Inflation risk and heterogeneous trading down

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Abstract

I examine how households adjust the quality of their purchases in response to adverse economic shocks. Using household scanner data from Germany, I document heterogeneous responses across income levels. Higher-income households tend to reduce the quality of the goods they purchase, whereas lower-income households—who typically consume lower-quality goods—show a limited propensity to trade down, likely due to a limited ability to do so. To assess the general equilibrium effects of an aggregate shift in demand toward lower-quality varieties, I implement a shift-share research design. This approach leverages two key components: (i) pre-determined spending shares on middle-quality varieties across the product space for a wide range of sociodemographic groups prior to the Great Financial Crisis, and (ii) variation in population growth across these groups during the crisis. I find that a 1% aggregate demand shift toward lower-quality varieties following a recession raises the relative price of low-quality varieties by an additional 0.5%, and by 1.9% relative to high-quality varieties, on average.

JEL Classification: E21, E31, E32, E60

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1 Introduction

Inflation is unequal across households and, moreover, has distributional effects. In particular, low-income households tend to experience higher levels of inflation compared to their higher-income counterparts (see, for example, Kaplan & Schulhofer-Wohl (2017) and Argente & Lee (2021)). Other researchers have concentrated on understanding the reasons behind these disparities (see Jaravel (2019)), on understanding how monetary policy affects inflation heterogeneity (see Ampudia et al. (2023)), or on quantifying the channels through which inflation has distributional effects (see Cardoso et al. (2022)). However, do households experience varying levels of inflation inequality over the business cycle?

In this paper, I contribute to this line of research by focusing on a novel mechanism, the *heterogeneous trading down* channel, which involves the purchasing of lower quality varieties of the same goods by certain households in the face of adverse shocks. In particular, I study the aggregate implications of this phenomena for heterogeneuos inflationary risk over the business cycle and across households. To achieve this, I use household scanner data from supermarket expenditures by German households.

Jaimovich et al. (2019) documented that during economic recessions households tend to lower the quality of goods they purchase. The authors argue that this adjustment in purchasing behavior amplifies the magnitude of the recession because lower quality goods tend to be less labour intensive and, therefore, the aggregate demand for labour decreases systematically during these periods. In this paper, I study whether differentials in inflation risk over the cycle and trading down in the quality of goods are related phenomenons. In particular, I delve deeper into how households trade down in the quality of purchased varieties and, more specifically, explore whether this phenomenon occurs heterogeneously across households. Additionally, I quantify the effect that heterogeneous trading down has on relative prices across the quality distribution of varieties within products.

The aim of this study is therefore to examine the importance of the quality margin as an insurance mechanism against aggregate shocks and, more specifically, to investigate the equilibrium effect in relative prices of an aggregate demand shift toward lower quality goods in the aftermath of an aggregate shock such as the great financial crisis. I show that the degree of trading down is heterogeneous across households, and more specifically that low-income households lack the capacity to engage in this margin of adjustment. Moreover, when the rest of households do trade down, the aggregate demand shift towards lower quality goods leads to an increase in the relative price of low-quality compared to higher quality varieties. For it I employ household scanner data which contains a representative sample of German households from 2005 to 2018. It includes information on each item bought by participating households, the transaction date, the specific barcode, the quantity purchased and the price paid. Additionally, socio-demographic information of the participating households such as age, income and region are observable.

I first document the tendency of lower-income households to purchase lower quality goods on average. Additionally, I show that households use the quality margin to decrease their overall expenditures in the aftermath of an adverse aggregate shock, depending on their income group. I find that lower-income households exhibit a limited capacity to engage in trading down given the fact that they are at a lower bound, in contrast with the rest of households who are likely to trade down further in the quality of goods. In particular, I find that in general between 10 and 20% of households find themselves in this lower bound. I additionally provide evidence that in the when households use more intensely the quality margin by trading down in the quality of goods, lower income households experience higher inflationary risk.

To understand the equilibrium implications of this shift in aggregate demand towards lower quality goods, I employ a shift-share research design. It relies on two components: predetermined spending shares for middle quality varieties across the product space for a large number of sociodemographic groups before the great financial crisis, and heterogeneity in the population growth for these groups during the great financial crisis. This helps predict trading down once households concerns about the crisis start appearing, therefore identifying a plausibly exogenous demand shifter. The intuition is that for the varieties whose consumption is more focused on the household groups that grow faster, the amount of trading down will be larger. I find that a 1% aggregate demand shift toward lower-quality varieties following a recession raises the relative price of low-quality varieties by an additional 0.5%, and by 1.9% relative to high-quality varieties, on average.

By shedding light on the heterogeneous trading down behavior and its effects on product inflation at different quality margins, this paper contributes to our understanding of the complex dynamics between income distribution, consumption patterns, and inflation over the business cycle. This has important implications for welfare analysis. On the one hand, when households can trade down in the quality of goods, this insures them against shocks by lowering the quality of the purchased goods. The fact that a fraction of households find themselves in the lower bound of the quality distribution indicates that this margin is not available for them. Moreover, the effect on the relative price of lower quality varieties increases inflationary risk over the business cycle for lower income households.

Review of the literature. A growing body of literature focuses on documenting inflation heterogeneity at the household level (Kaplan & Schulhofer-Wohl (2017), find that almost all variability in a household's inflation rate comes from variability in household-level prices relative to average prices, and Argente & Lee (2021) construct income-specific price indexes).

Some authors have explored the drivers of inflation inequality (Jaravel (2019) investigates the hypothesis that firms introduced more products to high-income households due to an increased demand by these) and the consequences, where a few examples include Cardoso et al. (2022), Yang (2022) or Boel et al. (2021). On the distributional effects of monetary policy on inflation, Cravino et al. (2020) establish that prices of goods consumed by high-income households are more sticky and less volatile, Lauper et al. (2021) find that contractionary monetary policy significantly and persistently decreases inflation dispersion in the economy, and that middle-income households experience higher inflation rates that are more reactive to a contractionary monetary policy shocks. Relatedly, Ampudia et al. (2023) focus on understanding how monetary policy shocks affect inflation heterogeneity though product substitution. Rodnyansky et al. (2022) studies the role of endogenous adjustment in product quality in amplifying monetary policy shocks. Several studies have leveraged currency depreciations as natural experiments to examine the heterogeneous effects on inflation (see Burstein et al. (2005) or Colicev et al. (2022)).

Previous literature has documented that during economic downturns, households tend to reduce the quality of the goods they purchase. Jaimovich et al. (2019) show that a shift towards lower quality goods has effects in the labour market because lower quality goods tend to be less labour intensive. Others have studied the role of consumer behaviour over the business and life cycles and its aggregate implications for relative prices (see Nord (2022), Carvalho et al. (2021), Michelacci et al. (2022), Aguiar & Hurst (2005), Kaplan & Menzio (2015) and Michelacci et al. (2022) for non-durables; Gavazza & Lanteri (2021) Bertolotti et al. (2021) for durable goods). Orchard (2022) documents that during recessions prices rise more for necessities compared to luxury products as the aggregate share of spending devoted to necessities is counter-cyclical. More recently, Cavallo & Kryvtsov (2024) examine the inflation surge following the COVID-19 pandemic and document a shift in consumer expenditure towards cheaper varieties, along with a faster increase in their relative prices.

The remaining of the paper is organised as follows. Section 2 presents the dataset, Section 3 compares households habits along the income distribution; Section 4 studies differences in trading down over time and along the income distribution; Section 5 presents a shift share research design to identify exogenous demand shifts; and Section 6 concludes.

2 Data

2.1 Description of the data

I use GfK scanner data, a household panel that covers a representative sample of German households for the period from 2005 to 2018. Participants report their purchases of items typically sold in supermarkets, that is, fast moving consumer goods, including, but not limited to, groceries and personal care items. Additionally, the dataset contains some socio-demographic information of the participating households. The dataset includes information on each item bought by participating households, the transaction date, the specific barcode, the quantity purchased and the price paid. Around 30,000 households per year participate in the sample. The household characteristics observed include age, number of people in the household, income, social class, zipcode and province.

I classify purchased items into products and varieties. A product is characterized by its COICOP (Classification of Individual Consumption According to Purpose).[1] A variety in a product is characterised by its barcode. The dataset covers around 900,000 barcodes of purchased varieties.

While COICOP-5 classification is available, I employ the database category classification and barcode descriptions to achieve a more granular classification to COICOP-10 for products to improve the granularity of the shift-share analysis.[2] To achieve this, I use GPT-4o, a state-of-the-art large language model, to classify products into COICOP-10 categories. I use the product's barcode categorization and description as inputs for the model. I guide GPT-4o to accurately assign the appropriate COICOP-10 category to each product. This approach leverages the model's advanced natural language understanding capabilities to effectively interpret diverse product descriptions, enhancing the precision

[1] It is the international reference classification of household expenditure, and is an integral part of the System of National Accounts (SNA). Is is used for household expenditure statistics based on household budget surveys and for consumer price indices. Available here.

[2] For it, I follow the mapping from the Federal Statistical Office of Germany (2019) "Consumer price index for Germany. Weighting pattern for base year 2015", available online here.

of our classification process. For details see Appendix A.2.

Information on household income is available in the dataset, so I group households according to their income levels. Specifically, there are 17 income groups, each spanning 250€ intervals, ranging from 500€ to 5,000€ in monthly income. To account for economies of scale within the household, I use the modified OECD scale, where the first member is assigned 1 point and the rest of household members 0.5 points.[3] Household income is then divided by $(n+1)/2$. For each household I assume that their income is the centre of the interval provided; for the lowest I assume an income equal to its upper bound and for the highest I assume an income equal to its lower bound. While this simplification might be crucial when studying income processes, for the object of this study it is less important given that the income information is only used to rank and classify households.

For robustness, I follow three different income classifications. First, simply classifying households into their income decile at the country level. Second, by classifying households by their relative income level within their state of residence, with the aim to avoid sorting households geographically. Third, I classify households according to the social class variable available in the dataset. This variable, however, only has six groups.

I build a Laspeyres index of inflation at the year on year level and quarterly frequency at the household level and in the spirit of Kaplan & Schulhofer-Wohl (2017). The Laspeyres inflation rate for household i between t and $t+4$ is:

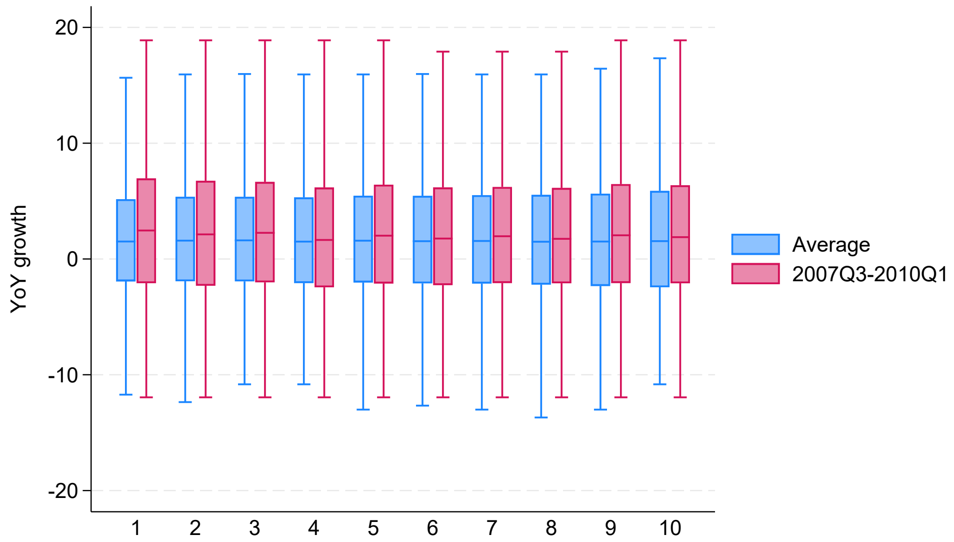
$$\pi_{i,t+4} = \frac{\sum_{j:q_t,q_{ij,t+4>0}} p_{ij,t+4} q_{ijt}}{\sum_{j:q_t,q_{ij,t+4>0}} p_{ij} q_{ijt}} \tag{1}$$

[3] While the official classification assigns 0.3 points for kids, the age is not observable in this dataset and therefore I assign 0.5 points to each additional member, irrespective of their age.

2.2 Stylized facts

Figure 1 depicts how the distribution of household inflation varies across income deciles and between normal times and the great financial crisis.[4] More importantly, right tail risk, that is, the risk of high inflation, appears to change substantially more for lower income households compared to higher income ones. Therefore, inflationary risk appears to increase more for lower income households at the onset of a recession.[5]

Figure 1: Inflation risk by income decile and over the business cycle



Notes: Laspeyres Inflation is computed at the household level. Income decile is defined between household within a given state. The data covers German households and spans from 2005 to 2018. The box depicts the median, 25th and 75th percentile. Upper and lower adjacent values are defined as 75th percentile plus 3/2 of the interquantile range.

Figure 2 shows the average relative price of low versus medium-quality varieties for each product over time.[6] During the great recession, the average price of lower quality

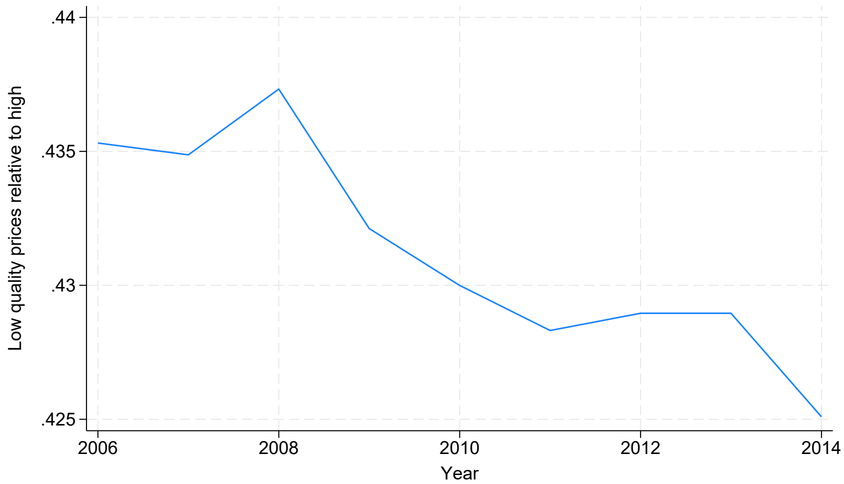
[4]Figure A.1 presents average inflation rates for each income decile in Germany during the 2005 to 2018 period and shows how lower income households tend to experience, on average, higher levels of inflation.

[5]As Figures A.3 and A.2 in the Appendix show, the disparity remains when different periods are studied. Alternatively, Figures A.4, A.5 and A.6 present median, 90th and 10th percentile for each income group. The Figures shows a generalised increase in inflation at the onset of the crisis and for all household groups, in line with official CPI data on food inflation for that period. This increase appears to be larger for lower-income households. Moreover, the difference in inflationary risk for lower income households (seen as the difference in the 90th percentile during the recession compared with normal times) appears to be more pronounced in the beginning of the crisis and to disappear by the end of it.

[6]For each product, low quality varieties are defined as those below the 25th percentile price within a

goods relative to that of high quality goods increased.[7]

Figure 2: Relative prices of cheap vs expensive varieties of products



Note: The relative price of cheap varieties within a product category is defined as the 25th percentile of a product category divided by the median price of that product category within each year. Relative prices are averaged across product categories. Product categories are defined by the COICOP-5 classification.

3 Decomposition

I first decompose total expenditures for each household to understand how households habits evolve over the business cycle. For it, I modify the decomposition in Nord (2022). In this paper, the author decomposes household expenditures into three different components: the direct effect of shopping behaviour (effort, or within varieties variation); the differences in substitution among similar goods, or between varieties variation; and quantities, which is a counterfactual expenditure that measures expenditure if all households purchased the same average quality variety of goods and at the average prices.[8] I

period of time. Medium quality varieties are defined as those whose price is between the 25th and the 75th percentile and those with a price higher than the 75th percentile are defined as high quality varieties.

[7]See Figure A.7 for the graph for selected individual products.

[8]Note that throughout the paper I define product quality primarily through the lens of consumer expenditure: higher-priced varieties within a product category are considered higher quality, while lower-priced varieties are deemed lower quality. This approach assumes that consumers perceive higher-priced items as offering superior quality, under the assumption that if consumers are willing to pay more for an item, they perceive it to be of higher quality. It follows Jaimovich et al. (2019), who also corroborate this assumption using data with independent measures of quality and price.

further decompose the second term into temporary differences in the price of products, that is, temporary discounts (temporary substitution) and permanent differences in the price of different varieties, which I assume they summarise quality differences between varieties of a given product.[9] To ensure comparability of prices across different product varieties, I exclusively compare barcodes within a product that are measured in the same unit (weight, volume, etc.). Therefore, a variety is a barcode measured in a specific unit. Additionally, I standardize prices and quantities based on the size of each product.

I decompose expenditure of household i at time t as:

$$\begin{aligned} e_{i,t} &= \textstyle\sum_k \sum_{j\in J_k} p_{jkit}c_{jkit} \\ &= \textstyle\sum_k \sum_{j\in J_k} \Bigg[\underbrace{(p_{jkit}-\bar{p}_{jkst})c_{jkit}}_{Effort} + \underbrace{((\bar{p}_{jkst}-\bar{p}_{jks})-(\tilde{p}_{kst}-\tilde{p}_{ks}))c_{jkit}}_{Temp.substitution} + \underbrace{(\bar{p}_{jks}-\tilde{p}_{ks})c_{jkit}}_{Quality} + \underbrace{\tilde{p}_{kst}c_{jkit}}_{Counterfactual} \Bigg] \end{aligned} \tag{2}$$

For household i at time t (quarters), k refers to the specific product and j to the variety; $\bar{p}$ refers to the average price of a barcode in a given state (länder) s and $\tilde{p}$ is the average price of a product in a given state.

The first term is the difference between what the individual household pays for the same variety relative to other households and therefore can be thought of as a measure of the effort or time invested in shopping, that is, search costs. The second term reflects the extent to which a household takes advantage of temporary discounts of products. The third term can be seen as the substitution between varieties within a given product. A more positive term indicates that the household is purchasing more expensive varieties of a given product, that is, higher quality varieties. How it evolves over time for each household would shed light on potential non-homothetic preferences. Finally, the last term is the counterfactual expenditure, and indicates how much a given household would

[9]As opposed to Nord (2022) the decomposition includes time variation, which gives rise to the temporary substitution component.

spend absent any price differences within each product, meaning that variations in this term are driven by differences in quantities consumed.

I first perform the decomposition at the household level, group households according to their income levels, and investigate the average contribution of each term in either increasing or decreasing the overall spending levels.

To test the robustness of the results, I define income groups in three different ways:[10] First, by household income decile at the country level by year. Second, by income decile at the state level.[11] I smooth household income as the average of the current, the last 4 quarters and the following 4 quarters income to avoid short-term fluctuations in income to affect the results.[12] The third measure uses the variable "social class", available in the dataset, and that depends on the level of education and the profession of the household. There are six social class groups.

3.1 Results

3.1.1 Spending decomposition

Figure 3 shows the magnitudes of each term, relative to overall spending levels, for each income group.[13] It shows the relative contribution of each of the terms into either increasing or decreasing the overall level of household spending, implying that the counterfactual term in Equation 2 as the exactly opposite magnitude for each income group.

A number of observations are worth mentioning. First, search effort, temporary substitution and quality choice decrease the overall level of spending for lower income house-

[10] Income data is available yearly for each household. While one cannot observe exact household income, there are 17 income bins, ranging from below 500 euros to above 5000 euros household income per month and with a range of 250 euros per income bin.

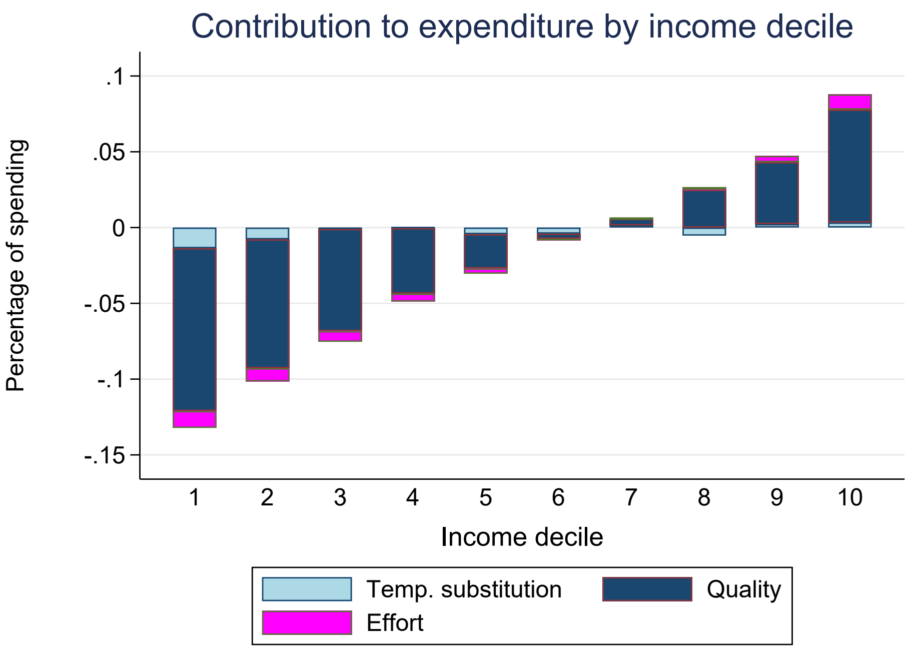
[11] The idea with this measure if to reduce the extent to which the first might be sorting households geographically. Moreover, this accounts for the fact that there might be regional differences in goods and supermarket brands available, given that households do not typically travel to purchase goods. Therefore the relevant income position within a region could be a relevant measure to account for these effects.

[12] In cases with limited data, I rely on the maximum number of observations available.

[13] Figures A.8 and A.9 replicate the results with a different income group measure, and exhibit very similar patterns.

holds, for a given basket of consumption. This difference monotonically increases with income, such that for income decile 7 and above, these choices increase the overall spending. For the lowest income group, the three components together decrease, on average, around 13% of the overall expenditures of the household and, for the highest income decile, they increase by around 8% overall expenditures for a given consumption basket. The second crucial observation highlights that the variation is primarily influenced by the quality margin, which is significantly larger by an order of magnitude compared to the other two components.

Figure 3: Decomposition by income group



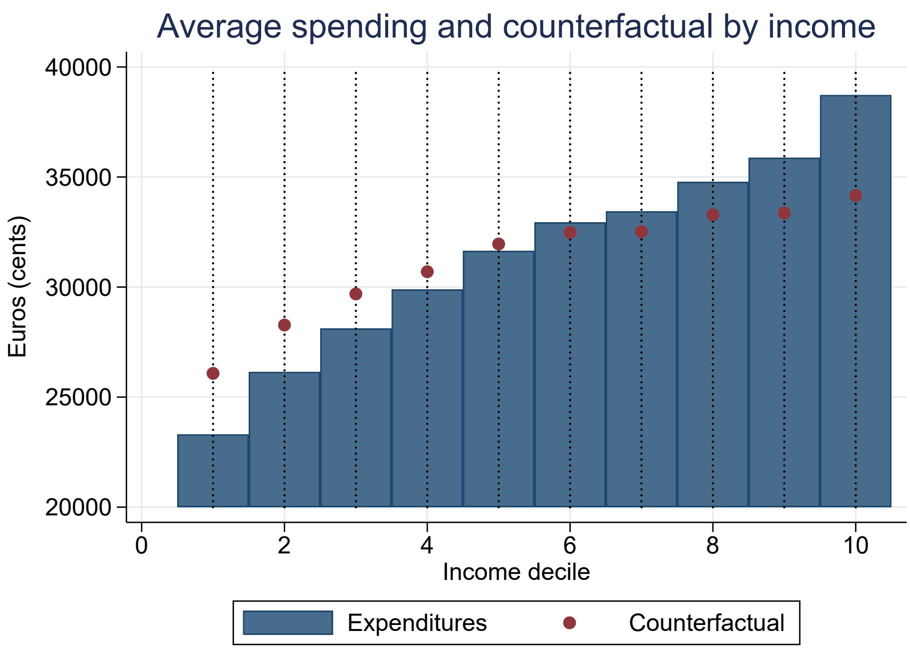
Notes: Average contribution of each temporary substitution, quality and effort into overall spending by income group and average over time. Each term in Equation 2 is divided by expenditures and averaged across households in an income group and over all periods of time (2005 to 2018).

The fact that these margins allow households to increase or decrease their overall spending create a wedge between household spending and the counterfactual term in Equation 2. Figure 4 shows the overall level of spending by household group in euro and the average counterfactual level by group.[14] First, as one could expect, consumption

[14]Figures A.10 and A.11 replicate the results with a different income group measure, and exhibit very

or expenditure levels are larger the higher the income level of households. The same happens with the counterfactual term but, in contrast with expenditure, the curve is steeper for the latter. That means that low income households would be spending more if they were purchasing the average product at the average price and, conversely, high income households spend more because of their relatively lower effort, the fact that they take less advantage of temporary discounts and their choice of quality for each product. This implies that consumption inequality is lower than one would observe by directly comparing expenditures.

Figure 4: Expenditures and counterfactual by income group



Notes: Average *per capita* household expenditure and the counterfactual expenditure term in Equation 2, adjusted for intra-household economies of scale as detailed in Section 2.1 and averaged across time for each income group.

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similar results.

4 Heterogeneous trading down

4.1 Heterogeneous trading down response to idiosyncratic and aggregate shocks

I next investigate whether and how households adjust the quality of the products they purchase in response to changes in income, and whether these adjustments vary across households. To do so, I focus on the quality component from the previous decomposition, normalized by household expenditure, and examine how it responds to fluctuations in income levels. Specifically, I define an income shock as a drop of at least one income band in the household income —calculated as described in Section 2— relative to that of four quarters before. Approximately 6.2% of observations meet this criterion. I estimate the following specification:

$$Quality^{y}_{i,t} = \beta^{y} \times Incomedrop^{y}_{i,t} + \alpha^{y}_{i} + \gamma^{y}_{t} + \epsilon^{y}_{i,t} \tag{3}$$

where y denotes the income group defined as in the previous section; α_i are household FE and γ_t are time FE, $Quality^{y}_{i,t}$ is the quality term divided by overall expenditures for household i at time t and $Incomedrop_{i,t}$ is a dummy variable equal to 1 if the household is hit by an idiosyncratic shock.

Table 1: Heterogeneous idiosyncratic trading down, by relative income

	(1) Income All HH	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Idiosyncratic shock	-0.315***	0.460	-0.697*	0.117	-0.111	-0.874***	-0.733***	-0.417***
	(0.052)	(0.431)	(0.415)	(0.232)	(0.237)	(0.170)	(0.138)	(0.113)
Observations	1,470,702	116,810	111,049	228,271	213,694	220,562	202,179	188,084
R-squared	0.758	0.775	0.798	0.770	0.785	0.784	0.793	0.773
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined as across country level.*** p<0.01, ** p<0.05, * p<0.1

Adopting a similar approach, I then shift the focus to aggregate shocks. Specifically, I examine whether households respond heterogeneously by trading down in product quality when faced with economy-wide shocks such as a recession. To analyze this, I estimate the following specification:

$$Quality^y_{i,t} = \beta^y \times recession^y_{i,t} + \alpha^y_i + \gamma^y_t + \epsilon^y_{i,t} \tag{4}$$

where y denotes the income group defined as in the previous section; α_i are household FE and γ_t are time FE, $Quality^y_{i,t}$ is the quality term divided by overall expenditures for household i at time t and $recession_{i,t}$ is a dummy variable equal to 1 if the household resides in a region with negative GDP growth for at least two consecutive quarters.

To focus the analysis on the period of the great financial crisis, I add an interaction term for the great financial crisis and regional crisis, with the aim of exploiting variation between regions in entering and leaving the crisis:

$$Quality^y_{i,t} = \beta^y \times recession^y_{i,t} \times GFC_t + \alpha^y_i + \gamma^y_t + \epsilon^y_{i,t} \tag{5}$$

where GFC_t is a dummy variable equal to 1 for the second half of 2007, all 2008 and 2009.

Tables 1, 2, and 3 present the baseline results. Results are shown in Table 1.[15] Column 1 in each table reports the estimates for the full sample of households, reflecting average effects at the aggregate level. Specifically, when households experience a negative income shock or a recession, they tend to trade down in the quality of the goods they purchase, thereby reducing overall expenditures. The extent of this adjustment varies across scenarios: following an idiosyncratic income shock, households reduce expenditures through quality downgrading by an additional 0.3 percentage points on average. This effect is

[15] Tables A.1 and A.2 redo the analysis with a different classification of households into groups: first, I classify households by income groups within a state and second, according to their social class. In both cases, the same results prevail and there is no evidence of trading down for the lower groups.

somewhat smaller during periods of negtive growth (around 0.2 percentage points) but becomes more pronounced during the great financial crisis, reaching 0.7 percentage points. These results are aligned with Jaimovich et al. (2019) and Cavallo & Kryvtsov (2024) who also document expenditure switching towards cheaper varieties in bad times.

The remaining columns present results by income group. To enhance the granularity of the analysis, I further disaggregate the lowest income quintile into the first and second deciles. Across all three tables, the results consistently show heterogeneity in household behavior along the income distribution. Notably, a subset of lower-income households does not appear to trade down in the quality of goods they purchase during economic downturns. Since these households already tend to consume lower-quality goods on average, they may lack access to this margin of adjustment when confronted with a negative shock. However, the share of households constrained by this lower bound varies across the different scenarios analysed. When focusing on the great financial crisis specifically, a smaller portion of the population seems to be constrained, which might be due to the severity of the crisis incentivizing a faster response of the producers of varieties. Moreover, the magnitudes are also larger than those obtained previously: during the recession, trading down in the quality of the varieties that households purchase appear to decrease expenditures by an additional 0.7 percentage points on average. In contrast, middle- and higher-income households do adjust their purchasing behavior under such conditions. In some instances, this trading down behavior is not stronly observed for the highest-income households. One possible explanation is that these households may prioritize maintaining consumption quality for reasons related to habit formation, perceived status, or a relatively lower sensitivity to income shocks. These results are robust to different income classifications.[16]

[16]Tables A.3, A.4, A.5 and A.6 redo the analysis with a different classification of households into income groups. In all cases, the same results prevail and there is evidence of no further trading down for the lower groups. One difference with the previous results is the highest income group when the classification is performed within a given state, where I find that in this case they do trade further down as opposed with the previous result. One explanation might be related to the fact that the classification in Table 2, at the country level, groups the households with the highest income in the country, whereas in Table A.3

Table 2: Heterogeneous aggregate trading down, by relative income

	(1) Income All HH	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Regional Recession	-0.220***	0.001	-0.138	-0.058	-0.294***	-0.218**	-0.187**	-0.145
	(0.047)	(0.160)	(0.143)	(0.110)	(0.100)	(0.094)	(0.094)	(0.099)
Observations	1,470,702	153,953	147,760	304,093	288,926	293,411	292,569	281,597
R-squared	0.758	0.767	0.786	0.760	0.777	0.778	0.782	0.763
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined as across country level.*** p<0.01, ** p<0.05, * p<0.1

Table 3: Heterogeneous trading down, by relative income GFC

	(1) Income All HH	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Regional Recession × GFC	-0.719***	-0.306	-0.866***	-0.613**	-0.793***	-0.451**	-0.746***	-0.600**
	(0.105)	(0.361)	(0.331)	(0.246)	(0.248)	(0.217)	(0.226)	(0.234)
Observations	1,470,702	153,953	147,760	304,093	288,926	293,411	292,569	281,597
R-squared	0.758	0.767	0.786	0.760	0.777	0.778	0.782	0.763
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined as across country level.*** p<0.01, ** p<0.05, * p<0.1*** p<0.01, ** p<0.05, * p<0.1

4.2 Trading down and heterogeneous inflation risk

In this section I present evidence of the association between trading down and inflation risk. For it I focus on the dynamics of inflation and inflation risk in different regions and periods depending on the extent to which households trade down in the quality of the varieties they purchase.

For it, I first build a Laspeyres index of inflation at the year on year level and quarterly frequency for each household.[17]

I construct different measures of inflation and inflation risk at the region, time, and income level: first, I compute the median level of inflation for each group. I estimate inflation risk as the 90th percentile of inflation within each group and, alternatively, as the difference between the 90th percentile and the median in each group. The specification I use is the following:

$$InflationRisk^{y}_{r,t} = \beta^{y} \times TradingDown_{r,t} + \gamma^{y}_{t} + \epsilon^{y}_{r,t} \tag{7}$$

Where $InflationRisk_{r,t}$ is one of the inflation risk measures of region r at time t and $TradingDown$ measures the average level of trading down in a given region. It is measured as the average contribution of the quality margin from Equation 2 into decreasing household expenditures in a given region and period, averaged across households, switched sign such that an increase points towards more trading down, and standardised for a better interpretation such that a unit increase is a one standard deviation increase. I run this specification for each income group y.

the highest income group within each state might not group the richest households of the country and therefore might include more variation of income levels within the groups.

[17] As detailed in Section 2, I build a Laspeyres index of inflation at the year on year level and quarterly frequency at the household level and in the spirit of Kaplan & Schulhofer-Wohl (2017). The Laspeyres inflation rate for household i between t and $t+4$ is:

$$\pi_{i,t+4} = \frac{\sum_{j:q_t,q_{ij,t+4}>0} p_{ij,t+4} q_{ijt}}{\sum_{j:q_t,q_{ij,t+4}>0} p_{ij} q_{ijt}} \tag{6}$$

Table 4 presents the results where the dependent variable is the median level of the Laspeyres household inflation. The results suggest that regions where trading down increases more, median inflation levels are unchanged for all household income groups except for the lowest income decile, for which inflation increases by 0.7p.p. In Table 5, the dependent variable is inflation risk at the group level, measured as the difference between the 90th percentile and the median level of inflation. It can be thought of as a measure of how large tail shocks to household inflation are in a given region. The results suggest that an increase in trading down in a given region is associated with a smaller inflation risk for all groups of households except for the first income decile, a result that is very in line with the previous table.[18] These results present suggestive evidence of a relationship between lower income household inflation and a generalised demand shift toward lower quality varieties derived from trading down. In the next section I aim at studying more in detail this relationship.

Table 4: Trading down and median inflation

	(1) All	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Average trading down	0.032	0.701**	-0.594	0.054	0.466	-0.198	-0.111	-0.064
	(0.189)	(0.278)	(0.635)	(0.344)	(0.365)	(0.362)	(0.253)	(0.314)
Observations	8,790	881	881	1,762	1,753	1,758	1,765	1,752
R-squared	0.677	0.825	0.737	0.772	0.658	0.678	0.694	0.646
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the time level. Relative income is defined within each region.*** p<0.01, ** p<0.05, * p<0.1

[18] Finally, Appendix Table A.7 shows that the results and their interpretation is similar if we focus on the 90th percentile only instead on its difference with the mean and therefore suggests that the results obtained in Table 5 are not driven simply by changes in the median level of inflation.

Table 5: Trading down and inflation risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Income decile 1	Income decile 2	Income quintile 1	Income quintile 2	Income quintile 3	Income quintile 4	Income quintile 5
Average trading down	-1.798***	-1.096	-1.975***	-1.532**	-1.360**	-2.314***	-1.754**	-2.095***
	(0.536)	(1.055)	(0.707)	(0.760)	(0.571)	(0.824)	(0.674)	(0.701)
Observations	8,790	881	881	1,762	1,753	1,758	1,765	1,752
R-squared	0.248	0.222	0.282	0.238	0.254	0.269	0.274	0.278
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the time level. Relative income is defined within each region.*** p<0.01, ** p<0.05, * p<0.1

5 The equilibrium response in the short run: a shift-share research design

5.1 A Shift-Share Research design

In the previous section, I document that households are heterogeneous in their ability to trade down in the quality of the goods they purchase. Specifically, low income households exhibit no significant change in the quality of the goods they buy when they are hit by a recession, presumably due to the fact that they already purchase lower quality varieties before the recession and, therefore, cannot use this margin of adjustment. This lower bound in the quality margin creates an aggregate demand shift toward lower-quality varieties and, therefore, could have aggregate implications for the price of low quality varieties compared with the higher quality ones. In this section, I aim at studying this effect in detail focusing on the period of the great financial crisis. I develop a shift share research design to assess the causal effects of changes in demand on the price index following the methodology proposed in Jaravel (2019).[19]

[19]The methodology I implement has a few differences compared to that of Jaravel (2019). First, it is not only be based on estimating demand shifters at the product level depending on population dynamics, but it adds a quality component to it. Moreover, it focuses on a shorter period of time, given that the aim is to understand the short run effects of a large demand shift.

5.1.1 Intuition

Regressing the demand for certain varieties driven by trading down on the price of low quality varieties at the onset of a recession would not identify a causal relationship for a number of reasons. First, because of reverse causality, that is, changes in the demand for specific varieties within products might be driven by changes in the relative prices across the different varieties. Second, omitted variable bias, given that there might be unobserved heterogeneity in how goods are priced in the quality space, which could happen to coincide with the income and spending patterns.

To address these concerns, I propose a strategy that aims at identifying demand shifters for lower quality varieties during the beginning of the great recession. It is based on predicting the demand for middle quality varieties based on population dynamics and consumption patterns before the crisis. Given the crisis, and households trading down, it identifies actual demand increases for lower quality varieties due to trading down. In essence, this strategy is aimed at identifying the causal impact of trading down on the relative price of low quality varieties.

The shift-share research design relies on two components: the predetermined spending shares across the product space for a number of sociodemographic groups in each state before the great financial crisis; and the heterogeneity in the population growth of each of these groups during the great financial crisis.

Regarding the first, I focus on households' spending on intermediate-quality varieties for each product for two reasons. First, because the consumers of these goods are likely to trade down in the quality of the goods towards the lower quality varieties at the onset of the recession and, second, given the lower bound in the quality space, this would translate into a heightened demand for the lowest quality varieties.

The second component is based on the heterogeneity in the population growth rates between a period before and a period during the great recession. For the groups whose population growth is largest, the predicted demand of the varieties of goods that these households tend to purchase absent a recession will be largest. Given the recession, the propensity to trade down will be large, and as a consequence so will be the demand for the lowest quality varieties. This identifies a plausibly exogenous demand increase for lower quality varieties during the great recession and, therefore, allows for a study on the effect it has on relative prices.

5.1.2 IV framework

Formally, the goal is to understand how the price index $P_p^{l \in L}$ of lower quality varieties $l \in L$ within each product p responds to changes in the quantity index $Q_p^{l \in L}$ induced by changes in demand. In other words, I wish to estimate β in the following specification:

$$\Delta log(P_{p,s,t}^{l \in L}) = \beta \Delta log(Q_{p,s,t}^{l \in L}) + \epsilon_{p,s,t} \tag{8}$$

where, $\epsilon_{p,s,t}$ is the unobserved potential outcome that would prevail in p, state s, time t absent changes in demand. Consistent estimation with OLS would require $\mathbb{E}[\Delta log(Q_{p,s,t}^{l \in L}) \times \epsilon_{p,s,t}] = 0$, which is not a plausible assumption because quantities are endogenous to prices. Conceptually, I aim at finding a demand shifter to vary $Q_p^{l \in L}$ and observe the impact on $P_p^{l \in L}$ across the cells of the product space indexed by p. The shift-share design uses variation in $Q_{p,s,t}^{l \in L}$ that comes only from the variation in the size of household groups consuming medium quality goods before the recession. As detailed in Section 5.1.1, this demand shifter takes the form of a shift-share instrument which uses variation in $Q_{p,s,t}^{l \in L}$ that comes only from the variation in the size of the household groups consuming medium quality goods before the recession.

The shift-share instrument is built to obtain variation in demand from the change in population growth across different household groups for each product and state as follows:

$$Z_{p,s,t}^{m \in M} = \sum_{h=1}^{H} s_{h,p,t-1}^{m \in M} \times g^{h,t} \tag{9}$$

Where $g^{h,t} \equiv \Delta log(L^{h,t})$ and H household groups indexed by h are of size L^h , $s_{h,p,t-1}$ denotes the share of sales in p to households of type h *spent in intermediate-quality goods* for a given product in the base period $t-1$.[20] Household groups are defined according to their age and region. As a consequence, the instrument only uses variation in the demographics, that is, the size of every defined household group, to predict changes in demand. It addresses the concern that prices and quantities are jointly determined in equilibrium.

I then use this instrument in a standard IV framework. The first-stage regression regresses the actual demand for low-quality goods during the financial crisis onto demographically-induced changes in the demand for middle quality goods before the financial crisis. The underlying hypothesis is that trading down should lead to a positive relationship between the two variables. The second-stage regression studies the effect of a higher demand for low quality goods, instrumented as detailed, on their relative prices.

$$\begin{aligned} \Delta log(P^{l \in L}_{p,s,t}) &= \alpha Z^{m \in M}_{p,s,t} + \gamma_{t,s} + \delta_p + \eta_{p,s,t} \\ \Delta log(Q^{l \in L}_{p,s,t}) &= \lambda Z^{m \in M}_{p,s,t} + \gamma_{t,s} + \delta_p + \epsilon_{p,s,t} \end{aligned} \tag{10}$$

where, $\gamma_{t,s}$ and δ_p are time-state and product category fixed effects, respectively, and $\epsilon_{p,s,t}$ is the unobserved potential outcome that would prevail in p absent changes in demand. As before, $l \in L$ denotes the fact that only low quality varieties l within each product p are included and $m \in M$ denotes the fact that only intermediate quality varieties m within each product p are included.

$Q^{l \in L}_{p,s,t}$ denotes the demand for a given product and $P^{l \in L}_{p,s,t}$ the relative price of the product. I substract to the price of low quality varieties the price of the high quality varieties. The reason is twofold: first, the price of high quality varieties serves as a benchmark to compare to and allows to focus on heterogeneous effects in prices across the quality distribution, eliminating all common price shifts. Second, while middle quality

[20] Note that this term sums 1: among all sales in the medium quality range, a given proportion goes to every household group.

varieties might experience more complex demand shits, given that the households that were likely buying them before the recession might be trading down but other households might begin acquiring these and, therefore, the dynamics of the prices might depend on the relative importance of the two factors. In contrast, the demand for high quality varieties is likely to not suffer an additional demand shift from households trading down.

In practice, the underlying assumption is that demographic growth in the short run is reasonably exogenous to the crisis and correlated with the amount of trading down in a given region. Under suitable identification conditions, discussed in the following section, $\frac{\alpha}{\lambda} \to \beta$, where β is the coefficient of interest in Equation 8.

5.1.3 Identification conditions

Instrument relevance requires $\Delta log(Q_p^{l \in L})$ and $Z_p^{m \in M}$ to be sufficiently correlated and can be directly checked in the first stage.

I refer to the work of Borusyak et al. (2022) to comprehend and verify the exclusion restriction that forms the basis of the instrument validity. Their results show that the exclusion restriction can be expressed as follows for a time t and region s:

$$Cov(Z_p^{m \in M}, \epsilon_p) = \mathbb{E}\left[\left(\sum_{h=1}^{H} s_{hp0}^{m \in M} \times g^h\right) \times \epsilon_p\right] = \sum_{h=1}^{H} s_h^{m \in M} \times g^h \mathbb{E}\left[\frac{s_{hp0}^{m \in M}}{s_h^{m \in M}} \times \epsilon_p\right] \to 0 \quad (11)$$

where the covariance and the expectation are taken over the middle-quality varieties $m \in M$ in the product space indexed by p. The key identification condition shown in equation 11 is a weighted covariance (in household space indexed by h, with spending weights s_h between the shocks g^h and the unobservable term $\mathbb{E}\left[\frac{s_{hp0}^{m \in M}}{s_h^{m \in M}} \times \epsilon_p\right]$. This term is a weighted average of product space unobservable potential outcomes ϵ_p.

In Jaravel (2019), a fundamental assumption is that manufacturers possess the foresight to predict shifts in market demand resulting from changes in the population sizes of diverse socio-demographic groups. Under this premise, the instrumental variable (IV) estimates capture the supply reaction to well-anticipated demand changes. In contrast, my focus lies in identifying the short-run supply curve, where manufacturers are not assumed to predict the impact of heterogeneous trading down. If they were to do so, this wouldn't solely involve accounting for population growth trends among households that buy their specific low-quality varieties, but would also require vendors to account for trends among household groups that typically purchase middle-quality varieties. These groups might initially buy such varieties before eventually trading down at the onset of a recession and selecting their own low-quality variety.

In practice, certain household shocks might violate the exclusion restriction. As pointed out in Jaravel (2019), older households tend to grow faster. This would imply a larger g^h for these. Older household groups are more likely to have defined their preferences earlier and, therefore, less likely to adopt new products or vary the quality of the goods they purchase over the cycle. This implies that their $\mathbb{E}\left[\frac{s_{hp0}^{m\in M}}{s_h^{m\in M}} \times \epsilon_p\right]$ might be systematically larger in absolute terms. This could invalidate the exclusion restriction across age groups.

In the following section I discuss the use of fixed effects to address such potential concerns.

5.1.4 Residualised shift-share instrument

To ensure that the aforementioned potential risks to the validity of the instrument are not problematic, I generate household population shocks that concentrate on fluctuations within groups, rather than across different household groups. Borusyak et al. (2022) show that residualising the instrument in the following way is equivalent to running a one-step IV specification with household characteristics onto the product space using initial spending shares.

I consider the following statistical decomposition of the shocks g^h:

$$g_t^h = \mu + g_{age} + g_{region} + \nu_{h,t} \tag{12}$$

This expression suggests that the observed shocks g_t^h can be decomposed into the average shocks along the three dimensions that segment the household space (age, region) as well as a residual component $\nu_{h,t}$.

One can compute a residualised household population shock $\tilde{g}_t^h$ after controlling for age and region either simultaneously or separately. Then one can build the residualised shift-share instrument $\tilde{Z}_p = \sum_{h=1}^{H} s_{hp0} \times \tilde{g}^h$.

Controlling for age fixed effects means that the instrument only relies on variation in household shocks that occur within each age group, addressing the concern about the validity of the exclusion restriction across age groups. I build the residualised shift-share in two steps. First, I regress g^h on household group fixed effects as in Equation 12 to obtain the residualised household population shocks $\tilde{g}_t^h$. Then, I build the shift-share instrument $\tilde{Z}_p$.

Table 6 presents summary statistics on the residualised household population shocks, introducing different controls. As observed in the standard deviation and interquartile ranges, the amount of variation in household shocks remains very similar across specifications and as controls are added. In particular, the standard deviation drops slightly from 0.016 to 0.015 and the interquartile range from 0.022 to 0.017 as controls are added. This implies that a singular dimension of the data doesn't exclusively drive the variability in household shocks, thus supporting the notion of employing them within a quasi-experimental framework. With the incorporation of additional fixed effects, the quasi-experimental interpretation gains greater credibility due to the potential reduction in bias. Nonetheless, there is a trade-off, as the instrument's effectiveness might diminish, potentially leading to an increase in variance.

Table 6: Changes in population of household groups (2005–2018, yearly averages)

	(1)	(2)	(3)
Mean	0.004	0.004	0.004
Standard deviation	0.016	0.016	0.015
Interquartile range	0.022	0.016	0.017
Residual change after controlling for			
Raw	✓		
Age f.e.		✓	✓
Region f.e.			✓
Sample sizes			
N total	47		
N age	3		
N regions	16		

5.1.5 Lagged population growth

An additional concern relates to the possibility that population growth itself may be influenced by the financial crisis, particularly through migration dynamics. For instance, a region experiencing a more severe economic shock might witness declining prices, which could suppress local inflation. Concurrently, such adverse conditions may prompt households to relocate to regions less affected by the crisis, thereby altering migration patterns and impacting population growth in both the origin and destination regions.

While incorporating region-time fixed effects controls for such variations at the regional level, it is also prudent to examine broader population trends rather than focusing solely on specific population changes during the crisis period. To this end, I construct a shift-share instrument using lagged population growth. This approach leverages historical population trends, thereby mitigating potential endogeneity concerns related to contemporaneous shocks and migration responses.

5.2 Implementation

To investigate the early effects of the financial crisis on consumption and price dynamics, I analyse two overlapping periods that capture the transition from pre-crisis stability to the initial phases of economic turmoil. The first period spans from the second half of 2006 to the second half of 2007, while the second covers the first half of 2007 to the first half of 2008. These intervals encompass the onset of the financial crisis, which began to manifest in mid-2007 and intensified through 2008.

By structuring the analysis around these periods, I aim to capture the evolution of consumption patterns and price levels as economic conditions shifted from stability to crisis. This approach allows for a comparative assessment of how early financial shocks influenced consumer behavior and price dynamics across regions.

As a placebo test, I select two periods preceding the recession which includes data from the first half of 2005 to the first half of 2006, and from the first half of 2006 to the first half of 2007, both being before the beginning of the crisis. These placebo tests are carried out to establish a comparison with periods where no aggregate trading down towards low-quality varieties is expected.

To validate the robustness of the main findings, I conduct placebo tests using two periods that precede the onset of the financial crisis. Specifically, I analyze data from the first half of 2005 to the first half of 2006, and from the first half of 2006 to the first half of 2007. Both intervals occur entirely before the crisis began to manifest in mid-2007. These placebo periods are selected to confirm that no similar patterns in consumption and price dynamics emerge in the absence of crisis-related shocks and, therefore, of a generalised trading down. Consequently, in these periods, no significant relationship should be observed between the predicted consumption of middle-quality varieties and the actual consumption of low-quality varieties.

I begin the analysis at the COICOP 5 level, which offers a detailed classification of household consumption expenditures. As a robustness check, I also utilize the COICOP 10-digit classification of varieties into products, as outlined in Section 2.1.

I classify varieties (barcodes) as being high quality if their price is above the 75th percentile of the prices of a given product (COICOP-5) and units of the package in a given pre-crisis period of time and in a given region. Likewise, I classify varieties as being of low quality if their price is below the 25th percentile of the prices of a given product and unit of measurement in a given period of time and in a given region. The rest are medium quality varieties.

Price growth of low-quality varieties at the product level is calculated as the log difference of the consumption-weighted price of low quality varieties for each product. Subsequently, I analyze price growth relative to, first, the overall price growth of the product, including all qualities, and second, the price growth of the high-quality varieties within each product category.

To construct the instrument, I first classify households into groups and aim at using the growth of these population groups as an indicator for changes in demand. I classify households according to their age and region. For age, I classify households in 3 groups according to the age of the head of the household: less than 45, between 45 and 60, and more than 60. The second dimension is the region (state) of residence of the household. Given that a small number of these groups are not represented in the dataset, this gives a total of 47 groups to study.

5.3 Results

Table 7 presents the baseline findings. Columns 1 and 2 examine different specifications where the dependent variable is the price growth of low-quality varieties relative to the overall product-level price growth. Columns 3 and 4 shift focus to the price growth of low-quality varieties relative to that of high-quality varieties within the same product category. Notably, the results consistently demonstrate a positive and significant relationship between the demand for low-quality goods (identified through the *predicted* demand growth of middle-quality goods in the absence of a recession and driven by demographic factors) and the *actual* increase in prices of low-quality goods during a recession. This suggests that the aggregate demand shift towards low-quality goods *causes* an increase in their relative prices.

Specifically, the results indicate that, on average, a 1% increase in the demand for lower-quality varieties causes around a 0.4% increase in their relative price compared to the price of the overall product category. When comparing the price low-quality to high-quality varieties, the same 1% demand increase causes around a 1.9% rise in their relative price. This suggests that low-quality varieties experienced more pronounced price increases relative to high-quality ones than to the broader product category. From a welfare perspective, this implies that consumers of high-quality varieties benefit from an additional channel beyond the ability to trade down: they may experience more favorable price dynamics even without altering their consumption basket. This effect could be attributed to a sudden decrease in demand for high-quality varieties. Conversely, consumers of low-quality varieties not only might lack the option to trade down further, as previously documented, but also face higher relative prices, potentially exacerbating their economic burden during the crisis.

For example, if demand for low-quality varieties increased by around 2% per year during the crisis, as implied in Jaimovich et al. (2019), this would correspond to around a 0.9% increase in their relative price compared to the average price of the product, and around a 3.6% increase relative to high-quality varieties.[21]

Note that the estimated coefficients are generally larger than those in Jaravel (2019). Moreover, Jaravel (2019) finds a negative relationship given supply response to demand dynamics through product innovation as the underlying assumption is that manufacturers are able to predict changes in demand driven by population shifts. Since the analysis focuses on short-run effects, it is intuitive to expect a larger and positive price response

[21] The authors report that in grocery stores, low-quality varieties accounted for 39% of market share in 2007 and 43% in 2012. Assuming total sales remained constant over this period, this corresponds to a 10.3% increase in sales of low-quality varieties, that is, around a 2% increase per year. Moreover, authors report that overall grocery store sales increased during this period, implying that the estimate effect could be larger. However, several caveats apply to this back-of-the-envelope calculation. First, the study period extends through 2012, making it longer than the comparison used here, and the change might not be constant over the period studies. Second, the classification of products into low-quality varieties is based on a different methodology.

to a demand shock.

Table A.8 displays the strength of the first-stage regression. A one percent increase in the shift-share instrument is associated with approximately a five percent increase in the endogenous dependent variable. While this coefficient may appear large, it is justified by the following consideration: a one percent increase in demand for middle-quality varieties likely corresponds to a disproportionately large increase in absolute quantities compared to a similar increase in demand for low-quality varieties. This is partly due to the way quality categories are defined, as middle-quality varieties encompass half of all available varieties. Additionally, even if consumption shares between low- and middle-quality varieties were similar, two further considerations are important. First, consumers of middle-quality varieties are likely to purchase larger quantities on average, given their higher income levels. Second, a substitution effect may be at play, whereby consumers shift their spending toward supermarket purchases at the expense of alternatives like dining out in restaurants as a response to the shock.

Table 7: Shift-share instrument results

	(1) Δ log Price low (rel. avg.)	(2) Δ log Price low (rel. avg.)	(3) Δ log Price low (rel. high)	(4) Δ log Price low (rel. high)
Δ log demand low q.	0.460***	0.443***	1.894***	1.856***
	(0.079)	(0.072)	(0.325)	(0.300)
Observations	2,854	2,854	2,697	2,697
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	104.4	131.6	104.6	125
Cragg-Donald F	57.90	62.22	54.28	58.98

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** p<0.01, ** p<0.05, * p<0.1

5.3.1 Robustness checks

Results with residualised shift-share. Table 8 presents the results once the instrument is residualised with for age and region fixed effects as exposed in Section 5.1.4. In all, the results remain robust. The magnitudes of the coefficients are also very in line with previous findings.

Results with lagged population growth. An additional concern relates to the fact that population growth itself could be driven by the financial crisis though, for example, migration. To address this concern, I build the shift-share instrument using lagged population growth. Results are visible in Tables 9 and 10, and they point towards the same direction.

Placebo results. Table 11 shows the results when focusing on data from the period before the great financial crisis. The lack of strength in the first-stage regression shows that in absence of trading down the predicted demand for middle-quality varieties does not correlate with the demand of low quality varieties. Moreover, the second-stage regression coefficients are not statistically significant.

Results at the COICOP-10 level. I replicate the analysis using the COICOP-10 product-level classification. This approach offers a more granular categorization of goods and services, and is constructed as detailed in Section 2.1. Using the COICOP-10 classification provides a finer segmentation of products, resulting in a larger number of observations. However, this increased granularity may lead to reduced variation in consumption within each product category, potentially missing part of the variation of interest. The results, displayed in Tables A.9 to A.14 generally point toward the same conclusion as in the previous section and suggest that the results are robust to the classification used. The magnitude of the effect on prices is smaller than in the previous results, which might be driven by a smaller variability in prices due to the product classification.

Results with alternative household groups. For a finer classification of households into different groups, I proxy population growth with that observed in the sample.

This allows to classify households according to their social class, age and region, relying on the social class classification available in the dataset constructed based on profession, role within the company and education levels of the head of the household. I divide households into 3 groups based on this variable. Regarding age and region I proceed as before.[22] The underlying assumption is that the growth of the population in each of these groups is correlated with their growth in the dataset. I demean population growth at the yearly level to prevent additional noise from sample increases.While the sample growths tend to display larger variation, the differential growths between groups and regions are generally well captured. One exception is the region of Bayern where growth of the oldest population group is larger than growth of second oldest population group, while the statistics show the opposite trend. Generally, trends are followed decently well, with a generalised decrease in population in the youngest cohort and a decreasing increase in the middle-aged group. While one can expect additional noise driven by the differentials in growth between the sample and the actual population growth, that should not affect the validity of the results other than by debilitating the second stage relationship. Results for baseline specifications are observed in Tables A.15 and A.16 for COICOP-5 a COICOP-10 product classification, respectively, and appear to go in the same direction.

[22] Given that some of these groups are not represented in the dataset, this gives a total of 112 groups to study. Household groups containing less than 200 observations are dropped.

Table 8: Residualised shift-share instrument results

	(1) Rel. avg Age	(2) Rel. avg Age	(3) Rel. avg Age-Region	(4) Rel. avg Age-Region	(5) Rel. high Age	(6) Rel. high Age	(7) Rel. high Age-Region	(8) Rel. high Age-Region
Δ log demand low q.	0.327***	0.308***	0.319***	0.300***	1.192***	1.167***	1.144***	1.121***
	(0.072)	(0.061)	(0.072)	(0.060)	(0.321)	(0.281)	(0.325)	(0.283)
Observations	2,854	2,854	2,854	2,854	2,697	2,697	2,697	2,697
Time FE	YES	-	YES	-	YES	-	YES	-
Region FE	YES	-	YES	-	YES	-	YES	-
Product Division FE	YES	YES	YES	YES	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES	NO	YES	NO	YES
Clustering	Region	Region	Region	Region	Region	Region	Region	Region
First Stage F	17.36	20.87	15.92	19.21	17.34	20.76	15.84	19.05
Cragg-Donald F	27.50	30.48	25.70	28.58	24.52	27.79	22.88	26.05

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level. Columns 1, 2, 5 and 6 depict results with residualised shift share by age fixed effects. Columns 3, 4, 7 and 8 also include region fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 9: Shift-share instrument results with lagged population growth

	(1) Relative avg 1 year lag	(2) Relative avg 1 year lag	(3) Relative avg 2yr trend	(4) Relative avg 2yr trend	(5) Relative avg 2yr lag	(6) Relative avg 2yr lag
Δ log demand low q.	0.428***	0.405***	0.395***	0.371***	0.354***	0.329***
	(0.080)	(0.070)	(0.078)	(0.068)	(0.077)	(0.065)
Observations	2,854	2,854	2,854	2,854	2,854	2,854
Time FE	YES	-	YES	-	YES	-
Region FE	YES	-	YES	-	YES	-
Product Division FE	YES	YES	YES	YES	YES	YES
Time $\times$ Region FE	NO	YES	NO	YES	NO	YES
Clustering	Region	Region	Region	Region	Region	Region
First Stage F	53.73	80.43	36.36	55.15	24.51	37.37
Cragg-Donald F	44.45	49.51	37.23	42.03	29.43	33.76

Table 10: Shift-share instrument results with lagged population growth (2)

	(1) Relative high 1 year lag	(2) Relative high 1 year lag	(3) Relative high 2yr trend	(4) Relative high 2yr trend	(5) Relative high 2yr lag	(6) Relative high 2yr lag
Δ log demand low q.	1.747***	1.694***	1.585***	1.534***	1.376***	1.332***
	(0.319)	(0.282)	(0.309)	(0.265)	(0.299)	(0.249)
Observations	2,697	2,697	2,697	2,697	2,697	2,697
Time FE	YES	-	YES	-	YES	-
Region FE	YES	-	YES	-	YES	-
Product Division FE	YES	YES	YES	YES	YES	YES
Time $\times$ Region FE	NO	YES	NO	YES	NO	YES
Clustering	Region	Region	Region	Region	Region	Region
First Stage F	54.81	78.03	36.90	53.99	24.47	36.35
Cragg-Donald F	40.92	46.37	33.77	38.95	26.10	30.77

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level. In columns 1 to 3, the shift-share instrument is constructed using one-year lagged population growth; in columns 4 to 6, the average population growth over the previous two years is used; and in columns 7 to 9, two-year lagged population growth is employed. *** p<0.01, ** p<0.05, * p<0.1

Table 11: Placebo Shift-share instrument results

	(1) Rel. avg.	(2) Rel. avg.	(3) Rel. high	(4) Rel. high
Placebo	0.840	-0.222	3.860	-1.118**
	(3.920)	(0.194)	(22.064)	(0.535)
Observations	2,839	2,839	2,710	2,710
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	0.0404	4.453	0.0294	4.228
Cragg-Donald F	0.394	5.900	0.305	6.180

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

6 Conclusions

In this study, I explore the significance of the quality margin as a protective mechanism against aggregate shocks, focusing specifically on the heterogeneous behavior observed among households along the income distribution. Using household scanner data from Germany, I analyze the degree to which households engage in trading down. I provide evidence that, on average, lower income households tend to opt for lower quality goods. Moreover, in the aftermath of an idiosyncratic or an aggregate shock, lower income households demonstrate a limited inclination to engage in trading down, presumably due to their constrained capacity to do so. This stands in contrast to other households, who exhibit a greater propensity to trade down by selecting lower quality goods. To comprehensively understand the broader implications of this shift in aggregate demand towards lower quality goods, I employ a shift-share research design. I find that this aggregate demand shift toward lower quality varieties in the aftermath of a recession increases the relative price of low quality varieties, which can have large implications for inflation risk over the business cycle for lower income households.

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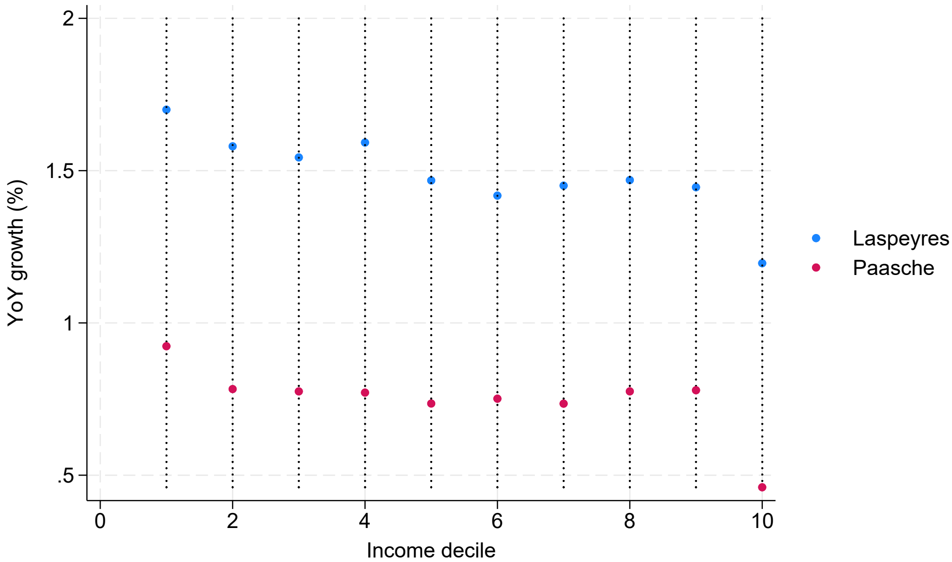
A Appendix

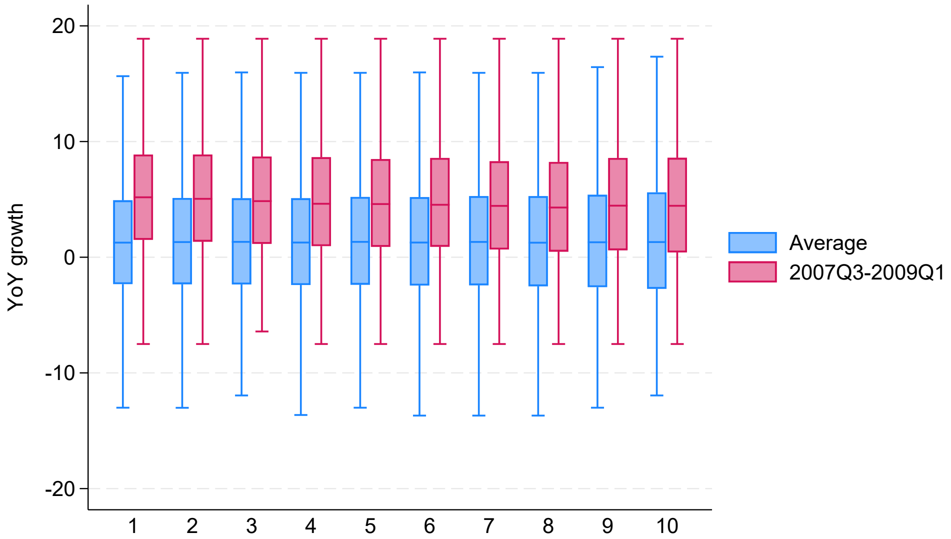
A.1 Appendix A: Additional Results

Figure A.1: Average inflation by income decile



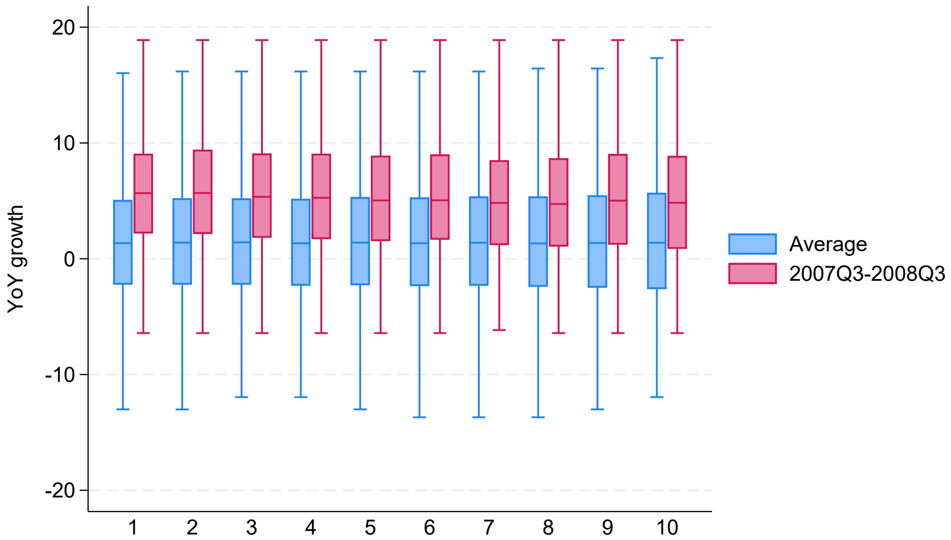
Notes: Inflation is computed at the household level and then averaged by groups across all time periods. The data covers German households, spans from 2005 to 2018, and covers supermarket goods.

Figure A.2: Inflation risk by income decile and over the business cycle



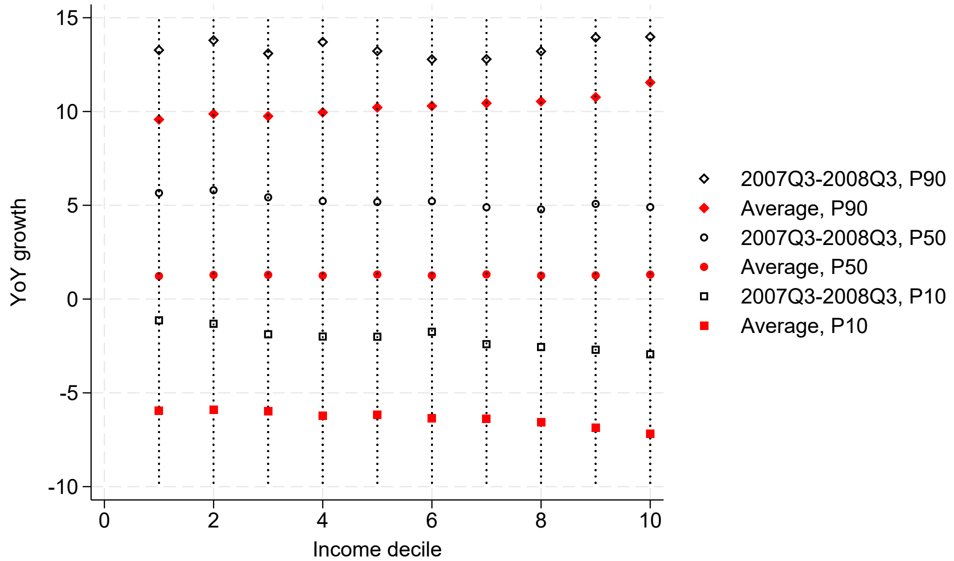
Notes: Laspeyres Inflation is computed at the household level. Income decile is defined between household within a given state. The data covers German households and spans from 2005 to 2018. The box depicts the median, 25th and 75th percentile. Upper and lower adjacent values are defined as 75th percentile plus 3/2 of the interquantile range.

Figure A.3: Inflation risk by income decile and over the business cycle



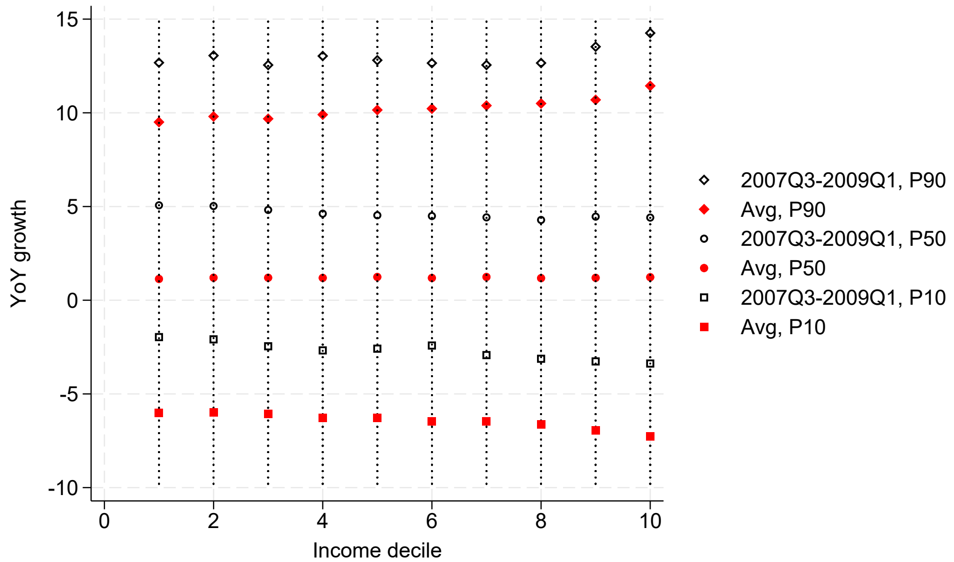
Notes: Laspeyres Inflation is computed at the household level. Income decile is defined between household within a given state. The data covers German households and spans from 2005 to 2018. The box depicts the median, 25th and 75th percentile. Upper and lower adjacent values are defined as 75th percentile plus 3/2 of the interquantile range.

Figure A.4: Inflation risk by income decile and over the business cycle



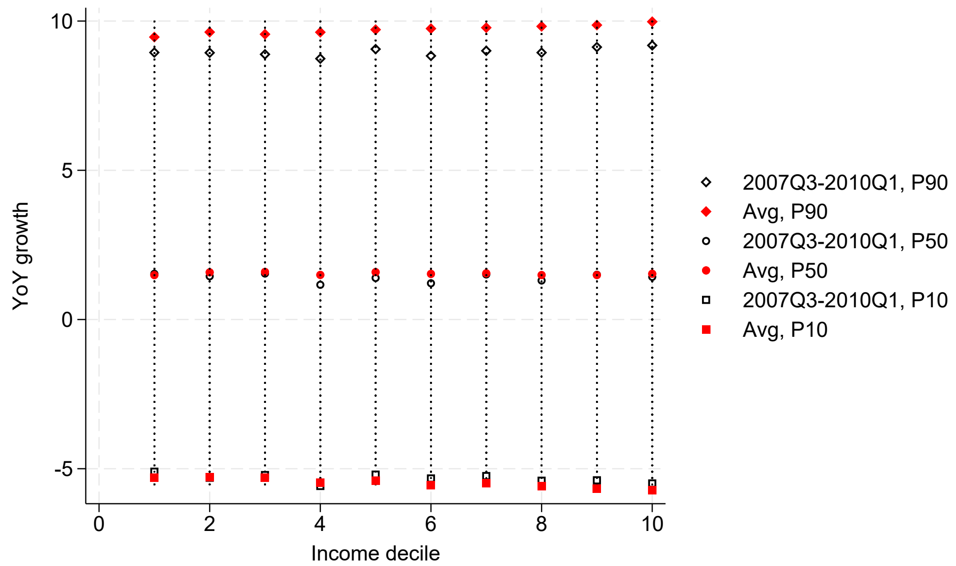
Notes: Laspeyres Inflation is computed at the household level. The data covers German households and spans from 2005 to 2018. GFC refers to the beginning of the financial crisis and includes the second semester of 2007 and all 2008.

Figure A.5: Inflation risk during the recession



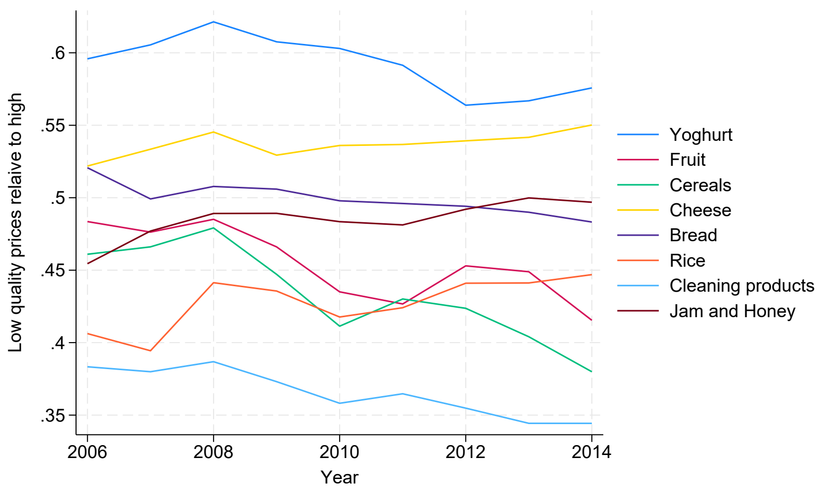
Notes: Laspeyres Inflation is computed at the household level. The data covers German households and spans from 2005 to 2018. GFC refers to the beginning of the financial crisis and includes the second semester of 2007 and all 2008.

Figure A.6: Inflation risk during the recession: all GFC



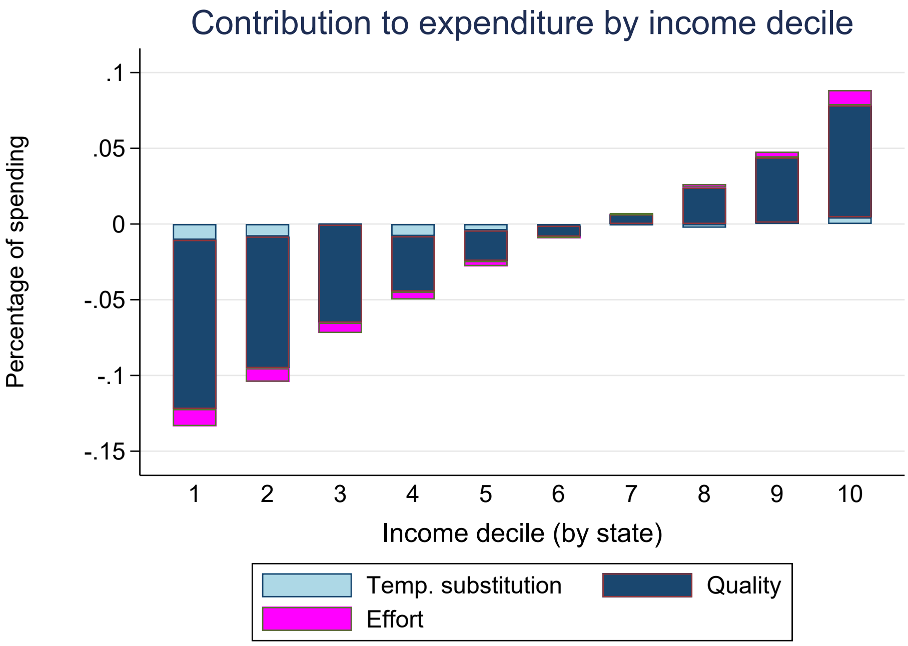
Notes: Laspeyres Inflation is computed at the household level. The data covers German households and spans from 2005 to 2018. GFC refers to the beginning of the financial crisis and includes the second semester of 2007, all 2008 and 2009.

Figure A.7: Relative prices of cheap vs expensive varieties within selected categories



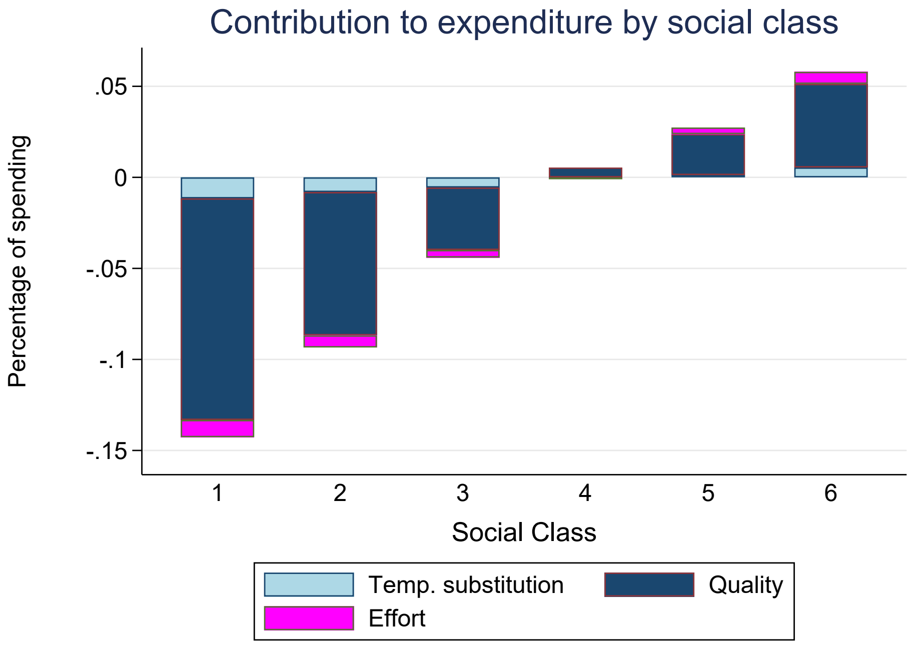
Note: The relative price of cheap varieties is defined as the 25th percentile of a product category divided by the median price of that product category within each year. Product categories are defined by the COICOP-5 classification.

Figure A.8: Decomposition by income group within state



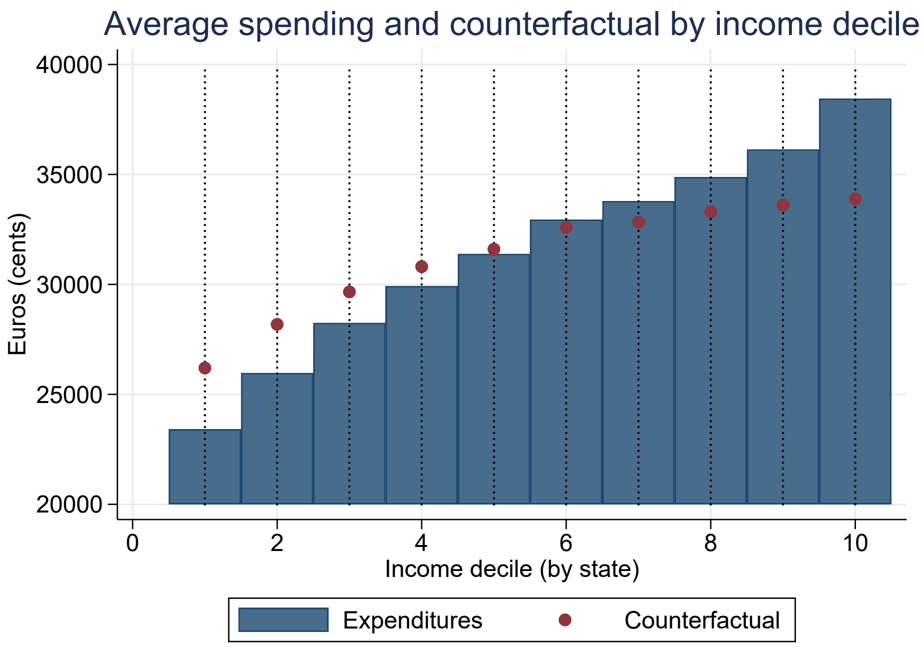
Notes: Average contribution of each temporary substitution, quality and effort into overall spending by income group and average over time. Each term in Equation 2 is divided by expenditures and averaged across households in an income group and over all periods of time (2005 to 2018). Income deciles are defined within state.

Figure A.9: Decomposition by social class



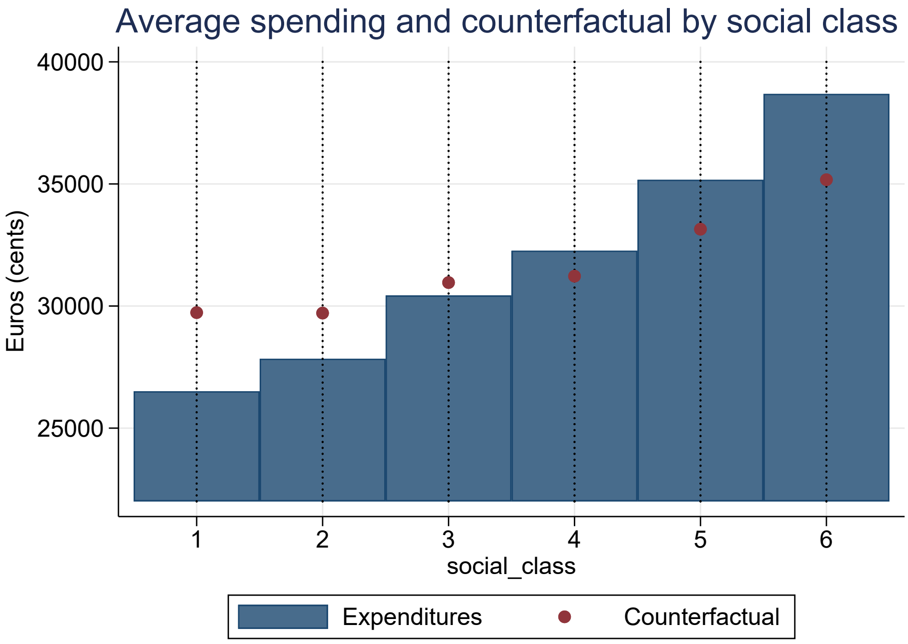
Notes: Average contribution of each temporary substitution, quality and effort into overall spending by income group and average over time. Each term in Equation 2 is divided by expenditures and averaged across households in an social class group and over all periods of time (2005 to 2018).

Figure A.10: Expenditures and counterfactual by income group within state



Notes: Average *per capita* household expenditure and the counterfactual expenditure term in Equation 2, adjusted for intra-household economies of scale as detailed in Section 2.1 and averaged across time for each income group. Income groups are defined within each state.

Figure A.11: Expenditures and counterfactual by social class



Notes: Average *per capita* household expenditure and the counterfactual expenditure term in Equation 2, adjusted for intra-household economies of scale as detailed in Section 2.1 and averaged across time for each social class group.

Table A.1: Heterogeneous idiosyncratic trading down, by relative income (within state)

	(1) Income All HH	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
income_drop	-0.315***	0.011	-0.344	0.188	-0.232	-0.835***	-0.825***	-0.483***
	(0.052)	(0.397)	(0.443)	(0.237)	(0.225)	(0.170)	(0.140)	(0.113)
Observations	1,470,702	122,997	110,369	233,710	215,699	216,379	201,068	185,911
R-squared	0.758	0.776	0.797	0.769	0.784	0.785	0.791	0.773
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined as within-state level.*** p<0.01, ** p<0.05, * p<0.1

Table A.2: Heterogeneous idiosyncratic trading down, by social class

	(1) All HH	(2) Social class 1	(3) Social class 2	(4) Social class 3	(5) Social class 4	(6) Social class 5	(7) Social class 6
income_drop	-0.315***	-0.862	0.221	-0.290***	-0.290***	-0.270	0.078
	(0.052)	(0.642)	(0.157)	(0.102)	(0.087)	(0.173)	(0.241)
Observations	1,470,702	10,614	166,042	334,443	406,185	88,935	48,005
R-squared	0.758	0.780	0.769	0.774	0.780	0.794	0.805
Household FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined within each region.*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Heterogeneous aggregate trading down, by relative income (within state)

	(1) Income All HH	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Regional Recession	-0.220***	0.040	0.005	0.042	-0.207**	-0.278***	-0.190**	-0.240**
	(0.047)	(0.156)	(0.146)	(0.108)	(0.099)	(0.094)	(0.094)	(0.099)
Observations	1,470,702	155,838	145,809	304,044	290,158	291,251	291,919	283,298
R-squared	0.758	0.767	0.783	0.759	0.778	0.778	0.780	0.763
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined as within-state level.*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Heterogeneous aggregate trading down, by social class

	(1) Social class all	(2) Social class 1	(3) Social class 2	(4) Social class 3	(5) Social class 4	(6) Social class 5	(7) Social class 6
Regional Recession	-0.220***	0.061	-0.161	-0.222***	-0.249***	-0.185	0.057
	(0.047)	(0.544)	(0.117)	(0.080)	(0.072)	(0.157)	(0.198)
Observations	1,470,702	15,575	242,561	474,601	554,436	119,253	62,288
R-squared	0.758	0.773	0.759	0.767	0.771	0.786	0.792
Household FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Households are grouped by their social class.*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Heterogeneous trading down, by relative income (within state) GFC

	(1) Income All HH	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Regional Recession × GFC	-0.719***	-0.328	-0.616*	-0.436*	-0.468*	-0.762***	-0.690***	-0.535**
	(0.105)	(0.356)	(0.330)	(0.245)	(0.242)	(0.224)	(0.226)	(0.230)
Observations	1,470,702	155,838	145,809	304,044	290,158	291,251	291,919	283,298
R-squared	0.758	0.767	0.783	0.759	0.778	0.778	0.780	0.763
Household FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Relative income is defined as within-state level.*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Heterogeneous trading down, by social class GFC

	(1) Social All HH	(2) Social class 1	(3) Social class 2	(4) Social class 3	(5) Social class 4	(6) Social class 5	(7) Social class 6
Regional Recession × GFC	-0.719***	0.030	-0.782***	-0.832***	-0.507***	-0.550	-0.389
	(0.105)	(1.187)	(0.262)	(0.187)	(0.168)	(0.351)	(0.450)
Observations	1,470,702	15,575	242,561	474,601	554,436	119,253	62,288
R-squared	0.758	0.773	0.759	0.767	0.771	0.786	0.792
Household FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the household level. Households are grouped by their social class.*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Heterogeneous trading down and inflation risk

	(1) All	(2) Income decile 1	(3) Income decile 2	(4) Income quintile 1	(5) Income quintile 2	(6) Income quintile 3	(7) Income quintile 4	(8) Income quintile 5
Average trading down	-0.879**	-0.093	-1.071*	-0.577	-0.258	-1.705**	-0.938*	-0.977**
	(0.364)	(0.622)	(0.555)	(0.401)	(0.585)	(0.693)	(0.553)	(0.405)
Observations	8,790	881	881	1,762	1,753	1,758	1,765	1,752
R-squared	0.519	0.564	0.574	0.557	0.544	0.508	0.500	0.540
Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes: Standard errors are clustered at the time level. Relative income is defined within each region.*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Shift-share instrument: first-stage regression

	(1) Baseline	(2) Residualised	(3) Residualised	(4) Lagged	(5) Lagged	(6) Lagged
Baseline shift-share	5.334***					
	(0.515)					
Residualised (age)		6.331***				
		(1.323)				
Residualised (age and region)			6.125***			
			(1.331)			
1 year lagged population				4.726***		
				(0.655)		
2 year trend lagged population					4.298***	
					(0.715)	
2 year lagged population						3.705***
						(0.739)
Observations	2,929	2,929	2,929	2,929	2,929	2,929
R-squared	0.540	0.534	0.534	0.537	0.536	0.534
Time FE	YES	YES	YES	YES	YES	YES
Product Division FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES

Notes: The table presents the results of regressing product demand growth on the shift-share instrument defined as described in Equation 9. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** p<0.01, ** p<0.05, * p<0.1

Table A.9: Shift-share instrument results with COICOP-10 classification

	(1)	(2)	(3)	(4)
	Δ log Price low (rel. avg.)	Δ log Price low (rel. avg.)	Δ log Price low (rel. high)	Δ log Price low (rel. high)
Δ log demand low q.	0.353***	0.337***	1.080***	1.067***
	(0.041)	(0.034)	(0.168)	(0.150)
Observations	7,105	7,105	6,530	6,530
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	31.42	37.46	28.42	31.26
Cragg-Donald F	63.74	67.59	69.51	73.49

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.10: Shift-share instrument: first-stage regression with COICOP-10 classification

	(1) Baseline	(2) Residualised	(3) Residualised	(4) Lagged	(5) Lagged	(6) Lagged
Baseline shift-share	4.228***					
	(0.747)					
Residualised (age)		4.920***				
		(1.523)				
Residualised (age and region)			4.566***			
			(1.433)			
1 year lagged population				3.636***		
				(0.890)		
2 year trend lagged population					3.242***	
					(0.916)	
2 year lagged population						2.737***
						(0.891)
Observations	7,229	7,229	7,229	7,229	7,229	7,229
R-squared	0.430	0.427	0.426	0.428	0.428	0.427
Time FE	YES	YES	YES	YES	YES	YES
Product Division FE	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES

Notes: The table presents the results of regressing product demand growth on the shift-share instrument defined as described in Equation 9. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** p<0.01, ** p<0.05, * p<0.1

Table A.11: Residualised shift-share instrument results with COICOP-10 classification

	(1) Rel. high Age	(2) Rel. high Age	(3) Rel. high Age-Region	(4) Rel. high Age-Region
Δ log demand low q.	0.551**	0.550**	0.548*	0.547**
	(0.261)	(0.241)	(0.291)	(0.267)
Observations	6,530	6,530	6,530	6,530
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	7.796	8.798	7.364	8.434
Cragg-Donald F	27.22	29.61	22.99	25.19

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level. Columns 1, 2, 5 and 6 depict results with residualised shift share by age fixed effects. Columns 3, 4, 7 and 8 also include region fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.12: Shift-share instrument results with lagged population growth with COICOP-10 classification

	(1) Rel. avg 1 year lag	(2) Rel. avg 1 year lag	(3) Rel. avg 2yr trend	(4) Rel. avg 2yr trend	(5) Rel. avg 2yr lag	(6) Rel. avg 2yr lag
Δ log demand low q.	0.306***	0.286***	0.259***	0.239***	0.199***	0.177***
	(0.037)	(0.031)	(0.035)	(0.032)	(0.040)	(0.042)
Observations	7,105	7,105	7,105	7,105	7,105	7,105
Time FE	YES	-	YES	-	YES	-
Region FE	YES	-	YES	-	YES	-
Product Division FE	YES	YES	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES	NO	YES
Clustering	Region	Region	Region	Region	Region	Region
First Stage F	16.32	21.26	12.16	16.28	9.070	12.57
Cragg-Donald F	45.26	49.64	36.05	40.04	26.86	30.30

Table A.13: Shift-share instrument results with lagged population growth with COICOP-10 classification (2)

	(1) Rel. high 1 year lag	(2) Rel. high 1 year lag	(3) Rel. high 2yr trend	(4) Rel. high 2yr trend	(5) Rel. high 2yr lag	(6) Rel. high 2yr lag
Δ log demand low q.	0.971***	0.953***	0.844***	0.828***	0.676***	0.665***
	(0.197)	(0.171)	(0.222)	(0.194)	(0.257)	(0.228)
Observations	6,530	6,530	6,530	6,530	6,530	6,530
Time FE	YES	-	YES	-	YES	-
Region FE	YES	-	YES	-	YES	-
Product Division FE	YES	YES	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES	NO	YES
Clustering	Region	Region	Region	Region	Region	Region
First Stage F	14.76	17.50	10.90	13.25	8.018	10.05
Cragg-Donald F	48.69	53.28	38.27	42.43	27.91	31.46

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level. In columns 1 to 3, the shift-share instrument is constructed using one-year lagged population growth; in columns 4 to 6, the average population growth over the previous two years is used; and in columns 7 to 9, two-year lagged population growth is employed. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.14: Placebo Shift-share instrument results with COICOP-10 classification

	(1) Rel. avg.	(2) Rel. avg.	(3) Rel. high	(4) Rel. high
Placebo	0.262	1.017	0.612	2.395
	(0.212)	(1.603)	(0.545)	(2.913)
Observations	7,158	7,158	6,679	6,679
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	1.453	0.381	1.629	0.743
Cragg-Donald F	14.71	0.983	16.47	1.405

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.15: Alternative shift-share construction

	(1) Δ log Price low (rel. avg.)	(2) Δ log Price low (rel. avg.)	(3) Δ log Price low (rel. high)	(4) Δ log Price low (rel. high)
Δ log demand low q.	0.546***	0.528***	2.270***	2.226***
	(0.076)	(0.070)	(0.290)	(0.271)
Observations	2,854	2,854	2,697	2,697
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	83.38	89.94	77.27	80.87
Cragg-Donald F	59.92	64.35	60.35	65.01

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A.16: Alternative shift-share construction with COICOP-10 classification

	(1) Δ log Price low (rel. avg.)	(2) Δ log Price low (rel. avg.)	(3) Δ log Price low (rel. high)	(4) Δ log Price low (rel. high)
Δ log demand low q.	0.407***	0.395***	1.128***	1.112***
	(0.045)	(0.040)	(0.126)	(0.117)
Observations	7,105	7,105	6,530	6,530
Time FE	YES	-	YES	-
Region FE	YES	-	YES	-
Product Division FE	YES	YES	YES	YES
Time × Region FE	NO	YES	NO	YES
Clustering	Region	Region	Region	Region
First Stage F	86.36	114.6	91.24	109.4
Cragg-Donald F	90.87	95.92	107.1	113

Notes: The table presents the results of the IV estimation specification in Equation 10. The instrumented variable is demand growth of a product category in a given state. Data includes growth data from two periods: 2006S2 to 2007S2 and 2007S1 to 2008S1. Product division FE refer to COICOP-2 product classification. The instrument is a shift share design as described in Equation 9. Standard errors are clustered at the region level and are robust to clustering at the product/region level.*** p<0.01, ** p<0.05, * p<0.1

A.2 Appendix B: Details on LLM classification

To achieve a more granular classification of products, from COICOP-5 to COICOP-10, I use GPT-4o, a state-of-the-art large language model, to classify products into the COICOP10 categories. I use the product's barcode categorization and description as inputs for the model. By designing specific prompts, I guide GPT-4o to accurately assign the appropriate COICOP10 category to each product. This approach leverages the model's advanced natural language understanding capabilities to effectively interpret diverse product descriptions, enhancing the precision of our classification process.

Around 17% of the observations are classified as 0, that is, because of insufficient information in the category and barcode descriptions. These are left out in the analysis. The system prompt used is:

You are an experienced analyst specializing in consumer products and brands, your expertise includes classifying product varieties. You speak and understand English and German. Your current task is to classify a specific barcode using the COICOP5 classification, along with a description of the barcode and its category, into a COICOP10 classification number. The output should include the COICOP10 number. Guidelines:

- *Consider the information included in "Category" and the Barcode description.*

- *Use information in both English and German*
- *When available, use information from brand names to assess the product classification*
- *If from the information provided you cannot assess with a high likelihood the COICOP10 classification, return "0" as output.*
- *Output only the COICOP10 number.*

Some examples:

- *If a specific barcode is classified within COICOP5 1114 ("Obstkonserven"), then there are 3 alternatives for the COICOP10 classification: "Apfelmus oder andere Kernobstkonserve", "Sauerkirschen oder andere Steinobstkonserve", "Ananaskonserve, Erdbeerkonserve oder Ähnliches". In this case, given is the barcode category is "Oliven", the most likely COICOP10 classification is "sauerkirschen oder andere steinobstkonserve".*
- *If a barcode is classified within COICOP5 1161 ("Obst, frisch oder gekühlt") it means that the possible COICOP10 varieties are: "Zitrusfrüchte", "Bananen", "Äpfel", "Birnen", "Pfirsiche, Kirschen o.a. Stein- oder Kernobst", "Erdbeeren, Himbeeren, Stachelbeeren oder Ähnliches", "Weintrauben", "Kiwis, Melonen oder Ähnliches". If the barcode category is: "lidl aegyptische" and barcode description is: "OBST FRISCHWARE", with this information it is not possible to assess the specific COICOP10 this barcode belongs to. Therefore the output to this should be 0.*

Table A.17: COICOP5 classification

COICIOP 5	COICOP 5 Description	Percent of barcodes
1111	Rice	.1550064
1112	Flours and other cereals	.1599959
1113	Bread	.6533998
1114	Other bakery products	3.804421
1115	Pizza and quiche	.1036703
1117	Breakfast cereals	.5435205
1118	Other cereal products	.2895006
1120	NA	1.771819
1124	Poultry	2.441407
1127	Dried salted or smoked meat	4.826045
1128	Other meat preparations	.9780485
1133	Fresh or chilled seafood	.2816283
1136	Other preserved or processed fish and seafood-based preparations	.953212
1141	Milk whole fresh	.268323
1143	Milk preserved	.0789446
1144	Yoghurt	.9047586
1145	Cheese and curd	4.798547
1146	Other milk products	.7810196
1147	Eggs	.6399837
1151	Butter	.1587763
1152	Margarine and other vegetable fats	.079499
1154	Other edible oils	.3369561
1155	Other edible animal fats	.099346
1161	Fresh or chilled fruit	5.118428
1163	Dried fruit and nuts	.7351164
1164	Preserved fruit and fruit-based products	.5630348
1171	Fresh or chilled vegetables other than potatoes and other tubers	4.620035
1173	Dried vegetables other preserved or processed vegetables	1.601622
1174	Potatoes	.8884597
1175	Crisps	.5260018
1181	Sugar	.1455819
1182	Jams marmalades and honey	.8597425
1183	Chocolate	1.628787
1184	Confectionery products	4.025178
1185	Edible ices and ice cream	.8624035
1186	Artificial sugar substitutes	.0342611
1191	Sauces condiments	1.351372
1192	Salt spices and culinary herbs	1.266108
1193	Baby food	.7405494
1194	Ready-made meals	2.295603
1199	Other food products n.e.c.	4.541977
1211	Coffee	.5622587
1212	Tea	1.022954
1213	Cocoa and powdered chocolate	.065085
1221	Mineral or spring waters	1.23484
1222	Soft drinks	1.04779
1223	Fruit and vegetable juices	1.354699
2111	Spirits and liqueurs	.818607
2112	Alcoholic soft drinks	.1159776
2121	Wine from grapes	3.91042
2122	Wine from other fruits	.0367004
2123	Fortified wines	.0197362
2124	Wine-based drinks	.3283076
2130	NA	.6636006
2134	Beer-based drinks	.1475777
5322	Coffee machines tea makers and similar appliances	.0165207
5403	Non-electric kitchen utensils and articles	.0436856
5611	Cleaning and maintenance products	4.072855
5612	Other non-durable small household articles	.9845903
6110	Pharmaceutical products	.5597085
9331	Garden products	.2681013
9341	Purchase of pets	1.927269
9342	Products for pets	1.521458
12113	Personal grooming treatments	.4980608
12121	Electric appliances for personal care	.1198583
12132	Articles for personal hygiene and wellness esoteric products and beauty products	21.74725