Who Gets the Dough? Explaining the Gluten-Free Price Premium

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Abstract

Gluten-free (GF) food is substantially more expensive than its standard counterpart, raising concerns about affordability for people with coeliac disease and gluten intolerance. This paper decomposes that premium into its underlying economic causes. Focusing on the bread market in Great Britain - where GF bread is 4.5 times as expensive, per kilogram, as standard bread - I estimate a structural discrete-choice demand model with household-specific price sensitivity, GF taste, and taste for buying bread. Using weekly household-level scanner data on bread purchases between 2015 and 2019, I recover marginal costs under the assumption of multi-product Bertrand–Nash competition. In the preferred specification, costs account for over 90% of the premium, with GF bread costing 4.2 times as much per kilogram to supply as standard bread. I find that a counterfactual per-unit subsidy on GF bread would be passed through to consumers in full. These results suggest limited scope for competition policy to lower GF prices, instead, policy measures that lower or offset supply costs are more promising.

JEL classifications: L11, L66, I12, D43, L18

Keywords: demand estimation; market power; price discrimination; marginal costs; gluten-free products; food prices

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1 Introduction

Gluten-free (GF) bread in Great Britain costs 4.5 times as much per kilogram as standard bread. GF bread sales are worth around £190 million a year (Worldpanel 2025), and more than one in ten British households bought GF bread at least once between 2015 and 2019.[1] For people with coeliac disease, avoiding gluten is the only treatment, so the premium is a cost of being ill rather than a choice. A sizeable market combined with a clear health inequality has made the premium a policy concern, and governments have responded with prescriptions (England, Wales, Scotland, Northern Ireland), vouchers or subsidy cards (Italy, Wales) and tax relief (Canada, US, and Ireland).[2]

Whether these policies are well designed depends on whether the premium reflects the cost of supplying GF bread, or a markup charged to consumers who cannot switch. Both explanations are plausible. Price discrimination requires a group with inelastic demand, and consumers who are medically unable to eat the substitute pose an obvious candidate for such a captive group. Equally, GF bread may simply cost more to make. Ingredients alone cannot explain the premium: once input shares are accounted for, rice flour costs only around 1.5 times as much as wheat flour. However, GF production may also require dedicated allergen-free lines, testing and short production runs. In this paper, I decompose the GF price premium into differences in marginal cost and differences in markups, to establish which explanation dominates and therefore which policies are likely to work.[3] I use the estimated model to ask directly whether a subsidy on GF bread would reach consumers or be absorbed into firms' margins.

Since data on marginal costs are unobservable, I develop a structural demand and supply model to estimate elasticities and back out marginal costs. More specifically, I estimate a structural demand system with 482 bread products, using transaction-level scanner data on 35,570 GB households and over 5.8 million choice occasions between 2015 and 2019. My preferred specification is a mixed logit model in which households differ in how much they care about price, how much they value GF bread, and how often they buy bread at all. Estimating the model on a household panel, rather than on aggregate market shares, identifies this heterogeneity from the persistence of each household's choices. This matters for substitution: a small group of households buys GF bread persistently, so 26% of the sales a GF product loses go to other GF bread, against 0.6% in a conditional logit. Once elasticities are estimated from the demand model, I recover markups, and hence

[1] 10.5% of households in the data (Section 4).

[2] `https://celiac.org/gluten-free-living/global-associations-and-policies/policies-around-the-world/`

[3] Fixed costs, such as dedicated facilities and certification, do not enter static pricing conditions and so lie outside the decomposition; I return to them in Section 6.4.

marginal costs, from the first-order conditions of multi-product Bertrand-Nash pricing by manufacturers.

The main empirical challenge is that prices are correlated with unobserved quality. I address this with a control function built on input-cost shifters, using rice prices for GF bread and wheat prices for standard bread. Because GF bread is almost entirely sold in one pack size, I interact the shifters with bread type as well as pack size, so that they vary across GF products. Without the correction, demand for both types of bread appears inelastic.

I find that the premium is mainly driven by cost. GF bread costs 4.17 times as much per kilogram to supply as standard bread, against a price ratio of 4.67,[4] so cost accounts for 93% of the premium in log terms. GF bread costs more to supply in every specification and under every conduct assumption I consider, and in 93% of parameter draws in the headline specification. The own-price elasticity of an individual GF product is somewhat lower than that of a standard product (-3.37 against -5.25), implying a modestly higher proportional markup. Running a simple hypothetical, where I apply the markup from standard bread to GF bread, I find that GF bread would be 11% (£0.59 per kg) cheaper. Again, this highlights that markups are not the primary reason for the higher GF bread prices. Furthermore, this difference is not statistically significant. Nor are GF consumers captive as a group. Because about three quarters of a GF loaf's lost sales leave GF bread altogether, demand for GF bread as a whole is more elastic than demand for standard bread (-2.44 against -1.67). I also find no evidence that firms target richer households. Solving the model for counterfactual prices, I find that a per-unit subsidy on GF bread would be passed on to consumers in full. A subsidy of £0.50 per kilogram lowers the price of GF bread by £0.53 when manufacturers set prices, and by £0.50 when retailers do. Firms still gain, through higher sales rather than wider margins, and about a third of the consumer gain goes to the 0.7% of households that buy GF bread persistently. These results suggest limited scope for lowering GF prices through competition, and that measures which lower or offset the cost of supplying GF bread are more promising.

Although the data cover Great Britain, coeliac prevalence is similar worldwide (about 1.4% of the population (Singh et al. 2018)), and GF premia are large elsewhere: 85% for bread in the US, even after controlling for time and manufacturer effects (Bauner & Lavoie 2024). The approach also applies to other niche alternatives, such as dairy-free, organic, alcohol-free, ethically sourced, and plant-based products, whose premia raise similar questions of affordability. These questions are particularly important in the case of meat-free alternatives, as governments encourage a shift away from meat (for example,

[4]The price ratio of 4.67 covers the 400g and 800g packs priced in the supply model, within the estimation sample; see Section 4 for the 4.5 headline.

the UK's Climate Change Commission recommends a 35% cut in meat consumption by 2050 (Climate Change Committee 2025)).

This paper contributes to three literatures. Firstly, it adds to work on the sources of price premia between variants of the same product. Small differences in product characteristics are often associated with large price differences: organic versus conventional food (Hong 2026, Cacicedo 2024), male- versus female-marketed hygiene products (Machado 2025), and different pack sizes (Cohen 2008). These studies ask whether a premium reflects differences in cost or price discrimination across consumer segments, and the answer varies. Hong (2026) finds that the organic premium in US baby food is driven by marginal costs rather than markups, and that it declines with county-level income, population and education. Cacicedo (2024) likewise finds that the organic premium reflects cost differences, as does Machado (2025) for deodorants. In contrast, Cohen (2008) attributes between 34% and 46% of the within-brand unit-price discount on multi-roll paper towels to markups, and Verboven (1996) finds that differences in car prices across European countries largely reflect price discrimination.

I provide the first such decomposition for GF products. This is the setting where intuition most strongly predicts price discrimination, - as a subset of consumers are medically unable to substitute to the conventional good - so finding that the premium is nonetheless largely cost-driven is informative beyond this market. Unlike studies that estimate demand from aggregate market shares, I use a household panel, so that, as in Berry et al. (2004), heterogeneity between persistent and occasional GF buyers is identified from repeated choices. This heterogeneity determines how far GF buyers substitute within the GF segment. In doing so, I build on the literature that recovers marginal costs from estimated demand (e.g. Berry et al. 1995, Petrin 2002, Conlon & Gortmaker 2020) and compares alternative models of conduct (Nevo 2001, Miller & Weinberg 2017, Backus et al. 2021). The results also relate to work on how fixed costs shape the products that markets offer to preference minorities (Waldfogel 1999, Berry et al. 2016*b*, Berry et al. 2016*a*, Berry & Waldfogel 1996).

Secondly, I add to studies documenting the GF price premium (Bauner & Lavoie 2024, Capacci et al. 2018, Lee et al. 2019). Rather than documenting the premium, I identify its source, and I measure it over the products households actually buy rather than over all products on offer or an inferred basket.

Thirdly, I contribute to the economics of food policy (Dubois et al. 2014, Dubois et al. 2020). Whether policies aimed at the GF premium should target margins, through competition policy, or costs, through support for consumers or producers, depends on the source of the premium. A premium driven by cost also suggests that demand-side sup-

port, such as prescriptions, subsidy cards or tax relief, is less likely to be absorbed into firms' margins. I show this directly for a per-unit subsidy on GF bread, which counterfactual equilibria show is passed through to consumers in full.

The rest of the paper proceeds as follows. Section 2 describes the bread market and the policies that support people with coeliac disease. Section 3 describes the scanner data and the cost shifters, and Section 4 presents descriptive statistics. Section 5 sets out the model of demand and supply, Section 6 presents the estimates and the decomposition of the premium, as well as the counterfactual analysis and Section 7 concludes.

2 Market and Institutional Setting

The UK bakery market is worth £5.74 billion, of which traditional wrapped bread accounts for £2 billion.[5] Bread is bought by 99.8% of British households, with the average individual consuming 465g of bread per week.[6] GF bread is a small but growing part of this market. Between 2015 and 2019, it accounts for 0.5% of the volume and 2.3% of the expenditure on bread, with both shares rising over the period (Section 4). It is nonetheless bought widely: 10.5% of households buy GF bread at least once over the period, and in 2019 GF products make up 9% of the bread products on sale.

Coeliac disease is an auto-immune disease, triggered by ingestion of gluten, a protein found in wheat, barley, and rye. Symptoms range from diarrhoea, nausea and tiredness to anaemia and, in the long term, osteoporosis, infertility and neurological problems, and the only treatment is a lifelong gluten-free diet (Coeliac UK 2025*a*). Around 1% of the UK population are believed to have this condition but only 36% are currently diagnosed (Coeliac UK 2025*a*). With better diagnostic tools and awareness, this rate seems set to increase, with around 500,000 people in the UK currently being undiagnosed (Coeliac UK 2025*a*). Coeliacs are not the only buyers of GF bread. Around 10% of people worldwide report non-coeliac gluten intolerance, and 40% of these individuals follow a gluten-free diet (Shiha et al. 2026). GF products are also bought by family members of coeliacs (to avoid contaminating a coeliac living in the same household), by people avoiding gluten for other reasons, and by consumers who prefer their taste or shelf life. GF demand therefore combines a group that cannot switch with a larger group that can, which is why the demand model allows both the taste for GF bread and price sensitivity to vary across households.

[5]Federation of Bakers: `https://www.fob.uk.com/about-the-bread-industry/industry-facts/uk-bread-market/` (accessed on 30th December 2025).

[6]UK Flour Millers, Flour and Bread Consumption (`https://www.ukflourmillers.org/knowledge-hub/market-insights/flour-bread-consumption`; accessed on 30th December 2025).

Food labelling in the UK is governed by a harmonised framework inherited from EU law. Since 2005, cereals containing gluten have had to be declared as an allergen on prepacked food, and since December 2014, they must be emphasised within the ingredients list.[7] Separately, claims about the absence of gluten have been regulated since January 2012, a product may be labelled "gluten-free" only if it contains no more than 20 mg/kg of gluten, and "very low gluten" only if it contains no more than 100 mg/kg.[8] The effect is to make gluten-free status a legally defined, verifiable product attribute rather than a marketing claim.

There is a well-documented price differential between gluten-free and non-GF products, with a weekly food shop being 34% more expensive for coeliacs in the UK (Coeliac UK 2024). The difference is larger for lower-income households, who spend a greater proportion of their food budget on GF-affected food categories (Capacci et al. 2018). As well as issues of fairness this raises concerns around health and income inequality and the ability for diagnosed coeliacs to afford foods consistent with their condition; 77% of coeliacs in the UK struggle to afford gluten-free products (Coeliac UK 2024).

Back-of-the-envelope calculations suggest that the GF price premium cannot solely be attributed to higher ingredient input costs. Regular bread typically uses wheat flour, whilst GF bread typically uses rice flour (and requires more emulsifiers and oils to bind the flour). Adjusting for size and inflation, and weighting by kilograms purchased, GF bread is 4.5 times as expensive as regular bread.[9] The difference in cost for the primary ingredient of GF bread (rice flour, instead of wheat flour) is only a factor of 1.5, adjusting for different average input shares. This points towards other marginal costs - such as testing, certification and lost economies of scale from lower production volume of GF breads - playing a large role or that other factors also contribute to the GF price premium (i.e. markups). Fixed costs may also play a role in contributing to the price premium, with higher overheads from maintaining a separate production facility to avoid cross-contamination. The model in Section 5 separates marginal costs from markups.

Governments are aware of the GF price premium and take action to ameliorate any adverse effects. However, these interventions normally apply only to coeliacs, who can be medically diagnosed, as opposed to gluten intolerants who rely on self-diagnosis. The approach in England involves diagnosed coeliacs being able to access gluten-free staple foods on prescription, which is collected from a pharmacy. A prescription fee applies for patients not in receipt of government benefits.[10] Several products are available in

[7]Directive 2003/89/EC (from 2005); Regulation (EU) No 1169/2011 (from December 2014).

[8]Commission Regulation (EC) No 41/2009, replaced in 2016 by Implementing Regulation (EU) No 828/2014. These rules were retained in Great Britain post-Brexit.

[9]See Section 3 for details on the dataset used to calculate this.

[10]The prescription fee applies to different products. So an individual could purchase multiple loaves

each product category but there is still limited choice. In England, since December 2018 only gluten-free bread loaves, rolls, and flour mixes are available on prescription (Coeliac UK 2025*b*). Furthermore, certain Integrated Care Boards (ICBs) have restricted access in recent times, in order to save costs. Nonetheless, 55% of the English population live in areas with access (Coeliac UK 2025*a*).[11] In the year to October 2025, English GPs prescribed 301,802 GF food items at a cost to the NHS of £6.5 million.[12]

Wales, Scotland, and Northern Ireland offer similar systems and in addition to the products offered in England, also include pasta, breakfast cereals, crackers, and pizza bases. Furthermore, these countries do not charge for prescriptions. The Scottish system is processed directly by pharmacies, without the need to visit a GP (for diagnosed coeliacs only). The Welsh system has traditionally followed the English system with gluten-free staples being available via the GP prescription system. However, one health board (Hywel Dda University Health Board, in West Wales) has trialled a subsidy card, whereby coeliacs are able to directly purchase gluten-free food from retailers, giving them choice and reducing the burden on GPs to issue prescriptions. The trial began in June 2018 (before being expanded in January 2019), and over 1,100 coeliacs have used the card, with the average patient receiving a subsidy of £15 a month.[13] In July 2025 it was announced that this subsidy card scheme was to be rolled out nationally across Wales. However, as of mid-December 2025, no individual has received a subsidy outside Hywel Dda.[14]

These schemes matter for interpreting the data. GF food supplied on prescription is not a retail purchase and so does not appear in the scanner data, so the households most reliant on GF bread may be under-represented amongst observed GF buyers. The model therefore describes demand in the retail market, where the prices studied here are set. Over the sample period, prescription withdrawals in parts of England and the restriction of prescribable products from December 2018 may have moved some coeliacs into retail purchasing.

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of bread and incur a single prescription charge but would have to pay multiple charges if they purchase multiple types of products. For individuals who purchase prescriptions frequently, a pre-payment certificate offers a bundled reduction.

[11] Of the 42 English ICBs, 13 offer routine GF prescriptions, 13 have fully withdrawn, 6 have partly withdrawn, and 10 have mixed policies (Coeliac UK 2025*a*).

[12] Based on an analysis of the English Prescribing Dataset (NHS BSA) by the author. An item means a unique product but multiple units can be purchased within an item. Therefore, the number of units dispensed likely exceeds 301,802.

[13] Source: a freedom of information request issued by the author to the Welsh Government (NWSSP ref: 105-25).

[14] Source: a freedom of information request issued by the author to the Welsh Government (NWSSP ref: 103-25).

3 Data

I use data on grocery purchases of bread items made by a representative panel of British households from Worldpanel by Numerator's Take Home purchase data. I use data from January 2015 to December 2019.[15] The data is collected at the household level using handheld scanners to record purchases at the barcode (UPC) level and includes detail on the exact price paid (including discounts and offers), quantity and volume purchased, retailer purchased from, retail characteristics, household characteristics, and product characteristics (size, nutritional values[16], bread type, organic status, and GF status).

I focus on the bread market, as one of the largest markets involving the sales of gluten products. Products include packaged and loose bread, rolls, baguettes, and brioche sold in GB retailers.[17] The dataset includes purchases from independent bakeries, although their sales in the UK are small.[18]

An observation is a weekly purchase of a product at a given retailer at the barcode-level. The dataset includes a flag for free-from products which is manually checked for accuracy. The pack size variable is cleaned to ensure consistency with the product description (a small number of observations are dropped if inconsistent or a non-standard pack size, this mainly affects loose bread). Product price is denoted in price per kilogram of bread and is calculated as expenditure divided by volume, whilst pack price is denoted as the price per pack/loaf.[19] Demand is estimated on the pack price, since households choose packs; per-kilogram prices are used only to report the price premium, markups and marginal costs. The expenditure data is the final consumer price and so includes any offered discounts. Prices are deflated using the monthly ONS Consumer Price Index for Households (CPIH) series and are given in 2015 prices.[20] I clean the nutritional data by taking the mean nutritional value within a barcode.[21]

[15] I choose this period as it is after the mandatory gluten labelling laws took effect and before the effects of the COVID pandemic, which may have affected consumer preferences.

[16] This includes calories, carbohydrates, fat, fibre, protein, and sodium (salt). There are many missing values for sodium, so I do not use this variable in estimation.

[17] This does not include products such as packaged sandwiches. Frozen bread is included.

[18] 85% of UK bread production is by large bakeries, 12% by in-store supermarket bakeries, and the remaining 3% by high street bakeries. Source: UK Flour Millers, Flour and Bread Consumption (`https://www.ukflourmillers.org/knowledge-hub/market-insights/flour-bread-consumption`; accessed on 30th December 2025).

[19] A small number of observations have zero expenditure (they are flagged as being on promotion) and are dropped. Within each barcode-week I compute the median transaction price across all households and retailers, and drop a small number of observations whose price exceeds three times, or falls below 0.4 times, that median. These observations appear to be outliers that may arise from mis-scanned quantities.

[20] Table L522 available at `https://www.ons.gov.uk/economy/inflationandpriceindices/datasets/consumerpriceinflation`.

[21] This will thus remove any product reformulations that occur over time.

At this point, there are 1,849 unique barcodes, which makes it infeasible to estimate a discrete choice demand model. This is because the discrete choice model involves estimating demand across all potential alternative options, such that the size of the dataset increases with the number of products and households sampled. I therefore aggregate products by range trading company × gluten-free status × pack size × bread-type. This reduces the product space to 522 products (henceforth I use product to refer to this aggregated barcode, so an observation is a weekly purchase of an aggregated product at a given retailer). The average non-GF product bundles 13 barcodes (4 if considering volume-weighted barcodes[22]), whilst the average GF product bundles 4 barcodes (2 volume-weighted).

Within each product, I create the characteristics of the products as a weighted average of the underlying barcodes in the aggregation. I use the barcode volume weights to do so. For continuous variables (nutrition and organic share) I use the mean, for categorical variables I use the mode. To calculate the price of a product, I use a fixed-weighted average of barcode prices. The weight is determined by the barcodes' total volume across a wider sample (2012-23). This means that the price of a product cannot change because of shifts in the relative popularity of barcodes that are observed. However, the price is only constructed on barcodes that are observed, so variation will arise from barcode entry/exit. This means that an individual household in the discrete choice model does not face a posted price but faces the fixed-weight indexed price.

I merge demographic data on household size, the number of adults and children, and household income. I group income into three bands (low: £0 to £29,999, middle: £30,000 to £59,999, high: £60,000 and above), which an additional specification allows to shift the mean price coefficient, the mean taste for gluten-free bread and the taste for buying bread.[23]

The cleaned dataset contains 7,265,408 observations across 522 products (49 of which are GF), 43,735 households, 11 retailers, and 260 weeks.[24] Further restrictions are made in order to build the choice set - resulting in a final sample of 35,570 households and 5,887,570 choice occasions, and 482 products (45 gluten-free) - these restrictions are explained further in Section 5.

[22]This is calculated as the inverse-Herfindahl over volume shares.

[23]A household that does not state its income in a year, or has no demographic match, is given its modal band from the years it does state. The 3,274 households (9.2%) for which there is no income data form a separate band.

[24]The retailers are: Aldi, Asda, Co-op, Iceland, Lidl, Marks and Spencer, Morrisons, Tesco, Sainsbury's, and Waitrose. An "other" category includes remaining fringe retailers of bread products.

3.1 Instruments

As explained more fully in Section 5, a variety of instruments are used to deal with the price endogeneity problem. These include the following cost-shifter instruments: wheat[25], rice[26], rapeseed oil, food packaging prices, diesel, and energy prices. For wheat, rice, and rapeseed oil prices, I use monthly world commodity prices from the World Bank's Pink Sheet.[27] I deflate these to 2015 prices using the same ONS CPIH data as above. Note that these prices do not account for milling, transport and processing costs.

Diesel fuel pump prices are taken from the UK Government Statistics website and are available weekly over the sample period.[28] Energy prices are an index from the ONS' Producer Price Index. Food packaging prices are an index from the ONS' Producer Price Index for Rubber and Plastic Products.[29] All instruments bar diesel prices are available monthly over the sample period and are converted to weekly by repeating the value within-month. Indexed prices are relative to 2015.

4 Descriptive Statistics

The total volume of products is 4.36m kg. This is 22,655 kg for gluten-free products (0.5%). The total expenditure of products is £5.65m. This is £132,111 for gluten-free products (2.3%).

The median product is observed for 120 (not necessarily consecutive) weeks with a mean of 133 weeks. The 1st percentile is 1 week.

Table 1 shows purchase-level (mean) averages for standard and GF bread products across key characteristics. There is a substantial GF price premium: weighting by kilograms purchased, gluten-free bread costs 4.5 times as much per kilogram as standard bread.[30]

[25]This captures the key ingredient of non-GF flour. I use the "US Hard Red Winter" variety.

[26]Rice flour is the most common substitute for wheat flour used in gluten-free bread products. It is made by milling raw rice grains into a powder. I therefore use rice prices as a proxy for this key input of gluten-free bread. I use "Thailand 100% broken (A1 Super) rice". This most accurately reflects the type of rice used in rice flour, which is low quality and therefore not consumed in its own right.

[27]Prices are provided in nominal terms in US$ per metric tonne, these are converted to GBP using exchange rate data from the IMF (daily data from 1st January 2005 until 1st January 2024, averaged to the monthly level).

[28]Diesel is the primary source of fuel used by lorries in the UK. The variable Pump prices + Duty rate is used. VAT is excluded as this is normally redeemable by businesses as an intermediate cost. Data source available at: `https://www.gov.uk/government/statistics/weekly-road-fuel-prices`.

[29]See `https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/g6sx/ppi`.

[30]This is the mean price per kilogram weighted by kilograms purchased, that is, total expenditure per kilogram. The simple mean across purchases in Table 1 gives a ratio of 4.2 (£5.65 against £1.35), because it counts a large, cheap standard loaf the same as a small pack. The structural results in Section

The average gluten-free purchase is smaller in volume than the average standard purchase, but costs more. Standard breads are more likely to be own- (retailer) brand compared with GF breads. GF bread is also typically sold in a smaller pack size. In terms of nutritional content, GF products have higher calories and fat and less protein than regular bread.

Table 1: Descriptive Statistics, 2015-19

	Standard Bread Products	GF Bread Products	All
Panel A: Purchase-Level Descriptive Statistics			
Number of Products	473	49	522
Price (per kg)	1.35	5.65	1.41
Volume (kg)	0.89	0.46	0.89
Expenditure	1.14	2.71	1.15
Pack size (g)	701	400	699
Own-brand	41%	31%	41%
Energy (KJ)	10,259	10,934	10,265
Calories	2,430	2,604	2,432
Protein	95	45	94
Carbohydrates	430	407	429
Fats	30	73	31
Fibre	41	77	42
Panel B: Number of Products by Package Size			
200g	1	0	1
400g	233	47	280
600g	15	1	16
800g	224	1	225

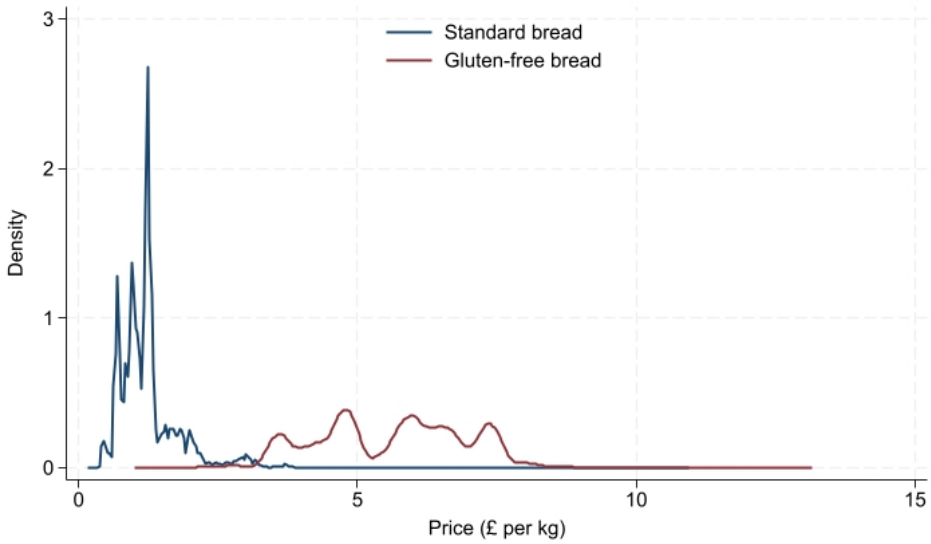
Note: Panel A provides descriptive statistics at the purchase level, i.e. the household-product-retailer-week observation (unweighted by market share). Volume is per purchase and can include more than one pack. Panel B provides the number of products by package size. Prices are denoted in 2015 prices. All nutritional info is given per 1kg.

In Figure 1, I show the distribution of prices of standard vs gluten-free bread products. GF products are more expensive than standard products, and their prices vary more in absolute terms. Standard bread purchases are concentrated in a narrow price band, with half of the volume being bought at or below £1.19/kg and 90% below £1.88/kg, and a thin tail of premium loaves. Gluten-free purchases span a much wider range of prices in absolute terms (P10–P90 of £3.70–£7.37/kg) and cluster into a few distinct price tiers. In proportional terms, however, GF prices are less dispersed than standard prices (a P90/P10 ratio of 1.99, against 2.65 for standard bread). Between 2015 and 2019, the

6 use a ratio of 4.67, which covers the estimation sample and only the 400g and 800g packs whose prices are set in the supply model (all but 2.6% of kilograms sold).

GF distribution shifts towards lower prices, in line with the declining premium in Figure 2, whilst both distributions become more dispersed in proportional terms (the P90/P10 ratio rises from 1.66 to 1.84 for GF and from 2.25 to 2.98 for standard bread; see Figures 6 and 7, in Annex A.1).

Figure 1: Kernel Distribution of Prices (standard vs GF products)



Note: Data is kg-weighted.

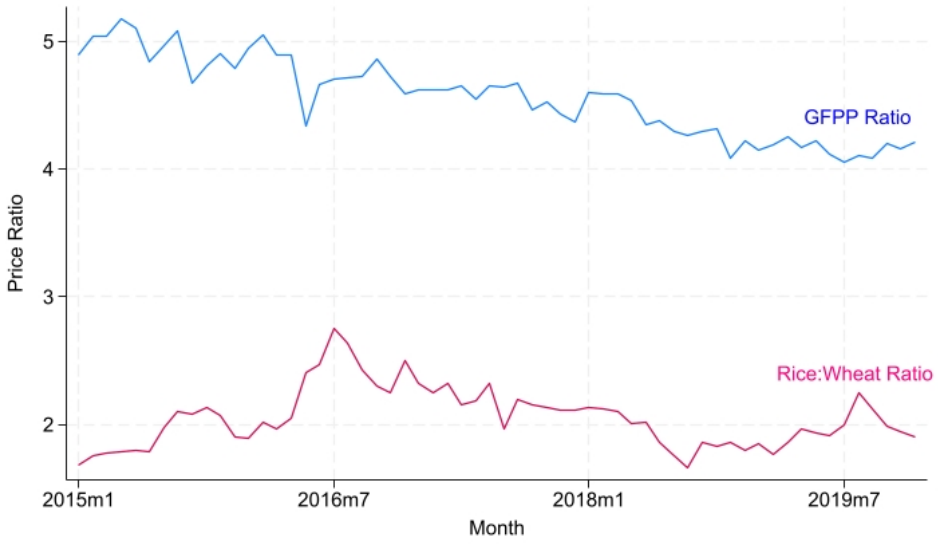
The GF price premium is fairly stable from month to month, but it declines over the period, from around 5 in 2015 to just over 4 by 2019, as shown in Figure 2. In the same figure, I plot the price ratio between rice and wheat, to reflect different underlying ingredient costs.[31] There does not seem to be a strong correlation between the GF price premium and the rice-to-wheat ratio, with the contemporaneous correlation coefficient being 0.10, increasing to 0.22 with a 4-month lag in the ingredient ratio. Whilst the GF price premium seems to be trending downwards, there is no such trend in the rice-to-wheat ratio. Furthermore, ingredient costs cannot explain the *level* of the premium, suggesting that factors other than just ingredient costs are important.[32]

Capacci et al. (2018) find that GF products in the bread category are 4.09 times as expensive as non-GF. This is lower than the 4.5 premium factor in this dataset, because they average prices over all products on offer, whereas I weight each product by the kilograms actually purchased.

Over time, the (deflated) prices of bread remained relatively stable (Figure 5 in Annex A.1). There seems to be slight downward pressure on GF bread prices.

[31]Rice flour is the primary alternative to wheat flour used in GF products.
[32]Note that less rice flour is used in GF bread than wheat flour is used in regular bread.

Figure 2: Gluten-Free Price Premium



Note: monthly ratio of average price per kilogram purchased (kg-weighted).

There are 90 manufacturers and 181 range trading companies. There are 10 manufacturers which only produce GF bread, 67 which only produce regular bread, and 13 which produce both types. The weekly Herfindahl-Hirschman Index (HHI) for the bread market overall is 0.12, 0.12 for the standard segment but the GF segment is twice as concentrated with an HHI of 0.24. The product-weighted share shows that consumers prefer branded bread (55% of purchases) to private label bread. Of the retailers which sell own-brand non-GF bread, only Lidl and Iceland do not also produce GF bread.

The median number of bread products per week is 267 (mean is 266), with a minimum of 239 and a maximum of 285.[33] The median number of GF bread products per week is 20 (mean is 19.8), with a minimum of 14 and a maximum of 26. Whilst the number of GF products has been increasing over time, the number of standard products increased and then decreased (see Figure 4 in Annex A.1). In 2019, there were 29 GF products out of 331 products, such that 9% of bread products were gluten-free, much higher than the expenditure or volume share of GF breads.

Gluten-free bread is bought far more widely than coeliac disease alone would imply. 10.5% of households buy it at least once between 2015 and 2019, and 4.6% do so even within a random draw of 26 of their shopping weeks. By contrast, with around 1% of the population coeliac and only a third of cases diagnosed (Coeliac UK 2025*a*), roughly 2% of households would contain a coeliac, and under 1% a diagnosed one. A substantial

[33]Recall that a product is defined as a range trading company × gluten-free status × pack size × bread type.

share of gluten-free purchases therefore comes from households without a medical need. Figure 3 shows that the weekly expenditure and volume share of gluten-free products has been increasing over time.

Figure 3: Monthly Expenditure/Volume Share of Gluten-Free Products, over time

Products included in the final sample are bread, rolls, baguettes, frozen bread, and brioche. Weighting by market-share, 0.3% are organic, and 60% are medium thickness (27% thick, 13% unsliced). Gluten-free products differ slightly in that 2.6% are organic, 78% are medium thickness (5% thick and 15% unsliced), (market-share weighted).

5 Empirical Strategy

5.1 Demand

I estimate demand using a discrete-choice framework applied to individual household purchases.[34] I make a number of restrictions to the existing dataset, in order to build the choice set. A choice occasion is defined as a household-week in which the household is active in the panel. A week is active if the household recorded at least £5 of take-home grocery spending, whether or not it bought bread. This is designed to distinguish weeks in which the household shopped and chose not to buy bread from weeks in which it did not shop, or did not record its shopping, which are uninformative about bread demand.

I treat the retailer visited by the household in a given week as predetermined. Bread is a small part of a typical grocery basket, so households are unlikely to choose where to shop on the basis of bread prices.[35] A market is therefore a retailer-week, and the choice set is the set of bread products listed at that retailer in that week. Product availability at the retailer-level is not observed directly, so I infer it from observed purchases. For each product-retailer pair I build availability spells. Consecutive purchases of a product belong to the same spell unless the gap between them exceeds a threshold that scales with how often the product is bought (between 4 and 26 weeks). Spells with fewer than three (total) purchases are discarded. Within a spell the product is available every week, at the price of the nearest week in which it was bought. The sample is restricted to 2015-2019 and to households observed in at least 26 weeks and in at least 32% of the weeks between their first and last appearance, and who buy bread at least once in the window.

The outside option, $j = 0$, is defined as an active week in which no bread was purchased. A household that buys no bread in a week is placed at the retailer where it buys bread most often, so its outside choice is made against that retailer's range and prices. Under this definition the outside option accounts for 39.2% of the over 5.8 million choice occasions in the estimation sample.

When a household purchases more than one bread product in a week I retain an observation at random, drawing over product-retailer rows (so that a product bought at two retailers in one week has two chances of selection). This affects 28.2% of household-weeks

[34] I estimate a static model. On average, consumers purchase bread in just over 60% of the weeks in which they shop. Whilst it is possible for them to freeze bread, stockpiling is unlikely to be important in this setting because (i) freezer space is limited and bread size is large, limiting the amount of stockpiling possible, and (ii) freezing deteriorates the quality of bread and affects the taste.

[35] If some households, for example those seeking particular gluten-free products, do shop around, their demand would be more elastic than the model implies.

in which bread is bought.[36]

With the choice set built, I now turn to the household's decision. The indirect utility that household i obtains from product j on occasion t, at retailer r in week w, is

$$U_{ijt} = a_{ij}\, p_{jt} + \beta_i GF_j + c_i + x_j'\gamma + f(\hat{v}_{jt}) + \epsilon_{ijt}, \qquad a_{ij} = \alpha_i e^{\kappa GF_j} + \lambda_{s(j)}, \tag{1}$$

and the utility of the outside option is

$$U_{i0t} = \eta_r + \tau_{y(w)} + \omega_{m(w)} + \epsilon_{i0t}, \tag{2}$$

where p_{jt} is the price of a pack (in 2015 £) and GF_j indicates gluten-free products. a_{ij} is household i's price slope for product j: its own price coefficient α_i, scaled by e^{κ} for gluten-free products, plus a pack-size shift $\lambda_{s(j)}$ (800g is the base, $\lambda_{800} = 0$). c_i is the household's taste for buying bread at all, relative to the outside option.

x_j captures observable bread characteristics including fixed effects for bread thickness, branded status, pack size × bread type, and manufacturer × gluten-free (nutritional characteristics enter in a robustness check). The manufacturer × gluten-free fixed effects give each manufacturer's gluten-free and standard ranges their own quality level. $\hat{v}_{jt}$ is the control-function residual (described below), and ϵ_{ijt} is an i.i.d. type-I extreme value error. η_r, τ_y and ω_m are retailer, calendar-year and month-of-year fixed effects. Because only differences in utility between the options available on an occasion affect choices, an effect common to every option cancels out; these effects therefore enter the outside option only, where they shift the probability of buying any bread at all relative to buying none. They capture, for example, seasonal variation in how often households buy bread and differences between retailers' shoppers, and they match the fixed effects in the first stage (see below).

Three parameters vary across households and are drawn once, so they are held fixed across a household's choice occasions: the price coefficient (α_i), the taste for gluten-free bread (β_i), and the taste for buying bread at all relative to not buying it (c_i). The price coefficient is lognormal, $\alpha_i = -\exp(u_i)$, so it is negative for every household, and

$$\begin{pmatrix} u_i \\ \beta_i \\ c_i \end{pmatrix} \sim N\left(\begin{pmatrix} \mu_u \\ \mu_\beta \\ 0 \end{pmatrix}, \Sigma \right) \tag{3}$$

with Σ unrestricted. The mean of c_i is normalised to zero, since its level is absorbed by

[36] I choose this approach, rather than selecting the maximum expenditure in a given week to avoid selecting on an outcome.

the outside-option effects in equation (2). The correlation between α_i and β_i determines whether households with a strong taste for gluten-free bread are also less price-sensitive, and so affects how elastic demand for gluten-free bread is. Its consequences for pricing are captured by the implied markups, which integrate over the whole distribution of tastes. The data do not pin the correlation down separately (see Section 6), and the inference on the markups allows for this uncertainty, so I assess price discrimination through the markups rather than through this parameter.

Estimating the model on individual household choices, rather than on aggregate market shares, exploits the panel structure of the scanner data to identify rich preference heterogeneity. With market-level data, the dispersion of tastes rests on instruments that shift choice sets (Berry & Haile 2014). Here, each household is observed on many occasions, so, as in Berry et al. (2004), the dispersion and correlation of tastes are identified from the persistence of each household's choices across repeated purchases. The shape of the taste distribution, and hence how far gluten-free buyers substitute to other gluten-free bread rather than to standard bread, is identified mainly from the panel, whilst the cost-shifter instruments (explained below) are used to identify the response of demand to price. This captures the "locked-in" nature of coeliac demand without relying on the aggregate share inversion of Berry et al. (1995).

Gluten-free status scales each household's own price coefficient by e^{κ}, so a household's price sensitivity for gluten-free bread is tied to its sensitivity for standard bread. Price also enters through additive pack-size slopes λ_s (800g is the base), because a single price coefficient across pack sizes is rejected by the data. Gluten-free bread is almost entirely sold in 400g packs, so I compare gluten-free and standard price responses at 400g. The multiplicative form ties each household's gluten-free price coefficient to its standard one, and at the estimates every household's gluten-free price slope is negative. Setting $\Sigma = 0$ gives the conditional logit, which I use as a benchmark. In the conditional logit model I enter the gluten-free price shift additively, as an interaction between price and gluten-free status; with a common price coefficient this is equivalent to the multiplicative form whenever the gluten-free slope is negative, but it also allows the slope to be positive, as it is at 800g without the control function. The correlation between price sensitivity and gluten-free taste is identified by whether the households that buy gluten-free bread respond more or less to price changes than other households. Because few households buy gluten-free bread, and the gluten-free price response is identified mainly from those households, this correlation and κ draw on overlapping variation and are less precisely separated than the other parameters. The taste for buying bread is identified by how often each household buys bread at all. Without it the model cannot reproduce how much households differ in purchase frequency: the variance of the number of bread purchases

across households is 25% larger in the data than the model implies, against 1% in data simulated from the model itself. That missing heterogeneity is otherwise captured by the price coefficient and its correlation with gluten-free taste.

It is well known that there exists a correlation between price and unobserved product quality that needs to be addressed to estimate unbiased coefficients. To account for this, I adopt a control-function approach (Petrin & Train 2010). In the first stage, I regress the pack price of each product-retailer-week on excluded cost shifters, the product characteristics in x_j, and retailer, calendar-year and month-of-year fixed effects. The residual from this first stage captures the part of a product's price that the cost shifters and fixed effects do not explain, and so proxies for unobserved quality. It enters utility as $f(\hat{v}_{jt}) = (\rho_{s(j)} + \rho_{GF}\, GF_j)\, \hat{v}_{jt}$, with a coefficient that can differ by pack size and between gluten-free and standard bread, so that the correlation between price and unobserved quality can differ across these groups.[37] Conditional on these terms, price is independent of the remaining error, and the residual coefficients capture the endogeneity correction. Price is therefore identified by relative prices within a store-week and by cost-driven movements in the level of bread prices within a retailer, year and season.

An alternative approach to the control function would be to include product fixed effects, which absorb time-invariant unobserved quality. Identification then rests only on price movements within a product, over time and across retailers. In this setting, product fixed effects remove, or reverse, the gluten-free price response. In the conditional logit, gluten-free demand becomes inelastic (an elasticity of about -0.6), so the implied marginal cost is negative for almost all gluten-free volume. In the mixed logit, gluten-free demand slopes upward in 77% of product-markets, or 99.7% when the control function is added as well (Annex Table 10). No static pricing model can rationalise either result.[38] I therefore focus on the control-function approach rather than including product fixed effects to control for unobserved product quality.

I use cost-shifter instruments that shift the marginal cost of producing bread but are plausibly orthogonal to demand shocks. These are wheat prices, rice prices, rapeseed oil prices, diesel prices, energy price index, and packaging price index. Wheat prices are only applied to non-GF products, whilst rice is the principal flour substitute to wheat and is applied only to GF products. The remaining series are entered separately for gluten-free and standard products, so that cost variation affects the two ranges differently. Each series is interacted with pack size (in grams). Rice, wheat, energy and gluten-free rapeseed are

[37] The same fixed effects enter both stages: the first stage's retailer, year and month-of-year effects enter demand as effects on the outside option, equation (2), and the manufacturer × gluten-free effects through x_j.

[38] This is not a weak-instrument problem: with product fixed effects the cost shifters remain strong in the first stage ($F = 63$ for all 20 shifters, against 37.2 in the headline specification).

additionally interacted with an indicator for white and for brown bread. These bread-type interactions are important because GF bread is almost entirely one pack size (400g), so without the bread-type interactions the GF instruments collapse to a single national time series with no variation across GF products. All series except diesel are lagged eight weeks to reflect production lags.[39] First-stage standard errors are clustered by product and calendar month. The reported first-stage F statistics are clustered just by product, since a two-way F statistic is unreliable with only 60 monthly clusters for 20 instruments. These instruments shift production and distribution costs but are unlikely to directly affect consumer utility conditional on prices and fixed effects.[40]

In Section 6 I report two conditional logits, without and with the control function, and two mixed logits, without and with the random taste for buying bread (Tables 2 and 4). All use retailer, year and month-of-year effects in the first stage, which also enter the outside option, and manufacturer × gluten-free effects in both stages. These compare price only within a manufacturer's gluten-free or standard range, which addresses the concern that gluten-free products are priced highly simply because they are premium brands. The headline specification, column (4), includes the random taste for buying bread and is the most precisely estimated. Robustness checks drop the manufacturer × gluten-free effects and add calories and fibre (Section 6.3).

5.2 Supply

On the supply side, I assume that firms engage in static Bertrand-Nash price competition in each market t (a retailer-week). In each market, manufacturers set prices for their portfolio of products to maximise contemporaneous profits, taking the prices of competing products as given. This framework abstracts from dynamic pricing considerations and from explicit manufacturer-retailer bargaining and is a common approach in the literature. Whilst these features may be relevant in grocery retail settings, the static Bertrand assumption provides a tractable and widely used benchmark for recovering marginal costs from observed prices and estimated demand elasticities.

Let J_f denote the set of products owned by firm f. Firm f's profit in market t is given by

$$\pi_{ft} = \sum_{j \in J_f} (p_{jt} - c_{jt})\, q_{jt}(p_t) \tag{4}$$

[39] Diesel is not lagged because it is used in the transportation of the completed product.

[40] I also considered incorporating differentiation instruments based on the configuration of competing products (Gandhi & Houde 2019); but because product availability in my data is inferred from observed purchases, these instruments are mechanically related to demand, so I do not include them in the control function approach.

where p_{jt} is the price of product j, c_{jt} is its marginal cost, and $q_{jt}(p_t)$ is the quantity demanded, which depends on prices p_t. Under Bertrand-Nash competition, each firm chooses prices for all its products to maximise π_{ft}, taking rivals' prices as fixed. The first-order conditions for each product $j \in J_f$ are:

$$q_{jt} + \sum_{k \in J_f} (p_{kt} - c_{kt}) \frac{\partial q_{kt}}{\partial p_{jt}} = 0 \tag{5}$$

Stacking the first-order conditions across products gives:

$$q_t + \Delta_t (p_t - c_t) = 0 \tag{6}$$

where q_t is the vector of quantities and Δ_t is the matrix of demand derivatives, with element (j, k) equal to the effect of product j's price on the demand for product k if the two products have the same owner, and zero otherwise:

$$\Delta_{jk,t} = \Omega_{jk} \frac{\partial q_{kt}}{\partial p_{jt}} \tag{7}$$

Here, Ω is the ownership matrix, with element $\Omega_{jk} = 1$ if products j and k are owned by the same firm and 0 otherwise. Ownership is assigned at manufacturer level, with own-label products assigned to the retailer that sells them. I consider two alternatives as robustness. Under category-brand ownership, following Zhan et al. (2026), a manufacturer prices its gluten-free and standard ranges separately, which internalises less substitution than the baseline. Under retailer ownership, each store prices its entire bread range jointly. This internalises more, and I report it as an alternative conduct assumption.

With heterogeneous tastes, market shares and their derivatives integrate over the estimated distribution of (α_i, β_i, c_i):

$$s_{jt} = \int s_{ijt} \, dF(\alpha_i, \beta_i, c_i), \qquad \frac{\partial s_{kt}}{\partial p_{jt}} = \int a_{ij} \, s_{ikt} \, (\mathbb{1}[j = k] - s_{ijt}) \, dF(\alpha_i, \beta_i, c_i), \tag{8}$$

where a_{ij} is household i's price slope for product j, defined in equation (1). I evaluate the integrals on the estimation grid, holding the control-function residual fixed as part of unobserved quality. Unlike the conditional logit, this allows gluten-free buyers to substitute to other gluten-free bread, which is what disciplines gluten-free markups.

Quantities are $q_{jt} = M_t s_{jt}$, where M_t is the number of choice occasions in market t, so M_t cancels from the first-order conditions and markups depend only on shares and their

derivatives. Inverting equation (6) gives the markup of each product:

$$p_t - c_t = -\Delta_t^{-1} q_t, \tag{9}$$

and marginal cost is price less this markup. Because prices are per pack, markups and marginal costs are per pack and I convert them to per kilogram by dividing by pack weight.

These recovered marginal costs are the total marginal cost of bringing a loaf of bread to the shelf, including production, distribution and retailing. The set-up abstracts from the retailer's role in the vertical relationship. Except under retailer ownership, the manufacturer is treated as setting the shelf price directly, so no separate retail margin is modelled and no double marginalisation arises. The estimated marginal cost is a residual, and depends upon the accuracy of the estimated markup. Any gap between the true markup and the estimated markup - which could come from collusion, manufacturer-retailer bargaining, retailer margins, or dynamic pricing considerations - is attributed to cost. For the decomposition, what matters is whether such deviations differ between gluten-free and standard bread. If gluten-free bread were priced less competitively than the model assumes, the cost share of the premium would be overstated.

From the estimated demand system, I compute own- and cross-price elasticities, aggregating the predicted individual choice probabilities to the product-market level. I recover marginal costs and markups at the product-retailer-week level. I then aggregate these separately for gluten-free and standard products. For 200g and 600g packs, I hold their prices at their observed levels and retain them in demand and in each firm's substitution patterns but do not enter them in the system of first-order conditions, due to their irregular behaviour.[41] I report markups and marginal costs for 400g and 800g packs, weighting by kilograms sold so that the reported premium is the one consumers face, and using the population distribution of tastes.

5.3 Decomposition

To decompose the price premium, three approaches are possible: (i) a ratio decomposition, giving the decomposition in rates, (ii) an accounting split, giving the decomposition in terms of monetary value, (iii) a counterfactual approach, where I apply the same markup rate from standard bread to gluten-free bread and calculate how GF prices

[41] 200g is a single product whose price response is not identified whilst 600g demand is estimated imprecisely and in some specifications slopes upwards. Together they account for about 2.6% of kilograms sold.

change. I elaborate below, how these different approaches work and their pros and cons. I report all three calculations but favour approach (i).

Firstly, I compare the ratio of prices (between GF and standard breads) with the ratio of marginal costs and the ratio of Lerner indices. Price is a function of marginal cost and the Lerner index (which is itself a function of the own- and cross-price elasticities of demand): $p = \frac{mc}{1-L}$. The ratio of GF to standard price can therefore be seen as a function of the ratio between marginal costs and Lerner indices:

$$\frac{p_{GF}}{p_S} = \frac{mc_{GF}}{mc_S} \times \frac{1 - L_S}{1 - L_{GF}} \tag{10}$$

Price discrimination against gluten-free buyers implies a marginal-cost ratio below the price ratio. How far the marginal-cost ratio lies below the price ratio therefore measures the role of differential markups, and how far it lies above one measures the role of cost. Taking logs gives:

$$\ln(p_{GF}) - \ln(p_S) = (\ln(mc_{GF}) - \ln(mc_S)) + (\ln(1 - L_S) - \ln(1 - L_{GF})) \tag{11}$$

The cost share of the price premium is given as $\frac{\ln(mc_{GF}) - \ln(mc_S)}{\ln(p_{GF}) - \ln(p_S)}$.

Secondly, I compute the share of the price premium (per kilogram) accounted for by cost, $(mc_{GF} - mc_S)/(p_{GF} - p_S)$. This is an accounting statement, denoted in pounds rather than in rates. It is an imperfect measure because even with a common Lerner index, a costlier product carries a larger markup in absolute terms, so this measure overstates the role of market power. This measure therefore describes who receives the premium, rather than testing for price discrimination.

Thirdly, as a simple counterfactual, I use the markup rate calculated from standard bread and apply it to gluten-free bread. I then recalculate the price charged using the Lerner index, as above. Comparing the observed GF price with the counterfactual price allows me to attribute the difference to the higher proportional markup on gluten-free bread.

5.4 Counterfactual Prices

The decomposition approach describes the premium at observed prices. To ask how prices would respond to a change in costs, or to a subsidy, I solve the pricing conditions for prices rather than for marginal costs. Unlike the simple counterfactual approach (iii) in Section 5.3 - which holds the GF Lerner index fixed - markups here adjust as demand responds to the new prices, and every firm re-optimises.

Given counterfactual marginal costs $\tilde{c}_t$, the counterfactual prices $\tilde{p}_t$ in market t solve equation (6) with demand evaluated at the new prices. Written in shares, since the number of choice occasions in a market cancels:

$$s_t(\tilde{p}_t) + \Delta_t(\tilde{p}_t)\,(\tilde{p}_t - \tilde{c}_t) = 0, \tag{12}$$

holding fixed the demand parameters, the product characteristics, ownership and the control-function residual $\hat{v}_{jt}$, so that unobserved quality does not change. Following Morrow & Skerlos (2011), I split the share derivatives in equation (8) as $\partial s_{kt}/\partial p_{jt} = \mathbb{1}[j = k]\,\Lambda_{jt} - \Gamma_{jk,t}$, with $\Lambda_{jt} = \int a_{ij}\, s_{ijt}\, dF$ and $\Gamma_{jk,t} = \int a_{ij}\, s_{ijt}\, s_{ikt}\, dF$. Equation (12) then rearranges into the fixed point

$$\tilde{p}_t = \tilde{c}_t + \Lambda_t^{-1}\left[(\Omega \odot \Gamma_t)\,(\tilde{p}_t - \tilde{c}_t) - s_t\right], \tag{13}$$

where Λ_t is the diagonal matrix of Λ_{jt} and every term on the right is evaluated at $\tilde{p}_t$. I iterate on equation (13) separately in each of the 2,860 retailer-weeks until no price changes by more than 10^{-10} pounds. As in the supply model, the prices of 200g and 600g packs are held at their observed levels.

Two checks confirm that the solver recovers the observed equilibrium. Firstly, at the recovered marginal costs the observed prices satisfy equation (13) exactly, with the solver leaving every price unchanged (the largest change is 4×10^{-15} pounds) after one iteration. Secondly, when every markup is started at between one half and one and a half times its observed value, in 100 randomly chosen markets with two starting points each, the solver returns to the observed prices in every case, so there is no sign of a second equilibrium near the observed one.[42]

The policy experiment is a per-unit subsidy of σ pounds per kilogram on GF bread, paid on every purchase. If firms receive p and consumers pay $p^c = p - \sigma$, a firm's profit on product j is $(p_j^c + \sigma - c_j)\,q_j(p^c)$. Equilibrium consumer prices under the subsidy are therefore the equilibrium prices when gluten-free marginal costs are lower by σ per kilogram, whether the subsidy is paid to firms or to consumers through lower prices. The same calculation gives the price effect of a fall in GF marginal cost, for example from cheaper inputs. The counterfactual can therefore be interpreted either as a per-unit subsidy on GF bread - paid to firms or to consumers - or as a fall in the marginal cost of supplying it, for example from longer production runs. I report the pass-through rate, the fall in the price consumers pay for gluten-free bread per kilogram divided by σ, for 400g and 800g packs weighted by observed kilograms sold. A rate of one means that

[42] This check is run under manufacturer ownership. In every counterfactual below, all markets converge and the first-order conditions hold to within 10^{-11}.

consumers receive the full subsidy at the till, whilst a rate below one means that firms retain part of it.

To measure who gains from the counterfactual subsidy, I compute the change in consumer surplus as the area under each household type's demand curves along the path from observed to counterfactual prices. This gives the gain in pounds directly.[43] Each household's gain uses its posterior distribution of tastes, given its own choices, and the markets in which it actually shopped over all its choice occasions, and is expressed per year in the panel. I also compute the change in firms' variable profit and the cost of the subsidy, paid on counterfactual purchases. Uncertainty in pass-through and welfare comes from 200 of the parameter draws described in Section 5.5, with the counterfactual re-solved in each.

5.5 Estimation and Inference

I estimate a conditional logit as a benchmark, with and without the control function, before estimating the preferred mixed logit, which allows more realistic substitution patterns. The conditional logit can be estimated on counts of choices by product and market, since the choice set, prices, and characteristics vary only across retailer-weeks.[44] I estimate it as a Poisson regression with market fixed effects on all choice occasions, with standard errors clustered by product and calendar month (Guimaraes et al. 2003, Correia et al. 2020); these do not account for the estimated first stage. To compare fit with the mixed logit, I also re-estimate both conditional logits by maximum likelihood on the mixed-logit estimation sample described below.

I estimate the mixed logit by maximum likelihood. Each household's likelihood is the product of its logit choice probabilities across occasions, integrated once over (u_i, β_i, c_i) by Gauss-Hermite quadrature on a $20 \times 20 \times 12$ grid (4,800 nodes), checked at $25 \times 25 \times 12$ and $20 \times 20 \times 16$. Specifications without c_i integrate over (u_i, β_i) on a 40×40 grid, checked at 30×30 and 50×50. The marginal-cost ratio moves by at most 0.1 across grids. A fixed grid cannot accurately integrate a product over the roughly 165 occasions an average household contributes. I therefore estimate on a random subsample of up to 26 occasions per household: 924,816 occasions, including 5,067 gluten-free choices. The subsample is drawn independently of choices, so it does not bias the estimates. Doubling the cap

[43] Because GF status scales the price coefficient by e^{κ}, no single price coefficient converts utility into pounds for every product. Dividing the change in expected utility by the standard price coefficient would value a fall in the GF price at $e^{\kappa} \approx 0.32$ of the cash a household saves on an unchanged basket, below what any consumer must gain. The area under demand needs no such choice. The two conversions by the standard and the GF price coefficient give about a quarter and three quarters of it, respectively.

[44] There are 174,595 product-market cells and 2,860 markets.

to 52 occasions per household (giving 1,790,009 occasions, 9,719 gluten-free choices, on a $40 \times 40 \times 12$ grid) leaves the decomposition unchanged (Section 6.3). The model is estimated in Python with analytic gradients.

The control-function residual is a generated regressor, so inference must account for the first stage. I treat the two stages as a single two-step estimator and compute its variance analytically (Murphy & Topel 1985). The demand scores are corrected for the effect of the first-stage estimates on the residual, and the scores of both stages are summed by product before forming the sandwich (483 clusters: 482 products and the outside option).[45] Clustering by product allows for arbitrary correlation across all households' choices of the same product, which is where unobserved quality induces dependence.[46] The Hessian is ill-conditioned along a few nuisance directions, so I use its pseudo-inverse.[47] Elasticities, markups and marginal costs are nonlinear functions of the parameters, so I take 2,000 draws from the estimated asymptotic distribution of the parameters of both stages, recomputing the control-function residual for every product from the drawn first-stage coefficients and recomputing the elasticities and the supply side for each draw (Krinsky & Robb 1986).[48] Because gluten-free demand is inelastic in some draws, the implied gluten-free marginal cost, and so the marginal-cost ratio, is negative and can be very large in those draws, so I report the share of draws supporting each claim and a robust dispersion measure rather than standard errors.[49] I use this analytic approach rather than a bootstrap because neither resampling scheme suits a panel mixed logit with product-level dependence. Resampling products counts some of a household's choices twice and drops others selectively on tastes, so the replicates do not reproduce the sampling distribution of the estimator, whilst resampling households does not capture the dependence between households that buy the same product.[50]

[45] Each alternative's score is measured relative to the mean of its retailer-week, as in the Poisson score with market fixed effects, so that store-week shocks are not attributed to products.

[46] O'Connell et al. (2025) similarly treat product-level moments as a separate block in their variance. In a bootstrap over households, the variance from the household dimension is less than 1% of the product-clustered variance, so I cluster by product only.

[47] These are the 200g price terms, the level of the outside option, and the mean gluten-free taste, which is shared with the manufacturer $\times$ gluten-free effects. The reported quantities do not load on these directions.

[48] Dubois et al. (2020) use the same approach to obtain confidence intervals for their elasticities.

[49] The dispersion measure used is the interquartile range divided by 1.349, which equals the standard deviation for a normal distribution.

[50] A bootstrap over households nonetheless gives the same answer on the sign of the cost gap (Section 6.3).

6 Results and Discussion

Table 2 reports the demand estimates from the conditional logit and mixed logit models. The conditional logit models (shown in columns (1) and (2), without and with the control function) are used as a benchmark to demonstrate the limitations imposed by strict substitution patterns. Columns (3) and (4) are mixed logits, without and with the random taste for buying bread. Every specification includes retailer-week choice-situation effects and absorbs thickness, branded status, pack size $\times$ bread type and manufacturer $\times$ gluten-free effects, which also absorb gluten-free status. Retailer, year and month-of-year fixed effects enter the outside option. The price coefficients are therefore identified from relative prices across the products a store sells in the same week, compared within a manufacturer's gluten-free or standard range, and, through the control function, from cost-driven movements in the level of bread prices within a retailer, year and season. Across all specifications, the price coefficient is negative and statistically significant at the 10% level or better.

In column (1), I report estimates from the conditional logit model without the control function. The price coefficient is negative but small and statistically significant only at the 10% significance level. Taken literally, these estimates imply that demand for both types of bread is inelastic (elasticities of -0.63 and -0.82, see Table 4), which no profit-maximising firm would choose. Column (2) adds the control function, which causes the price coefficient to increase in absolute magnitude, almost tripling, demonstrating the strong attenuation bias in the absence of handling the endogeneity caused by the correlation between price and unobserved quality. In both specifications, the coefficient attached to the interaction of price and GF status is positive but statistically insignificant, so the conditional logit cannot distinguish the gluten-free price response from the standard one.

The first stage regresses pack price on the 20 cost shifters, the product controls and the fixed effects. Its residual then enters demand interacted with pack size and gluten-free status. The instruments are strong: the first-stage F statistic is 37.2 for all 20 cost shifters and 49.3 for the 11 gluten-free-specific shifters.[51] Table 9 in Annex A.2 reports the full first stage. Most cost shifters raise prices, as expected, but some coefficients have the opposite sign; for example, energy costs are associated with lower prices for brown and white gluten-free bread. The shifters are highly collinear national series, so individual

[51] I report the F statistic from a first stage clustering over product only. This is because clustering over both product and calendar month produces unreliable F statistics given a small number of clusters. For reference, the F statistics from the first stage clustering over both product and calendar month are 225.7 and 43.2.

Table 2: Demand Estimates

	Conditional logit		Mixed logit	
	(1)	**(2)**	**(3)**	**(4)**
Panel A: Price response				
Price coefficient (800g; mean in (3)–(4))	-0.68*	-2.00*	-4.75**	-6.55***
	(0.41)	(1.18)	(1.87)	(2.32)
Price × 400g	-0.39	0.24	0.25	0.28
	(0.56)	(0.85)	(0.89)	(0.92)
Price × 600g	3.50***	3.18	3.01	2.21
	(0.70)	(1.97)	(3.75)	(4.15)
Price × Gluten-Free	0.70	0.73	-	-
	(0.47)	(1.45)		
GF price scale κ	-	-	-1.35*	-1.15**
			(0.72)	(0.54)
Control function residual	-	1.41	3.65***	5.92***
		(1.30)	(1.28)	(1.88)
Residual × 400g	-	-0.83	-0.87	-1.07
		(0.98)	(1.09)	(1.17)
Residual × Gluten-Free	-	0.17	-2.04*	-3.55**
		(1.40)	(1.19)	(1.74)
Implied standard price slope (400g)	-1.06**	-1.76	-4.50**	-6.27***
	(0.42)	(1.20)	(1.92)	(2.40)
Implied GF price slope (400g)	-0.37*	-1.03	-0.98	-1.80
	(0.21)	(0.71)	(1.52)	(1.24)
Panel B: Taste heterogeneity				
SD of price coefficient	-	-	1.37***	1.88*
			(0.47)	(0.99)
SD of GF taste	-	-	3.78***	3.77***
			(0.41)	(0.73)
Corr(price coefficient, GF taste)	-	-	-0.21	0.21
			(0.15)	(0.34)
SD of taste for buying bread	-	-	-	2.08***
				(0.42)
Corr(price coefficient, taste for bread)	-	-	-	-0.74***
				(0.15)
Control function	No	Yes	Yes	Yes
Random price coefficient and GF taste	No	No	Yes	Yes
Random taste for buying bread	No	No	No	Yes
Log-likelihood	-2,525,216	-2,524,752	-2,433,915	-2,394,704
Choice occasions	5,887,570	5,887,570	924,816	924,816

Note: Columns (1) and (2) are conditional logits estimated as Poisson regressions on choice counts by product and retailer-week, using all choice occasions of 35,570 households. Standard errors are clustered on product and calendar month and, in column (2), ignore first-stage estimation error. Columns (3) and (4) are mixed logits estimated by maximum likelihood on up to 26 randomly drawn occasions per household using Gauss-Hermite quadrature (Section 5.5). Standard errors are analytic, clustered by product and account for the first stage. For transformed parameters they are the standard deviation of 2,000 draws from the estimated distribution. In the mixed logit, the price coefficient is lognormal and gluten-free status scales it by e^{κ} (the pack-size terms are not scaled); implied slopes are those of the mean household. The 200g price term and the residual × 200g and × 600g terms are estimated but not shown. Every column includes retailer-week choice-situation effects, price × pack-size terms (800g base) and absorbs thickness, branded status, pack size × bread type and manufacturer × gluten-free effects (which absorbs gluten-free status). Retailer, year and month-of-year effects enter the outside option and the first stage regression (in columns (2) to (4)). The first-stage F statistic is 37.2 for all 20 instruments, and 49.3 for the 11 GF-specific instruments (Table 9). Log-likelihoods are on the mixed-logit sample (924,816 occasions); for columns (1) and (2) they come from the conditional logit re-estimated on that sample. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01, two-sided; tests on the standard deviations are conservative because the null lies on the boundary of the parameter space.

first-stage coefficients are not structural, what matters for the control function is their joint explanatory power.

In columns (3) and (4) I report estimates from the mixed logit model. Column (3) has a random coefficient for price and GF taste, allowing these variables to vary across households. Column (4) additionally has a random coefficient for buying bread (thus allowing households to vary in their preference for purchasing the inside good). Allowing for this heterogeneity improves the log-likelihood by 90,836 points relative to the conditional logit in column (2). The (mean) price coefficient also increases substantially in absolute terms, and in statistical significance, moving from a coefficient of -2.00 to -4.75 in column (3) and -6.55 in column (4). Part of this rise is a change of scale but the permitted heterogeneity also changes substitution patterns. The conditional logit model imposes the independence of irrelevant alternatives, so a gluten-free buyer facing a price rise diverts to other products in proportion to their market shares, although a gluten-free buyer's second choice is disproportionately another gluten-free loaf. The mixed logit relaxes this.

Table 3: Diversion of Lost Sales

	Share of lost sales diverted to		
Price rise on	**Gluten-free**	**Standard**	**No bread**
Panel A: Conditional logit (column 2)			
Standard bread	0.5%	59.1%	40.4%
Gluten-free bread	0.6%	59.3%	40.1%
Panel B: Mixed logit (column 4)			
Standard bread	0.3%	68.3%	31.4%
Gluten-free bread	26.4%	36.3%	37.3%

Note: Columns as in Table 2. The diversion ratio from product j to group g is $-\sum_{k\in g,k\neq j}(\partial s_k/\partial p_j)/(\partial s_j/\partial p_j)$, the share of the sales that j loses after a small rise in its price that go to products in g. "No bread" is the outside option. Ratios are computed in each retailer-week and averaged over products, and each row sums to 100%. Panel A weights by purchases over all pack sizes; Panel B weights by kilograms sold over 400g and 800g packs and integrates over the estimated taste distribution, as in Table 4. Diversion depends on demand only, not on the ownership assumption.

Table 3 shows where the sales that a product loses to a price rise go. Under the conditional logit the two rows of Panel A are almost identical: whichever type of bread becomes dearer, about 0.5% of its lost sales go to gluten-free bread, 59% to standard bread and 40% out of the market, because the independence of irrelevant alternatives forces substitution in proportion to market shares. The mixed logit breaks this pattern. A price rise on standard bread still sends almost nothing to gluten-free bread (0.3%), but a price rise on gluten-free bread sends 26.4% of lost sales to other gluten-free bread, more than forty times the conditional-logit figure. This is the substitution that disciplines gluten-

free markups in the multiproduct pricing conditions (Section 5.2). Panel B also shows, however, that gluten-free demand is not captive at the margin: almost three quarters of the sales a gluten-free product loses leave gluten-free bread altogether, 36.3% to standard bread and 37.3% to not buying bread on that occasion. In the mixed logit, the households who respond to a gluten-free price rise are those with weaker gluten-free tastes rather than the persistent buyers, and their willingness to switch to standard bread limits how far firms can mark up gluten-free bread. This is consistent with a gluten-free Lerner index of 0.32 (Table 4), only modestly above the 0.24 for standard bread, and with cost accounting for most of the premium.

Gluten-free status scales the price coefficient down: $\kappa = -1.15$ in the headline specification. This means that a household's price coefficient on gluten-free bread is about a third of its coefficient on standard bread. A gluten-free pack costs several times as much as standard bread, so this does not by itself imply less elastic gluten-free demand.

Turning to Panel B, which shows the taste heterogeneity for the mixed logit models, it can be seen that tastes for GF bread are very dispersed. The standard deviation for GF taste is 3.8 in both specifications and is precisely estimated, reflecting a small group of households that buy gluten-free bread persistently and a large majority that never do. Price sensitivity also varies considerably across households, with a standard deviation of 1.4 in column (3) and 1.9 in the preferred specification (4). The correlation between price sensitivity and GF taste is weakly identified, taking a value of -0.21 in specification (3) and 0.21 in specification (4). In the headline specification (4), its 95% range runs from -0.57 to 0.67. The data therefore cannot say directly whether households with a strong taste for gluten-free bread are more or less price-sensitive than others, and I assess price discrimination through the implied markups instead.

The random taste for buying bread, included in the preferred specification (4), matters, as it increases the log likelihood by 39,211 points relative to column (3). The standard deviation of the taste for buying bread is 2.1 and its correlation with the price coefficient is -0.74; both are significant at the 1% level, and the 95% range of the correlation, $[-0.88, -0.30]$, excludes zero. Households that buy bread more often are more price-sensitive, consistent with frequent buyers paying closer attention to bread prices.

The control function residual is positive in every specification, consistent with prices being positively correlated with unobserved product desirability. In the conditional logit model it is imprecisely estimated, but it is economically important. Including it moves the price coefficient from -0.68 to -2.00, almost exactly the size of the residual coefficient. In the mixed logit models the residual is significant at the 1% level. Because logit coefficients are identified only relative to the scale of the idiosyncratic error, they rise in the mixed logit

models once taste heterogeneity is modelled explicitly; the residual rises in proportion with the price coefficient, whilst the use of repeated choices within households sharpens its precision.

Table 4 reports own-price elasticities and the results of inverting the first-order conditions of Section 5.2, for 400g and 800g packs weighted by kilograms sold (the conditional-logit elasticities are weighted by purchases). Without the control function (column 1), demand for both types of bread is inelastic, so the pricing conditions cannot be satisfied. They imply Lerner indices above one and negative marginal costs for almost all standard bread. The control function makes demand elastic (column 2), but the conditional logit model's elasticities remain low, implying a Lerner index of 0.74 for standard bread, negative marginal costs for 23% of standard volume and a marginal-cost ratio of 9.8, about twice the price ratio. The mixed logit model resolves both problems. In the headline specification, the own-price elasticity is -5.25 for standard bread and -3.37 for gluten-free bread. The implied Lerner indices are 0.24 for standard and 0.32 for gluten-free bread, and marginal costs are £0.92 and £3.84 per kilogram.

Gluten-free bread costs 4.17 times as much per kilogram to supply as standard bread, against a price ratio of 4.67. Substituting these values into equation (11) reveals that the cost channel accounts for 1.43 of the 1.54 log points of the premium (93%), and a higher proportional markup on gluten-free bread for the remaining 0.11.[52] Applying the same Lerner index to GF bread as standard bread results in a price of £5.05 (per kilogram) rather than the observed price of £5.64. The higher proportional markup on gluten-free bread therefore raises the gluten-free price by £0.59 per kilogram, so that without it gluten-free bread would be 11% cheaper. This is consistent with the figure from the ratio decomposition in that it is both small and points to cost being the predominant factor in explaining the gluten-free price premium.

The decomposition is similar in the two mixed logits. Without the random taste for bread (column 3), gluten-free bread costs 3.72 times as much per kilogram to supply and cost accounts for 85% of the premium; with it, 4.17 times and 93%. In both, gluten-free bread carries a slightly higher Lerner index than standard bread. This ranking depends on controlling for brand-range quality: without the manufacturer $\times$ gluten-free effects, gluten-free bread carries the lower Lerner index (Section 6.3). As I discuss next, the ranking is not statistically determined in any specification.

The bottom rows of Table 4 report the uncertainty in the decomposition, from 2,000

[52] In pound terms, the gluten-free premium of £4.43 per kilogram splits into £2.92 of marginal cost (66%) and £1.51 of markup. However, as explained in Section 5.3, the monetary split overstates the role of market power, since a common proportional markup is mechanically larger on a costlier product.

Table 4: Elasticities, Markups and Marginal Costs

	Conditional logit		Mixed logit	
	(1)	**(2)**	**(3)**	**(4)**
Own-price elasticity				
Standard	-0.63	-1.62	-3.47	-5.25
			[-6.72, -1.64]	[-9.62, -2.69]
Gluten-free	-0.82	-2.32	-2.27	-3.37
			[-10.31, 0.86]	[-8.27, -0.10]
Lerner index				
Standard	n/a	0.74	0.35	0.24
Gluten-free	n/a	0.46	0.48	0.32
Marginal cost, £ per kg				
Standard	n/a	0.31	0.79	0.92
Gluten-free	n/a	3.04	2.95	3.84
Decomposition of the premium (price ratio 4.67)				
Marginal-cost ratio	n/a	9.77	3.72	4.17
			(1.81)	(0.87)
Cost share, ratio (log points)	n/a	148%	85%	93%
Cost share, £ per kg	n/a	62%	49%	66%
GF price at the standard Lerner index (£/kg)	n/a	11.79	4.50	5.05
Share of draws: GF costs more per kg	-	-	85.7%	93.1%
Share of draws: MC ratio above price ratio	-	-	48.4%	34.4%
Lost GF sales diverted to other GF bread	0.6%	0.6%	30%	26%
Standard volume with negative marginal cost	98.9%	22.8%	0.2%	0.1%
Control function	No	Yes	Yes	Yes
Random price coefficient and GF taste	No	No	Yes	Yes
Random taste for buying bread	No	No	No	Yes

Note: Columns as in Table 2. Multiproduct Bertrand-Nash pricing with manufacturer ownership (private label assigned to the retailer). 400g and 800g packs, weighted by kilograms sold (conditional-logit elasticities are purchase-weighted); 200g and 600g packs are held at observed prices. Prices per kg: standard £1.21, gluten-free £5.64. In column (1) demand for both types of bread is inelastic, so the pricing conditions cannot be satisfied: they imply Lerner indices of 1.96 (standard) and 1.28 (gluten-free) and negative marginal costs for 98.9% of standard volume. The ratio cost share is $\frac{\ln(mc_{GF})-\ln(mc_S)}{\ln(p_{GF})-\ln(p_S)}$ and exceeds 100% when gluten-free bread carries the lower Lerner index; the £ cost share is $\frac{mc_{GF}-mc_S}{p_{GF}-p_S}$. The GF price at the standard Lerner index is $mc_{GF}/(1-L_S)$. Draws are 2,000 draws from the analytic variance of the two-step estimator, clustered by product and including the first stage; the marginal-cost ratio's standard error (in parentheses) is the interquartile range of the draws divided by 1.349. Brackets give the 2.5th and 97.5th percentiles of the draws. "MC ratio above price ratio" is the share of draws in which gluten-free bread carries the lower Lerner index.

draws of the parameters with the supply side recomputed for each (Section 5.5). The finding that gluten-free bread costs more to supply is robust. 93.1% of draws put gluten-free marginal cost per kilogram above standard in the headline, and 85.7% in column (3). The headline is also the more precise specification. The robust standard error of its marginal-cost ratio is 0.87, against 1.81 in column (3), and its 95% range for the gluten-free elasticity, $[-8.3, -0.1]$, excludes zero, whereas that of column (3), $[-10.3, 0.9]$, does not. The draws with a negative ratio (5.4% in the headline) are those in which gluten-free demand is inelastic, so that the pricing condition implies a negative gluten-free marginal cost.

The ranking of the Lerner indices, by contrast, is not determined. In the headline, 34.4% of draws put the marginal-cost ratio above the price ratio, that is, give gluten-free bread the lower Lerner index; and 48.4% in column (3). The data therefore support the claim that gluten-free bread costs more to supply, but cannot say whether its proportional markup is higher or lower than that of standard bread.

As a sensitivity check, I ask how far the estimated elasticities would have to be wrong before the cost finding reverses. If the true elasticities differ from mine by a common factor k, each Lerner index becomes L/k and the marginal-cost ratio becomes $(p_{GF}/p_S)(1 - L_{GF}/k)/(1 - L_S/k)$. If demand is more elastic than estimated ($k > 1$), the ratio rises towards the price ratio of 4.67. If demand is less elastic, the ratio falls, but it stays above one unless the true elasticities are about a third of those estimated ($k \approx 0.34$): around -1.8 for standard and -1.2 for gluten-free bread. At that point gluten-free demand would be close to inelastic, and the static pricing condition could barely be satisfied. Because the gluten-free elasticity is the less precisely estimated of the two, I also scale it alone, holding the standard elasticities at their estimates. The marginal-cost ratio then becomes $(p_{GF}/p_S)(1 - L_{GF}/k_{GF})/(1 - L_S)$. It falls to one only if gluten-free elasticities are overstated by a factor of about 2.6 ($k_{GF} \approx 0.38$, an own-price elasticity of about -1.3).[53]

The elasticities in Table 4 are for a single product, holding every other price fixed. Whether gluten-free consumers are captive as a group is a different question, answered by raising every gluten-free price at once. Table 5 reports these aggregate elasticities, showing the percentage change in the kilograms of each group of bread demanded when every price in a group rises by 1%. Based on the preferred specification (mixed logit model with a random taste for buying bread) demand for GF bread as a whole has an elasticity of -2.44. This is larger in magnitude than that of standard bread as a whole (-1.67). This stands in contrast to the single-product elasticity (-3.37 against -5.25)

[53]This is approximate: scaling gluten-free demand alone does not rescale markups exactly, because firms that sell both types internalise some diversion between them.

shown in Table 4. This is because a standard loaf loses most of its sales to other standard loaves (see Table 3), a route that closes when every standard price rises. On the other hand, a GF loaf loses almost three quarters of its sales outside GF bread (again, see Table 3), and those routes stay open when every GF price rises.

These aggregate elasticities demonstrate that GF bread producers have limited ability to exploit any potential market power. A simple thought exercise illustrates this well. Suppose a single firm set every GF price, with a common proportional markup. The inverse-elasticity rule at observed prices would then give a GF Lerner index of about $1/2.44 = 0.41$, against 0.32 estimated in Table 4. Holding standard bread at its headline Lerner index of 0.24, the marginal cost implied for GF bread would still be 3.6 times that of standard bread, so cost would account for 84% of the premium.

Table 5: Aggregate Elasticities

	1% rise in every price of		
% change in kg of	**Gluten-free**	**Standard**	**All bread**
Gluten-free bread	-2.44	1.80	-0.64
Standard bread	0.01	-1.67	-1.66
All bread	0.00	-1.65	-1.65

Note: Headline specification (column 4 of Table 2). Each entry is the point estimate of the percentage change in the kilograms of a group demanded when every price in a group rises by 1%, all other prices held fixed. Groups include all pack sizes. Elasticities are computed in each retailer-week and averaged, weighting by the kilograms of the responding group bought there. Elasticities integrate over the estimated taste distribution. The outside option is a week in which the household buys no bread, so the all-bread elasticity includes delayed purchases but not switching between stores. Aggregate elasticities depend on demand only, not on the ownership assumption.

Demand for bread as a whole has an elasticity of -1.65. This is the elasticity facing a store that sets all its bread prices together, and it matches the retailer-ownership row of Table 11, where the standard Lerner index of 0.59 is close to $1/1.65 = 0.61$. It is larger in magnitude than estimates from demand systems estimated on household expenditure surveys, which put the own-price elasticity of bread and cereals between about -0.5 and -1.0 (Andreyeva et al. 2010, Marioni et al. 2022, Capacci et al. 2018). This is to be expected, because the outside option here is a week in which a household buys no bread, so the category elasticity includes households delaying a purchase, for example by freezing bread, as well as buying less bread overall. The cross effects show the same asymmetry as Table 3. A rise in every gluten-free price barely moves standard demand (0.01%), whereas a rise in every standard price raises gluten-free demand by 1.8%, because a small flow of standard buyers is large relative to GF volume.

6.1 Counterfactual Analysis: Pass-Through of a Gluten-Free Subsidy

The decomposition, above, suggests that policy support for GF consumers is unlikely to be absorbed into firms' margins, given the limited market power GF firms seem to exert. The counterfactual analysis tests this directly by studying the pass-through effect of a per-unit subsidy on GF bread. As discussed in Section 5.4, this could alternatively be thought about as a reduction in marginal costs, perhaps brought about from longer production runs as the market grows. Table 6 reports the results from a subsidy (on GF bread) of £0.10, £0.50 and £1.00 per kilogram (4p, 20p and 40p on a 400g loaf), with every price re-solved in every retailer-week.

Under manufacturer pricing (Panel A), the subsidy is passed through slightly more than in full. A subsidy of £0.50 per kilogram lowers the price of gluten-free bread by £0.53, a pass-through rate of 1.06, and the rate barely changes with the size of the subsidy (1.05 to 1.06). The pound markup on gluten-free bread falls slightly as its price falls (from £1.80 to £1.78 per kilogram for a £0.50 subsidy). This is because a lower price raises GF purchases proportionally most amongst the households that are most responsive to price. These are the households with high price sensitivity, and those with a weak GF taste, for whom GF bread is a marginal choice. The mix of GF bread consumers therefore shifts towards price-responsive households, demand becomes more elastic (in monetary terms), and the markup that firms can sustain falls.[54] Standard bread prices do not move, and purchases of standard bread fall by at most 0.3%. Purchases of gluten-free bread rise by 4.9%, 27% and 60%. The smallest subsidy lowers the GF price by 1.9%, which implies an elasticity of about -2.6, a figure close to the aggregate GF elasticity of -2.44 in Table 5.

Under retailer pricing (Panel B), pass-through is 0.99 to 1.00. A store that sets all its bread prices jointly takes into account that part of the extra GF sales comes from its own standard bread, so it passes on marginally less of the subsidy and raises standard prices by at most 0.3p per kilogram.

Under either conduct assumption, therefore, a subsidy on GF bread is received (almost) in full by consumers, in the form of lower prices, rather than being absorbed by firms into margins. This is robust to parameter uncertainty: across the parameter draws, pass-through of a £0.50 subsidy under manufacturer pricing has a median of 1.03, is at least 0.97 in 97.5% of draws and is at least 0.9 in all of them.[55] A subsidy (or reduction in

[54] In a conditional logit, where every household has the same price coefficient, this composition effect is absent and a single-product firm passes on less than the full change in its cost. It is the spread of price sensitivity across households - permitted in the mixed logit model - that allows pass-through to exceed one (Weyl & Fabinger 2013).

[55] The upper tail of the distribution is long (a 97.5th percentile of 3.46). It comes from the roughly

marginal cost) of £1.00 per kilogram, around a quarter of the marginal cost of GF bread, would reduce the GF price premium from 4.67 to 3.8 times the price of standard bread.[56]

Table 6: Pass-Through of a Per-Unit Subsidy on Gluten-Free Bread

		Subsidy (£ per kg)		
	Observed	**0.10**	**0.50**	**1.00**
Panel A: manufacturer pricing (headline)				
GF bread price (£/kg)	5.643	5.537	5.115	4.589
Fall in gluten-free price (£/kg)		0.106	0.528	1.054
Pass-through rate		1.06	1.06	1.05
GF bread markup (£/kg)	1.804	1.798	1.776	1.750
Change in GF bread kg (%)		4.9	26.7	60.4
Standard bread price (£/kg)	1.210	1.210	1.210	1.210
Change in standard bread kg (%)		0.0	-0.1	-0.3
Price ratio (GF/standard)	4.67	4.58	4.23	3.79
Panel B: retailer pricing				
GF bread price (£/kg)	5.643	5.543	5.147	4.656
Fall in GF bread price (£/kg)		0.100	0.496	0.987
Pass-through rate		1.00	0.99	0.99
GF bread markup (£/kg)	2.743	2.743	2.747	2.756
Change in GF bread kg (%)		4.9	26.8	60.4
Standard bread price (£/kg)	1.210	1.210	1.211	1.213
Change in standard bread kg (%)		-0.1	-0.4	-0.8
Price ratio (GF/standard)	4.67	4.58	4.25	3.84

Note: Point estimates from the headline specification (column 4 of Table 2); Section 6.1 reports their uncertainty. Each column re-solves the Bertrand-Nash prices of every retailer-week with GF marginal costs lowered by the subsidy. This gives the equilibrium prices consumers pay under a per-unit subsidy of that size (Section 5.4). The subsidy applies to 400g and 800g gluten-free packs; 200g and 600g prices are held at their observed levels. In Panel B, marginal costs are those recovered under retailer ownership. Prices are per kilogram, net of the subsidy, for 400g and 800g packs, weighted by observed kilograms sold. Pass-through is the fall in the GF price divided by the subsidy. The markup is the price firms receive less marginal cost, per kilogram. Changes in kilograms scale the observed kilograms of each product-retailer-week by the ratio of its predicted share after and before the subsidy.

Table 7 reports who gains. Full pass-through does not mean that firms gain nothing. Their markup per kilogram barely changes, but they sell considerably more GF bread, so their variable profit rises by £0.61 for every pound of a £0.50 subsidy (95% interval 0.33 to 0.78). Consumers gain £0.91 per pound of subsidy. This is less than one even though pass-through slightly exceeds one, because part of the subsidy pays for additional

5% of draws in which GF demand is close to inelastic, so that the implied GF marginal cost, and hence the markup's response, is extreme. In one draw no GF market's prices could be re-solved, and in 6.5% of draws some markets could not be; their statistics use the markets that converged.

[56]The counterfactuals hold marginal cost constant as output changes. If GF marginal cost fell with scale, pass-through would be higher.

purchases that consumers value at less than their subsidised cost. Consumer and producer gains together exceed the cost of the subsidy (a net gain of £0.52 per pound), because the subsidy offsets part of the under-consumption caused by the markup on GF bread. The gains to consumers are concentrated. The 247 households that buy gluten-free bread on at least half of their bread purchases (0.7% of households, close to the diagnosed prevalence of coeliac disease) receive about a third of the consumer gain, and households that buy GF bread occasionally receive about half. Gains barely vary with income: £0.050, £0.056 and £0.062 per household per year for low-, middle- and high-income households under the £0.50 subsidy. The gains per household are small in pounds, because the model counts one pack per shopping occasion and prescription GF bread is not recorded in the scanner data, so the figures per pound of subsidy are the more informative.

Table 7: Welfare Effects of a Per-Unit Subsidy on Gluten-Free Bread

	Subsidy (£ per kg)			
	0.10	**0.50**	**0.50: 95% interval**	**1.00**
Panel A: per pound of subsidy				
Consumer surplus	0.99	0.91	[0.73, 3.37]	0.81
Firm variable profit	0.68	0.61	[0.33, 0.78]	0.54
Net (surplus + profit − subsidy)	0.67	0.52	[0.19, 2.35]	0.35
Panel B: consumer surplus, £ per household per year				
Persistent GF buyers (247 households)	0.47	2.53	[2.31, 4.71]	5.52
Occasional GF buyers (3,373)	0.05	0.30	[0.24, 0.65]	0.69
Never buy GF (31,950)	0.00	0.01	[0.00, 0.04]	0.02
All households	0.01	0.05	[0.04, 0.14]	0.13

Note: Headline specification with manufacturer pricing, as Panel A of Table 6. Consumer surplus is the area under each household type's demand curves between observed and counterfactual prices (Section 5.4). Firm variable profit covers the 400g and 800g products whose prices firms set. The subsidy is paid on counterfactual purchases. Persistent buyers are households for which gluten-free bread is at least half of their bread purchases; occasional buyers bought gluten-free bread at least once. Household figures use each household's posterior tastes and its own choice occasions, per year in the panel. Intervals are 95% percentile intervals from 200 parameter draws; their upper tails come from draws in which gluten-free demand is close to inelastic.

6.2 Distributional Effects

The decomposition compares average markups, regardless of household income, and therefore ignores any distributional effects. Price discrimination could still occur if firms extract higher markups from a particular group of buyers - the most natural candidate being richer households - if they are less price-sensitive. Because the major UK grocers largely set prices nationally (Competition and Markets Authority 2019), a retailer charges the

same price for a product whichever neighbourhood its store is in, so firms cannot charge richer households more directly. However, they can do so indirectly, by setting higher markups on the products, or at the retailers, that richer households choose. The model captures this channel, because markups vary across products and retailers with the price sensitivity of each product's buyers. I therefore test for it by comparing the markups that each income band pays on its own purchases.

I allow three income bands to shift the mean price coefficient, the mean gluten-free taste and the taste for buying bread (Table 8). The point estimates go in the expected direction. High-income households are about 11% less price-sensitive than low-income households (gluten-free elasticities of -3.15 and -3.56), like gluten-free bread slightly more and buy bread less often. However, none of these differences is statistically significant at the 5% level, individually or jointly, although assigning each household its modal band attenuates them towards zero. The decomposition is unchanged (a marginal-cost ratio of 4.20), and so is its incidence: each band pays almost the same proportional markup on its bread (a Lerner index of 0.25 for low-income, 0.24 for middle-income and 0.23 for high-income households). High-income households pay more per kilogram for gluten-free bread (£5.84 against £5.56) because they buy more expensive products, but the composition of the premium they pay is the same: cost accounts for 93% of it in every band, as in the market as a whole.

6.3 Robustness

A number of robustness checks are conducted to explore how sensitive the headline results are to the assumptions made. Firstly, I re-estimate the preferred model on up to 52 occasions per household, rather than the standard 26, to address concerns that the random sampling was affecting the outcome. Secondly, I add nutritional characteristics (calories and fibre) as control variables to the preferred specification, as they are observed variables which may affect consumers' choices. Thirdly, in the headline specification I assume that manufacturers set prices in the supply model.[57] Here, I vary this along two dimensions: (i) I allow manufacturers to set prices differently for their gluten-free and standard ranges, and (ii) I change the price-setter from manufacturer to retailer. Fourthly, I drop the manufacturer $\times$ gluten-free effects from both stages. The results of these robustness tests are summarised in Table 11 in Annex A.2. Finally, I re-estimate the specification without manufacturer $\times$ gluten-free effects or the random taste for bread using a bootstrap rather than the analytic variance. It gives the same answer on the sign

[57]For own-brand products, I assume that the retailer is the manufacturer of the product.

Table 8: Demand and Incidence by Household Income

	Low	Middle	High	Not stated
Share of households	47.1%	33.5%	10.3%	9.2%
Tastes				
Mean price coefficient	-6.78	-6.40	-6.03	-6.45
Relative to low income	1.00	0.943	0.889	0.951
		(0.045)	(0.073)	(0.029)
Shift in mean gluten-free taste	-	0.26	0.72	0.58
		(0.64)	(0.84)	(0.39)
Shift in outside-option utility	-	0.26	0.79	0.18
		(0.35)	(0.49)	(0.23)
Own-price elasticity				
Standard	-5.40	-5.16	-4.94	-5.19
Gluten-free	-3.56	-3.35	-3.15	-3.37
What each band pays, £ per kg				
Standard price	1.20	1.20	1.27	1.23
Gluten-free price	5.56	5.66	5.84	5.69
Lerner index paid	0.245	0.241	0.232	0.238
Gluten-free share of kg bought	0.5%	0.5%	0.7%	0.6%
Decomposition of the premium paid				
GF price premium ratio	4.63	4.71	4.61	4.63
Marginal-cost ratio	4.17	4.25	4.16	4.13
Cost share of the premium	93%	93%	93%	93%
Wald test, Middle and High shifts: $\chi^2(6)$		3.67 (p = 0.72)		

Note: Headline specification (column 4 of Table 2) with three income bands (low: £0 to £29,999, middle: £30,000 to £59,999, high: £60,000 and above), and a band for households with no income data, that shift the mean of the log price coefficient, the mean gluten-free taste and the utility of the outside option. The dispersion of tastes and κ are common to all bands. Shifts are relative to the low-income band. A positive outside-option shift means the band buys bread less often. Standard errors (in parentheses) are analytic, clustered by product and account for the estimated first stage. The relative price coefficient is e^{shift}, with a delta-method standard error. The Wald test uses the same variance and covers the middle- and high-income shifts only. Each household is assigned its modal income band over 2015-2019, amongst the years in which an income is recorded. 16% of households report incomes in more than one band within the window, so differences between bands are attenuated towards zero. Households for which income is missing form their own band. Elasticities are computed from each band's own taste distribution for 400g and 800g packs, weighted by kilograms sold. Prices, marginal costs and Lerner indices paid are weighted by each band's own purchases, and markups and marginal costs come from the market equilibrium. The premium paid is decomposed as in equation (11) at each band's own purchase weights: the cost share is the log marginal-cost ratio over the log price ratio. The per-band elasticities and incidence rows are point estimates.

of the cost gap, and it likewise leaves the ranking of the Lerner indices undetermined.

Occasions per household. Re-estimating the preferred model on up to 52 occasions per household, which roughly doubles the estimation sample, leaves the results unchanged. The elasticities are -5.19 for standard and -3.37 for gluten-free bread (against -5.25 and -3.37), the Lerner indices are 0.24 and 0.32, and the marginal-cost ratio is 4.20 (against 4.17), so cost again accounts for 93% of the premium in log terms. The model still reproduces the dispersion in how often households buy bread. Longer household panels need a finer quadrature grid: the estimates are stable between $40 \times 40 \times 12$ and $40 \times 40 \times 16$ (a marginal-cost ratio of 4.20 and 4.16), but not on a $25 \times 25 \times 12$ grid (4.03). This is why the headline uses 26 occasions per household.

Nutrition. Adding nutritional characteristics (calories and fibre)[58] to the headline specification gives elasticities of -5.27 for standard and -2.92 for gluten-free bread, a marginal-cost ratio of 3.86 and a cost share of the premium of 88%. 91.1% of draws put gluten-free marginal cost above standard, and 28.3% put the marginal-cost ratio above the price ratio.

Conduct. Under category-brand ownership, where a manufacturer prices its gluten-free and standard ranges separately, the headline marginal-cost ratio is 4.22 (costs account for 93% of the premium). Under retailer ownership, where each store prices its whole bread range jointly, it is 5.66 (a cost share of 112% of the premium), with a standard Lerner index of 0.59 and negative marginal costs for 5.8% of standard volume. Gluten-free bread costs more to supply under every conduct assumption.

Manufacturer × gluten-free effects. Dropping the manufacturer × gluten-free effects from both stages reverses the ranking of the Lerner indices but not the cost finding. The marginal-cost ratio is 5.34 without the random taste for bread and 5.13 with it (cost shares of 109% and 106%). In both, gluten-free bread carries the lower Lerner index, so the marginal-cost ratio exceeds the price ratio (in 75.3% and 77.5% of draws), and 89.2% and 94.7% of draws put gluten-free marginal cost above standard. Controlling for brand-range quality therefore moves the point estimates towards a modestly higher proportional markup on gluten-free bread. Note that a cost share above 100% does not mean that gluten-free bread is sold at a loss. Its Lerner index remains positive (0.27 against 0.34 for standard bread in the specification with the random taste for bread), so the markup term of the decomposition is negative and cost differences alone would imply a larger premium than is observed.

[58] I focus only on calories and fibre as nutritional characteristics as energy is proportional to calories, and carbohydrates, fat and protein are close to collinear with calories; sodium is missing for many products. Fibre distinguishes wholemeal and seeded ranges. Most remaining nutritional variation is absorbed by the bread-type and manufacturer × gluten-free effects.

Inference. As a check on the analytic variance, I bootstrap the two-step estimator over households. Each replicate resamples households in the demand stage and, independently, products in the first stage, and recomputes the control-function residual for every product and refits demand (100 replicates). This is done for the mixed logit without manufacturer × gluten-free effects or the random taste for bread. The bootstrap gives the same answer on the sign of the cost gap: 90.0% of replicates put gluten-free marginal cost above standard, against 89.2% of the analytic draws. Resampling households does not capture the dependence between households that buy the same product, which the analytic variance clusters on, so the bootstrap is a check on the analytic draws rather than an alternative to them.

6.4 Discussion

Taken together, the results point to cost, rather than price discrimination, as the main source of the gluten-free premium. Gluten-free bread costs about four times as much per kilogram to supply as standard bread, in every specification, under every conduct assumption, and in 86% to 95% of draws. In the headline specification, cost accounts for the vast majority (93%) of the premium. Once brand-range quality is controlled for, the point estimates suggest that gluten-free bread also carries a somewhat higher proportional markup, worth about 7% of the premium in the headline, but this cannot be statistically distinguished from equal markups. The inelastic demand implied by the uncorrected estimates is an artefact of price endogeneity.

This has a direct implication for policy. If the premium reflected market power over a captive group of consumers, the appropriate response would lie in competition policy or in regulating gluten-free prices directly. The results here instead point to the cost of supplying gluten-free bread. These costs could include dedicated allergen-free production, more expensive ingredients, and short production runs. Remedies that lower or offset those costs, or that support entry into gluten-free production, would do more for gluten-free consumers than measures aimed at margins. The pass-through counterfactual supports this. A subsidy on GF bread would lower its price by the full amount of the subsidy, so support delivered through prices reaches consumers rather than being absorbed into margins. Firms still gain, through higher sales at an almost unchanged markup per kilogram (Section 6.1).

Several caveats qualify these conclusions. Firstly, fixed costs lie outside the model. Dedicated production lines and certification are plausibly large fixed costs in gluten-free baking, and they do not enter a static pricing first-order condition, so the decomposition does not exclude fixed-cost recovery as part of the premium. Secondly, I am not account-

ing for the vertical relationship between manufacturers and retailers and any bargaining that occurs between them. Thirdly, all gluten-free products share one price scale, so the model has little power to detect segmentation within gluten-free bread, for example higher markups on premium brands; allowing the price response to differ between branded and own-label gluten-free bread would require instruments that move their prices differently.

7 Conclusion

In this paper I investigate the underlying causes of the gluten-free price premium to better understand why GF bread costs more than four times as much as standard bread. Using household-level scanner data on 35,570 households and over 5.8 million choice occasions between 2015 and 2019, I estimate a mixed logit model of bread demand, in which households differ in their price sensitivity, their taste for gluten-free bread and their taste for buying bread at all, and I recover marginal costs under multi-product Bertrand-Nash pricing.

I find that the premium is primarily driven by differing costs. Gluten-free bread costs about four times as much per kilogram to supply as standard bread (4.17 times, against a price ratio of 4.67 for the 400g and 800g packs the model prices, in the headline specification). This holds in every specification and under every conduct assumption I consider. Cost accounts for 93% of the premium in log terms. Once brand-range quality is controlled for, the point estimates suggest a somewhat higher proportional markup on gluten-free bread, worth about 7% of the premium, but this cannot be distinguished statistically from equal markups. Nor do I find evidence that firms target richer households: income makes little difference to price sensitivity, and every income band pays the same proportional markup.

Ingredients alone cannot explain a fourfold cost difference: once input shares are accounted for, rice flour costs only around 1.5 times as much as wheat flour (Section 2). The results therefore point to other costs of supplying gluten-free bread, such as small-scale production, dedicated allergen-free lines, cleaning, testing and low capacity utilisation. This is consistent with Hong (2026), who finds that the organic premium in baby food is driven by marginal costs rather than markups.

Reaching this conclusion requires instrumenting for price in a way that the structure of the market makes difficult. Gluten-free products are almost entirely a single pack size, so conventional cost-shifter instruments have no variation within the gluten-free segment and cannot detect gluten-free-specific price endogeneity. Left uncorrected, that endogeneity

biases price responses towards zero and makes demand appear inelastic, leading to the finding a market-power account would predict. To overcome this problem, I interact the cost series with bread type, so that the instruments vary across GF products.

The policy implication is that there is limited scope to reduce gluten-free prices through competition policy or markup regulation. If the premium mainly reflects cost, measures that lower or offset the cost of supplying gluten-free bread, or that encourage entry into gluten-free production, are more promising. Demand-side support for coeliacs is also unlikely to be absorbed into firms' margins. When I solve the model for counterfactual prices, a per-unit subsidy on GF bread is passed through to consumers in full. Firms nonetheless gain through higher sales, and about a third of the consumer gain goes to the small group of households that buy gluten-free bread persistently. More broadly, the approach taken in this study applies to other specialised food products, such as dairy-free, vegan and organic alternatives, whose price premia raise similar questions of affordability.

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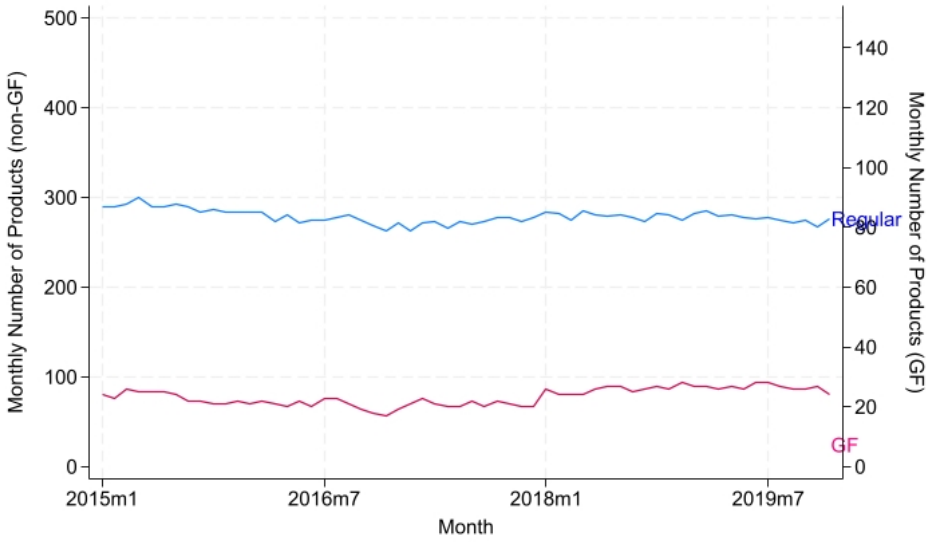
A Annex

A.1 Additional Descriptive Statistics

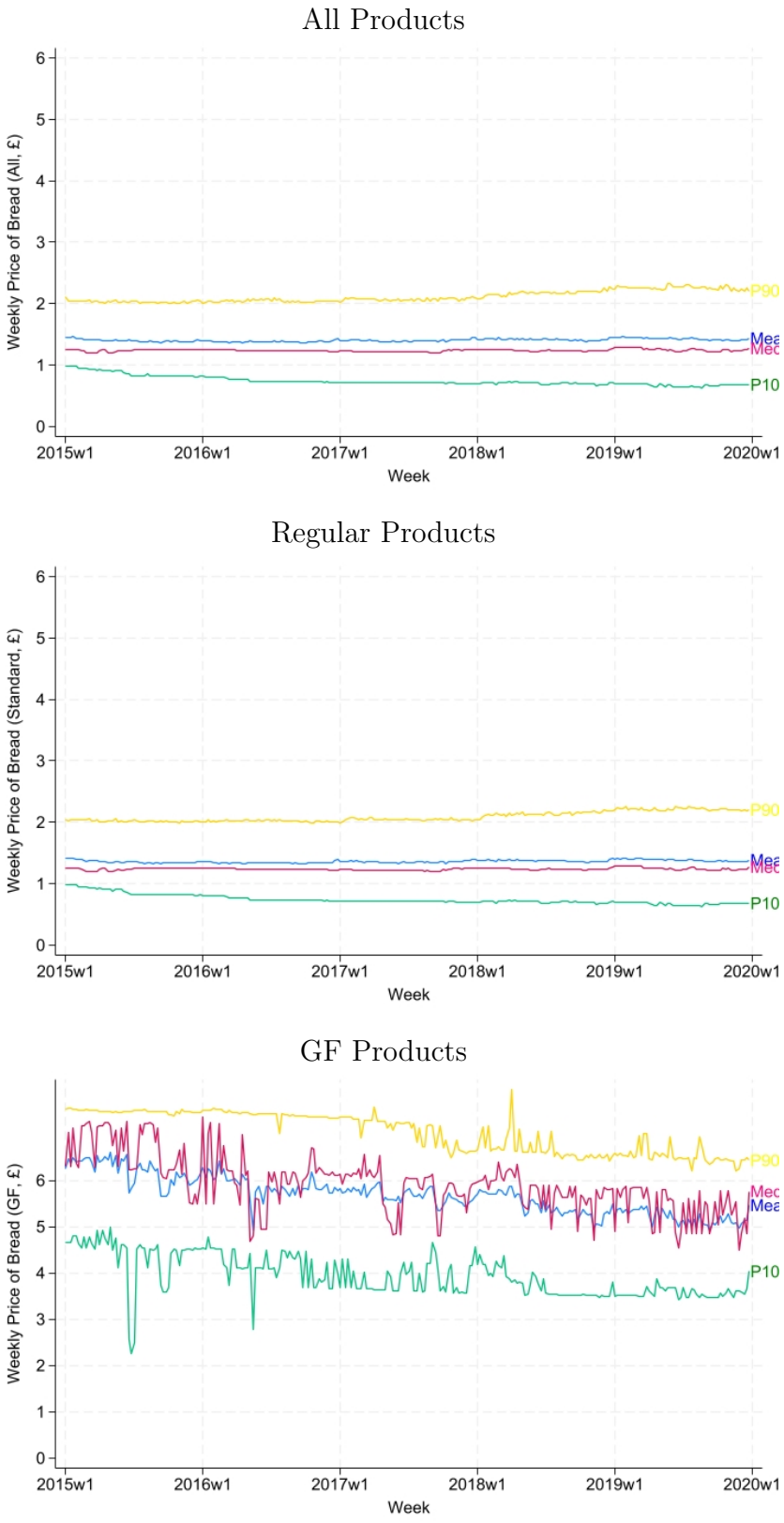
Figure 4: Monthly Number of Products, Standard and GF Bread (separate axis)



Note: Left-hand axis shows non-GF products, right-hand axis shows GF products.

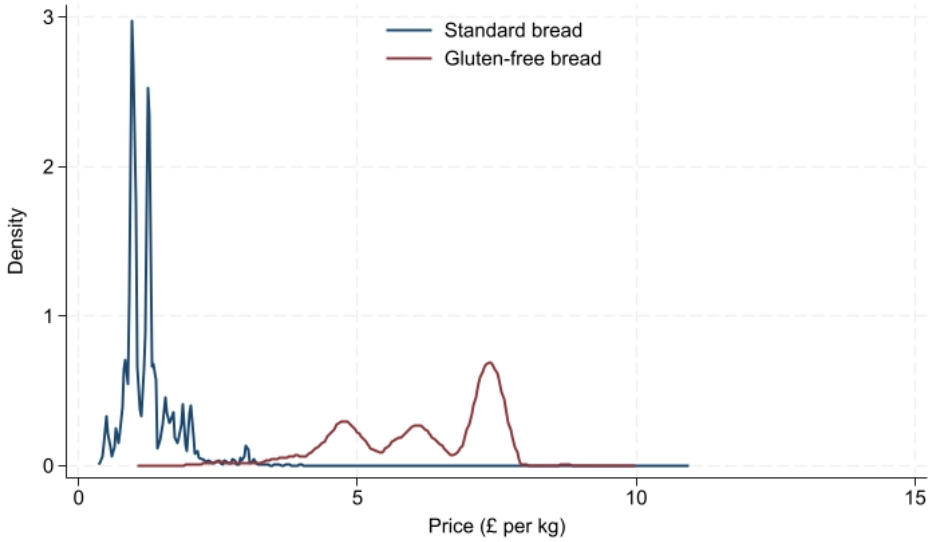
A.2 Additional Results

Figure 5: Price Time Series



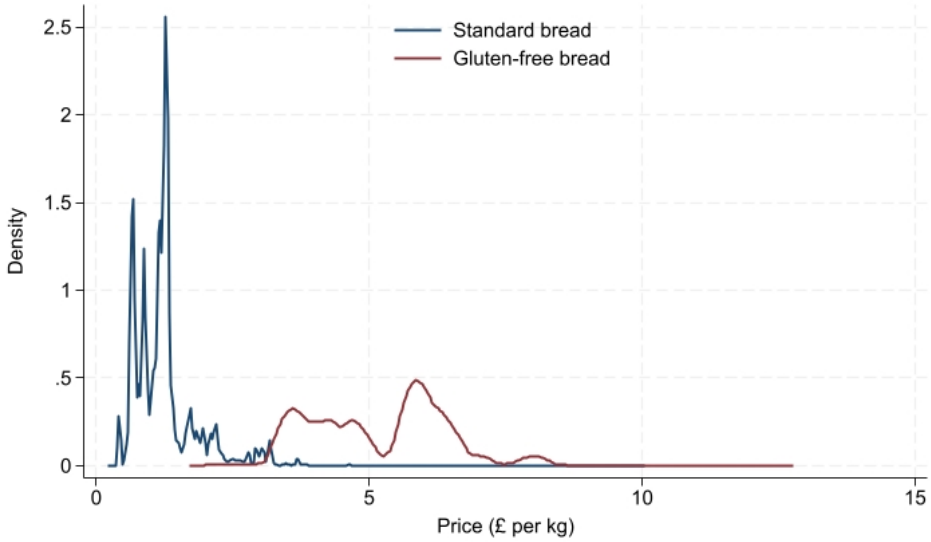
Note: prices are deflated using ONS data to 2015.

Figure 6: Kernel Distribution of Prices (standard vs GF products), 2015



Note: Data is kg-weighted.

Figure 7: Kernel Distribution of Prices (standard vs GF products), 2019



Note: Data is kg-weighted.

Table 9: First-Stage Regression of Pack Price on Cost Shifters

	Standard bread	Gluten-free bread
Flour (wheat/rice) × size	0.509***	0.566**
	(0.144)	(0.265)
× brown	-0.188	2.39
	(0.220)	(1.57)
× white	-0.306**	0.691
	(0.140)	(1.34)
Rapeseed oil × size	-0.017	-0.105
	(0.022)	(0.405)
× brown	-	2.26***
		(0.745)
× white	-	3.05***
		(0.470)
Energy × size	1.34	17.9***
	(0.822)	(5.17)
× brown	-0.008	-40.0***
	(1.86)	(7.34)
× white	1.13	-34.3***
	(1.35)	(5.83)
Diesel × size	0.157	9.98
	(0.341)	(6.76)
Packaging × size	-21.7**	-40.5**
	(8.55)	(17.3)
F statistic: all 20 cost shifters	37.2	
F statistic: 11 gluten-free shifters	49.3	
R^2 (within)	0.738 (0.244)	
Product-market cells	174,595	

Note: One regression of pack price (2015 £) on the 20 cost shifters, estimated on all product-retailer-week cells; the two columns show the standard-bread and gluten-free versions of each shifter. Flour is the wheat price for standard bread and the rice price for gluten-free bread. Each series is interacted with pack size in grams and, where shown, additionally with an indicator for brown or white bread. All series except diesel are lagged eight weeks. Commodity prices are in £ per tonne, diesel is the pump price and energy and packaging are producer price indices (2015 = 100), so coefficients are not comparable across rows; coefficients and standard errors are multiplied by 10^6. As an illustration, a £100 per tonne rise in the wheat price raises the price of an 800g standard loaf by about 4p. The regression controls for pack size, thickness, bread type, branded status and pack size × bread type, and absorbs retailer, year, month-of-year and manufacturer × gluten-free effects. Standard errors (in parentheses) are clustered by product and calendar month; F statistics are clustered by product only (Section 3.1). The 11 gluten-free shifters are those in the right-hand column; the 6 bread-type shifters are its brown and white interactions with rice, rapeseed oil and energy. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Product Fixed Effects in Place of the Control Function

	Headline	Product FE		Product FE + CF	
	Mixed (1)	CL (2)	Mixed (3)	CL (4)	Mixed (5)
Own-price elasticity					
Standard	-5.25	-1.44	-2.35	-1.32	-6.36
Gluten-free	-3.37	-0.60	0.61	-0.56	2.22
Product-markets with upward-sloping demand					
Standard	0.0%	0.0%	0.9%	46.9%	0.0%
Gluten-free	0.0%	0.0%	77.0%	0.0%	99.7%
Lerner index					
Standard	0.24	0.87	0.59	-0.19	0.21
Gluten-free	0.32	1.71	-1.27	1.78	-0.53
Volume with negative marginal cost					
Standard	0.1%	34.4%	8.1%	11.7%	0.0%
Gluten-free	0.0%	99.9%	19.4%	99.4%	0.0%
Marginal-cost ratio (price ratio 4.67)	4.17	n/a	25.96†	n/a	9.00†
First-stage F statistic, 20 cost shifters	37.2	-	-	63.0	63.0
Log-likelihood	-2,394,704	-2,326,683	-2,181,733	-2,325,312	-2,171,365
Control function	Yes	No	No	Yes	Yes
Manufacturer × GF effects	Yes	-	-	-	-
Product fixed effects	No	Yes	Yes	Yes	Yes
Random price coefficient and GF taste	Yes	No	Yes	No	Yes
Random taste for buying bread	Yes	No	Yes	No	Yes

Note: Column (1) is the headline specification (column 4 of Tables 2 and 4). Columns (2) to (5) replace its product characteristics and manufacturer × gluten-free effects, which are all fixed within a product, with 480 product fixed effects, so price is identified only by a product's own price movements over time and across retailers; the retailer, year and month-of-year effects on the outside option are kept. In columns (4) and (5) the product fixed effects also enter the first stage, which absorbs product, retailer, year and month-of-year effects. CL denotes a conditional logit. All columns are estimated on the same sample of up to 26 occasions per household, so the conditional logits differ slightly from columns (1) and (2) of Table 2, which use every occasion. Elasticities, Lerner indices and marginal costs are for 400g and 800g packs under multiproduct Bertrand-Nash pricing with manufacturer ownership, weighted by kilograms sold, under the population distribution of tastes; 200g and 600g packs are held at their observed prices. A positive elasticity means demand slopes upward. Upward-sloping demand is the share of product-markets whose own-price derivative is non-negative. n/a: the average gluten-free marginal cost is negative, so the ratio is not defined. †Gluten-free markups are negative, so the recovered marginal cost exceeds the price and the ratio has no cost interpretation. The first-stage F statistic is clustered by product (481 degrees of freedom). Log-likelihoods are on the same occasions but the models are not nested: the fixed-effect columns add 480 parameters and, in columns (4) and (5), a different first stage.

Table 11: Robustness of the Cost Decomposition

	Elasticity	Lerner index	MC	Cost	Share of draws		Standard volume
	std / GF	std / GF	ratio	share	GF costs more	MC ratio > price ratio	with MC < 0
Headline (Table 4, col. 4)	-5.25 / -3.37	0.24 / 0.32	4.17 (0.87)	93%	93.1%	34.4%	0.1%
Sample and demand specification							
52 occasions per household	-5.19 / -3.37	0.24 / 0.32	4.20	93%	-	-	0.1%
Adding calories and fibre	-5.27 / -2.92	0.24 / 0.37	3.86 (1.07)	88%	91.1%	28.3%	0.0%
No manufacturer × GF effects:							
without bread taste	-2.53 / -2.95	0.45 / 0.37	5.34 (2.78)	109%	89.2%	75.3%	1.0%
with bread taste	-3.45 / -3.93	0.34 / 0.27	5.13 (1.35)	106%	94.7%	77.5%	0.2%
Conduct (headline demand)							
Category-brand ownership	-5.25 / -3.37	0.24 / 0.31	4.22	93%	-	-	0.1%
Retailer ownership	-5.25 / -3.37	0.59 / 0.50	5.66	112%	-	-	5.8%

Note: Each row changes one feature of the headline specification (column 4 of Tables 2 and 4). Elasticities, Lerner indices and marginal costs are for 400g and 800g packs, weighted by kilograms sold, under the population distribution of tastes; the price ratio is 4.67 in every row. The cost share is $\frac{\ln(mc_{GF})-\ln(mc_S)}{\ln(p_{GF})-\ln(p_S)}$ and exceeds 100% when gluten-free bread carries the lower Lerner index. The 52-occasion specification is estimated on a $40 \times 40 \times 12$ grid. The conduct rows use the headline demand estimates, so their elasticities are unchanged; under category-brand ownership a manufacturer prices its gluten-free and standard ranges separately, and under retailer ownership each store prices its whole bread range jointly. Robust standard errors of the marginal-cost ratio (interquartile range of the draws divided by 1.349) and the shares of draws come from 2,000 draws from the analytic variance of the two-step estimator, clustered by product and including the first stage; a dash means no draws were computed for that specification. "MC ratio > price ratio" is the share of draws in which gluten-free bread carries the lower Lerner index. The last column is the share of standard-bread volume with a negative implied marginal cost.