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CPG consumption in times of recession: novel evidence from matched administrative data

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Abstract

We utilize a novel dataset that merges household administrative income and socio-demographic information from tax records with scanner data on CPG consumption. Our analysis reveals significant variation in household per-capita expenditures. However, we find only a modest economic relationship between CPG spending and income, even amidst substantial within-household income fluctuations during the Dutch "double-dip recession" from 2011 to 2018. This relationship remains small for households with low income and low liquidity and holds across both food and non-food expenditures.

Keywords Income effects · Consumer-packaged goods · Administrative data

JEL Classification D12 · E21 · E32 · M30

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1 Introduction

Consumption of consumer packaged goods (CPGs) constitutes a sizable fraction of all except the richest households' consumption and disposable income (on average 9.95% in our sample). Analyzing how changes in income affect household CPG expenditure, for example over the business cycle, is thus of interest both to marketing scholars and practitioners as well as to macroeconomists and policymakers. Yet, quantifying this relationship with survey data proves challenging due to measurement errors in household-specific income and wealth components and a lack of granularity in expenditures.

In this paper, we address those challenges by drawing on a novel data source that links individual households' CPG expenditures from GfK's scanner panel¹ with total disposable income from administrative data, as collected by the Dutch statistical office (Centraal Bureau voor de Statistiek, CBS). As a main result, we find only an economically small relationship between CPG spending and income as a 10% change in disposable household income is related to only a 0.55% change in CPG consumption.²

Our empirical strategy exploits the granular panel structure of our dataset and draws on institutional specifics of grocery retailing in the Netherlands and pronounced household-specific income variations. Notably, the time frame of our analysis covers the period between 2011 and 2018 and thus the "second dip" (2011 to 2013) of the Netherlands' double-dip recession following the financial crisis. Over this period, GDP growth dropped by 3.6 percentage points from the fourth quarter in 2011 to the third quarter in 2013 and unemployment rose by 3.3 percentage points. One-third of income changes in our data are negative. We also document considerable remaining heterogeneity between households even after stripping out (year-by-year) aggregate fluctuations. Thanks to this institutional setup, household-specific income variation can be considered as good as randomly assigned. We also note that our measure of income, namely household disposable income, is more comprehensive than main earner income alone, which is commonly used in the literature and typically (self-)reported in household scanner data. Moreover, relying on administrative data reduces the risk that results are downwards biased by measurement errors. Still, to test this more formally, we corroborate our finding of only an economically small relationship between household income and CPG expenditure using GfK self-reported figures. Our findings are robust to a series of different alternative specifications. First, our key finding of only an economically small relationship between household income and CPG expenditure holds for both food and non-food

¹ Researchers from the U.S. may be more familiar with Nielsen's household (or homescan) panel data. In many other countries, the panels provided by GfK or the sister organization Kantar furnish the same service. In the Netherlands, Nielsen does not have a household panel, making GfK's panel the industry standard.

² Though in our main regression, the income coefficient is statistically significant at the 1%-level, given its small size confidence intervals are relatively large. Still, in the reported case the upper boundary of the 95%-confidence interval corresponds to only a 0.74% increase in consumption following a 10% increase in income.

categories. Second, it also holds for households with low income or low savings. Third, our findings still apply when considering only negative income changes, which account for around one-third of observations in our sample.

Despite the robustness of our results, our analysis reveals considerable differences in cross-sectional per-capita CPG spending per household, even though in the Netherlands, the retailing landscape is particularly homogeneous. As we document national pricing and assortment strategies of supermarket and discounter chains, we can rule out such supply side explanations for this variation. Our findings thus suggest that differences in household (per-capita) CPG expenditures may be largely a result of differences in taste and, consequently, households do not show strong adjustments in expenditures when facing changes in income.

Our findings are relevant for marketing professionals in the CPG and retailing industry. In addition, they are of relevance for policy-oriented (macroeconomic) work. It suggests that in countries with a similar institutional and socioeconomic background as the Netherlands, CPG consumption is particularly stable across the business cycle, despite pronounced differences in per-capita household expenditures and often large price differences between products in the same category, such as between store brands and national brands.

Our disaggregate analysis contributes to a large strand of literature on business cycle research in marketing (Dekimpe & Deleersnyder, 2018). While this literature has identified large effects for some categories such as consumer durables (e.g., Deleersnyder et al., 2004), generally effects are much less pronounced for necessary consumer goods (cf. Dutt & Padmanabhan, 2011, which uses aggregate data in a cross-country analysis of currency crises). Relying on within-household variations, we find only an economically small relationship. Dubé et al. (2018), whose approach we follow, find a small relationship between reported income and households' private-label share in the US. Biswas et al. (2021) extend this to a joint analysis of how households vary their budget allocations across product categories as well as store formats and brand types, which allows them to derive more nuanced business implications, e.g., regarding the effects of a recession on non-food vs. food items sold in different store formats. Brancatelli et al. (2022) apply this methodology to the choice of store brands in the Netherlands, confirming an economically small relationship with income changes. The economically small relationship between store brand consumption and income change over the business cycle contrasts strongly with earlier findings using only aggregate data (e.g., Lamey et al., 2007).

There is also sizable literature in macroeconomics, especially household finance, that seeks to measure the response of (households') aggregate consumption to changes in income.³ There, changes in consumption are often measured

³ Still, a strand of the large literature studies the shape of consumer demand responses to income changes also for different consumption categories. Typically, food, which makes up the bulk of CPG expenditure, is found to be a normal good, so that spending increases with income, albeit its share in overall expenditure decreases. While we stipulate a linear relationship between log income and log expenditure, the literature has also analyzed more flexible functional forms (e.g., Banks et al., 1997).

by surveys, based on diaries or interviews, rather than by recording actual expenditures.⁴ In such surveys also hypothetical questions can be asked, which allows for disentangling responses to anticipated vs. non-anticipated as well as temporary vs. permanent changes in income (see, for instance, Jappelli & Pistaferri, 2014 or Christelis et al., 2019). A key finding of this literature is that households would consume a surprisingly large fraction of only transitory income shocks, contradicting the “permanent income hypothesis”. These studies often stress the importance of household liquidity as a mediating factor. While research has also documented such excess sensitivity of consumption to real transitory income shocks (such as from the federal government shutdown in 2013, Baker & Yannelis, 2017, or from tax rebates in 2018, Misra & Surico, 2014), interestingly a study by Parker et al. (2013) documented only small effects for expenditures on food and non-durable items. Notably, our data does not allow us to distinguish between anticipated and non-anticipated income changes. Still, we corroborate our finding of only a small relationship with actual CPG spending by including lags. In contrast to this macroeconomic literature, we do not find that households with low income or savings react significantly more strongly.

The remainder of this paper is organized as follows: In section “Data”, we introduce our dataset. In section “Stylized facts”, we present stylized facts about CPG consumption and retailing. Section “Estimation results” represents the results from our empirical analysis. We conclude in section “Conclusion”. Additional results are provided in an appendix.

2 Data

We use and enrich a novel dataset introduced by Brancatelli et al. (2022) matching household scanner data from the Dutch GfK consumer panel with administrative data on wealth, income, and sociodemographic characteristics, as provided by CBS.⁵ Matching the datasets was possible as more than 5,000 households individually consented.⁶ Between 2011 and 2018 we are thus able to observe on the level of individual households both their purchases and actual, rather than only reported, information regarding income and wealth. Our level of aggregation is the household, rather than individuals both for the considered expenditures as well as for income. When using household scanner data alone, typically reported income instead only relates to the main earner.

In the following subsections, we describe each of our two main datasets in detail.

⁴ Macroeconomic research has only recently turned towards the use of household scanner data, see for instance Kaplan and Schulhofer-Wohl (2017) for the measurement of inflation. A comprehensive review of the use of household scanner data in various strands of economic literature is provided by Dubois et al. (2022).

⁵ Household scanner data from the GfK consumer panel are provided by the AiMark foundation.

⁶ Matching, based on household characteristics provided directly by GfK, took place in the secure environment of CBS and was undertaken by its statistical staff. All analyses with matched data took place in the secure environment of CBS.

2.1 Household scanner data

We use household scanner data from the GfK consumer panel, which is the main provider of such information in the Netherlands. It covers household purchases for a wide range of CPGs, both food and non-food.⁷ To register purchases, households selected for the GfK consumer panel are equipped with an electronic home scanning device. Our unit of observation is thus a single product on the barcode level bought by an individual household on a certain day at a specific retail chain. For our analysis, we aggregate the data on a household-year level.

Matching with CBS data is only possible for those households that explicitly consented to the matching of their data.⁸ This restricts our unbalanced panel from originally 11,041 to 6,151 distinct households in 2018. Of these, we observe 89% over the entire period. Also, note that we are still able to draw on the full Dutch population from CBS and we use this information both to analyze the representativeness of our sample and to construct regression weights.

We obtain from GfK also households' self-reported (mean earner) income data, which is collected annually by GfK. We use this to corroborate our main findings based on CBS administrative income data. Panelists are asked to report average monthly income net non-financial income (including salary, income from self-employment, pensions, and social benefits). Responses are provided at the end of a given year and GfK refreshes panel information in the first quarter of the subsequent year. We take this lag into account.

We conduct the following data selection. We neglect households for which we observe less than six months of purchase data or less than three shopping trips on average per month. Next, we exclude transactions with unreasonably high or low prices by removing transactions with prices that are four times higher than the median or less than a quarter of the median of the same product. We identify the same product via barcodes and calculate median prices across households and months for each year. Overall, we lose less than 1% of total expenditures. To capture full years of transactions for each household, thereby avoiding seasonal biases as our level of observation consists of household-years, we exclude panel members that entered the panel after January of a particular year. We thereby lose 6.42% of households.

⁷ This includes fresh, frozen, refrigerated food, alcoholic and non-alcoholic beverages, health and beauty products as well as pet needs, cleaning, detergent products, and general merchandise at a wide variety of retail outlets.

⁸ In the European Union in May 2018 the General Data Protection Regulation (GDPR) came into force, which severely limits the creation, storage, and use of personal data. Due to the GDPR, GfK is obliged to ask for the consent of each household. In 2018 all households, which were in the panel at the time, had the opportunity to voluntarily agree to their household scanner data being linked to CBS data.

2.2 CBS data

The Dutch Centraal Bureau voor de Statistiek (CBS), also referred to as Statistics Netherlands, is a governmental institution that collects statistical information in the Netherlands. It provides microdata to authorized institutions under strict conditions of confidentiality. CBS microdata data have been used previously in the literature, for instance in De Meijer et al. (2013), Lammers et al. (2013), and Raymond et al. (2010).

CBS data include, in our case, households' sociodemographic information and information on income and wealth. We use CBS information on the number of household members (at the same address), the number of children, the number of male or female persons, and the number of household members receiving an income. Changes in these variables may affect the required consumption basket and thereby expenditures. We thus account for the composition of a household through the inclusion of these variables in our regression analysis below.

In the descriptive parts of this paper, we adjust income, wealth, and consumption figures for household size. We follow Attanasio and Pistaferri (2016) and define household size as $1 + 0.7(n - 1) + 0.3k$, where n is the number of adults and k the number of children in the household.⁹ For instance, if a single-person household grows with the addition of an adult, the headcount increases from 1 to 1.7.

Our key explanatory variable refers to disposable household income. CBS provides researchers with highly accurate income data from Dutch tax authorities. As some components of income, such as that from self-employment, are only available yearly and as this generally applies to net income after taxes, which is correctly calculated only at the end of the year, we use yearly income for our analysis. Disposable (household) income is defined as gross household income minus deductions, consisting of transfers and tax payments of all household members.¹⁰

CBS also provides detailed information about households' financial wealth. Financial assets consist of deposit and current account balances and the market value of stocks and bonds as of 1st January of the following year. Dutch households need to declare this information in their annual income tax declaration to derive the base for the income tax on return on assets.¹¹ As we explain below, the use of

⁹ We note that this does not fully correspond to scales referred to as the OECD (modified or equivalence) scales (see <https://www.oecd.org/els/soc/OECD-Note-EquivalenceScales.pdf>). We thank a referee for pointing this out. None of the insights from our descriptives would, however, be affected by changing the scale.

¹⁰ Gross household income comprises labor income, business income, capital income, social transfers, insurance benefits, allowances, and alimony from ex-spouses of all household members. Deducted transfer payments comprise income transfers, such as alimony to ex-spouses, as well as mandatory social transfers for social assistance and national insurance benefits. Taxes deducted from gross household income consist of all income tax and a wealth tax paid within a household.

¹¹ Whenever no such information is provided in the income tax declaration, CBS uses reported data from the respective financial institutions to impute these values individually. As of 2016, this applies also to foreign financial assets that are in countries that are part of the OECD Common Reporting Standard adopted by the European Commission.

financial wealth data allows us to analyze whether households with smaller savings react more strongly to income changes as often suggested by the literature.

Through CBS we also have access to the granular data on the income of all Dutch households. We use this both to check for the representativeness of our sample and to perform a weighted analysis. We comment below on the representativeness and, in this context, also provide descriptive statistics for socio-demographic characteristics, including income and financial wealth, both for our sample and the population (cf. also Table 10 in the appendix).

2.3 Representativeness of matched data

Via CBS, we have access to household-level information for the whole Dutch population and can compare this to our sample. In Table 1, we first provide detailed information on our main explanatory variable of interest, disposable income, which we have deflated and standardized for household size.

Table 1 shows that the mean, median, and key percentiles of the income variable in our sample are similar to those obtained from the population as a whole. Table 10 in the appendix provides, in addition, key statistical descriptives for all relevant sociodemographic variables, including income and financial wealth, and for both endpoints of our considered period from 2011 to 2018. Once more, we report figures

Table 1 Summary statistics of disposable income in sample and population

	Disposable per capita income	
	2011	2018
Mean—S	23,379.33	24,037.68
Mean—Pop	23,532.35	24,852.26
P10—S	14,736.30	14,683.00
P10—Pop	12,164.27	12,513.91
P25—S	17,660.22	17,795.22
P25—Pop	15,925.80	16,552.00
P50—S	21,993.73	22,571.00
P50—Pop	21,001.24	22,349.00
P75—S	27,269.93	28,410.00
P75—Pop	27,768.59	29,635.88
P90—S	33,986.74	35,008.50
P90—Pop	36,471.79	38,164.17
N—S	3,110	5,451
N—Pop	7,544,704	7,973,137

Table 1 shows summary statistics for disposable income per standardized household member. Values are expressed in constant 2018 Euro. Household size is standardized using an OECD scale defined as $1 + 0.7(n - 1) + 0.3k$, where n is the number of adults and k the number of children in the household

both for our sample and for the whole population. Overall, this confirms that along these dimensions our sample is largely comparable to the whole population.

Notably, when looking at similarities along the distribution, we find that the largest differences prevail at the 10th and 90th percentiles. In particular, this may reflect well-known problems in the under-representativeness of commercial panels at the tails of the income distribution. To alleviate concerns that this may bias the effects of interest in our analysis, we exploit the access to CBS registry data to construct sampling weights based on the procedure described in Brancatelli et al. (2022). For our main regression and robustness checks we provide separate results including those weights.¹²

3 Stylized facts

3.1 CPG consumption and retailing

Figure 1 illustrates that household expenditures for CPGs represent a sizable component of total disposable income, namely between 9.5% and 11.5% over time.

The products under consideration are divided into two main segments: food and non-food items. The non-food segment includes, for example, detergents, cleaning products, and pet supplies. Food items consist of beverages as well as various types of fresh and refrigerated foods. Our data allow us to break down total CPG expenditures into food and non-food components, which we distinguish between at various points in the analysis. Overall, food consumption accounts for 82.1% of total CPG expenditure.

Table 2 depicts the distribution of CPG (food and non-food) spending levels pooled across all household-year observations, where, again, household size has been standardized using the OECD scale. Values are expressed in constant 2018 Euro (using as a deflator the Dutch Harmonized Index of Consumer Prices, HICP). The median CPG consumption level per year and standardized household members is 1,968 euros, which masks substantial heterogeneity. Remarkably, total CPG consumption per standardized household member at the 90th percentile is three times larger than consumption at the 10th percentile.

This heterogeneity remains evident even when examining variations within relatively narrow brackets of household disposable income (e.g., quintiles of

¹² Specifically, we construct year-specific adjustment weights using post-stratification. We follow Bethlehem and Biffignandi (2011) and start by stratifying our regression samples into strata using disposable income from the CBS household income registry INHATAB. For each year, we first split the population into income deciles to create 10 strata of equal size. Next, we compute for each stratum a correction weight as the ratio between the population percentage of households over the sample percentage of households. Finally, we multiply the correction weight by the inverse probability of each household being in the sample. Since the true (and household-specific) probability of being sampled is unknown and since we assume that households within the stratum are homogeneous concerning their inclusion probability, we assign an equal inclusion probability to each household within the stratum. We impute the stratum-specific inclusion probability with the ratio of households within the stratum over the total number of households in the population.

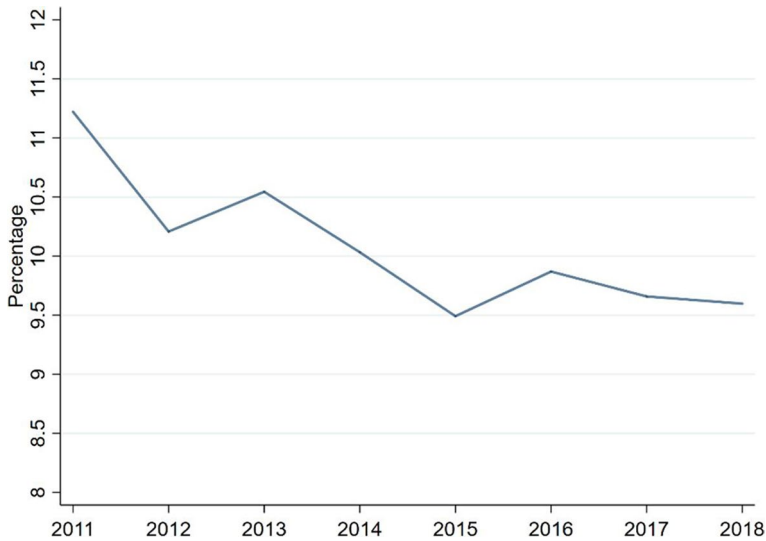


Fig. 1 Average household CPG expenditure share in terms of disposable household income. Notes: Fig. 1 shows the average share of CPG expenditures across households expressed as a percentage of total CPG consumption over nominal disposable household income per year

Table 2 Summary statistics of CPG, food, and non-food standardized consumption levels

Variable	p5	p10	p25	p50	p75	p90	p95	N
CPG consumption level (in 100 EUR)	8.36	10.60	14.68	19.68	25.47	32.39	37.66	30,593
Food consumption level (in 100 EUR)	7.06	8.99	12.28	16.21	20.70	25.82	29.51	30,593
Non-food consumption level (in 100 EUR)	0.61	0.89	1.60	2.85	4.87	7.96	10.84	30,593

Table 2 shows the main percentiles of CPG, food, and non-food consumption levels for the sample used in the baseline regression. All values are expressed in constant 2018 Euro. Household size is standardized using an OECD scale (defined as $1 + 0.7(n - 1) + 0.3k$, where n is the number of adults and k the number of children)

standardized household disposable income), as shown in Fig. 2. In each income bin, the 10th percentile displays total CPG expenditures around 1,000 Euros, while standardized per-capita expenditure at the 90th percentile is consistently three times higher. In contrast, the median standardized per-capita expenditure shows much less variation across income bins: in the lowest income quintile (up to 15,000 Euros), it is 1,683 Euros, compared to 2,045 Euros in the highest income quintile (over 35,000 Euros).

Retailers in the Netherlands fall broadly into two categories: supermarket chains and hard discounters. Hard discounters have a much smaller assortment, consisting mainly or even almost exclusively of store brands, and consequently, on average, lower prices.

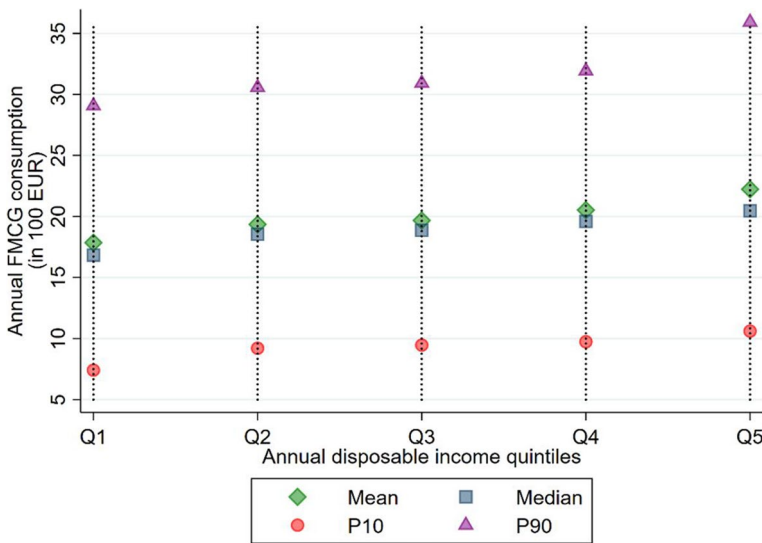


Fig. 2 CPG consumption by disposable income bin. Notes: Fig. 2 shows the mean, median, p10, and p90 of CPG consumption by quintiles of disposable household income across all household-year observations. Consumption expenditures and income are expressed in constant 2018 Euro. Household size is standardized using an OECD scale defined as $1 + 0.7(n - 1) + 0.3k$, where n is the number of adults and k the number of children

The availability of store brands provides a key source of savings. According to industry reports, even at the largest supermarket chain, Albert Heijn, private labels are, on average, 31% to 55% cheaper than comparable national brands (IPLC, 2016). In a cross-country comparison (IRI, 2016), the ratio of private label to national brand prices was 73.8% in the Netherlands, compared to 88.5% in the US. The granular nature of our data allows us to confirm this. We considered categories that are both important to households and that allow us to identify the units of purchase. Across the whole sample of observed purchases, the price ratio of private labels to brands equaled 86.79% for coffee, 67.75% for ketchup, and 66.16% for washing detergents.

Industry experts indicate that retail chains in the Netherlands implement national pricing, a practice that diverges notably from those in other countries. One possible reason for this approach is the Netherlands' small geographic size and the relative homogeneity in living conditions. The Appendix provides supporting evidence for national pricing practices. Additionally, experts suggest that, aside from regional specialties, retailers in the Netherlands adopt a national assortment strategy. Using granular data, Brancatelli et al. (2022) examined potential regional differences in assortments and find that the Euro share of store brands—typically much cheaper than national brands—did not vary significantly across regions within the same retailer. The prevalence of national retailing strategies can be attributed to the small size of the Netherlands and its relatively uniform living conditions, including

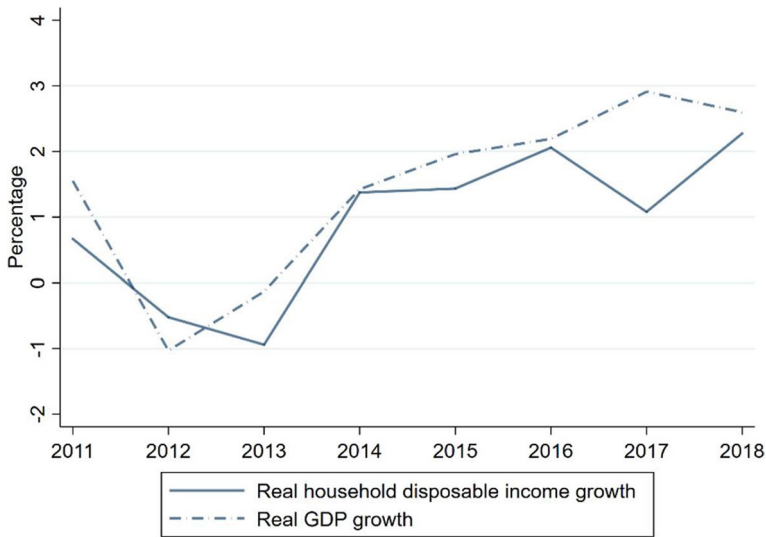


Fig. 3 Real GDP and disposable household income growth. Notes: Fig. 3 shows annual growth rates of real GDP and real disposable household income in the Netherlands. Source: World Bank World Development Indicators and OECD National Accounts Data

consistent household access to outlets of major supermarket and discount chains. Overall, substantial differences in household per-capita CPG spending are not attributable to regional price or assortment differences, nor to disparities in access to various stores or store types.¹³

3.2 Variation in disposable income

Over the considered period, the Netherlands underwent the second “dip” of the so-called double-dip recession in the aftermath of the financial crisis (and the consequent “Great Recession”). Figure 3 depicts the percentage changes in GDP and household income. The figure highlights that both GDP and household income dropped between 2011 and 2013 and increased subsequently. This macroeconomic development provides a natural source of exogenous variation.

We next depict variation of per-household income in our estimation sample. Such variation has two sources: first, adjustments in any of the recorded income components, as described in section “CBS data”, and second, changes in the household’s composition. While in our regression analysis below we account for household composition through the inclusion of household size and members characteristics, for the descriptive analysis in this subsection we calculate disposable income

¹³ Such differences are, instead, the focus of various research on so-called “food deserts” conducted in the US and the UK, such as Allcott et al. (2019).

Table 3 Main percentiles of annual percentage changes in household disposable income

Variable	p5	p10	p25	p50	p75	p90	p95	N
Income (%)	-19.73	-12.11	-3.35	0.77	5.92	16.66	28.06	25,338

This table shows the main percentiles of annual disposable income growth for the sample used in the baseline regression. Underlying values are expressed in constant 2018 Euro. Household size is standardized using an OECD scale (defined as $1 + 0.7(n-1) + 0.3k$, where n is the number of adults and k is the number of children

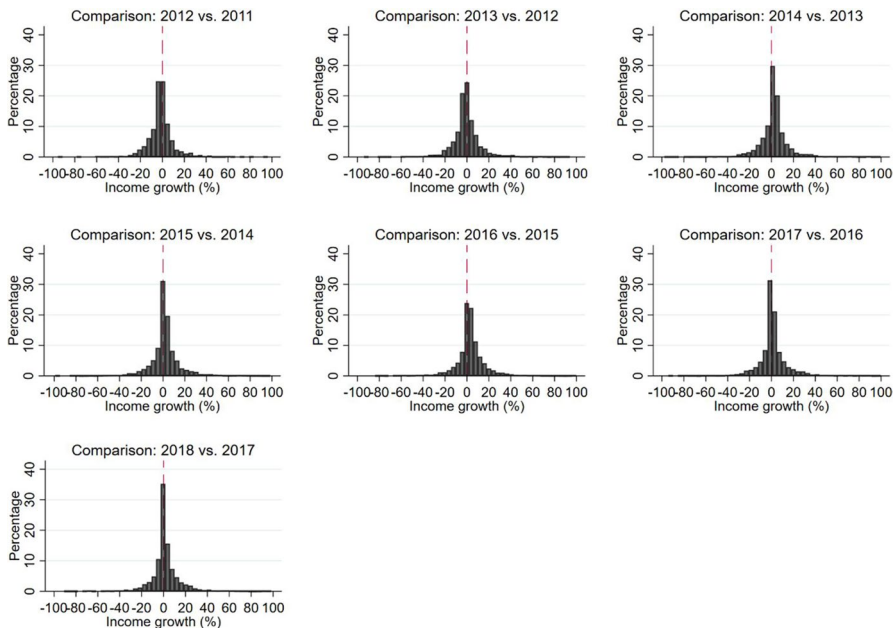


Fig. 4 Changes in disposable income. Notes: This figure shows the distribution of disposable income growth rates over time. Household size is standardized using an OECD scale defined as $1 + 0.7(n-1) + 0.3k$, where n is the number of adults and k the number of children. Income is expressed in constant 2018 Euro. The figure is truncated at values below -100% and above $+100\%$

per (adjusted) household member, using the OECD scale introduced above.¹⁴ Table 3 shows the main percentiles of the income growth distribution across households and time.

Median income shows an observed annual increase of 0.77%, with approximately one-third of changes being negative. Figure 4 illustrates the year-by-year distribution of income changes, revealing macroeconomic shifts, as the proportion of positive changes rises over time. Notably, significant variation in income changes persists

¹⁴ We note, however, that by the nature of our data from CBS, changes to disposable income also comprise potential gains and losses in terms of applicable tax brackets.

each year. Even after accounting for aggregate year-to-year changes, as done in our regression analysis, substantial within-household variation in income remains evident.

4 Estimation results

4.1 Empirical strategy

Our research question is how changes in income affect households' total CPG expenditures, notably in the context of the Dutch double-dip recession. For this purpose, we estimate a two-way fixed effects regression of CPG consumption on disposable household income:

$$\log(C_{ht}) = \beta \log(I_{ht}) + \gamma X_{ht} + \phi \log(I_{rt}) + \alpha_h + \psi_t + \epsilon_{ht}$$

Here, $\log(C_{ht})$ denotes the logarithm of CPG consumption of household h in year t . The term $\log(I_{ht})$ captures the logarithm of disposable income of household h in year t . The vectors α_h and ψ_t represent household and year fixed effects, respectively, together with a constant. We represent estimates both with and without sampling weights, constructed directly from administrative CBS, to address concerns about potential selection bias.

The coefficient β represents our primary coefficient of interest. In our main regression, income is only considered contemporaneously, capturing both permanent and transitory changes in income. However, we cannot fully distinguish between (perceived) permanent changes and temporary fluctuations. For example, during a downturn, recorded negative income changes may include both short-term impacts perceived by younger workers and permanent reductions for those near retirement age due to job losses.

We re-estimate our model by including the first lag of (yearly) income. While we do not claim that this distinction allows us to separate different types of income changes precisely, examining both the current and lagged coefficients together should help mitigate concerns about underestimating household responses. Additionally, our focus on the recession may address concerns that the coefficient could be attenuated if households had already anticipated income changes (e.g., by planning reduced working hours or transitioning into retirement).

The vector X_{ht} collects a set of time-varying household socio-demographics as derived from CBS data. The variables comprise household size, calculated as the number of officially registered persons in the household, as well as the fraction of children and female members, all obtained from the matched administrative data.

Aggregate income shocks, notably over the covered double-dip recession, may induce retailers to change prices and assortment. Given the documented national pricing and assortment strategies of all major retailers, this should be captured by the inclusion of year fixed effects. Income effects are thus identified by idiosyncratic changes on the household level that deviate from aggregate changes, which may affect retail prices. Our key identification assumption is thus that the remaining

variation used to estimate β is as good as random. Recall from Fig. 4 that after stripping out the common component, there is still considerable variation in within-household changes in disposable income.

We acknowledge, however, a possible channel for only “local” adjustments: the opening and closing of outlets. For instance, hard discounters may open outlets during a crisis, and a household’s expenditure may change with increased access to cheaper products. For this reason, in a robustness analysis, we include the following supply-side control variable. From Distrifood Dynamics we acquired a panel of retailer outlets and their geographical location (geo coordinates) quarterly. Linking households to the respective geo coordinates allows us to measure distances between retailer outlets and homes.¹⁵ We group retailers into supermarkets and discounters. To control for changes in households’ access to different types of outlets, we include these distances as additional controls in a robustness analysis.

4.2 Main estimation results

Table 4 presents the results of our baseline analysis. Column 1 reports results from the two-way fixed effects regression without controls, while column 2 contains our key result using our demand-side controls. We find that a 10% change in disposable income is associated with a 0.57% change in CPG consumption.¹⁶ Using weights (column 3) the relationship is slightly reduced to 0.55%. While in both cases the coefficient is statistically significant at 1%, it is economically small. Though confidence intervals are relatively large, compared to the size of the respective coefficient, we note that the coefficient remains economically small also at the upper end of, for instance, the 95% confidence interval, corresponding to 0.76% for the estimate in column 2. Results are virtually unaffected when we introduce our supply-side controls for robustness (column 5). Taken together, our finding suggests that households hardly adjusted CPG consumption in response to income variation as experienced during the recession and the subsequent boom.

The results in column 4 show that also the income lag is highly significant, but again economically small. The cumulative effect of the contemporaneous and the lagged income change is larger, though still economically small: For a 10% change in disposable income, the associated cumulative shift in CPG consumption stands now at 0.91%.¹⁷

¹⁵ Distances are calculated as the shortest line between the midpoint of the 6-digit zip code of household residency and store location. The resulting imprecision is assumed to be below 1 km on average as there are overall 459,438 6-digit postal codes in the Netherlands, each yielding approx. 37 inhabitants.

¹⁶ To obtain the exact average effect for a 10%-change, we transform the elasticity in the following way: $100 * (e^{0.060 * \log(1.1)} - 1)$. Accordingly, the average effect for a 25% change in income would be 1.34%. Note that the coefficient needs to be one so that CPG expenditures would account for a constant fraction of income.

¹⁷ For this calculate $0.048 + 0.047 = 0.095$ before transforming this into the cumulative percentage change.

Table 4 Main regression analysis

	(1)	(2)	(3)	(4)	(5)
	Log(CPG)	Log(CPG)	Log(CPG)	Log(CPG)	Log(CPG)
Log(HH income)	0.134*** (0.012)	0.060*** (0.010)	0.058*** (0.011)	0.048*** (0.011)	0.060*** (0.010)
L.Log(HH income)				0.047*** (0.009)	
Share of females in HH		-0.110*** (0.036)	-0.108*** (0.038)	-0.090** (0.038)	-0.109*** (0.036)
Share of children in HH		0.126*** (0.030)	0.138*** (0.034)	0.128*** (0.033)	0.125*** (0.030)
Share of income earners in HH		0.007 (0.018)	0.003 (0.022)	-0.003 (0.020)	0.007 (0.018)
HH members		0.082*** (0.007)	0.078*** (0.008)	0.075*** (0.007)	0.081*** (0.007)
Household fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Supply-side controls	No	No	No	No	Yes
Sample weights	No	No	Yes	No	No
Observations	30,543	30,543	30,543	25,309	30,543
R ²	0.900	0.903	0.901	0.917	0.903
Adjusted R ²	0.880	0.884	0.881	0.898	0.884

Table 4 presents the estimation results of the baseline regression. The dependent variable is the log of total CPG expenditures per year. Column 1 presents results including only the log of disposable income, next to household and year fixed effects. Column 2 adds demand side variables, column 4 includes the lag of log disposable income. Column 5 adds supply-side controls to the specification in column 2. Standard errors, clustered at the household level, are displayed in parentheses. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models are estimated using a constant

We interpret these results to be consistent with the view that households may adjust consumption also with some delay to an initial income change, for instance, due to a change in perceptions or due to revised expectations about future income.

4.3 Potentially asymmetric responses

Various studies have documented asymmetries between up- and downswings in the economy or likewise income increases and decreases. For instance, Deelersnyder et al. (2004) document this over the business cycle for durable goods. With regards to CPG, there is also some evidence regarding asymmetric responses to consumers' share of private labels (Lamey et al., 2007). In macroeconomics, based on survey questions various studies find that households react more strongly to negative changes (Christelis et al., 2019). Such asymmetries may derive from the way households gain or lose trust in the economic climate. Also, it has been suggested that consumers may first use additional financial slack to pay back debts during recovery

or that differences are accounted for by loss aversion or a precautionary savings motive (see also below for a specific analysis of consumers' financial situation).

We define an income change by calculating the year-on-year percentage change of deflated disposable income for each household. Next, we divide the sample by separating negative rates from those being positive or zero. Overall, 36% of all measured income changes are negative.

As reported in Table 5, the coefficient remains economically small also for negative income changes: The coefficient's size in column 2 implies that a 10% decrease in disposable income is associated with a 0.81% decrease in CPG consumption. We note also that while the reported coefficient is slightly larger for negative income changes than for positive income changes, the respective confidence intervals are again relatively large. When we estimate a single regression with a dummy denoting negative income changes, the respective coefficient is not statistically significant (even on a 10%-level).

Table 5 Negative vs. positive income changes

	Negative income changes		Positive income changes	
	(1)	(2)	(3)	(4)
	Log(CPG)	Log(CPG)	Log(CPG)	Log(CPG)
Log(HH income)	0.162*** (0.024)	0.085*** (0.023)	0.139*** (0.016)	0.063*** (0.015)
L.Log(HH income)				
Share of females in HH		-0.128** (0.058)		-0.111** (0.045)
Share of children in HH		0.079 (0.069)		0.142*** (0.034)
Share of income earners in HH		-0.004 (0.035)		0.022 (0.022)
HH members		0.086*** (0.012)		0.079*** (0.009)
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Supply-side controls	No	No	No	No
Observations	10,994	10,994	19,549	19,549
R ²	0.932	0.935	0.910	0.912
Adjusted R ²	0.890	0.894	0.877	0.881

Table 5 presents the estimation results separated by negative (columns 1 through 2) and positive (columns 3 through 4) income changes. The dependent variable is the log of total CPG expenditures per year. Column 1 (respectively 3) presents results including only the log of disposable income, next to household and year fixed effects. Column 2 (respectively 4) adds demand side variables. Standard errors, clustered at the household level, are displayed in parentheses. Significance levels are defined as follows:

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models are estimated using a constant

4.4 Using GfK self-reported income data

We next conduct our main regression using now GfK self-reported income.

As shown in Table 6, the income coefficient remains small even with the updated measure: a coefficient of 0.079 indicates that a 10% change in disposable income is associated with a 0.76% change in CPG consumption. While this aligns with our previous findings, a detailed comparison between coefficients derived from administrative versus reported income data warrants further examination. Using GfK self-reported income, one might expect a weaker relationship with expenditures for several reasons: (1) GfK data only captures the income of the household's main earner, (2) it is recorded in 200-Euro brackets, potentially limiting variability, and (3) it may contain reporting inaccuracies, including reluctance

Table 6 Analysis using GfK self-reported income. (GfK's income figures are also censored at the bottom and the top, with respective categories of below 700 EUR and above 4.100 EUR, though only ca. 6% of households fall into these categories. As we associate each household with the mean of the respective bracket, we lose those in the highest band. In addition, for around 7% of household years income is missing, which together explains the drop in observations.)

	(1)	(2)	(3)	(4)
	Log(CPG)	Log(CPG)	Log(CPG)	Log(CPG)
Log(HH income)	0.114*** (0.014)	0.079*** (0.013)	0.075*** (0.015)	0.079*** (0.013)
L. Log(HH income)			0.002 (0.015)	
Share of females in HH		-0.106*** (0.037)	-0.086** (0.040)	-0.105*** (0.037)
Share of children in HH		0.081*** (0.031)	0.069** (0.035)	0.080** (0.031)
Share of income earners in HH		0.020 (0.019)	0.014 (0.021)	0.019 (0.019)
HH members		0.094*** (0.007)	0.090*** (0.007)	0.094*** (0.007)
Household fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Supply-side controls	No	No	No	Yes
Observations	28,328	28,312	23,233	28,312
R ²	0.901	0.905	0.918	0.905
Adjusted R ²	0.880	0.885	0.899	0.885

Table 6 presents the estimation results of the baseline regression using self-reported income. The dependent variable is the log of total CPG expenditures per year. Column 1 presents results including only the log of disposable income, next to household and year fixed effects. Column 2 adds demand-side variables, column 3 includes the lag of log disposable income, and column 5 supply-side controls to the specification in column 2. Standard errors, clustered at the household level, are displayed in parentheses. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models are estimated using a constant

among panelists to update their reported income. In Brancatelli et al. (2022), we suggested that these factors likely contributed to the weaker relationship between self-reported income and households' private label shares. However, self-reported income may better capture households' perceived economic well-being, possibly indicating a stronger link to consumption. Our current findings on total CPG consumption support this perspective, and we revisit this issue in our concluding remarks.

4.5 Analysis of potential heterogeneity

Our finding of only a modest relationship between income measures and CPG consumption may conceal effect heterogeneity within the sample, suggesting potentially larger coefficients for certain subgroups. To investigate this possibility, we analyze

Table 7 Analysis of potential heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Log(CPG)	Log(Food)	Log(Non-food)	Log(CPG)	Log(CPG)
Log(HH income)	0.060*** (0.010)	0.060*** (0.010)	0.058*** (0.020)	0.069*** (0.013)	0.062*** (0.011)
Low Income x Log(HH income)				−0.024 (0.021)	
Low liquidity x Log(HH income)					−0.010 (0.027)
Share of females in HH	−0.110*** (0.036)	−0.133*** (0.036)	0.060 (0.059)	−0.109*** (0.036)	−0.110*** (0.036)
Share of children in HH	0.126*** (0.030)	0.131*** (0.031)	0.109** (0.052)	0.128*** (0.030)	0.126*** (0.030)
Share of income earners in HH	0.007 (0.018)	−0.000 (0.018)	0.034 (0.034)	0.007 (0.018)	0.007 (0.018)
HH members	0.082*** (0.007)	0.086*** (0.007)	0.066*** (0.011)	0.081*** (0.007)	0.082*** (0.007)
Household fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Supply side controls	No	No	No	No	No
Observations	30,543	30,543	30,540	30,543	30,543
R ²	0.903	0.906	0.862	0.903	0.903
Adjusted R ²	0.884	0.887	0.834	0.884	0.884

Table 7 presents the estimation results of modified baseline regressions. All columns use the same set of control variables as in baseline Table 4. Column (1) repeats the baseline from Table 4. In column (2) the dependent variable is the log of total CPG food expenditures per year. In column (3) the dependent variable is the log of total CPG non-food expenditures per year. Column 4 presents results including an interaction term of Log(income) and a dummy variable for low household income. Column 5 presents results including an interaction term of Log(income) and a dummy variable for low household financial wealth. Standard errors, clustered at the household level, are displayed in parentheses. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All models are estimated using a constant

potential heterogeneity and present the results in Table 7. Each column shows the outcome of our baseline analysis (repeated in column 1) when the regression is applied to subsamples. Column 2 focuses solely on food categories, and column 3 on non-food categories. The effect size remains similar and thus economically modest across both food and non-food categories.

As suggested by macroeconomic research (e.g., Baker, 2018¹⁸; Jappelli & Pistaferri, 2010), households under tighter financial constraints may react more strongly to income changes. To examine if this applies to CPG consumption in the Netherlands, we classify a household as low-income if its deflated standardized income falls within the lowest quintile. Similarly, we define a low-liquidity household based on low financial assets, using data from CBS. Columns 4 and 5 of Table 7 show results when introducing an interaction term for low income or low liquidity. The statistically insignificant coefficients of the interaction term do not suggest a stronger response among these groups. Although the confidence intervals are broad, the values remain modest even at the upper bounds of standard confidence intervals.

5 Conclusion

In this paper, we combine household scanner data with administrative income data and explore CPG consumption patterns of households in times of recession. Our key finding is an economically small relationship between household income and expenditures for CPGs.

Our empirical results rest on a series of unique institutional factors that considerably mitigate estimation challenges. First, our data cover the second episode of the Dutch double-dip recession following the financial crisis which ended in 2018. As noted above, this ensures that around one-third of yearly income changes are negative. Second, we document national pricing and assortment strategies in the Netherlands which allows to rule out a series of supply side factors. We also document that in the Netherlands, households have comparable access to discounters or store brands and that such offers are considerably cheaper. Third, administrative data allows us to minimize measurement error for our two key variables so that we can rule out such concerns as an explanation for our estimated small coefficient. Access to administrative data also enables us to learn about households' financial savings, so we can explore whether households respond more pronouncedly to income changes when they are more likely to be financially constrained. Disaggregate consumption data in turn allows us to analyze effects within food and non-food categories. Yet, our key finding of an economically small relationship remains robust across various model specifications and sample splits that cater to these factors. In sum, we are confident that the (albeit small) estimated coefficient indeed captures behavioral changes.

Despite this, we show also that households' (per-capita) CPG expenditures vary widely, even within income brackets despite controlling for common over-time

¹⁸ From a marketing science perspective, see, for instance, Orhun and Palazzolo (2019).

variation via year fixed effects. Households' limited reaction to negative income shocks may thus be largely due to consumption preferences, which may not have been sufficiently "tested" in the analyzed recession environment. This supports earlier research by Brancatelli et al. (2022), which documents that in the Netherlands also the relationship between income and households' consumption of store brands is economically small. While not reported there, we find such a small relationship also for households' propensity to frequent discounters (cf. Biswas et al., 2021 for an analysis of households' choice of store formats in the US).

Casual evidence from market research suggests that the recent surge in inflation, which not only affects (relative) prices but also real income and wealth, may have had a larger impact and may indeed have tilted CPG choices. Contrasting this episode with that of the recession documented in this paper (and with it our finding of only an economically small adjustment of households) could be an avenue for future research with the matched data.¹⁹

Finally, our data enables a comparison between findings based on administrative income data and those using self-reported income data. As discussed earlier, Brancatelli et al. (2022) find that, for households' private-label share, the income coefficient was significantly attenuated when relying on self-reported data. That study explored potential reasons for this attenuation, including the income bracketing applied by both GfK and Nielsen. By leveraging both self-reported and administrative income data, we verified that findings from Dubé et al. (2018), which used Nielsen self-reported income, are not solely due to measurement error in self-reported income. The relationship between income and households' private-label share remains economically modest regardless of data type.

Our current analysis corroborates this for total CPG consumption, showing that the relationship between income and consumption remains modest both with administrative and self-reported income data. While the small effect sizes and relatively broad confidence intervals prevent us from examining in depth why one income measure might produce a more pronounced relationship than the other, we propose that future research should address this question. Such investigation could enhance our understanding of the limitations associated with self-reported income data.

Finally, our data allows us to contrast findings with administrative income data to those with self-reported income data. As discussed above, Brancatelli et al. (2022) find that for households' private-label share, the coefficient was much attenuated when relying on self-reported data. The paper tried to disentangle various reasons for this, including the bracketing of income reports, as practiced by both GfK and Nielsen. Using both self-reported and administrative data allowed us to confirm

¹⁹ The matching of administrative and household scanner data for the present analysis ended in 2018, given also the focus on the Netherlands' past recession. In contrast, while CPG supply was severely disrupted in the first phase of the COVID-19 crisis, contrary to other countries income that was not derived from self-employment was largely unaffected in the Netherlands, given extensive public support programs to firms and employees.

that the findings in Dubé et al. (2018), which uses Nielsen self-reported income, are not due to measurement errors in self-reported income: The relationship between income and households' private-label share remains economically small in either case. Our present analysis confirms this for total CPG consumption, as again the relationship remains economically small both with administrative income data and with self-reported income. While the small effects, together with relatively large confidence intervals, do not allow us to dig deeper into whether and why the relationship with one measure of income is more pronounced, we suggest addressing this issue in future work. This should allow a better understanding of potential limitations when working with self-reported income.

Appendix

Sociodemographic characteristics: Overall GfK data vs. regression data

We report key summary statistics of panelists in GfK data compared to only those who consented to the matching with CBS.

Table 8 Summary statistics of panelists in GfK compared to consenting households in 2011

	Panel A: Age		Panel B: Household size		Panel C: Social class		Panel D: Income class	
	All	Consent	All	Consent	All	Consent	All	Consent
Mean	6.94	7.40	2.49	2.40	4.53	4.61	14.35	14.72
SD	3.02	2.53	1.24	1.20	1.64	1.61	6.25	6.00
P5	1.00	1.00	1.00	1.00	1.00	1.00	3.00	3.00
P25	6.00	6.00	2.00	2.00	4.00	4.00	9.00	11.00
P50	7.00	8.00	2.00	2.00	5.00	5.00	16.00	16.00
P75	9.00	9.00	4.00	3.00	6.00	6.00	20.00	20.00
P90	11.00	11.00	4.00	4.00	6.00	6.00	21.00	21.00
P95	11.00	11.00	5.00	5.00	6.00	6.00	22.00	22.00

Table 8 shows key summary statistics for the year 2011 for sociodemographic variables obtained from GfK data for both all GfK households and households consenting to the matching with CBS. Panel A shows summary statistics for age, panel B shows summary statistics for household size, panel C focuses on social class, and panel D on the income of the household head. The table is based on appendix Table 14 in Brancatelli et al. (2022)

Table 9 Summary statistics of regional fixed effects across all years and retailers

	Mean	SD	Skew	P5	P10	P25	Median	P75	P90	P95	N
Regional FE	0.0017	0.0042	1.1826	-0.0031	-0.0022	-0.0009	0.0008	0.0031	0.0078	0.010	132

Table 9 depicts summary statistics of regional fixed effects from independent yearly regressions for six major retailers based on the household scanner data of the GfK consumer panel between 2011 and 2018. The table is based on Table 4 in Brancatelli et al. (2022)

National pricing

We describe how retailers in the Netherlands practice national pricing. To illustrate that national pricing existed throughout the entire period for Dutch retailers, we analyze price variation across regions for six major retailers in the Netherlands.

For this purpose, we remove products with prices that are fourfold higher than the median or smaller than a quarter of the median price. Furthermore, we also disregard barcodes artificially introduced by GfK to classify unpackaged fresh food products, which usually do not have a GTIN. From this set of products, we identify and keep the 500 most popular products per retailer per year and separately estimate a price regression for each retailer and year from 2011 to 2018. In our regression, the dependent variable is the log of a household shopping trip-specific price of any given product. The independent variables comprise a set of retailer-specific barcode dummies, monthly time fixed effects, and three regional fixed effects.²⁰ Throughout the analysis, we use North Netherlands as the basis. Overall, we estimate price regressions for six retailers and eight years²¹ and extract the set of regional fixed effects for each regression.

Summary statistics are represented in Table 9, showing that across all retailers and years, the fixed effects are considerably small, with more than 90% being smaller than 1%.

We finally note that even if a given retailer practiced regional price differentiation not captured by this approach, this would not risk confounding our interpretation of the income coefficient as long as price differences do not change over time.

²⁰ Household scanner data do not contain geo information about individual shopping trips. Therefore, we rely on household location (postcode) to construct regional fixed effects. Regions are derived from the official NUTS 1 codes of the Netherlands: North Netherlands, East Netherlands, West Netherlands, South Netherlands.

²¹ In sum, we estimate 44 regression specifications: Until 2014, we estimate the regression for six major retailers. Since two major retailers merged in 2014, we only estimate the regression for five retailers from 2015 onward.

Socio-demographics for households in regression data

Table 10 Summary statistics of key socio-demographic variables

Year	Label	m—S	m—Pop	p10—S	p10—Pop	p25—S	p25—Pop	p50—S	p50—Pop	p75—S	p75—Pop	p90—S	p90—Pop
2011	Disposable income p.c	23,379.33	23,532.35	14,736.30	12,164.27	17,660.22	15,925.80	21,993.73	21,001.24	27,269.93	27,768.59	33,986.74	36,471.79
2018	Disposable income p.c	24,037.68	24,852.26	14,683.00	12,513.91	17,795.22	16,552.00	22,571.00	22,349.00	28,410.00	29,635.88	35,008.50	38,164.17
2011	Financial assets p.c	29,624.24	37,910.28	1,060.96	344.06	3,333.90	1,943.71	11,589.33	9,032.25	29,338.02	26,900.76	66,394.65	76,083.19
2018	Financial assets p.c	27,996.16	36,221.45	715.00	346.15	2,677.65	1,790.77	9,814.00	8,731.18	25,378.06	26,476.00	58,580.00	70,196.00
2011	Household members	2.46	2.18	1.00	1.00	2.00	1.00	2.00	2.00	3.00	3.00	4.00	4.00
2018	Household members	2.40	2.12	1.00	1.00	1.00	1.00	2.00	2.00	3.00	3.00	4.00	4.00
2011	Number of children	0.49	0.43	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	2.00	2.00
2018	Number of children	0.49	0.39	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	2.00	2.00
2011	Number of females	1.26	1.10	1.00	0.00	1.00	1.00	1.00	1.00	2.00	1.00	2.00	2.00
2018	Number of females	1.25	1.07	1.00	0.00	1.00	1.00	1.00	1.00	2.00	1.00	2.00	2.00
2011	Number of inc. earners	1.94	1.72	1.00	1.00	1.00	1.00	2.00	2.00	2.00	2.00	3.00	3.00
2018	Number of inc. earners	1.92	1.73	1.00	1.00	1.00	1.00	2.00	2.00	2.00	2.00	3.00	3.00

Table 10 shows summary statistics for both the analysis sample and the population for the following socio-demographic variables for the years 2011 and 2018: disposable income per standardized household member, financial assets per standardized household member, the number of household members, the number of females, the number of children and the number of income earners in a household. Columns abbreviated with S. show the corresponding statistics for the sample and columns abbreviated with Pop. Show corresponding population figures Note that household size for disposable income and financial assets is standardized using an OECD scale (defined as $1 + 0.7(n-1) + 0.3k$, where n is the number of adults and k the number of children. Euro values are expressed in constant 2018 Euro

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Declarations

Competing interests None of the authors has competing interests.

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