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Abstract

Industry sentiment and practitioners' observations link income and wealth to private-label demand. The intuition is that decreasing income and wealth increase the demand for (cheaper) private labels. Recent academic research focusses on measuring the causal effect of income and wealth changes on demand for private labels. Whereas plausible causality is harder to establish in aggregate, time series analyses, such analyses suggest large effect sizes (e.g. Lamey, Deleersnyder, Dekimpe, and Steenkamp 2007). An individual-level perspective greatly facilitates plausibly causal estimates (Dubé, Hitsch and Rossi 2018) but poses measurement challenges. We overcome these challenges by linking household scanner data to administrative data. We analyse individual-level private-label shares measured in household scanner data as a function of income and wealth, both from a linked administrative database in the Netherlands in the period from 2011–2018 and both aggregated over all household members (rather than only from the main earner). We find that relying on within-household variation in surveyed income data attenuates income effects relative to using that from administrative data. Yet, we find an economically small effect. Using our direct measures of wealth, we find a statistically reliable but again economically small effect of financial wealth on private-label shares. Wealth from housing does not proxy this effect, nor does housing wealth seem to independently influence private-label shares.

JEL Classification: D12, M30

Keywords: Private-label demand, income and wealth effects, Recession, Consumer demand

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Measuring Income and Wealth Effects on Private-Label Demand with Matched Administrative Data[1]

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May 2021

Abstract

Industry sentiment links income and wealth to private-label demand. The intuition is that decreasing income and wealth increase the demand for (cheaper) private labels. Whereas plausible causality is harder to establish in aggregate, time series analyses, such analyses suggest large effect sizes (e.g. Lamey, Deleersnyder, Dekimpe, and Steenkamp, 2007). An individual-level perspective greatly facilitates plausibly causal estimates (Dubé, Hitsch and Rossi, 2018) but poses measurement challenges. We overcome these challenges by linking household scanner data to administrative data. We analyse individual-level private-label shares measured in household scanner data as a function of income and wealth, both from a linked administrative database in the Netherlands in the period from 2011 to 2018 and aggregated over all household members (rather than only from the main earner). We find that relying on within-household variation in surveyed income data significantly attenuates income effects relative to using that from administrative data. Yet, we still find an economically small effect. In addition, changes in wealth have at most an economically small effect on private-label shares.

JEL-Classification: D12, M30

Keywords: Private-label demand, income and wealth effects, recession, consumer demand

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I Introduction

The financial crisis reignited the interest in how household finances affect purchase and consumption behaviour. Such learnings should also be relevant in the context of the current COVID-19 crisis, in particular when its impact on household finances proves to be more than only transient. To obtain plausibly causal estimates, rather than relying only on aggregated data on consumption, marketing scholars and practitioners can typically avail themselves of various sources of highly granular data, such as from household or retailer scans. When this data includes information on the income or wealth of individual shoppers, however, it is typically self-reported and thus subject to measurement errors. In addition, as marketing companies typically use information on income as one of several inputs to broadly cluster shoppers or households, and timely updates of household-specific variables are costly, within-household variations may be measured less accurately – and such information is typically only reported in brackets (and censored at the top). Finally, panel participants rarely seem to be asked about aggregate household income or wealth, as such information may not be readily available to them.

In this paper, we introduce a novel data set that combines the high granularity of household scanner data with precise measures of household income and wealth obtained from administrative data. The novelty lies in the match of these data sources at the individual household level. Obtaining the explicit consent of panel members, we were able to match household purchases of Consumer Packaged Goods (CPG) recorded in GfK's consumer panel to data from the national statistical office, in our case the Centraal Bureau voor de Statistiek (CBS) in the Netherlands. Importantly, in contrast to some other European countries, such as Germany, in the aftermath of the financial crisis the Netherlands experienced a (double-dip) recession and with it a surge in unemployment and a particularly pronounced drop in house prices.

We use this data to contribute to a question that has recently received much attention in the marketing literature: To what extent do changes in income and wealth affect the choice of private-label products? The literature documenting that notably economic recessions are associated with an increase in the share of private-label products goes back at least to Quelch and Harding (1996) and Ang et al. (2000).[6] Departing from this earlier literature, we follow Dubé et al. (2018) and exploit a panel structure, while controlling for changes in relative prices as well as supply to measure putatively causal income and wealth effects.

Our focus lies on changes in income. We have two main findings. Depending on the employed (supply) controls, the statistically significant log income coefficient lies between -1.61 and -2.78. Thus, a 25 % decrease in income implies an increase of the private-label share of around 0.47 to 0.81 percentage points only. While

[6] Using time-series data from the US, such a correlation was confirmed, for instance, by Hoch and Banerji (1993). Lamey et al. (2007) extended this finding to countries beyond the US.

this effect cannot be compared directly with that in Dubé et al. (2018), given that their results pertain to the US and to a different period, we confirm their main conclusion: Changes in income alone may contribute only little to the share of private labels both at the individual level and across all CPG sales. For our second main finding, we compare results with those obtained when using instead self-reported main earner income in the household panel. Then, the effect of income is no longer statistically significant (and its absolute size only one quarter of the earlier estimate). As results are however comparable in cross-sectional or pooled regressions, we identify considerably smaller variations over time in reported main earner income as the main reason. Specifically, we show how the coarse reporting of income in brackets attenuates the effect. Notably, with respect to housing wealth, we do not find a significant effect also with administrative CBS data (while that of net wealth is again economically small).[7]

CPGs in the Netherlands exhibit a large and growing share of private labels. Excluding the fresh food category, which in the Netherlands is to a large extent unpackaged, the average household private-label share increases from around 39 % at the beginning of 2011 to around 43 % in 2013, while after the end of the recession it rises only slightly to around 44 % until 2018.[8] This is considerably larger than the shares reported for the US in Dubé et al. (2018), which up to 2012 remained at or below 20 %. While some of the larger penetration of private labels in the Netherlands is due to the presence of so-called hard discounters, which stock almost exclusively private labels, the share of private labels at all other retailers lies still at around 31 %.

Although our estimated effects are small, even absent additional controls, we are careful to rule out supply-side explanations, e.g. that the availability of private labels has increased or that private-label prices have decreased relative to those of national brands. As retailers differ considerably in their share of private labels, we control for changes in retailers' outlets in a household's neighbourhood. We also interact this with a measure of a retailer's offering of private-label vs. national-brand products and relative price changes. Both when controlling for changes in (relative) prices and offerings, we can rely on the observation that in the Netherlands large retail chains follow national strategies, and we confirm this empirically.

We organise the remainder of this paper as follows. Section II introduces the data. Section III describes the institutional background. This includes variations in key macroeconomic indicators, and how these are reflected

[7] With respect to housing wealth, Dubé et al. (2018) find a significant, albeit again small effect when they proxy changes in individual home value with regional changes of a commonly used home value index. Stroebel and Vavra (2019) also report correlations between house values and private-label expenditures for homeowners, which our analysis does not confirm.

[8] After a short phase of recovery, the financial crisis led to a second downturn in the last quarter of 2011, with the ensuing recession lasting until the third quarter of 2013. Averages include all observations from 2011 to 2018 (totalling 34,730 household-year observations). The share of private labels varies, however, widely across categories, from 9.88 % for Fragrances to 72.25 % for Paper Products (cf. Table 14 for summary statistics).

in variation in our data, as well as relevant facts about the grocery industry in the Netherlands. Section IV investigates the effect of income on the private-label share. Section V compares results to those obtained with self-reported income. Section VI offers concluding remarks, while additional material is contained in an appendix (Section VII).

II Data

We introduce a novel data set matching household scanner data from the Dutch GfK consumer panel with administrative data on income and wealth as well as socio-demographic characteristics, as provided by CBS.[9] We thus observe on the level of individual households both purchases and income and wealth between 2011 and 2018.[10] We further enrich this data with a panel of retail outlets and their geographical location (geo coordinates), thus providing additional supply-side information. We next introduce the individual data sets in more detail.

II.i Household scanner data

Household scanner data from the GfK consumer panel covers household purchases for a wide range of consumer packaged goods (CPG) categories (both food and non-food). As we already noted, in the Netherlands fresh food is largely unpackaged, which is also why this category is typically not included in industry reports. We thus also ignore this category.[11] GfK data is similar to that of the Nielsen Homescan panel, which may be more familiar to researchers in the US. In the Netherlands, GfK is the only provider of such data.

Households selected for the GfK consumer panel are equipped with an electronic home scanning device. After each shopping trip, the household scans the barcodes of purchased goods and reports additional information. The unit of observation is thus a single product on the barcode level bought by an individual household on a certain day from a specific retail chain. GfK enriches the data with additional attributes on the barcode level. For our analysis, we use a product's category and, notably, whether it is a private label. From 2011 to 2018 the

[9] Household scanner data from GfK consumer panel is provided by the AiMark foundation.

[10] The starting point is limited by the availability of comparable data from CBS. Matching the data sets was possible as more than 5,000 households individually consented. Matching took place in the secure environment of the CBS, based on household characteristics provided directly by GfK, and was undertaken by the statistical staff of CBS. All analyses with matched data took place in the secure environment of CBS. This excludes the export of matched data.

[11] Packaged goods comprise frozen food, refrigerated food, alcoholic and non-alcoholic beverages, health and beauty products as well as pet needs, cleaning, detergent products and general merchandise.

full panel comprises 22,161 different households with approximately 125 million transactions.[12] Matching with CBS data, as introduced below, is only possible for those households which explicitly consented.[13] This restricts our unbalanced panel from 11,041 to 6,151 distinct households in 2018, which explicitly consented to supplement income and wealth data from CBS; cf. the second and third column in Table 1.[14]

Table 1: Household sample sizes[15]

Year	GfK	CBS consent	CBS match	Regression
2011	11,664	3,173	3,110	3,108
2012	11,869	3,600	3,533	3,526
2013	11,242	3,831	3,758	3,751
2014	11,413	4,214	4,132	4,110
2015	10,985	4,476	4,396	4,385
2016	10,673	4,740	4,654	4,645
2017	10,649	5,177	5,078	5,065
2018	11,041	6,151	5,455	5,447

Notes: "GfK" denotes number of households in the full consumer panel, "CBS consent" the number of households which consented to have their data matched, "CBS match" the number of households with a successful match, and "Regression" the number of households in our regression analysis.

While our subsequent results are thereby limited to this sample, the following observations suggest that these are not biased by sample selection. Table 2 depicts summary statistics for socioeconomic characteristics and the private-label share (as measured in the GfK consumer panel; for consenting households, we later use administrative data to measure the household size and income, among other household characteristics). These

[12] While there is some attrition, 51.59 % of all households remain when restricting the panel to only those households present over the full period. The average annual retention rate is 90.99 %.

[13] 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, the 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.

[14] The subsequent analyses are restricted to transactions of consenting households in the GfK consumer panel. The complete consumer panel regardless of consenting is used for the national pricing and assortment analyses (cf. Appendix VII.vi), the construction of relative prices of private-label products compared to branded products (cf. Appendix VII.v) and the price index construction (cf. Appendix VII.vii).

[15] The ratio between CBS match and CBS consent is lower in 2018 compared to previous years, as we neglect households for which we observe less than six months of purchase data. The households in the last column of Table 1 are used in our regression analysis as we have complete data for all control variables.

numbers suggest that households' self-selection into the data match does not over- or undersample households along those dimensions within the GfK consumer panel. In Appendix VII.i, we make the same comparison for the first year of our sample, 2011. As we asked for consent in 2018, differences could increase for earlier time periods. Still, even in 2011, differences are small.

Table 2: Summary statistics of panellists in GfK compared to consenting panellists in 2018

	Age		Household size		Social class		Income bracket		PL share	
	All	Consent	All	Consent	All	Consent	All	Consent	All	Consent
Mean	7.02	7.03	2.47	2.43	3.99	4.05	14.13	14.05	44.29	44.42
SDV	2.80	2.77	1.25	1.22	1.72	1.75	6.22	6.14	21.15	21.63
Skewness	-0.61	-0.63	0.55	0.62	-0.52	-0.59	-0.47	-0.44	0.44	0.45
P5	1.00	1.00	1.00	1.00	1.00	1.00	4.00	4.00	13.40	12.82
P25	6.00	6.00	1.00	2.00	3.00	3.00	7.00	7.00	28.38	28.13
Median	7.00	7.00	2.00	2.00	4.00	4.00	15.00	15.00	41.98	42.01
P75	9.00	9.00	4.00	3.00	5.00	6.00	20.00	19.00	58.05	58.45
P90	11.00	11.00	4.00	4.00	6.00	6.00	21.00	21.00	74.35	75.10
P95	11.00	11.00	5.00	5.00	6.00	6.00	22.00	22.00	83.77	85.04

Notes: Table 2 depicts summary statistics of main socio-demographics of the GfK consumer panel and for the subsample of households which explicitly consented. In the table, P5 denotes the 5th percentile of the sample distribution, P10 denotes the 10th percentile and so forth. SDV denotes the standard deviation of the distribution. Table 10 in Appendix VII.i depicts the same summary statistics for 2011.

If the GfK consumer panel over- or undersampled particular strata of the population or if there is a self-selection bias from consenting, results may not be representative of all households in the Netherlands. Our coefficients could then be interpreted only as (local) average effects within our sample. To respond to such possible concerns, we also conduct a weighted regression analysis, where weights are obtained from post-stratification. Post-stratification is possible through our access to registry data for all Dutch households (via CBS). Results are robust, though slightly smaller, as we report in our main regression below.

In all our analyses, we neglect households for which we observe less than six months of purchase data. In addition, we eliminate three households for which we have less than three shopping trips on average per month.[16] Finally, we exclude transactions with unreasonably high or low prices. Removing transactions with prices four times higher than the median or less than a quarter of the median of the same product, [17] we lose less than 1 % of total expenditure.

[16] We calculate the average number of shopping trips per month for a given household as the number of distinct shopping trips divided by the duration in months in which the household remains in the panel.

[17] We identify the individual products via barcodes and calculate median prices across households and months for each year.

II.ii CBS data

The Dutch Centraal Bureau voor de Statistiek (CBS), also referred to as Statistics Netherlands, is a Dutch governmental institution that collects statistical information. Besides providing publicly available statistics at *Open Data Statline*, CBS also collects and provides *microdata* to authorised institutions under strict conditions of confidentiality.[18] The following data sets comprising income, wealth and socio-demographic data were matched with GfK household scanner panel data at the individual household-level.

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 on a yearly basis and as this generally applies to net income after taxes, which are correctly calculated only at the end of the year, we use yearly income for our analysis. This includes *all* household gross income earned in the respective year, including from transfers (cf. Appendix VII.ii). We thus refer to it as a household's *disposable income* for a given year. This administrative data differs in four potentially important ways from income data that is typically used in the analysis of household panel data. Such survey data, which accompanies scanned purchases, is self-reported, typically in the form of income brackets, and censored from above. The data may not be updated each year for each household, and it refers to the main earner and her main income from (self-)employment, rather than reflecting the total income of the household. We will return to these differences in detail below. CBS also provides detailed wealth data for each household. This includes information on real estate, which is important in the Netherlands as in our sample 67.2 % of households own the property they live in. CBS also provides information on financial assets and debt on the household-level. Together, this information determines a household's net wealth (cf. Appendix VII.ii). We acknowledge already here that changes in financial assets are endogenous, depending e.g. on a household's saving decisions, which opens up another potential link between (private-label) consumption and financial assets.[19]

Finally, CBS collects socio-demographic information for each household member. We use this information to build additional controls: the number of household members (at the same address), the number of children, the number of male or female persons, the number of household members receiving an income, and whether a household member was unemployed. Such variables may affect the size and composition of the consumption

[18] CBS microdata data has been used previously in the literature, for instance, in De Meijer et al. (2013), Lammers et al. (2013) or Raymond et al. (2010).

[19] For instance, in principle, it may be possible that a household decides to cut back on expensive national brands to build up savings for the subsequent acquisition of a larger-ticket item, such as a caravan.

basket and thereby the private-label share of consumption. Plus, we add a set of categorical variables for the region of residency.[20]

II.iii Data on retail outlet location

To control for supply-side changes, we enriched our data with a retail outlet panel for the Netherlands, comprising the 12 largest retail chains. Data was purchased from Distrifood Dynamics and consists of quarterly observations of all retail outlets, including addresses, for which we generated geo coordinates. Linking households to coordinates allow us to measure distances between retail outlets and homes. For each household in each quarter, we calculate the shortest distance between each retailer store in the Netherlands and the household.[21] We employ this data below to control for construct household-specific changes in supply.

III Institutional Background

III.i Macroeconomic variation

The financial crisis and its aftermath were severe in the Netherlands. A first recession starting in 2009 was accompanied by a fall in house prices, followed by a more severe recession, notably in terms of unemployment, and a steeper fall in house prices in 2012–2013. Figure 1 uses OECD and public CBS data to report quarterly changes in GDP, unemployment and an index of house prices as well as changes in annual disposable household income for the time period relevant to our analysis.[22]

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[20] NUTS 1 regions of the Netherlands are: North Netherlands, East Netherlands, West Netherlands and South Netherlands. Regions were derived from zip code data, which are included in the household scanner data.

[21] 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 1km on average, as there are overall 459,438 6-digit postal codes in the Netherlands yielding approx. 37 inhabitants for every postal code. This distance is measured for every household before importing the data to the CBS environment. CBS and AiMark do not provide street names or alike for data protection reasons.

[22] The house price index published by CBS is based on the same microdata obtained by the Dutch Land Registry Office (Kadaster), which we use in our analysis. It is based on a complete registration of sales of dwellings and the value of all dwellings in the Netherlands. Disposable income information is obtained from OECD National Accounts Data.

Figure 1: Macroeconomic development from 2011 – 2018 in the Netherlands

Notes: Figure 1 reports changes in GDP, disposable household income, unemployment and an index of house prices between 2011 and 2018 in the Netherlands. Data was obtained from the Dutch Land Registry Office (Kadaster), CBS and the OECD.

Starting from the fourth quarter in 2011 real GDP declined until the third quarter in 2013 along with disposable household income. During this time, unemployment rose by 2.5 percentage points and, according to the index, house prices dropped by around 15 percentage points. All indicators thus bear witness to the recession until 2013, followed by a recovery up to 2018, the end of our observational period. In contrast, for instance, to neighbouring Germany or other Western European countries, the Netherlands was thus more drastically hit by the financial crisis and recovered more slowly. This is important, as we are constrained to using data from 2011 onwards.

Variation in household disposable income. These macroeconomic changes are also visible in our data. To see this, in what follows we restrict attention to those household observations where, on a year-by-year comparison, the number of household members remained unchanged.[23] While observed income increases by 1.97 % per year at the median, there is considerable variation across households and time. Table 3 reports the respective percentiles of the distribution. Figure 2 depicts the respective changes per period, which uncovers the macroeconomic shifts, as over time the fraction of positive changes increases. The variability in positive and negative changes in household disposable income each year facilitates the subsequent identification of income effects.

Table 3: Percentiles of annual percentage changes in household disposable income

	P1	P5	P10	P25	Median	P75	P90	P95	P99
Income	-40.06	-15.53	-8.22	-1.24	1.97	6.79	15.98	25.31	68.70

Notes: Table 3 shows percentiles for annual percentages changes of household disposable income. In the table, P1 denotes the 1st percentile of the distribution, P5 denotes the 5th percentile and so forth. The number of observations considered in the statistic is 25,929.

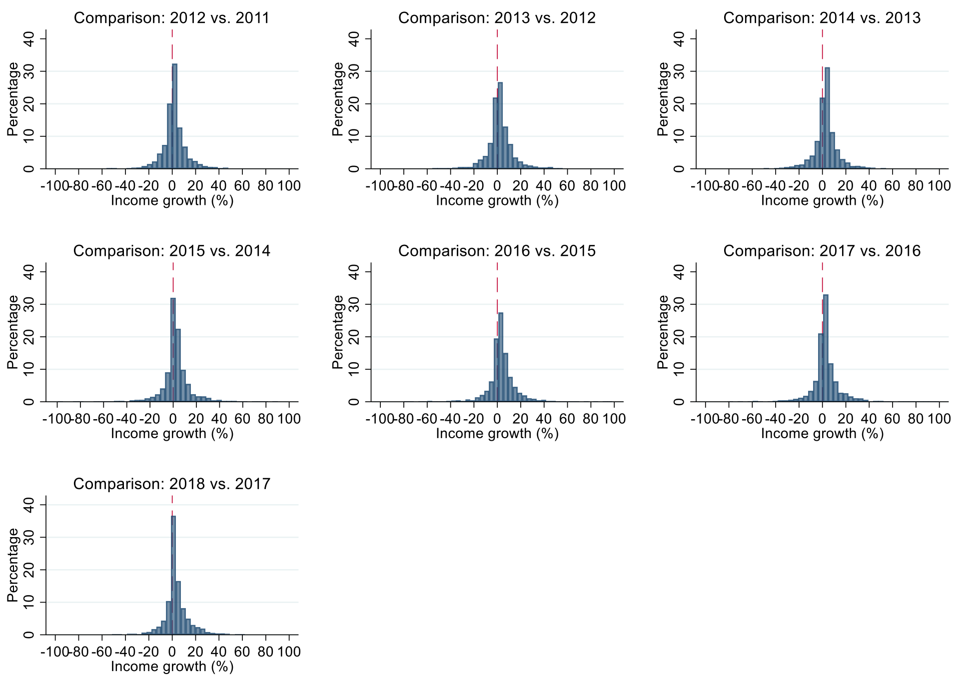

Figure 2: Distribution of annual (percentage) changes in household disposable income

Notes: Figure 2 illustrates the distribution of annual percentage changes of household disposable income. We truncate the distribution at 100 %.

[23] Otherwise, a change in household income may arise simply from the fact that the number of household members with an income increases or decreases. This leaves us with altogether 28,441 year-on-year differences on a household-level.

Variation in housing wealth. Also, the considerable variation in the aggregate value of housing wealth is reflected in our data. Recall that 67.2 % of all covered households own their residence, and this fraction is stable over the considered period. At the median, housing wealth changes by 2.25 % per year. Detailed percentiles are reported in Table 4.[24]

Table 4: Percentiles of annual percentage changes in residential housing wealth

	P1	P5	P10	P25	Median	P75	P90	P95	P99
Resid. housing wealth	-15.06	-10.77	-9.00	-3.19	2.25	5.34	9.05	12.89	19.13

Notes: Table 4 shows percentiles for annual percentages changes of household residential real estate values. The distribution is truncated at the bottom and top 2 %. In the table, P1 denotes the 1st percentile of the distribution, P5 denotes the 5th percentile and so forth. The number of observations considered in the statistic is 16,453.

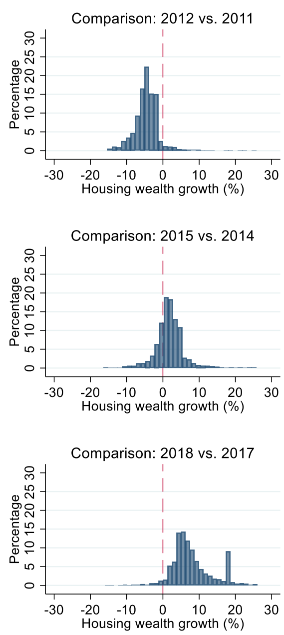

Figure 3: Distribution of annual (percentage) changes in residential housing wealth

Notes: Figure 3 illustrates the distribution of annual percentage changes of residential housing wealth. Figures are truncated at below -30 % and above 30 %.

[24] Throughout the analysis, we truncate the distribution of housing wealth at the bottom and top 2 %. The reason for this is that occasionally municipalities set artificially low housing values for properties that are under construction, which then renders annual growth rates implausible.

Figure 3 graphically depicts the respective percentage changes of own residential real estate wealth per year, which again uncovers the macroeconomic shifts, as, after three years of negative growth, over time, the fraction of positive changes increases considerably. We relegate a description of variations in household net wealth to Appendix VII.iii.

III.ii Household purchases and private-label products

In what follows, we first provide descriptive summaries of household CPG purchases. According to Table 5, across our whole panel, the median number of weekly purchased unique products (identified by barcodes) is 18, corresponding to total expenditures of around EUR 39. The median number of weekly shopping trips is 3, of which 2 are made at the large retail chains (for which we subsequently construct our supply-side controls).

Table 5: Summary statistics of CPG weekly purchases

	Mean	SDV	Skewness	P5	P10	P25	Median	P75	P90	P95
No. of products	20.06	12.82	1.18	4.00	6.00	11.00	18.00	27.00	37.00	44.00
Total expenditure in EUR	46.87	36.11	4.65	7.11	11.32	21.67	38.77	62.72	91.71	113.63
No. shopping trips – all retailers	3.42	2.31	1.35	1.00	1.00	2.00	3.00	5.00	7.00	8.00
No. shopping trips – major 6 retailers	1.96	1.57	1.16	0.00	0.00	1.00	2.00	3.00	4.00	5.00

Notes: Table 5 depicts summary statistics of the number of unique products (identified by barcodes), total expenditure and number of shopping trips per week per household between 2011 and 2018. The summary statistics are based on household scanner data from consenting households of the GfK consumer panel. In the table, P5 denotes the 5th percentile of the distribution, P10 denotes the 10th percentile and so forth. SDV denotes the standard deviation of the distribution. The number of weekly observations considered in the statistic is 1,669,853.

We now provide some aggregate information on the prevalence and purchases of private-label products in the Netherlands, as well as in our data.

Overall prevalence of private labels. We calculate the private-label expenditure share in a given month as the unweighted average of all household-level expenditure shares observed in that month from our data. Specifically, starting with the private-label share at the household-level, we define this as

$$s_{ht} = \frac{\sum_{j \in J_{PL}} y_{htj}}{\sum_{j \in K} y_{htj}}, \tag{1}$$

where y_{htj} is the total expenditure for product j by household h in month t, J_{PL} is the set of barcodes representing private-label products and K is the set of all products.[25] The aggregate private-label share is

[25] We note that for the classification of private-label products, we rely on GfK's classification. Discussion with data providers confirms that this represents a key variable in their own commercial reporting to clients.

calculated as the unweighted average over all households in the sample at the given month and is depicted in Figure 4.

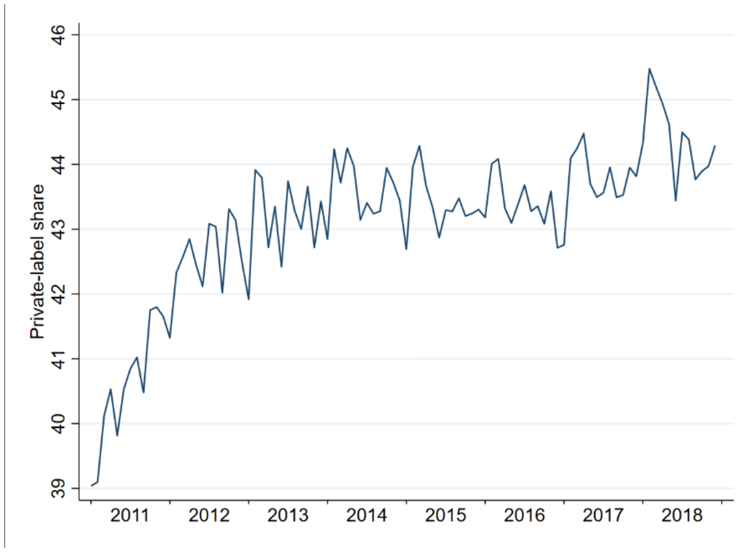

Figure 4: Average private-label expenditure share

Notes: Figure 4 depicts the unweighted average private-label share of all household-month observations of consenting households in the GfK consumer panel from 2011 to 2018.

The monthly private-label share increased from around 39 % at the start of 2011 to a yearly average of 42,65 % in 2013, ending up at a yearly average of 43.77 % in 2018.[26] The recession period 2011 and 2013 is thus associated with a pronounced positive slope, while from there on the average share increased only slightly. The latter observation is probably associated with the already high penetration rate of private labels, far exceeding, for instance, that of the US (cf. the Introduction). The prevalence of private-labels products varies considerably across product categories, with the lowest share of 9.88 % for Fragrances and the highest share of 72.25 % for Paper Products (cf. Table 14 in Appendix VII.iv). A household's specific needs should thus determine the value share of particular categories and thereby the household's private-label share. Across time, as we have already noted, our inclusion of key socio-demographic variables should capture some of the variation in category value shares.

[26] We note that in a working paper version we had included also fresh food products. As noted above, at least in the Netherlands much of this is unpackaged, which is why this category is typically excluded in industry reports. This also affects the nature and validity of a classification as private or national label. In fact, investigating this category in more detail, we found that there the share of private labels had seemingly increased considerably for all years, thus also from 2014 to 2018. With the growing importance of organic and regional products, one explanation is that products that were always supplied by retailers were classified as private label once they were supplied (also) as an organic or regional variant, so that the increase may be partly an artefact. Discussions with data providers and industry experts did not shed additional light on this issue, primarily as this category is of little interest to the purchasers of the data, i.e., brand manufacturers.

Variation of private-label shares between households. Figure 5 to Figure 7 show differences between households based on monthly household observations in 2018, both across all products and separately for food and non-food items. Evidently, private-label shares differ widely between households. For example, with respect to all private-label products, the share at the 10th percentile (of household-year observations) equals 21.75 %, the share at the 90th percentile equals 69.32 %.[27] That the private-label share for non-food products is more skewed may be due to the particularly high private-label shares in some non-food categories and households' more diverse needs with respect to such products.

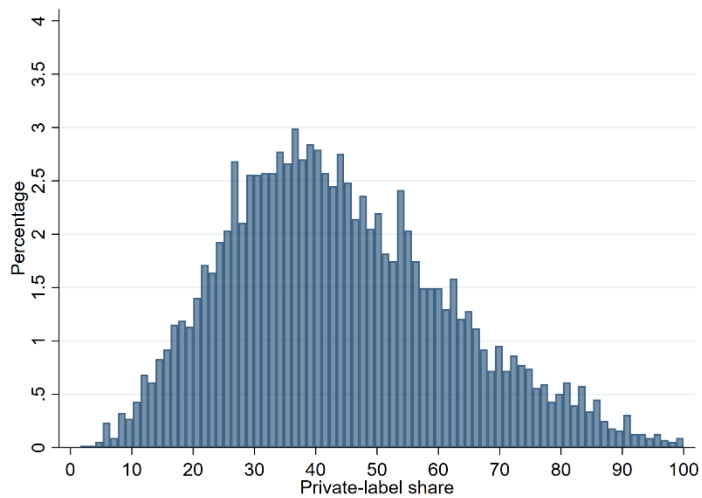

Figure 5: Distribution of private-label expenditure shares in 2018

Notes: Figure 5 illustrates the distribution of the private-label expenditure share using monthly household observations. The statistics are based on household scanner data of consenting households of the GfK consumer panel.

[27] The summary statistics of these distributions are reported in Table 14 in Appendix VII.iv.

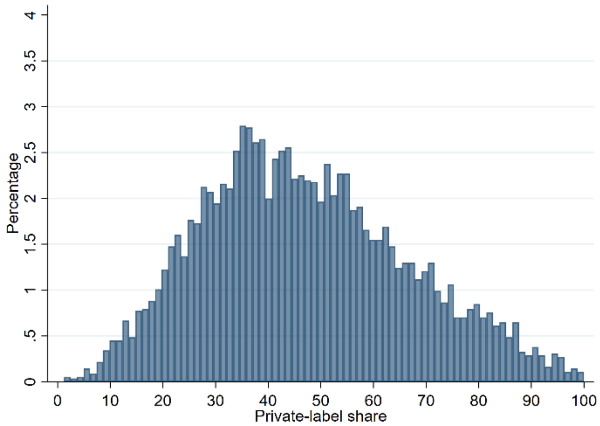

Figure 6: Distribution of private-label expenditure shares for food products in 2018

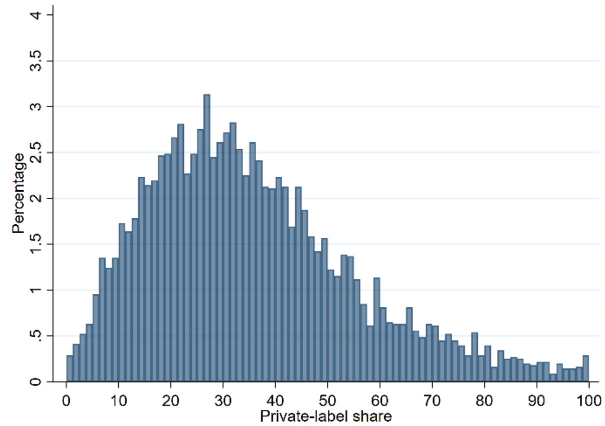

Figure 7: Distribution of private-label expenditure shares for non-food products in 2018

Notes Figure 6 and Figure 7 illustrate the distribution of private-label expenditure shares for food and non-food products from monthly household observations. The statistics are based on household scanner data of consenting households of the GfK consumer panel.

Pricing and assortment of private-label products. The assumption that private labels are cheaper (than national brands) is central to our subsequent analysis that relates changes in income and wealth to changes in the private-label share. Industry reports in the Netherlands indicate, for example, that private labels are, on average, 31 % to 55 % cheaper than comparable national brands at the largest retailer, Albert Heijn (IPLC, 2016). As discussed below, price differences are even larger when considering that hard discounters stock almost exclusively private labels. Indeed, according to another industry report, in 2015 private labels seem to be on average relatively cheaper in the Netherlands than in the US.[28]

We have also confirmed the price difference with our data, albeit only for selected categories that are both important to households and lend themselves to such a comparison. Across all years, we find that the price ratio of private labels to brands equals 86.79 % for coffee, 67.75 % for ketchup, and 66.16 % for washing detergents (cf. Appendix VII.v for details).

Over the considered period and across all retailers we do not see a noticeable shift in private-label innovation, as captured by the development of new product entries in Figure 8: For private labels these have remained virtually constant. Overall, this applies also to national brands, though Figure 8 exhibits a slightly decreasing

[28] IRI Special Report: Private label in Western Economies, 2016. According to the index constructed in this study, based mainly on store-level data, the ratio of private label to national brand prices was then 73.8 % in the Netherlands and 88.5 % in the US.

trend over the recession period. In what follows, we will control on a household level for possible time variation in the assortments households face.

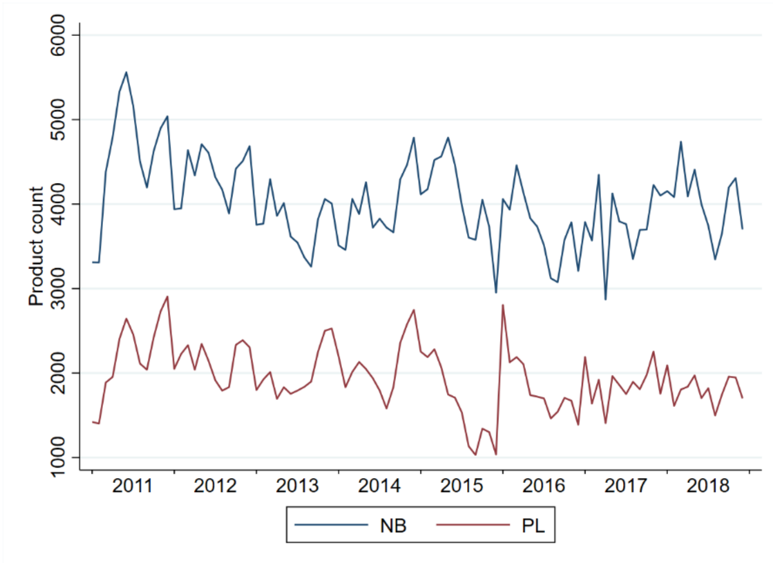

Figure 8: National-brand and private-label product entries

Notes: Figure 8 depicts the number of new private-label and national-brand products entering the market computed from the complete household scanner data, regardless of consenting. A product entry is defined as a newly observed barcode for the first time across all retailers (in a given month). Fresh food products as well as products with artificial GfK barcodes (XFV barcodes) are excluded.

(Hard) Discounters and private labels. In the Netherlands, the two hard discounters Aldi and Lidl stock almost exclusively private labels. Using the full household scanner data from GfK, over all observations the expenditure share for private-label products is above 90 % for the two retailers and thus considerably larger than for all other retail chains.[29] As their joint market share of households' CPG purchases increased considerably over the considered period, namely from 18.60 % in 2011 to 22.57 % in 2018 (excluding fresh food and based on the unweighted average across all households in the total sample)[30], this accounts for part of the overall growth in the private-label share. We can see from our outlet data that this growth was mainly extensive, with one hard discounter increasing the number of outlets from 335 in Q1 2011 to 418 in Q4 2018, i.e. by almost 25 %. The overall pattern of growth remains when we exclude hard discounters: The average

[29] For confidentiality reasons, we do not report individual private-label shares for each retail chain.

[30] Again, most of the growth occurs in the first years of the considered period, with the market share increasing steadily until 2014 (21.27 %), while from then on growing at a much lower rate (with 22.57 % in 2018). We also note that the respective share of total expenditure in the sample (excluding fresh food) is 17.40 % in 2011 and 22.06 % in 2018.

private-label share from national supermarket chains increased from 27.58 % at the beginning of 2011 to a yearly average of 30.28 % in 2014, ending up at a yearly average of 31.10 % in 2018.

III.iii National strategies by retail chains

The retailer landscape in the Netherlands is highly concentrated. In 2011, the six largest retailers in the Netherlands were Albert Heijn, Aldi, C1000, Jumbo, Lidl and Plus.[31] Together, they account for around 59 % of overall purchases in the panel, which increases to around 63 % in 2018.[32] In what follows, we restrict the construction of key control variables to these retailers. For these retailers, we have learnt that they follow national strategies with respect to pricing and assortment. This may be due to the relatively small size of the Netherlands and its uniformly high population density.[33] Because the construction of supply side control variables discussed below relies on national retailer strategies, we have also confirmed national strategies empirically.

First, we consulted the online shopping websites of the various national chains and found that offers (and notably also prices) were independent of a shopper's location.[34] Second, to examine pricing strategies also for past years, we identify the 500 most popular products for each considered retailer and estimate a separate price regression for each year between 2011 and 2018 and each retailer, using fixed effects for barcodes and fixed effects for regions. We find that, on average, regional fixed effects are small in magnitude: Around 80 % of all fixed effects lie between -0,22 % and 0.78 %. Third, we have analysed retailers' assortment strategy. We calculate for each retailer and year the number of observed distinct products and private-label products. Dividing the number of private-label products by the number of all products, for each retailer and each year we calculate the assortment share difference relative to a baseline region. The mean difference is only 0.04 percentage points, and even the bottom and top 5 %-percentiles are far below 1 percentage point. Further details are presented in Appendix VII.vi.

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[31] In February 2012 Jumbo acquired C1000, with rebranding of all stores finalized in 2014. In our construction of controls, we take this into account.

[32] In comparison, the 7th to 10th largest retailers jointly account for around 9 % in 2011.

[33] The Netherlands is the second-most densely populated country in the EU. Its population density is four times the EU average.

[34] This is different in other countries where prices and availability are only obtained after keying in the postcode.

IV Effects of income and wealth on private-label consumption

IV.i Empirical strategy

As discussed in the Introduction, our empirical approach follows closely that in Dubé et al. (2018). Our main innovation is the use of administrative (income and wealth) data at the household-level. One motivation for our analysis is the more pronounced upwards shift in the private-label share during the years of recession (see Figure 4). As private-label products are often substantially cheaper than national brands, as documented above, this suggests a potentially causal relationship. If such a causal relationship between, e.g., income and private-label choice exists, this should be observed also outside a recession when households experience change in income. The use of consumer panel data helps us avoid well-known problems with only cross-sectional variation or only time-series variation in aggregate data. Instead, we intend to isolate the contemporaneous link between within-household changes in income and the private-label share of CPG-expenditures.

Our key dependent variable, the private-label expenditure share s_{ht}, is calculated for each household in each month. We next describe our first key regression equation before discussing potential concerns regarding causality and additional controls:

$$s_{ht} = \beta_0 + \beta_1 log(I_{ht}) + \sum_{t=1}^{T} \beta_3^t D_t + \sum_{f=1}^{F} \beta_4^f x_{ht} + \sum_{r=1}^{R} \beta_5^r G_r + \epsilon_{ht}. \quad (2)$$

I_{ht} is the yearly disposable income of household h in period t. We reserve the coefficient β_2 for our subsequent inclusion of wealth. D_t represents time dummies (quarterly fixed effects to control for seasonality[35] as well as a trend that is interacted with a recession dummy[36]). G_r represents a set of regional fixed effect of households' residency. Finally, x_{ht} represents a set of household socio-demographics. These comprise household size, calculated as the number of officially registered persons in the household, share of children, share of females and employment share, measured accurately through the matched administrative data. Additionally, we add a dummy variable that captures whether at least one household member received unemployment benefits in a given month.

Since the dependent variable is measured in percentage points and we use log income, the β_1 coefficient can be interpreted in the following way: If income increases by 25 % then expenditure share increases by $\beta_1 *$

[35] To reflect changes in the relevance of different product categories, with a potentially different share of private labels, across the year (e.g. Christmas or Easter), we control for seasonality. We add fixed effects for the 2nd, 3rd and 4th quarter.

[36] The trend variable is defined as a monthly incremental number sequence starting from 0 in the base period January 2011. The recession dummy captures the second recession after the financial crisis in the Netherlands. Following the definition of the OECD, it began in October 2010 and lasted until September 2013.

$log(\frac{100+25}{100}) = \beta_1 * 0.22$ percentage points. If income decreases by 25 %, then expenditure share increases by $\beta_1 * log(\frac{100-25}{100}) = \beta_1 * -0.29$ percentage points.

The subsequent analysis compares several models based on the specification in Equation (2). First, we estimate a pooled OLS regression with clustered standard errors on the household-level. Second, we average over all observations for a given household ("between regression"). These two regressions, albeit clearly problematic for causal inference, will contribute to understanding the nature of the different inference from administrative (CBS) and self-reported (GfK) income data. Finally, we estimate within-regressions, exploiting the panel structure of our data.

Controlling for supply-side changes. We now turn to concerns that the coefficient β_1 may pick up other effects than the hypothesized causal relationship between income and private-label consumption. When retailers make private labels relatively cheaper during a recession, β_1 will confound households' reaction to such price changes. In addition, when retailers increase their offering of private-label products in regions that are particularly affected by the recession, this could again confound our estimates. We address concerns about such indirect effects as follows. We exploit the fact that large retailers employ national pricing and assortment strategies. This allows us to overcome the shortcoming of not having access to store-level data. That is, we can calculate retailer-specific assortment and price variables using observations from all purchases. To account for local changes in available retail outlets (that each follow a national strategy), we make use of our (panel) data on outlet locations. For each household, we determine the number of outlets of a given retailer within a certain radius and, as described next in detail, interact price and assortment controls with this measure of (changing) retailer availability.

We calculate for each retailer the share of private-label products (by barcode) in its assortment. For a given household, we then weigh the individual retailer's assortment variable with a specific weight that is calculated by dividing the number of this retailer's outlets by the number of all outlets within the household's neighbourhood (radius). Thereby, we capture changes in the (relative) availability of private-label products both as individual retailers change their assortment (over time) and as the presence of individual retailers (with different private-label shares) changes. With respect to changes in (relative) prices, we proceed likewise: We include household-specific price indices for private labels and national brands, again obtained by weighing the respective retailer-specific price indices by household-specific retailer presence. Details are contained in Appendix VII.vii. Summing up, the regression equation when controlling for supply-side changes reads as follows:

$$
\begin{aligned}
s_{ht} = \beta_0 + \beta_1 log(I_{ht}) + \sum_{t=1}^{T} \beta_3^t\, D_t + \sum_{f=1}^{F} \beta_4^f\, x_{ht} + \sum_{r=1}^{R} \beta_5^r\, G_r + \beta_6\, log\left(PI_{ht}^{PL}\right) \\
+ \beta_7\, log\left(PI_{ht}^{NB}\right) + \beta_8\, AS_{ht} + \epsilon_{ht},
\end{aligned}
\tag{3}
$$

where $log\left(PI_{ht}^{PL}\right)$ represents the logarithm of the household-specific price index for private-label products, analogously $log\left(PI_{ht}^{NB}\right)$ represents the logarithm of the household-specific price index for national-brand products and AS_{ht} represents the time-specific (private-label) assortment share (in the neighbourhood of household h).

By controlling for potential supply-side changes, we want to ensure that the income coefficient captures only the direct effect of changes in income and wealth, rather than also indirect effects through changes in prices and availability, to the extent that households would be exposed differently to such changes. To establish causality we must, however, still rely on the assumption that conditional on all used controls, including household fixed effects and the trend, within-household changes in the variable of interest, current income, are exogenous (“as good as randomly assigned”).[37]

Representativeness. The composition of our sample may suffer from self-selection.[38] First, the GfK consumer panel already represents a subsample of the population. Second, members of the GfK panel needed to consent to matching GfK data with CBS registry data. To formally address possible biases stemming from the described sampling procedure, we construct year-specific adjustment weights for post-stratification leveraging our access to data for *all* Dutch households (via CBS). Specifically, we stratify our regression samples into 10 strata of equal size based on disposable yearly income from the CBS household income registry.[39] For each stratum we compute a correction weight based on the respective percentage in the overall population.

IV.ii Main results

In Table 6, we report our main regression results. Column (1) shows results for the pooled regression, column (2) for the between-regressions, and columns (3) to (5) show results for the within-regressions. Our main coefficient of interest is the coefficient on log income. For the pooled and between regressions, the coefficient

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[37] As we already fully exploit our (matched) sample, we cannot further analyze whether households which experience a more negative shock in the recession period already showed a stronger increase in private-label consumption earlier (cf. Dubé et al. (2018)).

[38] Hence, following the terminology in the literature, e.g. in Henry (1990), it may represent a non-probability sample.

[39] The key assumption behind this stratification is that households within the strata are homogeneous with regard to their probability of being included in the sample. In the standard case of random sampling, all households would have equal probability of inclusion (cf. Bethlehem and Biffignandi (2011)).

is largely similar, as is that for the within-regressions across the two specifications (with and without supply-side controls). We note that also the coefficient from the stratified regression in column (5) is largely comparable, albeit lower by around one quarter.

Table 6: Private-label share regressions – Disposable household income

	(1) Pooled OLS	(2) Between	(3) FE	(4) FE + SS	(5) FE + SS Weighted
log(CBS income)	-6.693***	-7.332***	-2.279***	-2.268***	-1.606***
	(0.58)	(0.62)	(0.38)	(0.38)	(0.42)
Household size	3.063***	3.165***	1.425***	1.430***	1.242***
	(0.30)	(0.35)	(0.22)	(0.22)	(0.24)
Share of females	-0.530	-0.938	-1.121	-1.107	-0.789
	(0.86)	(0.83)	(1.03)	(1.03)	(1.07)
Share of children	0.467	2.891	-0.563	-0.542	-0.585
	(1.75)	(2.23)	(1.02)	(1.02)	(1.08)
Share of employed	2.807**	4.066**	0.341	0.344	-0.123
	(1.34)	(1.87)	(0.71)	(0.71)	(0.77)
Unemployment	2.749***	7.270***	0.175	0.161	0.319
	(0.82)	(2.24)	(0.33)	(0.33)	(0.37)
Trend			0.036***	0.036***	0.035***
			(0.00)	(0.00)	(0.00)
Trend x recession			0.026***	0.024***	0.025***
			(0.00)	(0.00)	(0.01)
log(PI_NB)				-11.262***	-8.558**
				(3.57)	(4.36)
log(PI_PL)				-2.857	-3.843
				(3.34)	(4.10)
Assortment index				9.061	11.464
				(6.77)	(7.51)
Observations	390,592	5,461	390,592	390,592	390,592
R^2	0.038	0.065	0.639	0.639	0.629
Adjusted R^2	0.038	0.063	0.634	0.634	0.624

Notes: This table presents the estimation results from the baseline regression models. In all specifications the dependent variable is the private-label share. The first column depicts results from a pooled OLS regression, column (2) represents the regression results from a between estimation, where all observations across a given household are averaged. Columns (3) and (4) represent the regression results from a within-estimation. In each specification, we include sociodemographic control variables and (omitted) dummies to control for seasonal and regional effects, as well as a constant. In column (3) we include in addition a linear trend and a trend variable interacted with a recession dummy. In column (4), we add to the specification in column (3) the logs of price indices and a private-label assortment index. Column (5) replicates the results from column (4) including sampling weights. We report standard errors clustered at the household-level in parenthesis. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Coefficients for the pooled and the between-regressions are three times larger than for the within-regressions. After accounting for unobserved time-invariant differences, the coefficient is still statistically significant but economically small. The estimate implies only a 0.51 percentage-point increase in private-label share for a 25 % reduction in income (column (3) with a coefficient of -2.279). That the coefficient is economically small confirms the key insight in Dubé et al. (2018), even though our estimated effect is around 5.5 times larger.[40] While adopting the approach of Dubé et al. (2018), we already noted that there are various differences to their study. In particular, we cover a different country and different period. There are also other differences, as we use household instead of main earner income and administrative instead of self-reported data. We discuss these differences in detail subsequently. Before discussing the reported other coefficients, we note that results remain essentially stable when focussing only on the smaller subset of households that remained in the sample for all of the considered eight years (see Appendix VII.viii).

Trend variables are statistically and economically significant: 12 months account for a positive change of 0.43 percentage points, increasing to 0.74 percentage points during the recession. Recall next that we constructed all socio-demographic variables at the household level, such as the size of the household and the share of children. This way we can use the same variables across all three specifications, though they largely remain insignificant in the within-regressions. Still, household size remains significant with positive sign. An increase in household size thus seems to independently lead to a higher private-label share. As the composition of the household and thus changes in household needs are controlled for separately, the effect should, ceteris paribus, be driven by a reduction in income per household-member.

The household perspective may mask the impact of unemployment, both as an unemployment incidence may not refer to the main earner and as the income of other household members should smooth the economic effect. In fact, when analysing only *single* households, the unemployment variable becomes statistically significant with a coefficient of 1.491 in our specification including all controls (cf. Section VII.viii for a complete table of results). Moving into or out of unemployment is thus associated with a change in the private-label share of around 1.5 percentage points, after controlling for the contemporaneous change in income. For single households, the absolute value of the income coefficient in the within-regression increases from -2.268 to -3.246. When unemployment reduces contemporaneous income by 25 %, which is a realistic figure for the Netherlands,[41] the overall effect on the private-label share would thus be 2.5 percentage points.

Finally, the addition of supply-side controls does not change results. The controls for (household-specific) assortment and the price of private-label products have the expected (positive) sign but are relatively small and insignificant. The control for the price of national brands has the wrong (negative) sign. This may be due to the specific construction of this variable, as when an outlet with both cheaper national brands and cheaper and a

[40] For this purpose, we compare our income coefficient in column (3) of our regression with the coefficient in Table 5 in Dubé et al. (2018) (coefficient of -0.412), where no supply-side controls have been added.

[41] In the Netherlands, for average wages unemployment benefits account for 75 % of last pay for the first month, then declining to 70 %. The overall duration depends on years of contribution, with payments extending for as long as 24 months.

potentially larger private-label assortment opens up in the neighbourhood of a household, this may both reduce the household-specific national-brand price index and push up its private-label share. We acknowledge this deficiency, as well as the overall problem to adequately control for changes in the household-specific consideration set, covering different outlets and their respective assortments. However, and reassuringly, dividing the (household-specific) national-brand price index by the private-label price index and including this ratio as a single price control yields a positive (0.057), albeit insignificant coefficient while the coefficient of income remains virtually unchanged (at now -2.277). We omit a full statement of the regression table.

Corroborating the economically small effect. In various analyses, we have looked into the relationship between household income and private-label share for CPGs at a more granular level. We briefly summarize the key results.[42] A split into food and non-food categories reveals that the respective coefficients are highly similar: Compared to the baseline coefficient of -2.268 over all categories, for food categories alone it is -2.190 and for non-food categories alone it is -2.419. This suggests either that food and non-food purchases are on average equally essential, or that when faced with, say, a decrease in income, Dutch households do not save more on non-essential items compared to essentials. Speaking in favour of the second hypothesis, when we investigate individual categories, there is not a single category in which we observe a strikingly stronger response.[43]

Next, introducing additionally lagged (logged) income, the respective contemporaneous coefficient decreases in absolute terms to -2.024 (from -2.268), while the lagged coefficient is also significant at the 1 % level and equals -1.157 %. The aggregate effect thus remains small. In sum, these additional analyses confirm that income changes are only marginally related to changes in the private-label share of households' CPG purchases.

In the subsequent section we confirm this also for changes in household wealth. We note that this observation of an only attenuated relationship between the private-label share and income and wealth is independent of whether the respective changes are idiosyncratic or concurrent with the business cycle. We acknowledge that this leaves open the question why the private-label growth rate was still particularly pronounced during the recession. When considered over the longer term, however, it seems that independent of the recession following the financial crisis, CPG retailing in the Netherlands underwent a considerably stark restructuring from the middle of the first decade to the middle of the second decade of this millennium, including an extensive market

[42] To save space, we omit a full statement of the respective regression tables.

[43] For our analysis of all food and all non-food categories combined we constructed again the respective supply-side controls, which again did not affect results. Given the reduced number of observations, however, we did not construct these variables for individual categories. The absolute value of the income coefficient was at -3.113 highest for pet needs (and significant at the 5 % level). The coefficient remained negative for all categories but cigarettes (at 1.173), though this was obtained from only 19,258 observations (compared to still 133,956 for pet needs, for instance) and not significant.

share growth of German hard discounters Aldi and Lidl and an expansion of private labels at national retail chains. We return to this larger picture in our concluding remarks.

IV.iii Changes in wealth

We now enrich our specification by including variables of household wealth. Our starting point is Equation (3), to which we add as additional right-hand side variable $log(W_{ht})$ for the logarithm of a household's respective wealth at a given time. In Table 7 we report separately regression results when including housing wealth (column 2) and net wealth (column 3).

Table 7: Private-label share regressions – Income and wealth

	(1) Income	(2) Income + Housing wealth	(3) Income + Net wealth
log(CBS income)	-2.268***	-2.196***	-2.174***
	(0.38)	(0.48)	(0.40)
log(Housing wealth)		-0.443	
		(0.66)	
log(Net wealth)			-0.311***
			(0.11)
Household size	1.430***	1.309***	1.540***
	(0.22)	(0.26)	(0.24)
Share of females	-1.107	-2.110	-1.214
	(1.03)	(1.33)	(1.14)
Share of children	-0.542	0.126	-1.020
	(1.02)	(1.22)	(1.09)
Share of employed	0.344	0.075	0.229
	(0.71)	(0.83)	(0.76)
Unemployment	0.161	0.413	0.298
	(0.33)	(0.42)	(0.35)
Trend	0.036***	0.034***	0.036***
	(0.00)	(0.00)	(0.00)
Trend x recession	0.024***	0.020***	0.020***
	(0.00)	(0.01)	(0.00)
log(PI_NB)	-11.262***	-10.053**	-8.875**
	(3.57)	(4.33)	(3.91)
log(PI_PL)	-2.857	-3.859	-3.793
	(3.34)	(3.94)	(3.61)
Assortment index	9.061	13.630*	18.707***
	(6.77)	(7.69)	(6.87)
Observations	390,592	248,494	312,169
R^2	0.639	0.664	0.652
Adjusted R^2	0.634	0.659	0.647

Notes: This table shows variations of our baseline within estimation incl. wealth variables. Column (1) replicates the baseline result presented in column (4) of Table 6 with the dependent variable being the private-label share. Column (2) presents results of the same regression, including the housing wealth variable and column (3) presents results of the regression, including the log of net wealth. We omit observations at the bottom and top 2 % of the housing wealth distribution. The reason for this is that, occasionally, municipalities set artificially low housing values for properties that are under construction, which then renders annual growth rates implausible. Furthermore, in column (3) we add 1 EUR to the net wealth variable if the value of the observation is zero since these observations would otherwise be lost due to the log transformation. This applies to 266 net wealth observations. In each specification, we included (omitted) dummies to control for seasonal and regional effects, as well as a constant. Clustered standard errors are displayed in parenthesis. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note that by construction, we only consider changes in housing wealth for those household who already own their residential property (and the number of observations decreases accordingly). Thus, the respective changes in the variable should indeed be exogenous. Instead, we already noted above that this cannot be claimed for net wealth, which includes financial assets, such as deposit savings.

We note first that the coefficient of income from our main regression (repeated in column 1) remains almost unchanged. Both coefficients for housing and net wealth have the predicted negative sign, but only the coefficient for net wealth is statistically significant, though at -0.311 once again economically small. This confirms the overall picture of a weak relationship between the private-label share and changes in households' financial positions.

V Comparison to results with self-reported income

GfK data also contains information on the net income of the main earner, which is thus in line with the respective information in the Nielsen Homescan panel. GfK asks panellists on a yearly basis to report average monthly net non-financial income (including salary, income from self-employment, pensions and social benefits), which thus notably excludes capital income as well as other positive and negative transfers. GfK informed us that panellists provide their responses at the end of a given year and that GfK uses these responses to refresh panel information in the first quarter of the subsequent year. When using reported income in the following analysis, we make sure that we take into account the resulting lag of one year. Table 21 in the Appendix reports the respective bracketing of monthly income, with the lowest category "below 700 EUR" comprising 0.66 % of household-month observations and the highest category "4100 EUR and more" comprising 5.48 % of observations. As we associate each household with the respective mean of the respective income bracket, we must exclude these observations, as well as those with missing income (7.01 % of observations). Losing thereby around 13 % of observations does however not explain the differences that we discuss below. In fact, with the same restricted sample, the main coefficient for CBS disposable income changes only marginally to -2.536 and does not change statistical significance.[44]

Compared to CBS disposable income, as used in the preceding regressions, we thus have the following differences: GfK's income is self-reported, it is censored at the top and only reported in brackets, it refers only to the main earner rather than to the household in total and it does not include all sources of income. Before proceeding we note that a priori behavior may even be associated more strongly with reported income, rather than "true" income, as such reporting may more closely reflect households' perceptions. Note, however, that

[44] For brevity's sake, we omit a full statement of the regression table.

this should apply more to current income, while GfK's reported income refers to last year's average monthly income.

Table 8 reports regression results when GfK net income data is used. To ensure comparability, we use the same controls as for the CBS disposable income regression (including socio-demographic controls from CBS data). Results for the pooled and between-regressions are largely similar to those with CBS disposable income data: The income coefficient for the pooled regression is -5.948 with GfK and -6.693 with CBS data, that for the between-regressions is -6.195 with GfK and -7.332 with CBS data. Results differ, however, substantially for the within-regression: With GfK data, the income coefficient becomes statistically insignificant. And at -0.650 (including supply-side controls; cf. column 4) it is only one quarter of that with CBS disposable income.

Table 8: Private-label share regressions – GfK net income data

	(1) Pooled GfK	(2) Between GfK	(3) FE GfK	(4) FE GfK + SS
log(GfK income)	-5.948***	-6.195***	-0.656	-0.650
	(0.68)	(0.73)	(0.54)	(0.54)
Household size	2.072***	2.026***	0.845***	0.852***
	(0.28)	(0.33)	(0.21)	(0.21)
Share of females	-0.817	-0.969	-0.453	-0.462
	(0.91)	(0.88)	(1.12)	(1.13)
Share of children	2.142	3.373	0.495	0.508
	(1.83)	(2.33)	(1.13)	(1.13)
Share of employed	1.259	1.396	0.329	0.332
	(1.40)	(1.92)	(0.77)	(0.77)
Unemployment	2.846***	8.224***	0.252	0.236
	(0.89)	(2.38)	(0.34)	(0.34)
Trend			0.031***	0.031***
			(0.00)	(0.00)
Trend x recession			0.024***	0.022***
			(0.00)	(0.00)
log(PI_NB)				-13.508***
				(3.87)
log(PI_PL)				-5.276
				(3.53)
Assortment index				3.166
				(7.82)
Observations	339,654	4,894	339,654	339,654
R^2	0.032	0.054	0.646	0.646
Adjusted R^2	0.032	0.052	0.641	0.641

Notes: This table shows variations of our baseline estimations using the income variable from GfK instead of CBS income. In all specifications the dependent variable is the private-label share. The first column depicts results from a pooled OLS regression, column (2) represents the regression results from a between estimation, where all observations across a given household are averaged. Columns (3) and (4) represent the regression results from a within-estimation. In each specification, we include sociodemographic control variables and (omitted) dummies to control for seasonal and regional effects, as well as a constant. In column (3) we include in addition a linear trend and a trend variable interacted with a recession dummy. In column (4), we add to the specification in column (3) the logs of price indices and a private-label assortment index. We report standard errors clustered at the household-level in parenthesis. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As we already noted, marketing companies like GfK use information on the income of the household's main earner as one determinant of the household's social-economic status. When comparing levels between households, the two income variables are however sufficiently correlated to translate into comparable income coefficients.[45] This is different with respect to intertemporal variations. Household total income exhibits a much higher variation for two reasons. First, more sources of (variable) income are considered (with the median yearly-household income being 1.4 times the median of GfK reported main earner income). Second, GfK bracketing, potentially accentuated by underreporting of small changes, additionally absorbs variations. The first and the second line of Table 9 report the respective distributions of household-yearly income growth. Note both that CBS income is slightly more dispersed at the tails and that it exhibits a wide range of small changes, compared to the many zeros with GfK's reported and bracketed income.

Table 9: Comparison of percentiles of income growth rates

Income type	P1	P5	P10	P25	P50	P75	P90	P95	P99	Obs.
GfK	-38.46	-16.67	-6.25	0.00	0.00	0.00	10.00	20.00	63.64	21,393
CBS	-40.06	-15.53	-8.22	-1.24	1.97	6.79	15.98	25.31	68.70	25,929
CBS bracketed	-40.00	-15.79	-9.09	0.00	0.00	8.33	16.67	26.09	69.23	25,929

Notes: This table shows percentiles for annual percentages changes of household income defined either as the midpoint of GfK income brackets, continuous CBS income or bracketed CBS income. In the table, P1 denotes the 1st percentile of the distribution, P5 denotes the 5th percentile and so forth.

For further comparison, in the third line of Table 9 we report the respective distribution if we also bracket CBS income similar to GfK income, resulting again in a wide range of zeros. When we run our key regression on such (artificially) bracketed CBS income, the absolute value of the log-income coefficient decreases substantially: It is then only -1.174 compared to -2.268, though still significant at the 1 % level.[46]

Another learning from our analysis is thus that the self-reported, bracketed income, as it is typical for industry surveys, may attenuate results from panel regressions. Still, we recall that even with CBS income data, the estimated relationship with the private-label share remained economically very small. While also the estimate with Nielsen Homescan data in Dubé et al. (2018), whose analysis we followed closely, may thus be attenuated, their main insight of such an economically small relationship remains.

[45] This suggests that for the intended use, as a determinant of social-status and thereby household preferences, GfK's self-reported income performs well.

[46] Again, we omit a full statement of the regression table. We note that through bracketing, small changes may both be deflated (when they remain within a bracket) as well as inflated (when they lead to a change in reported brackets). Both effects result in a downwards bias of the estimated coefficient.

VI Conclusion

For the analysis of CPGs, in particular, marketing professionals and scholars can rely on time series of highly granular purchase data on the level of individual households. However, the usefulness of such data is constrained by their more immediate professional purposes. In a time where the collection and storage of data becomes more and more ubiquitous, new research and business opportunities arise from matching different data sources, thereby extending their usefulness beyond their original professional intention. For this paper, we attempted and completed the match of household scanner panel data with administrative data for better measures of households' economic circumstances. The specific match opens the door to relating theories and findings from household finance to concrete consumption choices as usually studied in marketing, and to a more granular understanding of how macroeconomic changes affect these concrete choices.

We find that household income and wealth in our administrative data clearly reflect changes in the macroeconomic environment but only a weak, albeit statistically reliable, link to the CPG expenditure share of private labels, a consumption choice of historic and more recent research and practitioner interest. We qualitatively confirm earlier research in this regard but nevertheless find that, constrained by the intended purpose, standard household panel scanner data maybe lacking in its ability to reflect temporal changes in individual households' economic circumstances. Precisely, comparing the outcomes of pooled- and within-regressions when we use self-reported panel income and income from administrative sources, we find little differences at the pooled-level, while self-reported data appears to capture relevant individual temporal changes less accurately. This may reflect the fact that marketing organisations' main use of reported income is that of one of several determinants for socio-demographic clustering so that year-by-year variations are less important. Other variables relating to households' financial circumstances, such as information on household wealth, are not usually collected from household panels. Using matched administrative data, we do not find a significant relationship to house price changes, despite considerable variations in the considered period, and an again economically small relationship with households' net wealth, including financial assets.

One reason for why changes in income and wealth alone are not main determinants of private-label share, despite considerable price differences, could be that CPG expenditures account for only a one-digit share of total income, which for our regression sample is 9.29 % on average and 8.12 % for the median household in 2018. While we showed significant variations in income and wealth, combined with the high level of social security in the Netherlands households may not feel the need to cut back on CPG expenditures. In future research we intend to leverage our data to analyse how changes in income and wealth affect households' aggregate CPG consumption as well as their within-category choice between vertically differentiated products.[47]

Our data covers the two years of the second dip of the Netherland's "double dip recession" following the financial crisis. We documented for this period still a particularly large growth in the private-label share, and we noted that some of this growth is attributable to the expansion of hard discounters. As we control for supply-side changes, as well as a different trend during recession, part of this growth may still be attributable to the recession (though it is then not picked up by changes in individual income, *after* controlling for supply-side changes). In fact, we learned from industry reports that notably the worldwide expansion of discounters took place on the back of the financial crisis and its aftermath. Still, we showed that also national supermarket chains expanded their private-label shares. This however seems to have been mainly the continuation of a change that has gained considerable speed already around the middle of the first decade of this millennium. According to industry reports, focusing on national supermarket chains and excluding fresh food, in the Netherlands the CPG private-label share was still stagnant at around 19 % at the beginning of the first decade, followed by a steep growth already from 2003 onwards, ultimately hovering around 27 % since the end of the recession in 2014.[48] The reasons for this push may thus not be connected to the financial crisis or the macroeconomy more generally, but may instead reflect more fundamental changes in the industry, as retailers have taken over a larger share of functions and margins in the vertical chain.[49]

[47] While the literature on price-tier competition (e.g., Blattberg and Wisniewski (1989)) has found that demand diversion occurs primarily at the same tier, a priori one would expect that following shocks to income and wealth, individual consumers are both upwards and downwards mobile.

[48] The same report puts the total share including discounters at around 42 % in 2015. Though based on store data, while we reported averages from individual household purchases, this figure is highly comparable to our observations; cf. Global Retail Brands 2017. The Food Retail Landscape and Private Label in the Netherlands.

[49] This concluding discussion thus ties into a larger literature in International Marketing that tries to explain, for a given point in time, differences in private-label shares across countries (cf. Cuneo et al. (2015)).

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VII Appendix

VII.i Comparison of consenting sample in 2011

Table 10: Summary statistics of panellists in GfK compared to consenting panellists in 2011

	Age		Household size		Social class		Income bracket		PL share	
	All	Consent	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	40.58	40.62
SDV	3.02	2.53	1.24	1.20	1.64	1.61	6.25	6.00	20.14	21.00
Skewness	-0.56	-0.75	0.53	0.68	-1.15	-1.23	-0.61	-0.70	0.51	0.50
P5	1.00	1.00	1.00	1.00	1.00	1.00	3.00	3.00	11.83	10.42
P25	6.00	6.00	2.00	2.00	4.00	4.00	9.00	11.00	25.39	24.83
Median	7.00	8.00	2.00	2.00	5.00	5.00	16.00	16.00	38.17	38.15
P75	9.00	9.00	4.00	3.00	6.00	6.00	20.00	20.00	53.64	54.26
P90	11.00	11.00	4.00	4.00	6.00	6.00	21.00	21.00	68.98	69.97
P95	11.00	11.00	5.00	5.00	6.00	6.00	22.00	22.00	77.92	79.31

Notes: Table 10 depicts summary statistics of main socio-demographics for the GfK consumer panel and for the subsample of consenting households in 2011. P5 denotes the 5th percentile of the sample distribution, P10 denotes the 10th percentile, and so forth. SDV denotes the standard deviation of the distribution.

VII.ii Definition of key CBS variables

Disposable income. Disposable (household) income is defined as gross household income minus deductions, consisting of transfers and tax payments of all household members. Notably, in order to calculate the respective household-level components, we rely on the aggregation of individual gross income and deduction components within households as conducted directly by CBS. Gross household income comprises labour 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. Note that the wealth tax is levied as a fixed rate on the returns to net wealth (excluding residential housing). A detailed summary of all disposable income components is provided in Table 11.

Table 11: Decomposition of disposable household income

+	Income from labour	Gross household income
+	Income from business	
+	Income from capital	
+	National insurance benefits	
+	Social assistance benefits	
+	Allowances	
+	Income transfers received	
-	Income transfers paid	Deductions
-	Contributions to income insurance	
-	Contributions to health insurance	
-	Income and wealth return tax	

Wealth. CBS reports information on real estate owned by the respective household. Individual real estate values are determined annually by municipalities, based on the transaction value of similar properties in the neighbourhood, and are used as a basis for taxation.[50] For our measure of housing wealth, we only consider the value of the household's residence. As we ignore changes associated with acquisitions or moving to a new (own) home, we only consider exogenous variation from year-to-year.[51]

Household net wealth is defined as the value of household assets minus liabilities. To calculate the respective household components, we rely on the aggregation of all individual asset and liability components within households conducted directly by CBS. Household assets comprise financial assets in the form of deposit and current account balances and the market value of stocks and bonds as per 1st January of the following year (as well as of real estate in the form of residential and non-residential property).[52] Household liabilities comprise

[50] Specifically, the so-called WOZ value forms part of the base that is calculated to assess the amount of tax that is levied on returns to net wealth. (Though the value of residential housing itself is not subject to taxation, it still has to be declared.) The WOZ value of a property, however, refers to the year preceding reporting. CBS adjusts this by multiplying the pre-year value with the purchasing price index for existing homes in this area. We only have access to this adjusted value, which may be the source of additional measurement error.

[51] CBS provides us with a unique residential property ID, which we observe for every household in every year. This allows us to identify those households which have moved to a new home.

[52] Dutch households need to declare this information in their annual income tax declaration in order to derive the base for the income tax on return on assets. 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 located in countries which are part of the OECD Common Reporting Standard adopted by the European Commission.

the mortgage value of residential home, study loans and the sum of other loans, including loans for non-residential housing and the financing of financial assets. Consumer loans, such as credit card debt and alike, are excluded. A detailed summary of all net wealth components is provided in Table 12.

Table 12: Decomposition of household net wealth

+	Financial assets	Assets
+	Real estate	
+	Business assets	
+	Substantial interest	
+	Other assets	
-	Mortgage for residential real estate	Liabilities
-	Student loans	
-	Other debt	

VII.iii Variation in net wealth

In addition to the descriptives on income and housing wealth, we document changes in households' net wealth, first in the aggregate and then on a year-by-year basis. As the base can be both positive or negative, we report absolute changes.

Table 13: Percentile of annual absolute changes in net wealth

	P1	P5	P10	P25	Median	P75	P90	P95	P99
Net wealth	-12.99	-3.61	-2.07	-0.42	0.15	1.32	3.27	5.57	16.02

Notes: Table 13 shows percentiles of annual absolute changes in 10 TEUR of net wealth values. In the table, P1 denotes the 1st percentile of the distribution, P5 denotes the 5th percentile and so forth. The number of observations considered in the statistic is 25,417.

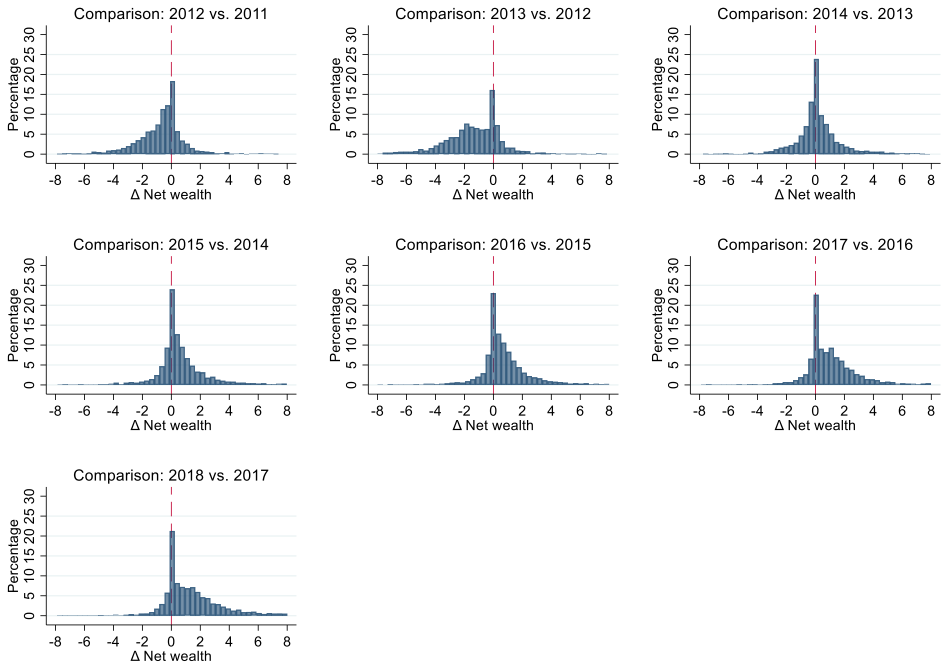

Figure 9: Distribution of annual (absolute) changes in net wealth

Notes: Figure 9 illustrates the distribution of annual absolute changes net wealth in 10 TEUR. Figures are truncated above 8 TEUR and below 8 TEUR.

VII.iv Private-label share

Table 14: Summary statistics – Private-label share by product category in 2018

Class	Mean	SDV	Skewness	P10	P25	Median	P75	P90
Alcoholic beverages	26.27	30.33	1.08	0.00	0.00	13.90	42.96	76.82
Beauty products	34.78	40.76	0.70	0.00	0.00	13.03	77.06	100.00
Candy	43.95	25.15	0.27	11.83	24.01	41.99	61.91	80.11
Canned food products	51.05	28.81	0.02	11.62	27.98	50.16	74.30	92.08
Cigarettes & other combust.	10.18	29.41	2.64	0.00	0.00	0.00	0.00	55.61
Cleaner	39.20	30.74	0.59	1.97	13.45	32.62	59.74	91.42
Dairy products, white	58.75	26.44	-0.31	20.19	39.10	61.42	80.81	93.11
Dairy products, yellow	56.67	28.31	-0.24	15.94	34.37	58.86	80.99	93.68
Detergent	35.63	36.35	0.65	0.00	0.00	23.10	65.41	100.00
Diverse Non-Food	35.62	25.65	0.87	6.68	16.52	30.43	49.18	74.52
Fragrances	9.88	25.43	2.81	0.00	0.00	0.00	0.00	33.91
Frozen food products	46.60	26.91	0.19	11.63	24.73	44.90	67.01	85.57
Hair care	18.76	31.40	1.72	0.00	0.00	0.00	23.35	80.06
Health care	25.30	33.47	1.22	0.00	0.00	8.24	40.20	97.63
Loose tobacco	28.63	42.99	0.94	0.00	0.00	0.00	86.99	100.00
Non-alcoholic beverages	43.37	29.30	0.24	5.00	17.71	40.45	67.72	85.86
Other food products	46.84	19.39	0.34	22.83	32.78	45.13	59.69	73.50
Other household products	52.42	32.29	0.03	8.38	24.70	51.40	80.55	100.00
Other personal care products	42.80	40.06	0.34	0.00	0.00	31.00	88.06	100.00
Other tobacco products	36.46	45.23	0.57	0.00	0.00	0.00	100.00	100.00
Paper products	72.25	32.17	-0.93	17.01	50.14	86.78	100.00	100.00
Pet needs	32.62	36.09	0.74	0.00	0.00	16.94	61.52	99.33
Skin care	29.36	35.40	0.98	0.00	0.00	13.07	50.32	100.00

Notes: Table 14 depicts summary statistics for private-label expenditure shares by product class in 2018. Statistics are calculated from pooled unweighted household-year observations in 2018. The summary statistics are based on the household scanner data of consenting households of the GfK consumer panel. Households observed for less than six months were excluded. P10 denotes the 10th percentile of the sample distribution, P25 denotes the 25th percentile, and so forth. SDV denotes the standard deviation of the distribution. In total 5,552 households are included.

Variation of private-label shares between households. Private-label share differs widely between households. Figure 5 to Figure 7 in the main text depict the distribution for our regression sample on the basis of household-year observations and separately also for food and non-food items in 2018. Additionally, Table 15 reports the summary statistics of the distributions. With respect to all private-label products, the share of the 10th percentile (of household-year observations) equals 21.75 %, the share of the 90th percentile 69.32 %.

Table 15: Private-label shares across households in 2018

	PL share	PL share – Food	PL share – Non-food
Mean	43.77	46.99	35.63
SDV	18.17	19.38	20.02
Skew	0.46	0.34	0.78
P1	10.18	9.93	3.28
P5	16.96	17.92	8.30
P10	21.75	22.86	12.38
P25	30.38	32.69	20.77
Median	41.63	45.11	32.41
P75	55.35	60.08	46.73
P90	69.32	74.39	64.06
P95	77.73	82.29	75.18
P99	90.00	93.44	92.74
N	5,552	5,552	5,549

Notes: Table 15 depicts summary statistics of private-label shares across households in 2018. The statistics are calculated from pooled unweighted household-year observations in 2018 of all households in the GfK consumer panel, which consented and, for which we observe purchases for at least six months. In total, the statistics are based on 5,552 in columns 2 and 3 including food products and 5,549 households in column 4 excluding food products, respectively. P1 denotes the 1st percentile of the sample distribution, P5 denotes the 5th percentile, and so forth. SDV denotes the standard deviation of the distribution.

VII.v Relative price of private-label products

To compare relative prices, we focus our analysis on three products that households regularly purchase and that allow for comparison through standardization of packaging units. Those products are coffee, ketchup, and washing detergents. With respect to coffee, we identify products on the barcode level with a package size of 500g and calculate the respective revenue-weighted average price per product unit.[53]

[53] The revenue-weighted average price per product unit is simply calculated as the ratio of the sum of expenditures and the sum of product units for a given product across all years. We calculate the sum of expenditures of relevant barcodes and the number of units sold (e.g. number of 500g packages of coffee) across all households, regardless of consenting, in the GfK consumer panel across all years.

For all private-label products we then calculate the (unweighted) average price. Proceeding likewise for national brands, we finally calculate the ratio of the two average prices. With respect to ketchup, we select products with a volume per bottle between 400 ml and 1000 ml. Based on this, we calculate the price per ml for each product. The subsequent computation follows that for coffee. With respect to washing detergent, we select washing powder products with laundry loads per package ranging from 30 to 100 loads. We then calculate prices per laundry load and proceed as with ketchup and coffee.

Table 16: PL/NB unit price ratio

Coffee	Ketchup	Washing detergent
86.79	67.75	66.16

Notes: The table shows price ratios as PL price over NB price for three different products. The price ratios are calculated from the complete GfK household scanner data as follows: First, we calculate the revenue-weighted average unit price at the barcode level and then calculate the unweighted average across all PL products and NB products, respectively. Finally, we obtain the ratio of the PL and NB average prices.

VII.vi National retailer strategies

To show first that national pricing existed throughout the entire time period for Dutch retailers, we analyse price variation across regions for six major retailers in the Netherlands. The analysis is based on the full household scanner data of the GfK consumer panel, independently of consenting, as we do not require CBS data (cf. column 2 of Table 10).

As in the main analysis, 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 "artificial barcodes", which represent products with no printed barcodes. We identify and keep the 500 most popular products per retailer per year and estimate a price regression for each retailer and year from 2011 to 2018, separately:

$$log(p_{jhst}) = \alpha + \sum_{j=1}^{J_{s\in S}} \beta_{js} D_{js} + \sum_{m=1}^{11} \beta_m D_m + \sum_{r=1}^{3} \beta_r D_r + u_{jhst}, \tag{4}$$

where $\sum_{j=1}^{J_{s\in S}} D_{js}$ is the set of barcode dummies of retailer s and $log(p_{jhst})$ is the log of a household-shopping-trip-specific price of product j. $\sum_{m=1}^{11} \beta_m D_m$ is a set of 11 monthly time fixed effects and $\sum_{r=1}^{3} \beta_r D_r$ represents three regional fixed effects. Household scanner data does not contain geo information about individual shopping trips. Therefore, we rely on the household location (postcode) to construct regional fixed effects.[54] Throughout the analysis, we use East Netherlands as the basis. Overall,

[54] Regions are derived from the official NUTS 1 codes of the Netherlands: North Netherlands, East Netherlands, West Netherlands, South Netherlands.

we estimate price regressions for six retailers and eight years[55] and extract the set of regional fixed effects for each regression.[56] Aggregate statistics are represented in Table 17, confirming that fixed effects are fairly small.

Table 17: Summary statistics of regional price fixed effects across all years and retailers

	Mean	SDV	Skewness	P5	P10	P25	Median	P75	P90	P95
Regional FE	-0.0001	0.0028	-0.1034	-0.0063	-0.0034	-0.0009	0.0002	0.0009	0.0024	0.0049

Notes: Table 17 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, regardless of consenting, between 2011 and 2018. In the table, P5 denotes the 5th percentile of the distribution, P10 denotes the 10th percentile and so forth. SDV denotes the standard deviation of the distribution.

We should note, however, that even when a given retailer practised regional price differentiation, this would not risk confounding our interpretation of the income coefficient as long as price differences do not change over time. We next present additional analysis for the retailer that accounted for the largest measured fixed effects (while not disclosing its identity for reasons of confidentiality). Table 18 depicts the magnitude of fixed effects by region and year for this retailer. There is no significant shift in differences between 2011 and 2018.

Table 18: Regional fixed effects in each year for a major retailer

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2011	2012	2013	2014	2015	2016	2017	2018
FE north	0,0050	0,0056	0,0027	0,0004	-0,0017	-0,0013	-0,0034	-0,0043
	(0,0008)	(0,0008)	(0,0008)	(0,0007)	(0,0008)	(0,0009)	(0,0009)	(0,0009)
FE west	0,0005	0,0017	0,0020	0,0009	0,0004	0,0009	0,0026	0,0003
	(0,0005)	(0,0005)	(0,0005)	(0,0005)	(0,0005)	(0,0006)	(0,0006)	(0,0006)
FE south	-0,0020	0,0013	0,0009	-0,0012	-0,0025	-0,0037	-0,0002	-0,0009
	(0,0006)	(0,0006)	(0,0006)	(0,0006)	(0,0006)	(0,0007)	(0,0008)	(0,0007)
Observations	477,376	573,259	548,642	508,857	493,117	482,404	451,796	456,629

Notes: Table 18 depicts regional fixed effects from independent yearly regressions for a major retailer based on the household scanner data of the GfK consumer panel between 2011 and 2018. North Netherlands, West Netherlands, South Netherlands each in comparison to the region East Netherlands. We control for monthly time fixed effects and barcode dummies, as specified in Equation (4).

We next turn to retailers' assortment strategy. In light of our interest in the private-label share, we want to confirm that retailers do not follow different private-label strategies across regions. Given our restriction to household scanner data, instead of store-level data, we proceed as follows. We calculate for each retailer and year the number of observed distinct products and private-label products, where we

[55] 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.

[56] Regions are derived from the official NUTS 1 codes of the Netherlands: North Netherlands, East Netherlands, West Netherlands, South Netherlands.

apply the following restrictions: We only account for products that are observed at least at 50 distinct shopping trips in a given region and year (across all retailers).[57] Dividing the number of private-label products by the number of all products, for each retailer and each year we calculate the assortment share difference relative to the baseline region East Netherlands in the following way: $\Delta\, AS_{srt} = AS_{st}^{r} - AS_{st}^{East}$, where s indexes the retailer in year t in region r. Table 19 depicts descriptive statistics of the so calculated assortment share differences in percentage points across major retailers and years. The results indicate that there is no significant variation across regions for any of the retailers: The mean difference is 0.04 percentage points, hence 0.0004 and even the bottom and top 5 %-percentiles are far beyond 1 percentage point.

Table 19: Summary statistics of regional assortment fixed effects across all years and retailers

	Mean	SDV	Skewness	P5	P10	P25	Median	P75	P90	P95
$\Delta\, AS_{srt}$	0.04	0.29	4.00	-0.17	-0.14	-0.07	-0.02	0.02	0.20	0.51

Notes: Table 19 depicts summary statistics of assortment share differences in percentage points compared to the base region east for six major retailers based on the household scanner data of the GfK consumer panel, regardless of consenting, between 2011 and 2018. In the table, P5 denotes the 5th percentile of the distribution, P10 denotes the 10th percentile and so forth. SDV denotes the standard deviation of the distribution.

VII.vii Supply side controls

We now formally define the supply side controls.

Price controls. As we rely on household scanner data, price observations are limited to those products bought by at least one household. Correspondingly, observed prices at a given retailer are potentially sparse. For the following reasons, this is, however, only a minor issue in our set-up. First, retailer chains practice national pricing.[58] Hence, there is no regional differentiation and therefore, the dimensionality of prices is small. Second, we construct price indices on the quarterly level and hence, the observation period is comparatively long. Finally, we restrict the set of products to the 50 most popular products per category and retailer, which were present at any given retailer s in a given year.[59] From this data, we construct household-specific price indices for private labels and national brands.

In a first step, we calculate mean prices per product j for all categories k, retailers s and periods t:

$$\overline{p}_{jkst} = \frac{1}{N_{I_{jkst}}} \sum_{i \in I_{jkst}} p_{ijkst}, \tag{5}$$

[57] We exclude fresh food and also barcodes that are artificially generated by GfK when no barcode is otherwise available.

[58] See discussion in Appendix VII.vi.

[59] Products are ranked by total revenue per category, retailer and year.

where i indexes a shopping trip of household h at retailer s within period t at which product j was bought. For convenience, $N_{I_{jkst}}$ denotes the product-retailer-specific number of price observations considered, i.e. $N_{I_{jkst}} = |I_{jkst}|$.

Next, we calculate time-dependent product-category-retailer-specific expenditure shares as:

$$\omega_{jkst} = \frac{y_{jkst}}{\sum_{j \in J_{kst}} y_{jkst}}, \tag{6}$$

where J_{kst} denotes the set of considered category-specific products at retailer s in period t and y_{jkst} has been calculated as the sum over all shopping trips i for product j in category k at retailer s in period t, hence, $y_{jkst} = \sum_{i \in I_{jkst}} y_{ijkst}$.

In the third step, we calculate retailer-category-specific price indices using a geometric average as follows:

$$PI_{kst}^{g} = \prod_{j \in J_{kst}} \left(\frac{\overline{p}_{jkst}}{\overline{p}_{jkst-1}} \right)^{\omega_{jkst}}. \tag{7}$$

In the fourth step, we first calculate category-retailer-specific expenditure shares as:

$$\omega_{kst} = \frac{\sum_{j \in J_{kst}} y_{jkst}}{\sum_{k \in K_{st}} \sum_{j \in J_{kst}} y_{jkst}}. \tag{8}$$

where K_{st} denotes the set of retailer-specific products in period t. We use these weights to construct retailer-specific price indices:

$$PI_{st}^{g} = \prod_{k \in K_{st}} \left(PI_{kst}^{g} \right)^{\omega_{kst}}. \tag{9}$$

Before we compute household-specific price indices, we construct household-specific retailer weights, as follows:

$$\omega_{hst} = \frac{n_{hst}}{\sum_{s \in S_t} n_{hst}}, \tag{10}$$

where n_{hst} is the number of outlets from retailer s within a specified radius for household h in period t and S_t denotes the set of retailers. We use a 20km radius so that we ensure that for all but very few households at least one of the considered retailers is relevant. Until 2014 we calculate retailer-specific price indices for six major retailers. Since two major retailers merged in 2014, we only include five retailers from 2015 onward. Finally, we calculate the household-specific price indices as,

$$PI_{ht}^{g} = \prod_{s \in S_t} \left(PI_{st}^{g} \right)^{\omega_{hst}}. \tag{11}$$

Assortment controls. For each quarter and each of the largest six retailers in the consumer panel we calculate the quarterly retailer-specific private-label assortment shares. Assortment shares are defined as the ratio of the number of unique private-label products and the number of unique products per quarter and retailer.[60] We only include products that are observed at least at 50 distinct shopping trips in a given year (across all retailers). Additionally, we exclude fresh food, as well as barcodes that are artificially generated by GfK when no barcode is otherwise available. To compute household-specific assortment shares, we compute household-specific retailer weights similar to Equation (10) using again a 20 KM radius.[61] Finally, we calculate the household-specific private-label assortment shares as

$$AS_{ht} = \prod_{s \in S_t} (AS_{st})^{\omega_{hst}}. \tag{12}$$

VII.viii Robustness

Column (1) in Table 20 reports regression results for our main (within) regression based only on households that are continuously present in the sample. Column (2) reports results for single households alone.

Table 20: Private-label share regressions – Robustness estimations

	(1) Continuous HH	(2) Single HH
log(CBS income)	-2.453***	-3.246***
	(0.68)	(0.90)
log(std. CBS Income)		
Household size	1.573***	
	(0.36)	
Share of females	-3.587*	
	(1.86)	
Share of children	0.130	
	(1.65)	
Share of employed	1.529	
	(1.10)	
Unemployment	-0.393	1.491**
	(0.52)	(0.65)
Trend	0.049***	0.034***
	(0.00)	(0.01)
Trend x recession	0.026***	0.027***
	(0.01)	(0.01)
log(PI_NB)	-14.218***	-12.482
	(4.90)	(7.90)
log(PI_PL)	-0.600	1.494
	(5.12)	(7.31)

60 A unique product is defined as a unique barcode. Moreover, as shown before, we do not observe regional variation and therefore calculate national assortment shares per retailer.

61 For the period until 2014 we calculate retailer-specific assortment shares for six major retailers. Since two major retailers merged in 2014, we only include five retailers from 2015 onward.

	(1)	(2)
Assortment index	4.153	9.745
	(13.18)	(15.72)
Observations	146,993	95,889
R^2	0.673	0.597
Adjusted R^2	0.669	0.590

Notes: This table shows variations of our baseline within estimation. In all specifications the dependent variable is the private-label share. Column (1) replicates the baseline result presented in column (4) of Table 6 restricting the sample to households continuously present in the sample between 2011 and 2018. Column (2) shows the results using single-member households. Households are defined as single-member households as long as they consist of only one household member in a given year and excluded otherwise. In each specification, we include dummies to control for seasonal and regional effects, as well as a constant. We report standard errors clustered at the household-level in parenthesis. Significance levels are defined as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

VII.ix GfK income variable

Table 21: Distribution of household-month observations across GfK income bins

GfK main earner income class (EUR/month)	Household-month observations	Percentage of total sample
Below 700 EUR	2,599	0.66
700-900 EUR	8,469	2.16
900-1100 EUR	20,682	5.28
1100-1300 EUR	15,410	3.94
1300-1500 EUR	14,785	3.78
1500-1700 EUR	28,009	7.16
1700-1900 EUR	37,767	9.65
1900-2100 EUR	24,121	6.16
2100-2300 EUR	39,754	10.16
2300-2500 EUR	23,468	6.00
2500-2700 EUR	34,587	8.84
2700-2900 EUR	19,879	5.08
2900-3100 EUR	18,553	4.74
3100-3300 EUR	15,360	3.92
3300-3500 EUR	13,687	3.50
3500-3700 EUR	10,767	2.75
3700-3900 EUR	7,430	1.90
3900-4100 EUR	7,152	1.83
4100 EUR or more	21,454	5.48
Missing	27,420	7.01
Total	**391,353**	**100.00**

Notes: The table reports the number of observations per GfK monthly income bin. The last two rows report the number of missing values and totals.