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ARTICLE

Product churn, tastes, and price indices

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Abstract

Price indices commonly used to measure inflation do not account for the entry and exit of products nor for systemic changes in consumer preferences over time. Recent developments in the theory of price indices show that these issues have significant impacts on the growth of prices that consumers experience. However, executing these developments requires access to household-level data. Analyzing the ready meal purchases of 30,000 UK households during 2013–2022, we evaluate the extent of the bias between standard price indices and those that accommodate product churn as well as changes in consumer tastes. Household data also permit the effects to be calculated across income groups. Our results show that price indices commonly used to measure inflation significantly overstate the extent of price increases due to: (i) "representative" prices used to measure the Consumer Prices Index do not adequately capture the prices of goods in household baskets, and (ii) the effect of the net entry of products and taste changes, the latter being particularly strong. Furthermore, differences in the shopping baskets across income groups suggest that inflation varies across the income distribution. We find that when product churn and taste changes are accounted for, ready meals prices rose over the period by around 3% in low-income households compared with a rise of 12% and 14% in middle- and higher-income households, respectively. These issues are important not only for measuring cost-of-living and how it varies across income groups but also in addressing policy issues more generally.

KEYWORDS

consumer prices index, elasticity of substitution, ready meal prices

JEL CLASSIFICATION
C43, D12, L11, L81

1 | INTRODUCTION

Recent developments in the theory and measurement of price indices identify large quantitative impacts of product innovation (i.e., the entry and exit of products) and underlying changes in tastes on consumer welfare (see inter alia, Broda & Weinstein, 2010; Feenstra, 1994; Jaravel, 2019; Redding & Weinstein, 2020). Ignoring these factors, as is customarily the case in the measurement of consumer price indices routinely reported by national statistical authorities, may significantly overestimate consumers' experience of inflation and its impact on the cost of living. These issues are likely to be especially pertinent when addressing changes in food prices over time. In this paper, we focus on the impact of product entry and exit (product churn) and underlying changes in tastes in a specific segment of the market to illuminate how these mechanisms operate at the micro level; the ready-to-eat (ready meals) sector being notable for its high rates of product churn and rapidly changing consumer preferences.

We also explore how the changes in price indices accounting for these factors vary across income groups. The recent experience of food inflation across many countries has highlighted how cost-of-living pressure has affected low-income households and ties with recent research on inflation inequality (Jaravel, 2021). Standard approaches to this issue are typically made with reference to Engel's law, in that, since poorer households spend a higher proportion of their income on food, increases in the cost of food will have a greater impact on these groups. For example, in 2022 the poorest quintile of US households spent 31% of their income on food, whereas the richest quintile spent 8% (USDA, 2024); for the UK the figures are 14% and 9%, respectively (ONS, 2024). However, there are strong reasons to suggest that differences in price indices between income groups extend beyond differences in expenditure shares. Specifically, across the income distribution, consumer shopping baskets differ in terms of the quantity and quality of products purchased, where consumers shop and the prices they pay. Consequently, responses to price changes (due to exogenous factors or policy changes) are likely to be non-homothetic (i.e., differ among income groups). While statistical authorities are beginning to respond to the need for inflation measures for socio-economic groups, there is still some way to go since such measures assume that consumers pay common prices irrespective of their socio-economic status.[1]

Central to the price indices we apply is the degree of product substitution when prices change. In addition to the direct effect of substitution on the price indices, it also mediates the impact of product turnover and changing preferences. Other things remaining constant, greater substitutability weakens the impact of product turnover and changing preferences on the price indices of Feenstra/Broda/Weinstein and Redding and Weinstein. In order to emphasize this mediating role, we detail the approach to measuring the elasticities of substitution in the paper.

As a consequence, we show that the Consumer Prices Index that is employed by the UK national statistical office (the Office for National Statistics) overestimates the change in prices experienced by UK households by up to 40% in the ready meals sector. This finding also holds when comparing against other commonly used price indices: the correlation between the Feenstra/Broda/Weinstein index (that accounts for product entry and exit) and Laspeyres, Paasche and Törnqvist indices (that do not) over the period 2013–2022 is relatively low; in the case of the Redding and Weinstein index that additionally accounts for consumer tastes and preferences, the correlation is actually negative.

[1]See, for example, the recently introduced household cost indices in the UK produced by the Office for National Statistics (ONS, 2023). For a recent review of methods adopted in the US, see Sichel and Mackie (2025).

The extent of this bias—and the low correlation with other price indices—is magnified for the lower income households.

Addressing these issues does not only rely on developments in the theory of price indices but also on having access to sufficiently granular data to enable the researcher to identify the content of shopping baskets at the household level.[2] The increase in access to household scanner data has been an important development for researchers in recent years and which—in the context we explore here—facilitates the study of inflation inequality between income groups. Specifically, we employ a decade of monthly *Kantar WorldPanel* data during 2013–2022 documenting chilled and frozen ready meal purchases at the product level for 30,000 households in the UK as well as household characteristics, most importantly, income. Our focus on the ready meals category is motivated by its status as an exemplar in the Fast-Moving Consumer Goods (FMCG) sector, and the importance of this category in UK household consumption, which is the highest in Europe and second only to the US globally. Not only do some 88% of UK consumers eat ready meals but expenditure has increased significantly in recent years (by 37% between 2013 and 2022).[3] Our data also spans a particularly turbulent period that includes the Covid pandemic and the UK's 2022 "cost-of-living crisis." Characterized by marked price rises, product churn and preference shifts, the period presents a good opportunity to assess the impacts of these factors on income group specific price indices and the extent to which they have contributed to cost-of-living inequality.

Our headline insights are as follows: product churn is commonplace and varies over time and across the income distribution, with low-income households typically experiencing greater product churn than higher-income households. Overall, around two-thirds of ready meal spending in 2022 was on products that did not exist in 2013, and only half of spending in 2013 was on products that were available in 2022. Poorer households are both more likely to drop products and buy new ones in this category than richer households. Consequently, product churn has lowered prices in the sector, substantively more so among low compared to high-income households. However, we find that the effect is scarcely half the impact arising from changing tastes over the period, which have lowered the price indices by nearly 15% among rich and poor households alike, but particularly so for those on low incomes. Taken together, we find substantial differences in the price indices of low-, middle- and high-income households but, notably, the observation that low-income groups face higher levels of inflation (Kaplan & Schulhofer-Wohl, 2017) does not hold here; note however that although their paper employs scanner data, they use a Laspeyres index that does not account for product entry and exit or changing consumer preferences.

Finally, we explore how these patterns of entry and exit and consumer tastes changed during Covid, a period characterized by unprecedented shocks to the food sector and, as we detail below, widespread product exit. While ordinarily amplifying the effects on prices, we find that owing to higher elasticities of substitution in all income groups during the Covid period, the impact of product entry and exit and consumer tastes is mollified. The net result is not dissimilar to that from orthodox indices during this period, in contrast to the pre-Covid period during which the indices of Feenstra/Broda/Weinstein and Redding and Weinstein diverged from more orthodox measures, once again highlighting the pivotal role of the elasticity of substitution in the experience of food inflation at the household level.

The paper is organized as follows. In Section 2, we provide an overview of the literature on the measurement of price indices, highlighting the role of product churn in the food sector and issues relating to cost-of-living inequality which form the basis of the recent developments in price indices we apply here, as detailed in Section 3. In Section 4, we provide details on the *Kantar WorldPanel*

[2]Theoretically-based price indices are important for a wider range of issues beyond measuring changes in the cost of living, including the measurement of poverty (Broda & Weinstein, 2008) and measuring the effectiveness of government policies. For example, Jaravel (2018) has noted that the cost–benefit of the US food stamp program is significantly affected when he accounts for the changes in product variety that impact the income groups that the food stamp program targets.

[3]As reported by Mintel *Ready Meals and Ready-to-Cook Foods Market Report 2022*. Ready-to-eat foods and Ready Meals Market Report UK 2022 (https://store.mintel.com/report/uk-ready-meals-and-ready-to-cook-foods-market-report-2022). Accessed 21st May, 2024.

scanner data in the UK ready meals sector which is the focus of our application. The results, which emphasize the importance of product churn and the evolution of consumer tastes on price indices at both the aggregate and across income groups, are presented in Section 5. We also compare these price indices with commonly used price indices to evaluate the extent of the bias that omits these features of consumer behavior and the characteristics of the food sector. In Section 6, we provide a series of robustness tests including a discussion of the changes in the impact of entry and exit and consumer tastes during the Covid period. We summarize and conclude in Section 7, highlighting the potential for further research on addressing price changes over time in the food sector. Addressing the issue of applying appropriate price indices when high-frequency scanner data is available is an ongoing issue facing researchers and national statistical offices across many countries (e.g., Ehrlich et al., 2022), Our insight here is that—particularly in the context of applying these price indices to the food sector—the characteristics of the economic environment (i.e., product entry and exit and changing consumer tastes) have to be taken into account. Given the attention paid to the potential value of using household data in the US and elsewhere, the results reported here may offer confidence in the use of these data in approaches that complement current methods of measuring price changes.

2 | RELATED LITERATURE

Common approaches to measuring price indices (such as those underpinning the measurement of various components of inflation) face two main challenges. One is the choice of index: the Laspeyres index has the characteristic that the weights attached to products are fixed at the start of the period; an alternative is the Paasche index, which uses the weights that are fixed at the end of the period. The former tends to overstate price changes; the latter understates price changes as neither captures the substitution of products whose prices are falling or products whose prices are rising (Jaravel, 2021). While superlative price indices such as Fisher and Törnqvist accommodate substitution as product prices change, both assume that the product assortment and consumer preferences remain constant over time.[4] In contrast, the exact price index (EPI) developed by Feenstra (1994) and generalized by Broda and Weinstein (2010) allows for entry and exit of products. Redding and Weinstein (2020) additionally allow for evolving consumer tastes to reflect that a preference shift toward a product is equivalent to a lowering of its price, as the impact on consumer utility is the same. Both EPIs are derived from the Constant Elasticity of Substitution (CES) utility function of which the Sato-Vartia exact price index (Sato, 1976; Vartia, 1976) is a baseline special case in which product assortment and consumer taste are constant over time. For this reason, it is called the "conventional" EPI for CES preferences (see below for details).

The second main challenge is data. National statistical offices such as the Bureau for Labor Statistics in the US or the Office for National Statistics in the UK collect price data in similar ways. Fox et al. (2023) detail the procedures involved. Essentially, price quotes are collected in person from a selection of retail outlets and combined with survey data. In the UK, prices are collected physically from 140 locations around the country and supplemented by online price quotes and checks by phone with large national retailers. Importantly, price quotes relate to a limited number of products that are intended to be "representative" of the category (called modules) they feature in.[5] For example, in the UK ready meals case we explore here, prices are collected for products typical of those in modules described as: "Frozen Ready-Cooked Meal," "Chilled Ready Meal-Meat" and "Chilled

[4]An overview of non-CES price indices and on the use of price indices with high-frequency data can be found in Jaravel (2021) and Fox et al. (2023).

[5]A similar approach is followed in the US by the Bureau of Labor Statistics. The CPI is based on 100,000 items in a fixed basket of goods and services. Price data is collected in person, online or by phone though two-thirds of the data collection is collected in person during in-store visits. Data on food prices relates to several categories: breakfast cereal, milk, coffee, chicken, wine, full-service meals, snacks. As with the UK case, these representative prices will not capture price dispersion across the range of products in each category that are on retail shelves.

Ready Meal-Fish/Veg." As we detail in the data section below, these "representative" products are limited in scope compared with the 3500 or so products that appear in the *Kantar WorldPanel* scanner data for the ready meals category. Further, official expenditure data is based on historical spending which consequently results in the category weights being fixed over periods of time (typically annually) with no scope for changing the expenditure shares as prices and preferences change. Given that the weights are fixed, it is a Laspeyres price index that is employed to measure the price changes of these representative products in the product category over time.

One other limitation of standard approaches to measuring price indices when addressing differences in the cost of living across different household groups, is that they rely on shares of expenditure occupied by the categories rather than the specific products that are purchased by households. In doing so, within-category substitution is ignored. Since households across the income distribution purchase different varieties, shop in different retail outlets and pay different prices (even for the identical item), the "representative" price is unlikely to apply equally to both rich and poor households. This further limits insights into inflation inequality since the opportunities for "trading down" are fewer for poorer households. Finally, adjusting the category weights only periodically, standard price indices do not adequately account for the entry and exit of products over time, a feature which intuition suggests may have a significant impact on price indices based at the product level. For example, with CES utility, a standard result from microeconomic theory is that the entry of new products will lower the aggregate price index at the product group level, and vice versa for the exit of products (see, inter alia, Feenstra, 1994, p.159). Recent developments in the theory of price indices and increased access to data at the household level have provided the potential to address these issues.

Take, first, the issue of inflation inequality. Early research (see, for example, Hobijn & Lagakos, 2005) largely concluded that there was relatively little variation in inflation across income groups. But access to data at the household level (such as the *Nielsen Homescan* data in the US or *Kantar WorldPanel* data in the UK) has provided new insights. Kaplan and Schulhofer-Wohl (2017) use US household scanner data to show that the degree of inflation inequality is considerable, inflation being higher for low-income households. They note that the source of inflation inequality is due to the heterogeneity of prices paid by households within product groups rather than the variability in average inflation across product groups. However, their observation that low-income households faced higher inflation was based on a Laspeyres index and, as such, did not address the issue of product entry and exit or changing consumer preferences, the focus of recent research on price indices.

The seminal contribution in this area was Feenstra (1994). Motivated by the gains from variety arising from trade, Feenstra provided an amendment to the CES price index that accounted for the entry and exit of products and derived an approach to estimate the elasticity of substitution across product groups. Broda and Weinstein (2006, 2010) also focused on the variety gains from trade and consolidated the contribution of Feenstra but, in their case, employed US scanner data to provide a more comprehensive coverage of the consumer gains from variety. Jaravel (2019) built on these approaches focusing on the entry and exit of products across different income groups to show that net entry is more likely to benefit higher income groups. In a model of endogenous innovation, he shows that this is due to higher rates of income growth within the higher income groups leading to a bias in the provision of new products demanded by richer consumers. Applying the Feenstra–Broda-Weinstein (FBW) approach to US household scanner data from 2004 to 2016, Argente and Lee found a positive difference in inflation between bottom and top quartiles that widened during the Great Recession. Finally, combining the issue of product entry and exit during a crisis period in the UK (in this case, Covid), Jaravel and O'Connell (2020) show that the incidence of entry and exit across income groups resulted in an increase in the FBW index, implying that the rate of inflation for low-income groups was higher compared to others, a result they ascribe to the net exit of products observed during the Covid period.

One potentially desirable feature of the FBW and RW price indices is that they can deal with the economic environment that applies to the food sector which is characterized by high levels of product churn (i.e., the high level of entry and exit of products). The agricultural and food economics literature has reflected only partially on the issue of new products and, as far as we are aware, not addressed the issue of product exit despite being a notable characteristic of food retailing. The closest link has been the issue of product proliferation; although focus here has been on how product proliferation ties with market structure (Connor, 1981; Zellner, 1989), this issue has also been addressed by Roder et al. (2000).[6] Battacharya and Innes (2016) also address the links between new products and competition issues, tying it with the growing concentration in the (US) food sector through mergers. Note that while the focus of the product proliferation stream of research has acknowledged the importance of product entry as a feature of the food sector, the role of product exit has been largely ignored, despite it being a feature of food sector dynamics and—as we show below—has dominated entry in recent years. The marketing literature has also addressed issues related to product proliferation and competition issues: see, for example, Piazzai and Wijnberg (2019) and Rao and McLaughlin (2018) but this line of research—although acknowledging the broader issue of new product varieties in the food sector—is largely orthogonal to the issue of how product entry and exit impacts on the measurement of price indices that we address here.

In a significant development in the theory of price indices, Redding and Weinstein (2020) augment the FBW index to account for changes in unobserved and systematic changes in tastes over time. Arguing that a shift in consumer preference toward a product lowers its taste-adjusted price and increases its expenditure share, changes in tastes serve to reduce the overall price index.[7] Thus, while the entry and exit of products highlight the "new goods bias" in the conventional EPI, the Redding and Weinstein (RW) index suggests an additional source of bias, that they refer to as "taste-shock bias." Since both sources of bias are also ignored in the consumer price indices routinely produced by the national statistical offices, the official rates of inflation will further deviate from changes in the actual cost-of-living experienced by households. Given changing consumer tastes and the appeal of products over time, this would seem pertinent to measuring price changes that apply in the food sector.

In the empirical analysis below which employs data on the UK ready meals sector, we report the extent of the bias in the consumer price index relative to the FBW and RW indices, report the comparison between the FBW and RW indices with other commonly used non-CES price indices and determine the relative impact of product entry/exit and changing tastes on households' experience of inflation. With access to household data, we are also able to delineate the extent to which these impacts vary across income groups.

3 | METHODOLOGY

We approach the methodological issues in three parts. First, we detail the constant elasticity of substitution (CES) exact price index extended to account for product entry and exit by Feenstra (1994) and Broda and Weinstein (2010). Importantly, this is shown to be an extension of the Sato (1976) and Vartia (1976) exact price index for varieties that remain over time scaled by a factor that accounts for the entry and exit of varieties. Second, we outline the approach of Redding and Weinstein (2020) that accounts for changes in underlying tastes with CES utility, highlighting that the FBW measure is a special case of RW when perceived tastes for each variety are constant over time. In doing so, it becomes clear how the "taste" effect is isolated in this context. We follow recent practice in empirically deriving the non-homothetic effect by splitting the data on households into income groups as explained in the data section, but for notional simplicity the group notation is

[6]This literature on product proliferation in the food sector followed from the industrial organization literature that addressed similar issues. See, for example, Schmalansee (1978).

[7]Specifically, given the focus on log expenditure shares, increasing the expenditure share of the taste preferred variety is not equivalent to the reduced expenditure share of varieties where tastes are shifting from, resulting in the effect that taste changes serve to reduce the price index.

suppressed below. Finally, since the elasticity of substitution is common to both approaches, we detail the econometric approach to measuring this parameter.

To begin, define P_t as the unit expenditure function for a single category (ready meals) comprising $k \in \Omega_t$ products consumed in period t with CES preferences as[8]:

$$P_t = \left[\sum_{k \in \Omega_t} \left(\frac{p_{kt}}{\varphi_{kt}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}, \tag{1}$$

where σ is the elasticity of substitution between varieties and $\sigma > 1$ implying that all products are substitutes. Prices p_{kt} are observed but the utility obtained from consumption (c_{kt}) depends on an unobservable taste parameter φ_{kt} that allows tastes to vary between products and over time. Note that in this set-up, tastes (i.e., consumers' perception of utility) are similar to, but conceptually distinct from, product quality (i.e., changes in product composition). In the theory that follows, any change in a product's physical characteristics (such as size or composition) is treated as a new product, the empirical counterpart of which is a new barcode.

3.1 | CES price index with entry and exit (the Feenstra–Broda–Weinstein [FBW] approach)

Defining Ω_t^* as the set of common products that are consumed in periods t and $t-1$ such that $\Omega_t^* = \Omega_t \cap \Omega_{t-1}$, Feenstra (1994) and Broda and Weinstein (2010) show that, providing the perceived quality of each product remains constant over time such as ($\varphi_{kt}/\varphi_{kt-1} = 1$ for all $k = \Omega_t^*$), the change in the cost-of-living assuming that can be written as:

$$\left[\frac{P_t}{P_{t-1}} \right]_{FBW} = \left(\frac{\lambda_t}{\lambda_{t-1}} \right)^{\frac{1}{\sigma-1}} \times \prod_{k \in \Omega_t^*} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{\omega_{kt}^*}, \tag{2}$$

where,

$$\lambda_t = \frac{\sum_{k \in \Omega_t^*} p_{kt} c_{kt}}{\sum_{k \in \Omega_t} p_{kt} c_{kt}}, \quad \omega_{kt}^* = \frac{\frac{s_{kt}^* - s_{kt-1}^*}{\ln s_{kt}^* - \ln s_{kt-1}^*}}{\sum_{k \in \Omega_t^*} \frac{s_{kt}^* - s_{kt-1}^*}{\ln s_{kt}^* - \ln s_{kt-1}^*}}, \quad s_{kt}^* = \frac{p_{kt}^* c_{kt}^*}{\sum_{k \in \Omega_t^*} p_{kt}^* c_{kt}^*},$$

In these equations, asterisks denote common products so that s_{kt}^* is the expenditure on product k as a share of overall expenditure on common products at period t and ω_{kt}^* are ideal log-change weights for product k relative to all common products at period t. As Equation (2) shows, when tastes are time invariant, the exact price index developed by FBW comprises two elements. The term $\prod_{k \in \Omega_t^*} \left(\frac{p_{kt}}{p_{kt-1}} \right)^{\omega_{kt}^*}$ is the exact price index of Sato (1976) and Vartia (1976), common products in the FBW set-up being equivalent to the fixed set of products over which the Sato-Vartia index is defined. As such, this term is called the "conventional" exact price index (CEPI) in the literature (see Feenstra, 1994). The key innovation of FBW is to allow for the entry and exit of varieties to impact on the change in the cost-of-living by scaling the conventional index by a factor $\left(\frac{\lambda_t}{\lambda_{t-1}} \right)^{\frac{1}{\sigma-1}}$ referred as

[8]Here, we have a single tier containing all varieties of ready meals purchased by all households. For simplicity we abstract from issues relating to geography and retail chain but note multiple tiers that allow for such aspects as well as additional categories can also be accommodated with CES preferences. See, for example, Redding and Weinstein (2020) Section III.

the "the Feenstra ratio," which corrects the conventional index for the entry and exit of products and where the λs refer to the share of common products in total expenditure of periods t and $t-1$.

There are two important insights from Equation (2). First, the greater the role of product entry, the lower $\left[\frac{P_t}{P_{t-1}}\right]_{FBW}$ is to the conventional exact price index since if new products occupy a substantial share of consumer expenditure, $\lambda_t < 1$. Similarly, if the expenditure on products that disappear in period t is substantial, $\lambda_{t-1} < 1$ and $\left[\frac{P_t}{P_{t-1}}\right]_{FBW}$ is higher than the conventional exact price index. Consequently, the bias can go either way, although it is the ratio of the two that determines that nature of the bias.

Second, the strength of the impact of product entry and exit on the price index depends on the elasticity of substitution, σ. The higher the elasticity of substitution, the lower the gains/losses from the net entry of products. The intuition is as follows: with CES utility, the entry of a new product will lower the aggregate price index as there are more substitute products now available and, as the products are competitive, the prices of other products should also fall. But the strength of this effect depends on the magnitude of the elasticity of substitution. If this elasticity is "high" ("low"), this indicates that products are close (weak) substitutes so the entry/exit of products will have lesser (greater) effects on the aggregate price index. In the limit, if the elasticity of substitution is infinite, product entry and exit will have no effect on the aggregate CES price index and, in turn, there will be no benefits/losses from product churn.

3.2 | CES price index accounting for changes in tastes (Redding and Weinstein [RW])

Redding and Weinstein (2020) contend that because standard price index measures do not account for underlying changes in tastes and product appeal, they will inherently mis-measure price changes. Specifically, since a change in consumers' preferences cannot fit the data exactly in both period t and $t-1$, an additional term is required that acts as a residual to reflect systematic unobserved changes in tastes. Denoting φ_{kt} as the measure of consumer taste for product k at time t, taste-adjusted prices (p_{kt}/φ_{kt}) will necessarily differ from the actual price paid (p_{kt}) when consumer tastes are allowed to vary. Consequently, the conventional exact price index (which ignores changes in tastes) will overestimate price changes of products for consumers whose tastes are moving away from the product $(p_{kt} > p_{kt}/\varphi_{kt})$ and under-estimate the price changes of products for which consumer tastes are increasing $(p_{kt} < p_{kt}/\varphi_{kt})$. Intuitively, increases in consumer tastes for a variety will reduce the taste-adjusted price thereby raising its expenditure share. Failure to account for this effect leads constant taste price indices to have an inherent bias toward over-estimating price changes as consumer preferences evolve.

Relaxing the time invariance of consumer tastes, RW substitute taste-adjusted prices (p_{kt}/φ_{kt}) directly into the exact price index to give the change in the cost-of-living as:

$$\begin{aligned}\left[\frac{P_t}{P_{t-1}}\right]_{RW} &= \left(\frac{\lambda_t}{\lambda_{t-1}}\right)^{\frac{1}{\sigma-1}} \times \prod_{k\in\Omega_t^*}\left(\frac{p_{kt}/\varphi_{kt}}{p_{kt-1}/\varphi_{kt-1}}\right)^{\omega_{kt}^*} \\ &= \left(\frac{\lambda_t}{\lambda_{t-1}}\right)^{\frac{1}{\sigma-1}} \times \prod_{k\in\Omega_t^*}\left(\frac{p_{kt}}{p_{kt-1}}\right)^{\omega_{kt}^*} \times \left(\prod_{k\in\Omega_t^*}\left(\frac{\varphi_{kt}}{\varphi_{kt-1}}\right)^{\omega_{kt}^*}\right)^{-1}.\end{aligned} \tag{3}$$

As (3) shows, the Redding and Weinstein innovation is to allow for both changes in tastes for each common variety $(\varphi_{kt}/\varphi_{kt-1})$ for all $k \in \Omega_t^*$ as well as Feenstra's entry and exit effect while preserving the exact price index for common varieties which expresses the index in terms of prices and expenditure shares only. Importantly, they isolate an additional term in the exact price index that is referred to as the "taste shock bias" that corrects the conventional exact price index for changes in consumer preferences for each common variety between period t and $t-1$. This is given by the term $\left(\prod_{k\in\Omega_t^*}\left(\frac{\varphi_{kt}}{\varphi_{kt-1}}\right)^{\omega_{kt}^*}\right)^{-1}$ in (3). In principle, the bias can go either way, depending on the correlation between the expenditure share weights (ω_{kt}^*) and the taste change ($\varphi_{kt}/\varphi_{kt-1}$) reflecting consumers' preferences toward common products. However, as Redding and Weinstein point out, there exists a mechanism for the correlation to be positive since a positive taste shock for a variety mechanically increases its expenditure share, thereby reducing the weights of other varieties. Specifically, given the focus on log expenditure shares, increasing the expenditure share of the taste preferred variety is not equivalent to the reduced expenditure share of varieties where tastes are shifting away from, resulting in the effect that taste changes serve to reduce the price index. Where preferences for common products remain constant ($\varphi_{kt}/\varphi_{kt-1}=1$ for all $k\in\Omega_t^*$), the last term in (3) equals unity and $\left[\frac{P_t}{P_{t-1}}\right]_{RW}=\left[\frac{P_t}{P_{t-1}}\right]_{FBW}$.

By relaxing the constant taste assumption, Redding and Weinstein's approach treats an increase in taste for a variety φ_{kt} as a decrease in the taste-adjusted price (p_{kt}/φ_{kt}) leading to a decrease in the cost-of-living. Conversely, a decrease in tastes increases the taste adjusted price leading to an increase in the cost-of-living but given the functional form, these two effects do not cancel. They refer to (3) as the CES unified price index (CUPI) owing to the symmetry with which demand shocks enter both the underlying demand system and the unit expenditure function.

3.3 | Measuring the elasticity of substitution

Common to both the FBW and RW price indices is the elasticity of substitution between products (σ). This is assumed to be constant across products but is allowed to vary across income groups to capture the non-homotheticity of household responses. To estimate the income-specific elasticity of substitution, we follow the method introduced by Feenstra (1994) and developed by Broda and Weinstein (2006, 2010). The basic challenge is to estimate parameters of demand and supply equations for each variety based only on information on prices and quantities. While this faces the standard identification problem owing to the simultaneity of demand and supply, the issue is resolved by exploiting the panel nature of the dataset. Here we merely sketch the steps in the procedure, full details are provided in Broda and Weinstein (2010).

The first step is to derive supply and demand for each product based on constant elasticity of substitution utility function. This leads to the following system of differenced demand (4) and supply (5) equations for each income group (not shown to simplify the notation) and product k at time period t:

$$\Delta^K \ln s_{kt} = -(\sigma-1)\Delta^K \ln p_{kt} + \epsilon_{kt}^K, \tag{4}$$

$$\Delta^K \ln p_{kt} = \left(\frac{\omega}{1+\omega}\right)\Delta^K \ln s_{kt} + \delta_{kt}^K, \tag{5}$$

where quantities are expressed as expenditure shares and $-(\sigma-1)$ is the demand elasticity at the product level. In the supply Equation (5) ω is the inverse supply elasticity so that $\omega=0$ corresponds to a horizontal supply curve in which there is no simultaneity bias in the estimation of the elasticity of substitution σ. In this set-up, all variables are expressed in first and referenced differences such that Δ^K is the first difference with respect the K^{th} product (i.e., $\Delta^K \ln s_{kt} = [(\ln s_{kt} - \ln s_{kt-1}) -$

$(\ln s_{Kt} - \ln s_{Kt-1})]$ and $\Delta^K \ln p_{kt} = [(\ln p_{kt} - \ln p_{kt-1}) - (\ln p_{Kt} - \ln p_{Kt-1})])$. Here, we define K to be the largest selling product in the ready meal category, although other reference products are evaluated in the robustness testing. Importantly, where $\omega \neq 0$, identification requires that the errors ϵ_{kt}^K and δ_{kt}^K of the demand and supply equations for each product are uncorrelated. More specifically, there are two aspects to the identification strategy using this method. First, as noted by Broda and Weinstein (2010), first and referenced ($\mathrm{K^{th}}$) differencing ensures that any shocks generic to the demand and supply for the category (e.g., seasonality, labor costs in production) are purged from the data. Leaving only intra-product variation, shocks to supply and demand are largely idiosyncratic rendering the error terms in (4) and (5) ϵ_{kt}^K and δ_{kt}^K uncorrelated.[9] Second, it is assumed that the inverse supply elasticity (ω) and the elasticity of substitution (σ) are constant over time and the same for all products.[10] The equation to estimate is therefore obtained from multiplying (4) and (5):

$$\left(\Delta^K \ln p_{kt}\right)^2 = \left(\frac{\omega}{(1+\omega)(\sigma-1)}\right)\left(\Delta^K \ln s_{kt}\right)^2 + \left(\frac{\omega(\sigma-2)-1}{(1+\omega)(\sigma-1)}\right)\left(\Delta^K \ln s_{kt}\right)\left(\Delta^K \ln p_{kt}\right) + \nu_{kt}, \quad (6)$$

where $\nu_{kt} = \epsilon_{kt}^K \delta_{kt}^K$. Given Equation (6), a set of moment conditions for the ready meal sector can be constructed as:

$$G(\beta) = E_t(\nu_{kt}(\beta)) = 0 \quad \forall k \in \Omega^*,$$

where β is a vector that contains σ and ω, and Ω^* is the set of products that are purchased in every period throughout the sample.[11] This choice is motivated by Ehrlich et al. (2023), who cautions against using all products on the grounds that those with very low market shares behave like outliers and distort GMM estimation. Using the set of products observed throughout the sample avoids this problem and is advantageous from a practical perspective since it greatly reduces the number of moment conditions and the dimension of the weighting matrix.[12]

Finally, the GMM objective function can be written as Hansen's (1982) estimator:

$$\widehat{\beta} = \arg\min_{\beta} G^*(\beta)' W G^*(\beta),$$

where $G^*(\beta)$ is the sample analog of $G(\beta)$, W is a positive definite weighting matrix.

4 | DATA

4.1 | Sources and definitions

Computing the price indices detailed above requires barcode-specific information on consumer purchases at the household level over a sufficiently long period of time to capture consumer behavior

[9]While controlling for time-category fixed effects using the double difference is likely to ensure that demand and supply shocks are uncorrelated, Grant and Soderbery (2024) further propose using the Sargan–Hansen J test of overidentifying restrictions to assess potential violations of the independence assumption, where rejection of the null signals correlation between demand and supply shocks. Using a cluster-robust weighting matrix and standard errors, we are unable to reject the null at conventional levels of significance and thus proceed on the basis that the errors are independent.

[10]We return to the assumption of the constancy of the elasticity of substitution in the context of the Covid period in the robustness section below.

[11]Note that the set defined by Ω^* is more selective than the common products given by Ω_t^* which refers to products present in period t and $t-1$. Dropping the subscript t indicate that these products are present over the full sample rather than just between two adjacent periods.

[12]Inference based on tests for weak instruments and error independence (see previous footnote) are invariant to whether the instrument set includes all products or the subset of long-lived products, however the estimates of the elasticity of substitution are much closer to those reported by Broda and Weinstein (2010) and Redding and Weinstein (2020) for the US and Jaravel (2018) for the UK if only the long-lived are used.

during periods of rapidly changing prices and incomes. We address this challenge using ready meals purchases recorded in the *Kantar WorldPanel* dataset for 30,000 UK households between 2013 and 2022 inclusive. *Kantar* employs a sampling procedure to appropriately match the household panel with population demographics reflecting region, household characteristics (e.g., size, presence of children, pensioners, etc.) to ensure that the weighting procedure they apply is representative of the population. The data covers all retailers not just a subset which is particularly relevant given that low-income households may shop at discount retailers or convenience stores. Ready meals are defined as "prepared dishes that are ready to eat (prepared, seasoned or cooked)" by *Kantar* and include a wide range of commonly purchased foods including traditional dishes such as pies and casseroles, as well as more exotic dishes such as curries. Products are identified at the barcode level including discounts and multi-buys along with household characteristics including age of the main shopper, gender, number of children and trips to shops and in what shops the purchases were made. Note that the same brand of ready meals sold in two retail chains constitutes two distinct products. Given the preponderance of private label products in the ready meals category (between 85% and 90% of products sold), many products are only sold in one retail chain. Prices for each product are unit values (i.e., expenditure divided by quantity); one limitation of the *Kantar* data is that they do not record prices passing through supermarket check-outs.

Kantar records data at weekly periodicity. To avoid the issues associated with zero purchases, we analyze ready meals prices at the monthly frequency aggregating weekly data into 13 statistical months per year (i.e., 4-week periods), making a total of 133 months over the 10-year sample period. The monthly frequency means that we have products in the sample that are seasonal and/or appear only sporadically. Following Broda and Weinstein (2010), we trim the sample and consider only products that are in the sample for 13 consecutive months, giving 8375 separate products. This varied between 3219 products in 2013 and 2955 products in 2022 (the maximum number of products was 4025 in 2018).

Product "entry" occurs when a product (a new barcode) that was previously unavailable enters and is purchased for at least 13 statistical months in at least one household. Product "exit" occurs where a product that was previously purchased by consumers disappears from the data for at least 13 statistical months. Although our frequency of observation is higher, this is essentially the same as Broda and Weinstein (2010) and Redding and Weinstein (2020).

To explore the behavior of different income groups, we split the sample of all households into three income group ranges: household income of less than £30,000 per annum (low-income accounting for 40% of households); household income in the range £30,000 to £50,000 per annum (middle-income accounting for 23% of households) and households with an income of more than £50,000 per annum (high-income accounting for 16% of households). Some households do not disclose their income.[13]

4.2 | Descriptive statistics

Table 1 summarizes the main features of the raw data we employ in this paper by income group and over time, delineated into two periods: pre-Covid (2013–2019) and the 2020–2022 period which spans both the pandemic years and 2022 which marked the onset of what is known as the "cost-of-living crisis" in the UK.[14] There are several notable features from these data. First, over the period as a whole, ready meals expenditure is found to be inversely related to income; low-income households spend over one-quarter more than high-income households, likely reflecting a preference for the convenience and low cost of the highly processed foods that have traditionally characterized a large

[13] We keep these households in the All-Households measure and to ensure transparency we report this group in the descriptive statistics but refrain from making direct comparison between this and the other groups.

[14] To simplify the discussion, we combine the Covid period (2020–2021) and the cost-of-living crisis period (2022) and refer throughout as the "Covid period."

TABLE 1 Characteristics of consumer purchases for ready meals in the UK across income groups, 2013–2022.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Average
Low income households											
Number of products	2491	2999	3104	3079	3012	3084	2959	2739	2596	2321	2838
Expenditure per household (£)	96.6	111.4	121.4	126.5	134.8	135.1	138.8	139.8	149.8	141.9	129.6
Price—average price (£)	2.4	2.6	2.5	2.6	2.6	2.7	2.7	2.8	2.9	3.1	2.7
Price—standard deviation (£)	1.3	1.4	1.4	1.4	1.3	1.4	1.4	1.6	1.6	1.6	1.4
Middle income households											
Number of products	1989	2378	2534	2600	2582	2662	2554	2391	2270	2038	2400
Expenditure per household (£)	73.5	87.4	94.5	100.2	105.6	107.3	114.2	122.5	127.6	124.0	105.7
Price—average price (£)	2.7	2.8	2.8	2.8	2.8	2.8	2.9	3.0	3.1	3.4	2.9
Price—standard deviation (£)	1.5	1.5	1.5	1.5	1.4	1.4	1.5	1.7	1.7	1.8	1.5
High income households											
Number of products	1599	1911	2081	2144	2153	2190	2087	1974	1880	1683	1970
Expenditure per household (£)	76.5	91.5	91.8	96.5	99.9	101.5	104.7	114.9	120.7	115.3	101.3
Price—average price (£)	2.9	3.0	3.0	3.0	3.0	3.0	3.0	3.2	3.3	3.6	3.1
Price—standard deviation (£)	1.5	1.5	1.6	1.6	1.5	1.6	1.6	1.7	1.8	1.9	1.6
Non-disclosure group											
Number of products	1693	1996	2129	2207	2214	2298	2305	2247	2245	2037	2137
Expenditure per household (£)	94.8	111.7	118.7	118.7	125.3	122.0	103.2	105.3	108.4	99.5	110.8
Price—average price (£)	2.6	2.7	2.7	2.7	2.8	2.9	2.8	2.9	3.0	3.3	2.8
Price—standard deviation (£)	1.4	1.5	1.6	1.5	1.4	1.5	1.6	1.7	1.7	1.8	1.6
All households											
Number of products	3219	3938	3994	3965	3918	4025	3805	3514	3390	2955	3672
Expenditure per household (£)	104.4	120.1	125.4	128.6	135.4	135.1	133.6	136.1	143.0	134.9	129.7
Price—average price (£)	2.7	2.8	2.8	2.8	2.9	2.9	2.9	3.0	3.1	3.4	2.9
Price—standard deviation (£)	1.5	1.5	1.5	1.6	1.5	1.5	1.6	1.7	1.8	1.8	1.6

Note: Low-income households have declared income less than £30,000 per annum, for middle income households it is between £30,000 and £50,000 per annum and for high income household it is more than £50,000 per annum. The All-Household group also contains households that have not declared their income.
Source: Own elaboration using *Kantar WorldPanel* data.

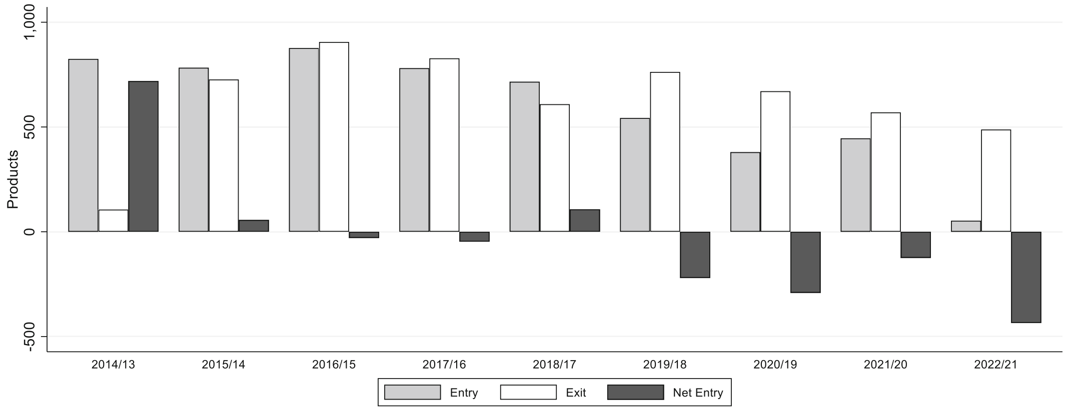

FIGURE 1 Product entry, exit, and net entry: UK ready meals sector, 2014–2022. *Source*: Own elaboration based on *Kantar WorldPanel* data.

segment of the category. As expected, low-income households purchase cheaper products in a narrower price range than higher income groups; this may reflect a higher propensity for bargain shopping or switching to lower-priced products. Second, spending has grown (around 50%) in all income groups over the period, but growth has been strongest in middle-income households, particularly in the pre-Covid period, potentially reflecting the growth of premium ready meals. Table 1 also highlights changes in the number of barcoded products purchased. Having peaked in 2018, product assortment declined some 10% during the pandemic and a further 15% in 2022.[15] The net exit of products was a consistent feature across all income groups.

Figure 1 shows the extent of entry and exit of products in the UK ready meals sector between 2013/14 and 2021/22. In the early part of the period, product entry outweighed product exit; however, since 2018/19, net exit has been the main feature of the product turnover process. This is consistent with Jaravel and O'Connell's (2020) observation of net product exit during the Covid pandemic. As Figure 1 shows, while both ready meals entry and exit have been in decline since 2018/19, product entry has failed to keep pace with the number of exiting.

Given that households in different income groups vary in the content of their shopping baskets and that retail chains can target different segments of the retail market, the dynamics of entry and exit can vary across income groups. This is confirmed in Figure 2. Here we highlight net entry by income group. Although all income groups show the same pattern (i.e., net entry in the first 2 years of the data period but predominantly net exit thereafter), there are differences across income groups, most notably in the Covid period where net exit has been highest for low-income households.

Although the data presented in Figures 1 and 2 give an indication of the process of product entry and exit, it does not directly correspond to changes in the exact price indices presented in Section 3. Close inspection of the Feenstra ratio in Equations (2) and (3) shows that what matters about entry and exit is the impact on the expenditure share of common products. So, for example, even if the number of products entering household shopping baskets is less than the number of products exiting, the observation of net exit can be consistent with a decline in the price index because of the impact entry and exit has on the expenditure share of common products.

In Table 2, we present an alternative characterization of the entry and exit process in the ready meals sector. As well as the number of products entering and exiting by income group per year and over the period as a whole, the table also highlights entry and exit rates which relate to the expenditure on new and disappearing products expressed as a percentage of total spending (Broda &

[15]For a general overview of the impact of Covid on the UK food system, see UK Parliament (2020).

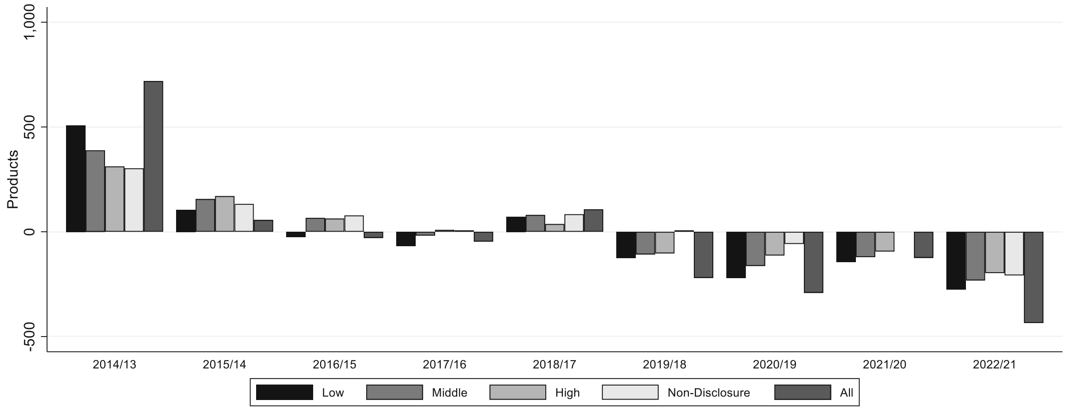

FIGURE 2 Product net entry: Differences across income groups, 2014–2022. *Source*: Own elaboration based on *Kantar WorldPanel* data.

TABLE 2 Product entry and exit and product entry and exit rates: Annual averages and period totals, 2013–2022.

	Product entry (number)		Entry rate (%)		Product exit (number)		Exit rate (%)	
	Per year	Period	Per year	Period	Per year	Period	Per year	Period
Low income	411	1672	7.67	64.69	429	1842	6.56	60.90
Middle income	329	1437	7.56	64.32	323	1389	6.09	44.09
High income	248	1155	6.95	63.53	239	1071	5.85	49.06
All	600	2231	8.56	67.51	630	2495	6.74	50.37

Note: The Entry Rate is the ratio of expenditure on new products in year t to expenditure on all products in year t. The Exit Rate is the ratio of expenditure on products that have disappeared in year t and expenditure on all products in year $t-1$. The column headed "Period" for the entry rate represents the percentage of spending at the end of the period devoted to products that were not available at the beginning of the sample period. Similarly, the "Period" column for the exit rate represents spending on products available in 2013 that were subsequently discontinued as a percentage of all spending in 2013.

Weinstein, 2010, p.697). The entry rate period totals show the expenditure on products in 2022 that were not available in 2013 as a percentage of total expenditure in 2022. The exit rate period totals show the spending on products in 2013 that have subsequently disappeared, as a percentage of total expenditure in 2013.

The data show that over the sample period, 2231 products were introduced and 2495 products were withdrawn (or 600 and 630 per year, respectively). However, despite greater numbers disappearing from supermarket shelves, expenditure on new products exceeded that on disappearing products, with 8.56% of spending devoted to new products per year compared to 6.74% on products that disappeared. In other words, the entry rate exceeded the exit rate despite the net exit of products over the period. More surprising is the magnitude of product churn. As the period totals reveal, nearly 68% of expenditure in 2022 was on products that did not exist in 2013. The value of disappearing products, that is, those that existed in 2013 but not in 2022, is much smaller, representing only 50% of expenditure in 2013.

5 | RESULTS

There are five aspects of the results to highlight. First, we report estimates of the elasticity of substitution across income groups for ready meals. Second, the extent to which price indices with entry/

exit and consumer tastes differ from the CPI for ready meals produced by the UK Office of National Statistics is examined.[16] Third, we compare these price indices with other conventionally used price indices and highlight the extent of correlation between them. Fourth, we derive estimates of the impact of the entry and exit of products and changes in tastes in terms of their impact on the exact price indices we calculate among income groups. Finally, we decompose the most general price index to reveal the contribution of changes in prices of continuing products, product turnover and changing tastes across income groups.

5.1 | Estimates of the elasticities of substitution

As discussed in Section 3, both the FBW and RW exact price indices rely on estimates of the elasticities of substitution to capture the consumer response to price changes. Following the discussion above on the empirical approach, estimates are reported in Table 3 where the elasticities of substitution for ready meals are found to lie between 4.05 (low-income households) and 4.98 (high-income households). All estimates are significantly different from zero at the 1% level.[17] By means of comparison, studies using the *ACNeilsen Homescan* database for the US covering over 100 food and non-food categories find a wide range of elasticities, with the variation over categories greatly exceeding the variation across income groups. For example, Broda and Weinstein report the median elasticity of substitution of 11.5 compared to the estimate in Redding and Weinstein (2020) of 6.48, though in both studies there is a wide distribution of the estimates across product groups. Focusing on the variation by income, Jaravel (2018) estimates the elasticity at 3.5 for the 10th income percentile, 5.7 for the 50th percentile, and 9.3 for the 90th percentile. Colicev et al. (2024) report estimates for the elasticities of substitution between 1.32 and 3.17 with notable differences across income groups. Dellavigna and Gentzkow (2019)—focusing on US food retailers—report an average elasticity of substitution for food products within stores of around 2.8. In contrast, Argente and Lee (2021) produce higher estimates with US data: the lowest income group (less than US $25k per annum) has an elasticity of substitution estimated at 20.31; for the next income group (between US $25k and US $50k per annum), it is 19.14; for the higher income group (US $50k and US $100k), it is 18.21; and for the highest income group (>US $100k) it is 19.33.[18]

5.2 | Comparison of price index measures

In Figure 3, we present our headline result: standard price indices used by national statistical authorities to measure changes in aggregate food prices exhibit substantial bias. The CPI for ready meals (which is based on representative products and is based on the Laspeyres price index with fixed weights) rose by 37% between 2015 and 2022; whereas the FBW index (accounting for what households buy and the entry/exit of products) rose by considerably less (17%). When taste effects are also accounted for, as is the case in the RW index, we find that households faced declining ready meals prices for much of the period. Though all measures showed a marked up-turn following Covid, by the end of sample the RW measure is 40 percentage points lower than the CPI for ready meals. The existence of bias is consistent with recent research using these newly developed price indices.

[16]The UK's Office of National Statistics began publishing the Consumer Prices Index for Ready Meals in 2015(1).

[17]The elasticity of substitution used to produce the All-Households price indices is an expenditure weighted average of those reported in Table 3. Group weights are 0.44, 0.21, 0.14 and 0.21 respectively, giving a weighted average elasticity of substitution of 4.26.

[18]There has been a lively literature on empirical approaches to measuring the elasticities of substitution particularly in the international trade literature; see Soderbery (2015) and Grant and Soderbery (2024). Restricting the instruments to common products, which circumvents issues of products with small market shares (see Ehrlich et al., 2022), results in estimates closely aligned with the more commonly reported US values. Further, Jaravel and O'Connell (2020) in their evaluation of entry and exit on (Fast Moving Consumer Goods) inflation in the UK considered a range of values for the elasticity of substitution between 3 and 7. While the size of estimates used determines the precise magnitudes of the entry/exit and tastes effects it does not change the overall insights about the impact of these factors on price indices across income groups.

TABLE 3 Estimated elasticities of substitution for ready meals across income groups.

Households	Estimated elasticities of substitution	Standard error
Low income	4.05***	(0.13)
Middle income	4.14***	(0.15)
High income	4.98***	(0.32)
Non-disclosure	4.37***	(0.20)

Note: Income groups are as defined in the text.
***Statistical significance at the 1% level.

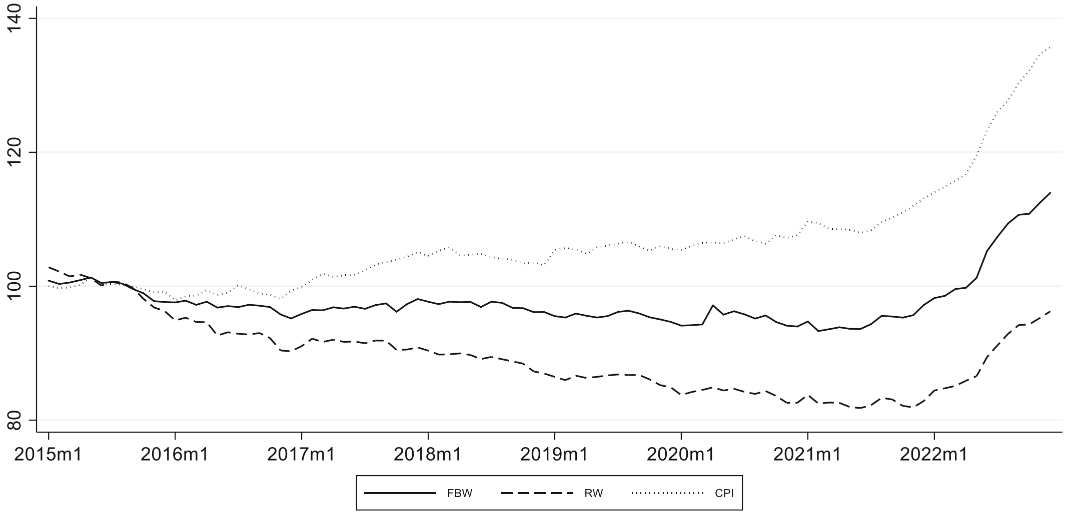

FIGURE 3 Comparison between CPI for ready meals and FBW and RW price indices.

The results presented in Figure 3 highlight a combination of factors that contribute to the difference between the standard CPI approach and recently developed measures: these include the granularity of the data used to derive these price indices; the effect of product churn; and the effect of unobserved and systematic taste changes. We decompose these issues below.

As discussed in Section 4, the use of scanner data highlights that households in different income groups vary in what they buy, where they shop and the prices they pay; consequently, price indices can be expected to vary by income. In Figure 4, we present evidence of the extent of non-homotheticity by comparing the FBW and RW price indices with the CPI for ready meals highlighting the differences across income groups. Specifically, Figure 4a reports the extent of the bias between the CPI and the FBW measures for each income group. The first point to note is that the bias is positive for each income group, but the extent of the bias is greatest for low-income households. By the end of the data period, the CPI overstated the price changes for middle- and high-income households by around 20 percentage points; for low-income households, the overstatement was closer to 30 percentage points. Figure 4b reports the extent of the CPI bias with respect to the RW measure across income groups. These show the same overall trends as reported in Figure 4a above but with the notable difference being that the extent of the bias increases and considerably so, most notably for the low-income group. By the end of the data period, the CPI overstates the price index for the low-income households by more than 40 percentage points compared to around 30 percentage points for the other income groups.

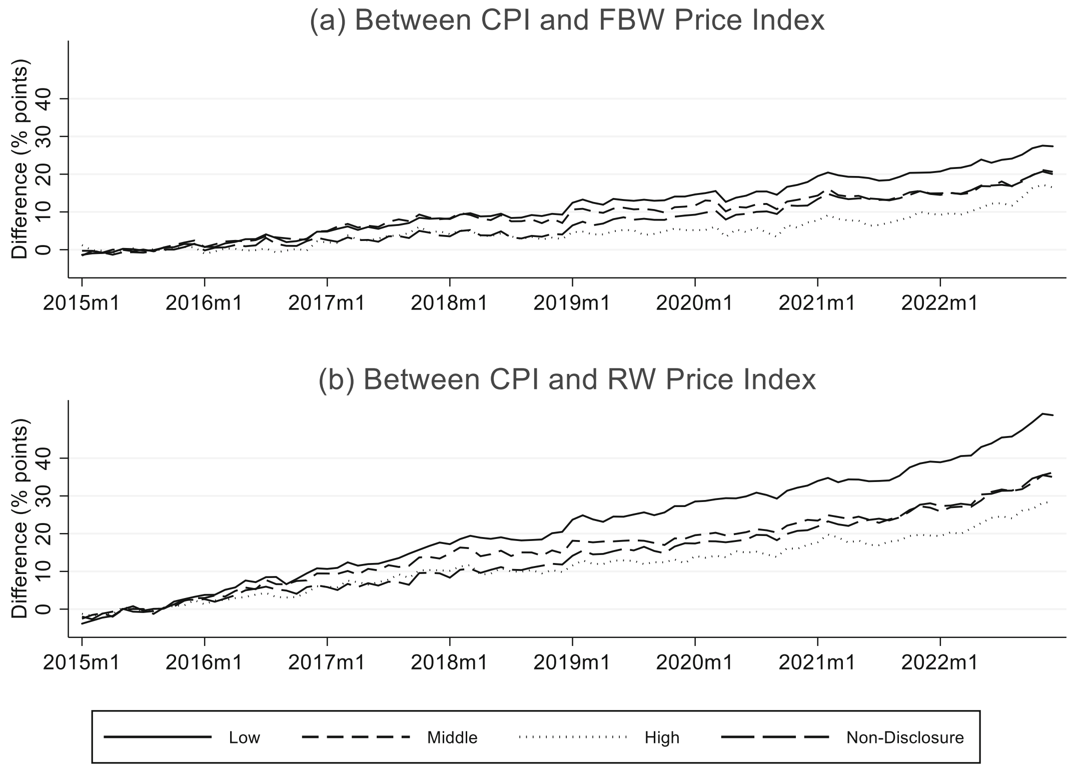

FIGURE 4 Extent of bias in CPI by income group.

5.3 | Comparison with alternative price indices

As detailed above, recent research has highlighted the use of CES price indices that can accommodate product entry and exit and consumer taste effects, both of which are pertinent in the food sector. In this section, we compare the FBW and RW indices with more commonly used price index measures, namely, Laspeyres, Paasche and Törnqvist. While both the Laspeyres and Paasche indices are based on fixed weights, Törnqvist is a superlative price index that is based on changing weights between periods.[19] As such, moving from Laspeyres to Törnqvist gives an indication of product substitution, while moving from Törnqvist to FBW and RW gives an indication of entry/exit and taste effects.[20] These price indices are detailed below (where h refers to household income group).

$$\text{Laspeyres}: \left[\frac{P_t}{P_{t-1}}\right]_L = \sum_{k \in \Omega_t^*} s_{k,t-1}^h \left(\frac{p_{k,t}^h}{p_{k,t-1}^h}\right),$$

$$\text{Paasche}: \left[\frac{P_t}{P_{t-1}}\right]_P = \sum_{k \in \Omega_t^*} s_{k,t}^h \left(\frac{p_{k,t}^h}{p_{k,t-1}^h}\right),$$

[19]As noted by Jaravel (2021), being based on expenditure weights that are fixed at the beginning of the period, the Laspeyres index will overstate inflation whereas the Paasche index understate inflation because it exaggerates the adjustment to price changes. The Törnqvist index treat prices and quantities equally across all periods and will therefore capture product substitution but not product entry and exit.

[20]As we comment below, there is an active agenda on appropriate price indices to measure inflation with high-frequency data. See, for example, Fox et al. (2023) though their coverage of price indices including GEKS-Törnqvist does not include CES indices that can account for taste effects.

TABLE 4 Correlation between price indices: 2013–2022.

	FBW	RW
Low income		
Laspeyres	−0.22	−0.63
Paasche	−0.14	−0.58
Törnqvist	−0.15	−0.59
Middle income		
Laspeyres	0.11	−0.42
Paasche	0.29	−0.303
Törnqvist	0.18	−0.38
High income		
Laspeyres	0.68	−0.11
Paasche	0.83	0.07
Törnqvist	0.79	0.01
Non-disclosure		
Laspeyres	0.21	−0.50
Paasche	0.42	−0.31
Törnqvist	0.35	−0.38
All households		
Laspeyres	0.09	−0.50
Paasche	0.24	−0.39
Törnqvist	0.18	−0.43

Note: Figures are the correlation coefficient between the Feenstra–Broda–Weinstein (FBW) and Redding and Weinstein (RW) price indices and the Laspeyres, Paasche and Törnqvist price index measures in each income group.

$$\text{Törnqvist}: \left[\frac{P_t}{P_{t-1}}\right]_T = \prod_{k \in \Omega_t^*} \left(\frac{p_{k,t}^h}{p_{k,t-1}^h}\right)^{\frac{s_{k,t}^h + s_{k,t-1}^h}{2}}.$$

In Table 4 we report the correlation coefficients between the non-CES price indices above and the FBW and RW indices (see Appendix Figure 1 for the series themselves). Taking the All-Households category first, the correlation coefficients between the FBW and the non-CES indices are 0.09, 0.24, and 0.18 for the Laspeyres, Paasche, and Törnqvist indices, respectively. These relatively low correlations highlight that the FBW index does better at capturing product substitution. Note that for low-income households, the correlation coefficients become negative compared with other income groups.

However, the correlation coefficients between the non-CES indices and RW are considerably lower. For All-Households, the correlation is negative for all non-CES indices which highlights the overall impact of the entry/exit and taste effects captured in the RW index. However, there is notable variation in these correlations across income groups. Specifically, for low-income groups, the correlations are negative while, for middle- and high-income households the correlations are lower than those reported with the FBW comparison. Taken overall, the comparison of the indices reported in Table 4 highlights the significant differences in assessing changes in prices over time when the entry/exit and taste effects are not accounted for.

5.4 | Effect of product churn and changing tastes

One factor determining the household experience of inflation is the effect of product churn (strictly, the expenditure share on new and disappearing products). Since the impact of net entry is primarily based in consumer utility, if entry dominates the exit of products, consumers benefit, and this will be reflected in a lower price index. The converse is true when exit dominates product entry. The extent to which consumers benefit, and how it varies across income groups, will depend on two main factors. First, the expenditure shares of products that enter and exit across income groups as detailed in Figure 2; second, the estimates of the elasticity of substitution at the group level as reported in Table 3. While the Feenstra ratio $\left(\frac{\lambda_t}{\lambda_{t-1}}\right)^{\frac{1}{\sigma-1}}$ appears in both the FBW and RW indices (see (2) and (3)) the size of the entry and exit effect will depend on whether this ratio is applied to prices that assume preferences are constant (FBW) or are allowed to vary (RW).

In Table 5 we gauge the size of this effect in terms of the FBW and RW exact price indices across income groups. Specifically, figures in the first column represent the effect of product churn assuming constant tastes using the FBW index, whereas figures in the second column express this effect relative to the RW index which additionally accounts for changing consumer tastes. In each case, numbers represent the average percentage point difference between the indices over the period. As is clear from the preponderance of negative entries in the table, product churn in the ready meals sectors effectively lowers prices, the effect being relatively greater with the constant as compared with the variable taste indices (−4.64% compared with 3.89%, respectively). Differences emerge across income groups, notably that the effect for low-income households is double that for the high-income group (−5.28% compared with −2.20%, respectively).

Table 5 also shows the effect of changing tastes. Entries in the final column express the taste effect in terms of the RW exact price index (tastes being constant by assumption in the FBW index). As with entry and exit, the estimates are negative implying that changing tastes and preferences act to lower prices, with the effect being strongest for low-income households, suggesting that it is among poorer households (−8.04%) that preferences favoring cheaper products have imparted the greatest effect over the period; this exceeds the impact of changing preferences for middle (−5.40%) and high-income households (−4.54%), respectively.

5.5 | Decomposing the household experience of price inflation

Whereas the discussion above offers an assessment of product turnover and changing tastes in terms of their effects as a percentage of the FBW and RW price indices, we now turn to their effects on the household experience of prices in the category. As Equation (3) shows, the RW exact price index

TABLE 5 The effect of entry/exit and tastes (%).

	Entry/exit effect		
	Under constant tastes (FBW)	**Under variable tastes (RW)**	**Taste effect (RW)**
Low income	−5.28	−4.18	−8.04
Middle income	−5.02	−4.44	−5.40
High income	−2.20	−1.87	−4.54
Non-disclosure	−4.18	−3.65	−5.27
All households	−4.64	−3.89	−6.49

Note: The results in the first two columns show the average effect of entry and exit expressed as a percentage of the Feenstra–Broda–Weinstein (FBW) and Redding and Weinstein (RW) indices. The final column measures the price effect of tastes expressed as a percentage of the Redding and Weinstein (RW) index.

TABLE 6 Experience of price inflation in ready meals by income group: Price changes between 2013 and 2022 (%).

	Household income		
	Low	**Middle**	**High**
Price index (SV)	23.3	25.8	26.7
Entry and exit	−13.0	−7.8	−3.7
Taste changes	−25.4	−16.0	−13.4
Overall	−15.1	2.0	9.6

Note: The results relate to the decomposition of price inflation over the 2013–2022 period across income groups with the price index relating to the Sato-Varta (SV) price index.

comprises three components: the conventional exact price index of Sato-Vartia measuring the effect of price changes among continuing products in the shopping basket, Feenstra's entry and exit effect and an adjustment for changing tastes. Table 6 presents a decomposition of the RW index into these constituent parts to reveal the contribution among low, middle and high-income groups between 2013(1) and 2022(12). Entries in the table represent the percentage point change in the RW index attributable to each component. The first of these components, the Sato-Vartia (SV) index, is responsible for an increase in ready meals prices over the period that is found to be 23.3% for low-income households compared with 25.8% and 26.7% respectively, for middle- and higher-income households. Entry and exit of products reduced the extent of the price increases for all income groups but most notably low-income households: specifically, the cumulative effect of entry/exit for low-income households was −13.0% which exceeds that for middle- and high-income households of −7.8% and −3.7%, respectively. However, by far the most significant impact comes via the taste bias effect; changes in tastes reduce the price index by around 25% for low-income households, by 16% for middle-income households, and 13.4% for high-income households. The results therefore suggest a different experience in food inflation (albeit confined to a single product group) than other recent studies which suggest that the experience of food inflation has been more significant for low-income households (e.g., Kaplan & Schulhofer-Wohl, 2017). Specifically, contingent on the estimated elasticities of substitution, the price index for low-income households fell over the 2013–2022 period (by 15%), rose slightly for middle-income households (by 2%), and rose more considerably for high-income households (by around 10%).

6 | ROBUSTNESS CHECKS

We test the robustness of our estimates of substitution elasticities, which are important for understanding patterns of product entry, exit, and changes in tastes.

6.1 | "Representative" ready meals products used for the CPI

To assess the impact of the use of representative products, as opposed to a more complete set of substitution possibilities embodied in the household level data, we have applied the exact price indices to a subset of the *Kantar* sample that mimics the sample used by the UK's Office for National Statistics (ONS). As detailed above, national statistical offices use "representative" products to obtain in-person or by-survey price quotes to measure changes in prices for specific food groups: in the case of ready meals data collected by the ONS these representative products are single portion products in three sub-classifications: "frozen ready cooked meal"; "chilled ready meal-meat"; and "chilled ready meal-fish/veg." Selecting products in the *Kantar WorldPanel* data that correspond to the ONS definitions, the data were then trimmed to exclude those products with multiple portion sizes to yield a new sample with the same price distribution as that reported by the ONS.[21] Since the CPI is an aggregate measure of price inflation, we estimate the elasticity of substitution for All Households and construct new FBW and RW series which we then compare with their counterparts using the complete *Kantar* sample; this comparison offers an indication of the impact of the bias due to the use of representative products. The estimated elasticity of substitution using this data is 3.78 (slightly lower than the elasticity of 4.26 reported in Table 3) and price indices based on the facsimile ONS data and full *Kantar* samples are reported in the Appendix Figure 2 (labeled "ONS" and "Scanner data," respectively). In summary, the bias induced by the use of representative products on the FBW and RW indices is substantial over the sample period: for the FBW index the price gap is around 15%; with the RW index, the difference in price levels is close to 35%. Overall, both the elasticity estimates and the index results confirm that the effect of entry/exit dynamics and taste shocks remains significant, even when using data aligned with the ONS methodology.

6.2 | Estimates of the elasticities of substitution

As discussed in Section 3, the procedure for estimating the elasticities of substitution is based on a reference product; common practice is to use the largest selling product in the (ready meals) category. We explored alternatives for the reference product and re-estimated the elasticities of substitution. Specifically, we considered two alternatives: (i) the median-selling product; and (ii) the average of three randomly selected products. The results are presented in Appendix Table 1 where it can be seen that choosing alternative reference products makes relatively little difference to the elasticities. For the low-income group, differences are particularly small (4.54 and 4.19 compared to 4.05 reported in Table 3) whereas the greatest difference is found in the high-income group (6.61 and 7.06 compared to 4.98 in Table 3). Such differences are likely to have only a minor impact on the indices and do not alter the conclusions that we draw.

6.3 | Impact of Covid

As noted, when detailing the estimation of the elasticities of substitution in Section 3, the values are assumed to remain constant over time. However, Covid was a major shock to the food system and involved changes in consumer behavior. In part, this is reflected in the data on entry and exit where, in the Covid period, net exit of products was the main feature of product churn. Given that the Covid shock may have also impacted product substitution, we have split the data into a pre-Covid period (2013–2019) and the Covid period (2020–2022) and re-estimated the elasticities of substitution for all income groups. The results (presented in Appendix Table 2) show that in the pre-Covid period, the elasticities are close to those reported in Table 3 yet increase significantly during Covid; for low (high)-income households for example, the estimates increase from 4.85 (5.27) to 12.44 (8.89), respectively.

Table 7 reports the impact of this on the experience of price inflation (expressed as cumulative totals) across income groups, broken down by source as in Table 6. In the first block the sub-period price changes are calculated assuming the elasticities of substitution for the entire period. The second block repeats the exercise with elasticities of substitution estimated for each sub-period.[22] Irrespective of the elasticity of substitution used, the pre-Covid period is characterized by falling prices while the Covid period is one of rapidly rising prices. The main effect of the higher elasticities

[21]The precise identity of the representative products is suppressed by the ONS to preserve confidentiality.

[22]Although most studies retain the assumption of constant elasticities over time, note that Broda and Weinstein (2006) estimated elasticities of substitution in different sub-periods reflecting the increase in globalization due to increased US imports in the post-1990 period. Their results show significant changes in the estimated elasticities with some estimates increasing and others decreasing.

TABLE 7 Experience of price inflation in ready meals by income group: Price changes between 2013-2019 and 2020-2022 (%).

	2013–2019			2020–2022		
	Low	Middle	High	Low	Middle	High
Same elasticities of substitution for the entire period						
Price index (SV)	3.7	5.8	7.6	20.9	20.8	19.5
Entry and exit	−10.9	−10.0	−5.3	0.6	5.1	3.2
Taste changes	−13.6	−8.0	−9.3	−11.1	−7.1	−2.6
Overall	−20.8	−12.2	−7.0	10.4	18.8	20.1
Different elasticities of substitution by sub-period						
Price index (SV)	3.7	5.8	7.6	20.9	20.8	19.5
Entry and exit	−8.8	−8.5	−4.9	0.2	2.3	1.6
Taste changes	−11.8	−7.4	−9.1	−3.7	−3.3	−1.2
Overall	−16.9	−10.1	−6.4	17.4	19.8	19.9

Note: The figures express the percentage point change in prices over the 2013–2019 and 2020–2022 sub-periods across income groups attributable to movements in the Sato-Varta (SV) price index, entry and exit and changes in preferences. Results in the top panel are based on an elasticity of substitution for each income group that is estimated over the entire 2013–2023 sample whereas the bottom panel uses elasticities that are specific to each sub-period.

of substitution in the Covid period is to dampen the entry/exit and tastes effects, giving greater prominence to the price changes measured by the Sato-Vartia price index. However, as in the constant elasticity case, the experience of price inflation for low-income households was more muted than for other income groups. For example, for low-income households in the 2013–2019 period, the price-lowering effect of entry and exit is weaker (−10.9% using the constant elasticity estimates falling to −8.8 using the sub-period estimates); for high-income households, the corresponding figures are −5.3% and −4.9%. Combining the effects of product churn and tastes the joint price effect in the Covid period falls from −10.5% to −3.5% for low-income households and from 0.6% to 0.4% for high-income households. Overall, the main insight is retained: whether using constant or period-specific elasticities of substitution, the effects of entry/exit and tastes in the 2013–2019 period had a negative influence on price inflation particularly for low-income households; in the Covid period, these effects were diluted and the main driver of the inflation experience was the increase in prices of common products reflected in the large values for the Sato-Vartia index.

7 | SUMMARY AND CONCLUSION

Recent developments in the theory of price indices require granular data at the household level to detail the entry and exit of products which are a key characteristic of food markets and crucial to appropriately measuring how price indices change over time. Without accounting for these factors, standard approaches to measuring cost of living are likely to be erroneous. In addition, consumer preferences and tastes may change over time and ignoring this aspect of the time dimension of consumer behavior is an additional source of bias with standard price indices used by national statistical offices. Addressing these issues is compounded when there is a requirement to assess how changes in prices impact across the income distribution when households differ in what they buy, where they shop and the prices they pay. As such, the effect of product churn and systemic changes in tastes differ across segments of the population.

In this paper, we have employed detailed scanner data covering 30,000 UK households between 2013 and 2022 and focused on applying the recent developments in price index theory to the ready meals sector, a sector where entry and exit is a common feature of how retail chains compete and where changes in tastes are likely to have arisen. Our main results are manifold: (i) standard price indices using "representative" prices overstate changes in prices across households as a whole, an observation consistent with the recent macroeconomics and trade literature; (ii) the underlying price changes for products that enter household shopping baskets vary, reflecting the heterogeneity of household choices of products and where they shop; (iii) the bias between nationally available measures and price indices that account for product net entry and changes in tastes varies considerably across income groups; (iv) the effect of taste changes on the price index matters more than product entry and exit across all income groups; and (v) in the Covid period, price changes were driven by changes in the prices of common products. Taking these effects together, low-income households experience lower levels of price increases over the data period compared with households in other income groups.

There are several important prospects for future research in this area. First, with the increasing availability of scanner data at the household level, national statistical offices can more accurately measure food inflation; though, as emphasized by Fox et al. (2023), there are ongoing issues associated with the choice of applying the appropriate price index that takes account of the features of high-frequency data. Second, as noted by Ehrlich et al. (2022), the challenge is to take account of the economic environment. In the context of measuring food inflation, these efforts should take account of the high level of product churn which is an important feature of food retailing. Moreover, changes in consumer preferences are an additional feature of the food sector. These issues need to be part of the agenda in the choice of price index to apply since, as we have shown here, their characteristics of the food sector will have an important determinant of the experience of price inflation. This extends, more relevantly, to the issue of inflation inequality which is an increasingly pressing issue for governments to address. The focus on the ready meals category has the advantage of exploring the impact of product entry and exit and taste changes in some detail; an obvious extension of the research reported here is to extend across a wider range of food groups. Finally, though these features of the food sector can have an important impact on the experience of food inflation, closer attention could also be given to the dynamics of product churn and how taste changes evolve over time.

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