0.92 |
| Overlapping options | | | | |
| Branded | | | | |
| Retail component | 0.65 | 0.52 | 0.52 | 0.40 |
| Manufacturer component | - | - | - | - |
| Private-label | 1.02 | 0.90 | 1.01 | 0.93 |
| Traditional retailer margins (£/kg) | | | | |
| Branded | | | | |
| Retail component | 1.45 | 1.48 | 1.48 | 1.50 |
| Manufacturer component | - | - | - | - |
| Private-label | 1.29 | 1.32 | 1.33 | 1.35 |
| C) $\Delta$ annual market surplus (£m) | | | | |
| Consumer surplus | - | -52.0 | -30.9 | -70.5 |
| *% of spending* | | *(-3.60%)* | *(-2.14%)* | *(-4.88%)* |
| Producer surplus | | | | |
| Traditional retailers | - | 43.7 | 22.5 | 58.2 |
| *% change* | | *(9.19%)* | *(4.75%)* | *(12.25%)* |
| Discounters | - | -43.4 | -19.1 | -53.4 |
| *% change* | | *(-45.29%)* | *(-19.88%)* | *(-55.69%)* |
| Total surplus | - | -51.7 | -27.4 | -65.6 |
| *% of spending* | | *(-3.58%)* | *(-1.90%)* | *(-4.54%)* |

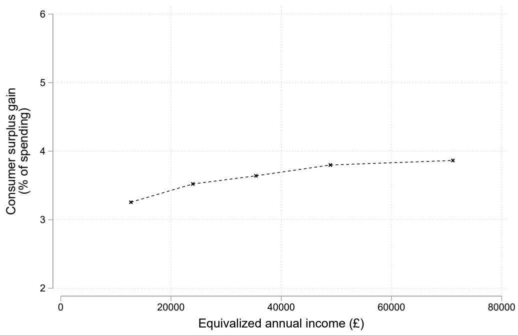
*Notes: Table compares average outcomes in the 2021 observed and counterfactual equilibrium. Unless otherwise stated the averages are unweighted. Panel (A) summarizes the change to market primitives in each counterfactual scenario. Panels (B) and (C) summarize the change in endogenous market outcomes. Marginal costs, prices, margins and surplus are expressed in 2021 £ per kg.*

Figure Q.1: *Distributional impact*

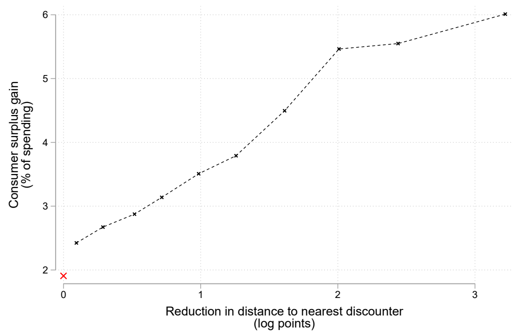
(a) Distribution across households




(b) Impact by income quintiles




(c) Impact by travel distance reduction




*Notes: Figures show the difference in consumer surplus, expressed as a fraction of total expenditure, between the observed and full counterfactual equilibria for the year 2021. Panel (a) reports the distribution of consumer changes across households. Panel (b) shows the average change for each household income quintile. Panel (c) presents the average change by the reduction in travel distance to the nearest discounter store.*

## Q.2 Manufacturer pricing

Table Q.3: *Average elasticities, cost and markups*

| | | Traditional retailers | | Discounters | | All options |
|---|---|---|---|---|---|---|
| | | Branded | Private-label | Branded | Private-label | |
| 2002 | Marginal cost c (£/kg) | 3.99 | 2.58 | 3.61 | 1.80 | 3.58 |
| | Total margin Γ (£/kg) | 1.00 | 0.69 | 0.48 | 0.93 | 0.94 |
| | Lerner index ($\frac{\Gamma}{p}$) | 0.20 | 0.22 | 0.11 | 0.35 | 0.21 |
| 2011 | Marginal cost c (£/kg) | 4.21 | 2.36 | 2.66 | 1.66 | 3.64 |
| | Total margin Γ (£/kg) | 1.07 | 0.71 | 0.92 | 1.11 | 1.01 |
| | Lerner index ($\frac{\Gamma}{p}$) | 0.20 | 0.24 | 0.26 | 0.41 | 0.23 |
| 2021 | Marginal cost c (£/kg) | 3.69 | 1.62 | 2.94 | 1.12 | 2.95 |
| | Total margin Γ (£/kg) | 1.00 | 0.85 | 0.91 | 1.04 | 0.98 |
| | Lerner index ($\frac{\Gamma}{p}$) | 0.21 | 0.37 | 0.24 | 0.52 | 0.28 |

*Notes: Table reports average own-price elasticities, total vertical marginal costs and Lerner indexes in 2002, 2012 and 2021. Retailer share is average share of total margins accruing to retailers. For private-label products this is 100%. Marginal costs and margins are expressed in 2021 £ per kg.*

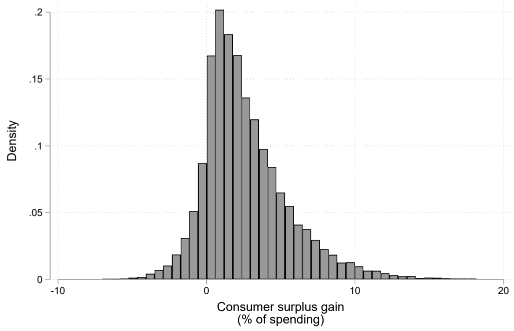
Table Q.4: *Counterfactual analysis*

| | Observed equilibrium | Counterfactual equilibrium: Store (CF1) | In-store (CF2) | Full (CF3) |
|---|---|---|---|---|
| A) Discounter primitives | | | | |
| Marginal cost (£/kg) | | | | |
| All options | 1.41 | - | 0.87 | 0.87 |
| Overlapping options | 0.77 | - | 0.59 | 0.59 |
| B) Market equilibrium | | | | |
| Concentration (HHI) | | | | |
| Retail | 1822 | 1975 | 1969 | 2082 |
| Manufacturer | 2074 | 2235 | 2236 | 2345 |
| Average market price (£/kg) | | | | |
| Unweighted | 3.93 | 3.93 | 4.06 | 4.06 |
| Sales-weighted | 3.29 | 3.38 | 2.98 | 3.15 |
| Margins (£/kg) | 0.98 | 0.98 | 0.99 | 0.99 |
| Discounter margins (£/kg) | | | | |
| All options | 1.02 | 0.93 | 1.02 | 0.92 |
| Overlapping options | | | | |
| Branded | | | | |
| Retail component | - | - | - | - |
| Manufacturer component | 0.65 | 0.54 | 0.49 | 0.44 |
| Private-label | 0.99 | 0.87 | 1.03 | 0.95 |
| Traditional retailer margins (£/kg) | | | | |
| Branded | | | | |
| Retail component | - | - | - | - |
| Manufacturer component | 1.01 | 1.02 | 1.02 | 1.03 |
| Private-label | 0.85 | 0.86 | 0.87 | 0.87 |
| C) Δ annual market surplus (£m) | | | | |
| Consumer surplus | - | -44.8 | -14.6 | -51.2 |
| *% of spending* | | *(-3.10%)* | *(-1.01%)* | *(-3.54%)* |
| Producer surplus | | | | |
| Trad. retailer private-label | - | 10.0 | 1.5 | 10.6 |
| *% change* | | *(9.43%)* | *(1.44%)* | *(9.98%)* |
| Discounter private-label | - | -38.9 | 1.3 | -35.8 |
| *% change* | | *(-46.58%)* | *(1.59%)* | *(-42.92%)* |
| Branded | - | 15.3 | 0.4 | 15.1 |
| *% change* | | *(6.33%)* | *(0.15%)* | *(6.25%)* |
| Total surplus | - | -58.3 | -11.4 | -61.3 |
| *% of spending* | | *(-4.04%)* | *(-0.79%)* | *(-4.24%)* |

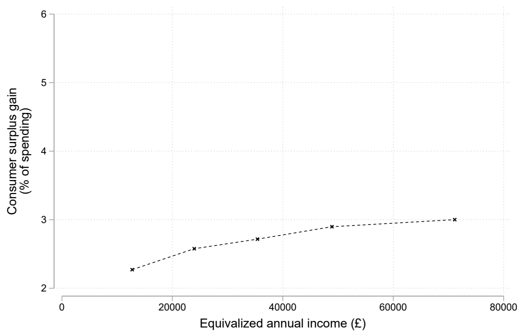
*Notes: Table compares average outcomes in the 2021 observed and counterfactual equilibrium. Unless otherwise stated the averages are unweighted. Panel (A) summarizes the change to market primitives in each counterfactual scenario. Panels (B) and (C) summarize the change in endogenous market outcomes. Marginal costs, prices, margins and surplus are expressed in 2021 £ per kg.*

Figure Q.2: *Distributional impact*

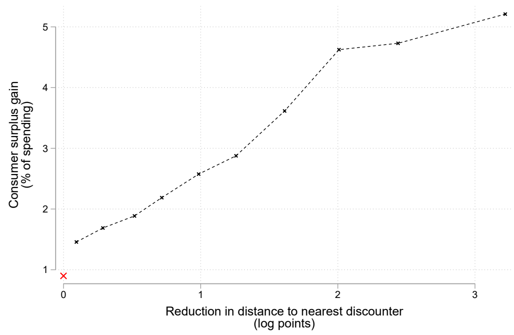
(a) Distribution across households




(b) Impact by income quintiles




(c) Impact by travel distance reduction




*Notes: Figures show the difference in consumer surplus, expressed as a fraction of total expenditure, between the observed and full counterfactual equilibria for the year 2021. Panel (a) reports the distribution of consumer changes across households. Panel (b) shows the average change for each household income quintile. Panel (c) presents the average change by the reduction in travel distance to the nearest discounter store.*

# R Product categories

Table R.1: *Product categories (1)*

| Category | Spending share (%) | Category | Spending share (%) |
|---|---|---|---|
| Ambient Cakes&Pastries | 1.61 | Pork | 0.78 |
| Morning Goods | 1.52 | Sausages | 0.76 |
| Total Bread | 1.84 | Chilled Cooking Sauces | 0.10 |
| Chilled Breads | 0.16 | Chilled Desserts | 0.77 |
| Chilled Cakes | 0.36 | Chilled Pate&Paste&Spread | 0.11 |
| Butter | 0.74 | Chilled Prepared Salad | 0.34 |
| Cheddar | 1.55 | Chilled Ready Meals | 2.83 |
| Eggs | 0.78 | Chilled Rice | 0.03 |
| Fresh Cream | 0.34 | Chilled Vegetarian | 0.09 |
| Margarine And Lard | 0.72 | Cooked Meats | 2.41 |
| Milk | 2.98 | Fresh Meat&Veg&Pastry | 1.21 |
| Non Cheedar Cheese | 0.78 | Fresh Pasta | 0.16 |
| Processed Cheese | 0.44 | Fresh Soup | 0.12 |
| Total Soft White | 0.24 | Fresh&Chilled Pastry | 0.05 |
| Yoghurt | 1.82 | Other Chilled Convenience | 0.28 |
| Yoghurt Drinks And Juices | 0.33 | Sandwich Fillers | 0.14 |
| Apples | 0.79 | Frozen Bread | 0.04 |
| Bananas | 0.65 | Frozen Meat Products | 0.24 |
| Brassicas | 0.59 | Frozen Pizzas | 0.55 |
| Chilled Prepared Frt&Veg | 0.96 | Frozen Potato Products | 0.79 |
| Citrus | 0.72 | Frozen Processed Poultry | 0.48 |
| Legumes | 0.22 | Frozen Ready Meals | 0.84 |
| Nuts - Fruit | 0.17 | Frozen Savoury Bakery | 0.22 |
| Other Vegetables | 0.83 | Frozen Vegetables | 0.57 |
| Pears | 0.21 | Frozen Vegetarian Prods | 0.20 |
| Potatoes | 1.16 | Other Frozen Foods | 0.15 |
| Root Crops | 0.81 | Ambient Slimming Products | 0.03 |
| Salads | 1.76 | Ambient Soup | 0.35 |
| Soft Fruit | 1.94 | Baked Bean | 0.39 |
| Tropical Fruits | 0.43 | Canned Fish | 0.53 |
| Chilled Prepared Fish | 0.26 | Canned Meats | 0.34 |
| Shellfish | 0.21 | Canned Puddings | 0.05 |
| Wet&Smoked Fish | 0.85 | Canned Rice&Pasta | 0.14 |
| Chilled Processed Poultry | 0.40 | Canned Vegetables | 0.16 |
| Cooked Poultry | 0.46 | Prepared Peas&Beans | 0.15 |
| Fresh Poultry | 2.20 | Tinned Fruit | 0.19 |
| Frozen Fish | 0.93 | Tomato Products | 0.24 |
| Frozen Poultry | 0.33 | Food Drinks | 0.19 |
| Bacon | 1.39 | Herbal Tea | 0.08 |
| Beef | 2.04 | Instant Coffee | 0.85 |
| Chilled Burgers&Grills | 0.20 | Liquid&Grnd Coffee&Beans | 0.29 |
| Chld Frnkfurter&Cont Ssgs | 0.12 | Tea | 0.57 |
| Flavoured Meats | 0.15 | Ambient Pastes&Spreads | 0.09 |
| Lamb | 0.56 | Breakfast Cereals | 1.66 |
| Other Meat & Offal | 0.13 | Honey | 0.10 |

Table R.2: *Product categories (2)*

| Category | Spending share (%) | Category | Spending share (%) |
|---|---|---|---|
| Peanut Butter | 0.07 | Savoury Biscuits | 0.24 |
| Porridge Oats | 0.20 | Cereal&Fruit Bars | 0.26 |
| Preserves | 0.19 | Childrens Biscuits | 0.14 |
| Toaster Pastries | 0.03 | Chocolate Biscuit Bars | 0.46 |
| Ambient Condiments | 0.09 | Confect. & Other Exclusions | 0.16 |
| Dips | 0.21 | Healthier Biscuits | 0.36 |
| Olives | 0.08 | Sweet Biscuits | 0.99 |
| Pickles Chutneys&Relish | 0.10 | Frozen Confectionery | 0.36 |
| Salad Accompanimet | 0.27 | Total Ice Cream | 1.00 |
| Sour&Speciality Pickles | 0.13 | Chocolate Confectionery | 2.25 |
| Table Sauces | 0.31 | Gum Confectionery | 0.09 |
| Ambient Rice&Svry Noodles | 0.48 | Ice Cream Cone | 0.01 |
| Cous Cous | 0.02 | Sugar Confectionery | 0.60 |
| Dry Pasta | 0.24 | Crisps | 0.94 |
| Dry Pulses&Cereal | 0.06 | Nuts - Savoury | 0.29 |
| Dry Food | 0.03 | Popcorn | 0.06 |
| Instant Hot Snacks | 0.12 | Savoury Snacks | 0.87 |
| Packet Soup | 0.12 | Colas | 1.01 |
| Ambient Cooking Sauces | 0.85 | Flavoured Milk | 1.34 |
| Cooking Oils | 0.33 | Lemonade | 0.15 |
| Ethnic Ingredients | 0.22 | Mineral Water | 0.40 |
| Flour | 0.12 | One Shot Drinks | 0.43 |
| Herbs&Spices | 0.18 | Other Soft Drinks | 0.65 |
| Meat Extract | 0.37 | Shandy, Ginger Ale | 0.05 |
| Pizza&Bases | 0.53 | Tonic, Soda Water | 0.11 |
| Salt | 0.03 | Total Fruit Squash | 0.61 |
| Stuffing | 0.05 | Beer&Lager | 1.74 |
| Sweet&Savoury Mixes | 0.10 | Cider | 0.43 |
| Vinegar | 0.05 | Fortifed Wine,Fabs | 0.42 |
| Ambient Sponge Puddings | 0.02 | Sparkling Wine | 0.44 |
| Artificial Sweeteners | 0.08 | Spirits | 2.35 |
| Defined Milk&Cream Prd(B) | 0.09 | Wine | 3.37 |
| Home Baking | 0.42 | Bar Soap | 0.05 |
| Instant Milk | 0.02 | Bath&Shower Products | 0.31 |
| Lemon&Lime Juices | 0.01 | Body Sprays | 0.38 |
| Milkshake Mixes | 0.03 | Liquid Soap | 0.13 |
| Mincemeat | 0.01 | Shaving | 0.07 |
| Nuts - Sweet | 0.06 | Skincare | 0.33 |
| Powd Desserts&Custard(B) | 0.09 | Sun Care | 0.05 |
| R.T.S. Custard | 0.06 | Talcum Powder | 0.01 |
| Rts Desserts Long Life | 0.08 | Hair Colourants | 0.10 |
| Ready To Use Icing | 0.03 | Hair Conditioners | 0.15 |
| Sugar | 0.31 | Hair Styling | 0.11 |
| Syrup & Treacle | 0.03 | Shampoo | 0.26 |
| Table&Quick Set Jellies | 0.03 | Analgesics | 0.18 |

Table R.3: *Product categories (3)*

| Category | Spending share (%) | Category | Spending share (%) |
|---|---|---|---|
| Cold Sore Treatment | 0.00 | Firelighters&Log | 0.01 |
| Cold Treatments | 0.16 | Household Cleaners | 0.41 |
| Contact Lens Cleaners | 0.01 | Household Food Wraps | 0.21 |
| Eye Care | 0.01 | Household Insecticides | 0.01 |
| First Aid Dressings | 0.02 | Kitchen Towels | 0.36 |
| Foot Preparations | 0.03 | Lmscle Rmvrs&Water Softener | 0.04 |
| Hayfever Remedies | 0.03 | Machine Wash Products | 1.00 |
| Oral Lesion&Teething Mrkt | 0.01 | Shoe Care Products | 0.01 |
| Sleeping Aids | 0.01 | Toilet Tissues | 1.18 |
| Smoking Cessation | 0.04 | Wash Additives | 0.11 |
| Spray Insecticide | 0.00 | Washing Up Products | 0.49 |
| Stomach Treatments | 0.11 | Dental Cleaners | 0.35 |
| Topical Antiseptics | 0.02 | Mouthwashes | 0.12 |
| Vitamins.Minerals&Splmnts | 0.18 | Total Toothbrushes | 0.15 |
| Air Fresheners | 0.33 | Cotton Wool | 0.04 |
| Batteries | 0.18 | Feminine Care | 0.28 |
| Bin Liners | 0.15 | Moist Wipes | 0.20 |
| Bleaches&Lavatory Clnrs | 0.26 | Razor Blades | 0.17 |
| Carpet Clnrs&Stain Rmvers | 0.06 | Cat Litter | 0.11 |
| Cleaning Accessories | 0.13 | Cat&Dog Treats | 0.36 |
| Electric Light Bulbs | 0.06 | Dog Food | 0.63 |
| Fabric Conditioners | 0.37 | Fish Foods | 0.01 |
| Facial Tissues | 0.24 | Total Cat Food Inc.Bulk | 1.35 |

*Notes: Authors' calculations using Numerator's Take Home Purchase Panel, 2002–2021. Reported spending shares are means across years.*

# References


Berry, S., J. Levinsohn, and A. Pakes (1995). Automobile prices in market equilibrium. *Econometrica 63*(4), 841–90.

Berry, S., O. B. Linton, and A. Pakes (2004). Limit theorems for estimating the parameters of differentiated product demand systems. *Review of Economic Studies 71*(3), 613–654.

CC (2000). *Supermarkets: A Report on the Supply of Groceries from Multiple Stores in the United Kingdom.* Competition Commission, The Stationery Office, London, U.K.

CC (2008). The supply of groceries in the uk market investigation. Technical report, Competition Commission, The Stationery Office, London, U.K.

de Fontenay, C. C. and J. S. Gans (2014). Bilateral bargaining with externalities. *The Journal of Industrial Economics 62*(4), 756–788.

Freyberger, J. (2015). Asymptotic theory for differentiated products demand models with many markets. *Journal of Econometrics 185*(1), 162–181.

Gandhi, A. and J.-F. Houde (2019). Measuring Substitution Patterns in Differentiated-Products Industries. Technical Report w26375, National Bureau of Economic Research, Cambridge, MA.

Low, H. and C. Meghir (2017). The use of structural models in econometrics. *Journal of Economic Perspectives 31*(2), 33–58.

Morrow, W. R. and S. J. Skerlos (2011). Fixed-point approaches to computing bertrand-nash equilibrium prices under mixed-logit demand. *Operations research 59*(2), 328–345.

O'Connell, M., H. Smith, and Ø. Thomassen (2025). A two sample size estimator for large data sets. *Econometrics Journal*, utaf002.

Rey, P. and T. Verge (2019). Secret contracting in multilateral relations. TSE Working Papers 16-744, Toulouse School of Economics (TSE).

Thomassen, Ø., H. Smith, S. Seiler, and P. Schiraldi (2017). Multi-category competition and market power: A model of supermarket pricing. *American Economic Review 107*(8), 2308–51.