NBS Working paper
9/2025

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ISSN 2585-9269 (online)

Attention to food prices and the upward bias in inflation expectations *

Ondrej Kusenda[†] Michal Marenčák[‡]

July 29, 2025

Abstract

During the 2022-2023 inflation surge, the gap between households' inflation expectations and realized inflation in Slovakia widened from 7 to 17 p.p., contradicting the view that greater attention to inflation might mitigate the upward bias. Using LASSO and other machine-learning variable-selection techniques, we find that movements in food prices which rose faster than headline inflation are strongly associated with the upward bias increase. This evidence highlights selective attention in expectation formation and suggests that, when sectoral price dynamics greatly exceed aggregate inflation, central banks might assign those sectors greater weight in their inflation target.

Keywords: inflation expectations, consumer expectations, inattention, bias.
JEL-Codes: C14, C38, C52, D83, D84, E31, E52.

*We would like to thank Pavel Gertler, Milan Gylánik, Patrik Kupkovič, Aleš Maršál, Nataliia Ostapenko, Patryk Perkowski, Lukáš Ružek, and an anonymous referee for the NBS working paper series for many valuable comments and suggestions. Our gratitude extends to the Statistical Office of the Slovak Republic for providing access to the microdata from the European Commission Harmonized Consumer Survey for Slovakia.

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1. Introduction

One of the most well-established stylized facts in the literature on household inflation perceptions and expectations is that consumers tend to systematically overestimate both current and future inflation relative to actual and ex-post realized levels (see, among others, D'Acunto et al. (2023)). This phenomenon, commonly referred to as the upward bias, has been documented across a wide range of countries and time periods. In this paper, we examine how the gap between quantitative inflation expectations vis-à-vis actual inflation varies with inflation over time. We show that it can paradoxically increase even when headline inflation is rising and consumers are paying more attention to inflation, if individuals disproportionately anchor their expectations on the prices of specific goods that rise faster than the overall price index.

Overestimation of inflation can be problematic for several reasons. First, it suggests that economic agents may not form inflation perceptions and expectations in a fully rational manner (D'Acunto et al., 2023; Coibion and Gorodnichenko, 2015; Lein and Maag, 2011; Jonung, 1981). Second, an upward bias in expectations can contribute to self-fulfilling dynamics, potentially fueling wage demands and actual inflation. Third, biased inflation expectations can distort household decision-making, thereby affecting the transmission of monetary policy. For example, Montag (2024) shows that biased inflation perceptions can reduce household welfare by leading to suboptimal consumption and saving choices.

While it is commonly known that households tend to overestimate expected inflation relative to official measures, less is known about how this upward bias correlates with actual inflation. For instance, during periods of high inflation, does the gap between inflation expectations and realized inflation widen or narrow?

On the one hand, theoretical considerations suggest a negative relationship between the upward bias and inflation. Recent empirical studies show that during periods of elevated and rising inflation, consumers tend to pay greater attention to inflation-related information, which in turn influences their expectations (see, in particular, Cavallo et al. (2017), Weber et al. (2023), Pfäuti (2023a), Pfäuti (2023b), and Bracha and Tang (2024)). Hence, if consumers are better informed about the current inflationary environment, one would expect the bias to decline as argued in D'Acunto and Weber (2023a).

On the other hand, a positive relationship is also conceivable. Even if consumers are more attentive to inflation and better informed about its levels during periods of high inflation, they may still disproportionately base their perceptions and expectations on a subset of salient goods, such as food or energy, whose prices tend to rise more rapidly than the overall index. If such price increases dominate consumers' mental models of inflation, the upward bias may increase despite their larger attention to the prevailing high aggregate inflation levels.

Understanding the correlation between the upward bias in inflation expectations and actual inflation is important for at least three reasons. First, a positive correlation may amplify the adverse consequences of the level bias discussed above, particularly during periods of high inflation. Second, if expectations are disproportionately influenced by the prices of specific goods, it could be optimal for policymakers to account for this in the design of communication strategies or policy interventions. Third, a positive correlation may increase the overall volatility of inflation expectations, potentially complicating monetary policy transmission and reducing its effectiveness.

An assessment of the dynamic relationship between inflation and the upward-expectations bias necessitates an extended time series. Therefore, in this paper we use micro-level data on households' inflation expectations from the European Commission's Harmonized Consumer Survey, collected monthly for Slovakia from January 2009 to December 2024. A key strength of this dataset is its length and consistency: the 16-year span covers a range of inflation regimes — including deflation, periods of low and stable inflation, the recent inflation surge, and subsequent disinflation. This temporal variation is essential for our research question. Unlike one-time randomized controlled trials, which are unsuited to capturing macroeconomic dynamics over time, this dataset consists of repeated cross-sections that are representative of the population each month, making it particularly appropriate for our analysis.

First, we document a positive correlation between the upward bias in inflation expectations and actual inflation. This pattern is particularly pronounced during Slovakia's recent inflation surge (2021–2023), when inflation rose from 2% to over 15%. Despite heightened household attention to inflation during this period, the upward bias increased rather than declined.

Second, we show that although consumers became more attentive, their attention was selective rather than comprehensive. In particular, they disproportionately focused on food prices—highly salient items that experienced inflation well above the headline rate. This selective focus reinforced rather than corrected misperceptions, thereby amplifying the upward bias in inflation expectations.

To formalize this analysis, we employ several econometric and machine-learning approaches to estimate the relationship between inflation expectations and price changes in main categories of the representative consumption basket according to the Classification of Individual Consumption according to Purpose (COICOP) methodology. We begin with the Least Absolute Shrinkage and Selection Operator (LASSO) for it is specifically designed to identify the parsimonious subset of variables that can best explain the variable of interest from a large set of possible covariates (Akyapı et al., 2025). Our results show that grocery prices are the primary driver of households' inflation expectations in Slovakia, and their influence intensified during the recent inflation surge, when grocery-price inflation outpaced the headline rate. Particularly, our variance decomposition of fitted inflation expectations shows that the contribution of food prices to inflation expectations increased from less than 50 percent before the inflation surge to more than 80 percent at its peak. This shift implies that consumers' views of overall inflation became increasingly anchored to grocery-price movements, thereby biasing their assessment of the broader price environment.

Following the recent methodological approach proposed by Buckmann and Joseph (2023), we extend our analysis beyond LASSO by incorporating additional ridge regression and further machine learning models — random forests, and gradient boosting machines. These models can be particularly useful for capturing non-linear and time-varying relationships. Our results prove robust across specifications, underscoring the value of machine learning tools in uncovering heterogeneous drivers of inflation expectations.

These findings carry some important policy implications. If inflation expectations are primarily shaped by selective attention to salient goods — such as food — then standard monetary policy strategies, which typically emphasize aggregate inflation measures, may be insufficient to anchor public expectations effectively. Policymakers may need to more explicitly address food price dynamics or adapt their communication strategies to counteract persistent misperceptions. More broadly, our results contribute to the emerging debate on whether inflation targets should give greater weight to food prices, potentially making them a more effective anchor for public expectations, as suggested recently by Dietrich (2023) and Hahn and Marenčák (2025).

Literature Our paper is thus connected to several strands of literature. First, salient prices have been shown to play a key role in shaping consumer inflation expectations. D'Acunto et al. (2021), Trehan (2011), and Bonciani et al. (2024) emphasize the role of food prices for inflation expectations, while Coibion and Gorodnichenko (2015) and Trehan (2011) the importance of energy prices. The evidence on energy prices is, however, mixed as for instance Binder (2018) does not find a significant impact of gasoline prices. Recent comprehensive summaries of the extending literature on inflation expectations are given by Coibion and Gorodnichenko (2025), or D'Acunto and Weber (2024). We contribute to this literature by documenting that the importance of salient food prices can increase in periods in which food inflation exceeds headlines inflation numbers.

Second, since we provide an explanation not only for the positive correlation of the upward bias with actual inflation but also for the existence of the upward bias in the first place, our paper is related to papers that explain its existence too. Common explanations for inflation bias include personal consumption patterns Weber et al. (2022), memory effects (D'Acunto and Weber, 2023b; Malmendier and Nagel, 2016), uncertainty (Reiche and Meyler, 2022), and over-weighting of extreme price changes (Bruine de Bruin et al., 2011). A review of the literature findings on why an exposure to grocery prices can bias inflation expectations systematically upward is given by D'Acunto et al. (2023). We add to this literature the evidence on a positive correlation of the upward bias with actual inflation, which is a novel finding.

Yet despite its novelty, the evidence on the positive relationship between the upward bias and inflation in Slovakia does not appear to be universal. For instance, as shown in Marenčák and Nghiem (2025) who use the ECB Consumer Expectation Survey data, the upward bias decreased in Germany, France, Italy, Spain, Belgium, and the Netherlands during the 2022-23 inflation surge. This is in line with the theory of larger attention to inflation decreasing the gap between expected and actual levels of inflation. The evidence for Slovakia, however, suggests that when food inflation strongly exceeds the headline inflation, the upward bias might rise and higher inflation expectations - driven by food prices - can lead to larger propensity to consume as shown in Marenčák (2023) and argued by Kukk et al. (2025).

The remainder of the paper is organized as follows. Section 2 describes the data and documents the increase in the upward bias during the 2021-2023 inflation surge in Slovakia. In Section 3 we provide evidence linking food price salience to inflation expectations. Section 4 concludes with a discussion of policy implications.

2. Data

Our primary data source for household inflation expectations is the confidential microdata from the harmonized European Commission (EC) Consumer Survey for Slovakia. The survey is conducted monthly by the Statistical Office of the Slovak Republic on behalf of the Directorate-General for Economic and Financial Affairs of the European Commission as part of the EC's harmonized consumer survey program. The Slovak sample consists of a cross-section of 1,200 consumers, ensuring representativeness without requiring sample weights. Individual responses remain confidential, with only aggregate results publicly available. Access to the microdata for this study was granted by the Statistical Office of Slovakia.

The key survey question used in our analysis is the question Q6A eliciting households' subjective point estimates of the inflation rate in the next 12 months. This question is asked conditionally on reporting a different than zero or missing expectation of future inflation qualitatively:

Q6 *Which development of consumer prices do you expect over the next 12 months? They will [Increase more rapidly, Increase at the same rate, Increase at a slower rate, Stay about the same, Fall, Don't Know].* If the answer it not "Stay about the same" or "Don't know," the respondent will be asked for a point estimate (Question 6A).

Q6A *By what percentage do you think consumer prices will change over the next 12 months? [... percent]*

A full list of survey questions is provided in Appendix Appendix A. To ensure data quality and mitigate the impact of extreme outliers, we discard the top and bottom 2.5% of inflation expectations in each survey round. The dismissing of outlier observations reduces the influence of overly optimistic or pessimistic responses while preserving the underlying distribution of expectations.

In this paper, we focus on the upward bias in quantitative inflation expectations vis-à-vis actual inflation in a given period t. Hence, the upward bias, denoted by ub_t, is defined as the difference between the cross-sectional average of households' inflation expectations 12 months ahead, π_t^e, and the realized inflation rate over the preceding 12 months. The realized inflation can be the headline mea-

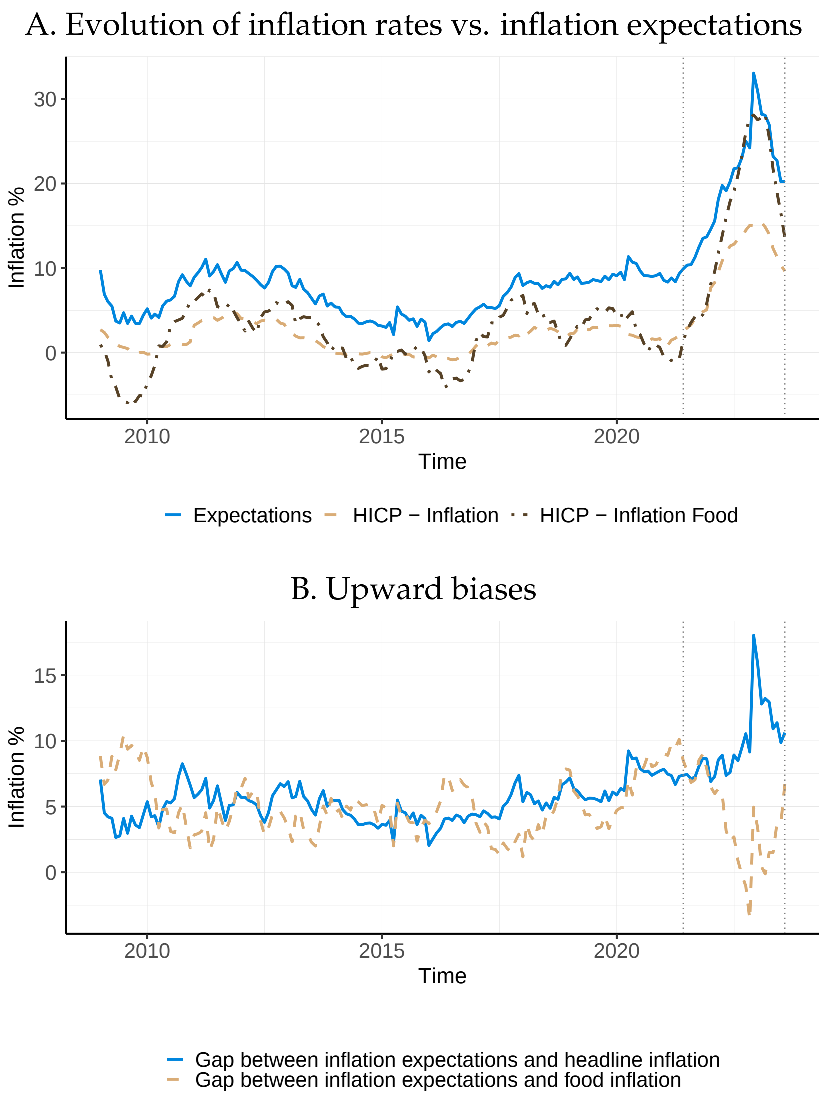


Figure 1: Inflation expectations, headline inflation, and food inflation over time, showing a growing divergence between expectations and actual inflation.

Notes: Panel B depicts the upward biases $ub_t^{headline}$ and ub_t^{food}, i.e. the differences between the cross-sectional average of inflation expectations after removing outliers and the headline inflation (COICOP CP00 category), versus food inflation (COICOP CP01 category).

sure for the whole economy, $\pi_t^{headline}$, or for the food sector, π_t^{food}.

$$ub_t^{headline} \equiv \pi_t^e - \pi_t^{headline} \tag{1}$$

$$ub_t^{food} \equiv \pi_t^e - \pi_t^{food} \tag{2}$$

This is motivated by the striking co-movement of current and expected inflation and by the literature (Reiche and Meyler, 2022). Specifically, Figure 1, Panel A illustrates the evolution of headline inflation, food inflation, and aggregate inflation expectations. We observe that inflation expectations are highly correlated with actual inflation, indicating a strong backward-looking expectation formation process (see Marenčák (2023) for a detailed comparison with inflation perceptions).

Panel B of Figure 1 shows the significant increase in the upward bias of inflation expectations relative to headline inflation during Slovakia's 2021–2023 inflation surge. Contrary to the expectation that greater attentiveness should reduce bias, we observe that household inflation expectations diverged further from actual inflation rates over this period. While the bias relative to headline inflation increased sharply, the bias relative to food inflation decreased, suggesting that households primarily could have relied on grocery prices when forming their inflation expectations.

Table 1 shows the correlation coefficients of the upward biases, defined respectively in equation (1) and equation (2), and the headline inflation in two different samples. We observe a positive and significant correlation in the upward bias between inflation expectations and headline inflation readings. The strenght of the relationship increases when expanding the sample to include the inflation surge period. In contrary, the upward bias based on food inflation is significantly negatively correlated with the headline inflation.

	2009:01 - 2021:05	2009:01 - 2023:08
$ub_t^{headline}$ vs. $\pi^{headline}$	0.49***	0.79***
ub_t^{food} vs. $\pi^{headline}$	-0.20**	-0.38***

Table 1: Correlation coefficients

Notes: The table shows the correlation coefficients between the headline inflation and the upward biases defined in equation (1) and equation (2) and shown in Panel B of Figure 1 in two different sample periods. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Before formally testing the hypothesis that the food price salience is associated with the larger upward bias in inflation expectations despite larger households' attention to inflation, it is imperative to show that attention in fact increased. To this end, Figure 2 shows the households' inflation attention measure of Bracha and Tang (2024). Their measure captures the share of respondents who provide a specific estimate of past inflation (Q5 and Q5A in Appendix A) rather than answering "I do not know." The figure shows that attention to inflation rose significantly in parallel with headline inflation, reinforcing the idea that households became more attentive to inflation in general.

3. Empirical strategy

If households overweight grocery goods when forming their expectations about future price changes, we can expect them to explain a disproportionately large share of inflation expectations. To analyze this formally, we regress the aggregate inflation expectations in time t for 12 months ahead on the year-on-year inflation rates in period t in the main 12 sub-groups of the HICP consumption basket. We provide details about the HICP and COICOP categories in Appendix Appendix C.

We first apply the least absolute shrinkage and selection operator (LASSO) fol-

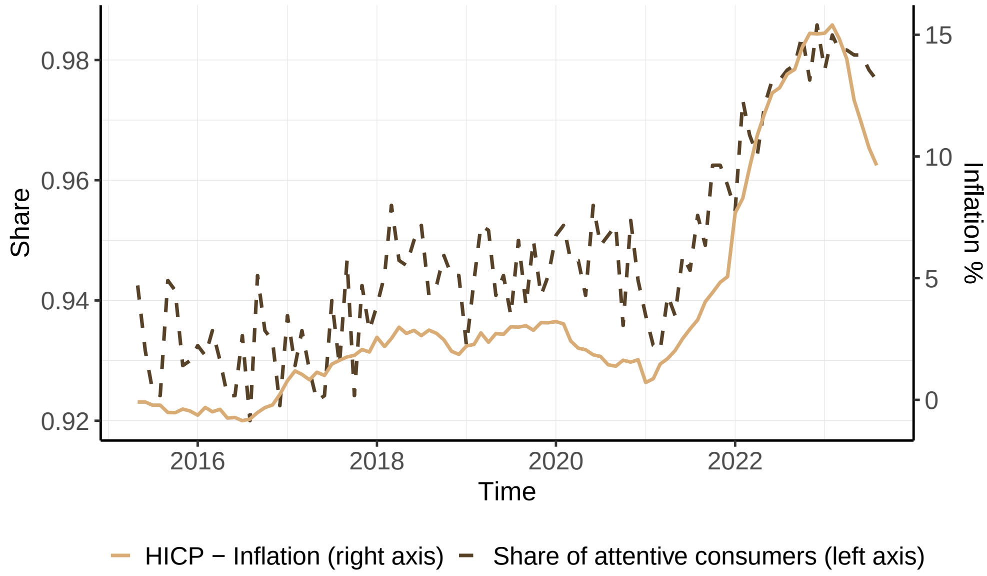


Figure 2: Attention to inflation

Notes: The figure shows that attention to inflation measure of Bracha and Tang (2024) calculated as the share of consumers at a time who do not answer the question on qualitative inflation perception with "I do not know" against the headline HICP inflation in p.p.

lowing Tibshirani (1996) to select the variables that can best explain inflation expectations.[1] Applying LASSO to select the subset of most important covariates is a common approach, see e.g. Akyapı et al. (2025) or Campos et al. (2022) in the inflation expectations literature for the US. As a robustness check, we later consider further approaches including the ridge regression, random forests and gradient boosting algorithms following Buckmann and Joseph (2023).

To assess the economic importance of each driver in our main LASSO specification, we decompose the fitted variance of inflation expectations across the twelve COICOP categories that make up the Harmonised Index of Consumer Prices (HICP). Once the LASSO delivers coefficient estimates $\widehat{\beta}_j$ for category j,

[1]The LASSO is a shrinkage method balancing the bias-variance trade-off by penalizing explanatory variables with low explanatory power. For a thorough exhibition see e.g. Hastie et al. (2001). We provide more details in Appendix Appendix B.

we compute the share

$$S_j = \frac{\widehat{\beta}_j^2 \ \mathrm{Var}(X_j)}{\sum_{k=1}^{12} \widehat{\beta}_k^2 \ \mathrm{Var}(X_k)}, \tag{3}$$

which, by construction, sums to one across all regressors. We deliberately omit the cross-covariance terms so that highly correlated HICP sub-components do not generate spuriously large contributions and so that the resulting shares are directly comparable to the official COICOP expenditure weights used to construct the HICP. We calculate S_j separately for the pre-surge and surge subsamples, allowing us to track how the influence of each price category evolves in different time samples. It is important to note that the ordering of categories remains qualitatively unchanged when we compare these variance shares with the raw LASSO coefficients (see Appendix Appendix D).

Because the LASSO does not yield conventional standard errors, we adopt a repeated cross-validation procedure to obtain non-standard confidence bands for the variance shares S_j. In particular, we reestimate the model $1{,}000$ times, each time drawing a fresh ten-fold cross-validation split, and recompute S_j in every replication. We summarize the resulting empirical distribution of S_j by reporting its mean together with the 2.5th and 97.5th percentiles, which form a non-parametric 95% confidence interval. Additional diagnostic plots and robustness checks are provided in Appendix Appendix B.

3.1. Main results

Figure 3 shows the results of the variance decomposition for both periods prior to and post inflation surge. The resulting variance decomposition shares are plotted against the mean official HICP weights of the twelve categories over the whole sample. We observe that already before the inflation surge food prices played a dominant role in shaping households' inflation expectations, exceeding their actual HICP weight. However, the impact of food prices intensified during the surge period with food prices explaining approximately 80 % of the variance of fitted inflation expectations.

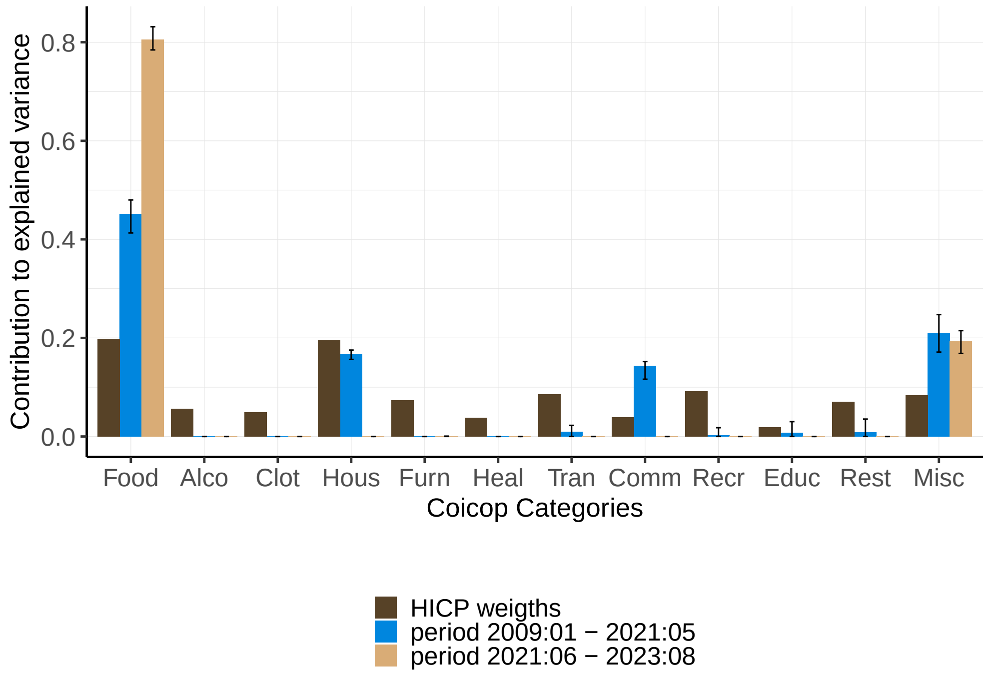


Figure 3: Main results - Relative importance of price categories for households' inflation expectations compared to HICP weights

Notes: The figure plots the average official HICP weights for the twelve main COICOP categories (January 2009 – August 2023) against their contributions to the variance of fitted inflation expectations from the LASSO regression. Full category names are listed in Table A1.

The results show that while food inflation has been always the category with the highest explanatory power for inflation expectations in Slovakia, it basically became the almost exclusive driver of inflation expectations during the recent inflationary period. This result suggests that the positive correlation of the upward bias with inflation can be attributed to a higher attention to certain items such as groceries.

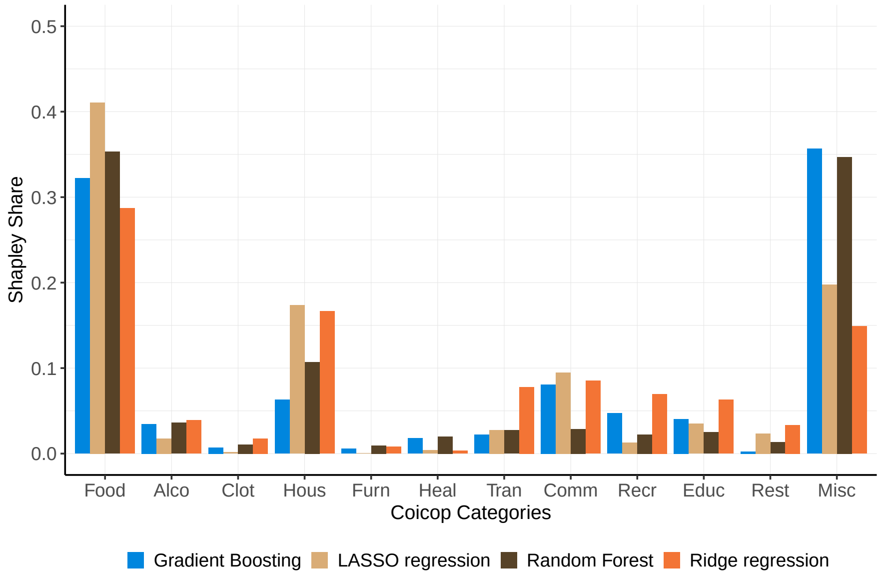
3.2. Alternative methods

In a recent contribution, Buckmann and Joseph (2023) propose a workflow for making the machine-learning techniques more interpretable for economic analysis. They combine a suite of linear methods (ridge, LASSO) and nonlinear methods (random forest, gradient boosting) in a time-series setting to identify the variables that best predict key macroeconomic targets. In particular, their feature-importance approach can be used to select the variables that most strongly explain Slovak households' inflation expectations, thereby complementing our LASSO analysis from before.

Figure 4 presents the robustness checks. Panel (a) displays Shapley-based feature importance for the pre-surge period, whereas Panel (b) reports the same statistics for the full sample that includes the surge period. Estimating a random forest on the full sample allows us to address potential non-linearities such as the potentially larger impact of grocery prices on expected inflation using one model over a longer period of time. Consistent with our main results, grocery prices become relatively more influential in the full-sample model than in the pre-surge specification. This can be seen by comparing the Shapley shares across categories for the same model. While in the pre-surge period, some models attribute a dominant role for the 12th COICOP category of miscellaneous goods and services, for the whole sample all models suggest a leading role of food prices. Note that we do not compare Shapley shares across models but only within models across categories, since models can feature different hyperparameters which dampens their direct comparability (Lundberg and Lee, 2017).

An important note is in order. The LASSO approach in Section 3 differs from

A. Robustness results for the pre-surge period 2009:01 - 2021:05



B. Robustness results for the whole sample period 2009:01 - 2024:12

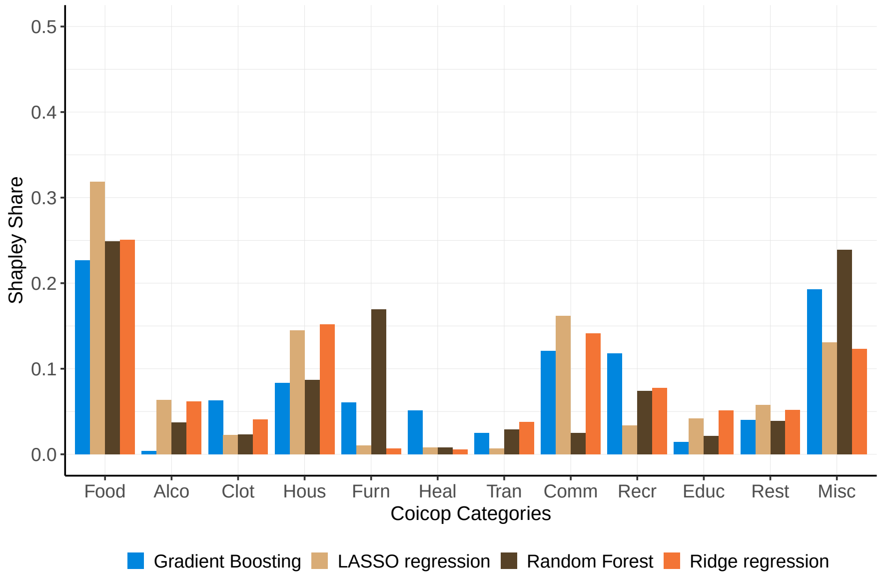


Figure 4: Robustness analysis

Notes: The figure compares variable importance using the Shapley value share, calculated as the average contribution of each feature based on Shapley values obtained from bootstrap samples. The metric is averaged over 50 bootstrap samples to ensure robustness.

the LASSO results following the Buckmann and Joseph (2023) workflow. We first employ an approach in which the penalty term for shrinkage is chosen by ten-fold cross-validation on a random 90% training slice. The model is then refit on the full sample, and this tune-and-refit cycle is repeated 1,000 times to obtain mean variance shares with 95% bands. Buckmann and Joseph (2023) tune the penalty term entirely inside an 80% training window, coefficients are never reestimated on the hold-out block, and variable importance is computed on test data via Shapley values, averaged over 50 redrawn 80/20 splits. The two procedures lead to identical rankings — grocery prices remain the dominant driver.

3.3. Futher results

In addition to the main ressults, in Appendix Appendix F we explore the heterogeneity in expectation formation across demographic groups and consider more granular COICOP categories. We find that the evidence on the salient role of food prices in shaping inflation expectations of Slovak consumers is remarkably robust across various socio-demographic groups. Furthermore, the food categories which appear to be the best predictors are meat in the pre-surge sample and milk, cheese, and eggs in the inflation surge sample.

As an additional robustness check, we examine an alternative information set for expectation formation. Because the survey is fielded during the first two weeks of each month, respondents cannot observe that month's official CPI release when they report their expectations. In Appendix Appendix E we therefore repeat all specifications from Section 3.2, but lag every predictor by one month. The results strengthen our main conclusion: grocery-price inflation continues to act as the primary leading indicator and, if anything, exerts an even larger influence on household inflation expectations than in the baseline model.

4. Discussion

This paper demonstrates that the upward bias in households' inflation expectations — defined as the difference between the cross - sectional average of quantitative expectations and the actual inflation rate — can increase even as inflation rises and attentiveness to inflation intensifies. Contrary to the expectation that greater awareness should reduce bias, we find that the upward bias is positively correlated with inflation levels in Slovakia.

Our results suggest that this puzzling relationship can be explained by heightened attentiveness to specific price categories, particularly food prices. During the inflation surge, households exhibited greater sensitivity to grocery prices, which rose disproportionately compared to headline inflation. This selective focus led to an overestimation of overall inflation, reconciling the observed increase in bias with the theoretical expectation that higher attention should reduce misperceptions.

These findings reinforce the importance of understanding how households perceive inflation and form expectations, a key concern in the monetary policy literature. In particular, they support the argument that central banks may need to place greater emphasis on inflation targets including food prices rather than solely core inflation when communicating with the public, as suggested by Dietrich (2023) and Hahn and Marenčák (2025). Given that food prices play a dominant role in shaping expectations, policymakers might consider strategies to mitigate the disproportionate influence of volatile but salient price categories.

Additionally, our results highlight a critical methodological consideration: the interpretation of the upward bias depends on the benchmark against which expectations are compared. Future research should carefully specify whether expectations are evaluated relative to headline inflation, core inflation, or specific consumption categories, as this choice significantly influences conclusions about inflation perception biases.

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A. Survey Questions

Q1 How has the **financial situation of your household** changed over the last 12 months?

Q2 How do you expect your household's financial position to change over the next 12 months?

Q3 How has the **general economic situation in Slovakia** changed over the past 12 months?

Q4 How do you expect the general economic situation in Slovakia to develop over the next 12 months?

Q5 How do you think **consumer prices** have developed over the last 12 months?

- Risen a lot, Moderately, Slightly, Stayed the same, Fallen, Don't Know

Q5A By what percentage do you think consumer prices will change over the next 12 months? [%] *(Asked only if Q5 $\neq$ "Stayed the same" or "Don't know.")*

Q6 How do you expect consumer prices to develop in the next 12 months?

- Increase more rapidly, At the same rate, At a slower rate, Stay the same, Fall, Don't Know

Q6A By what percentage do you think consumer prices will change over the next 12 months? [%] *(Asked only if Q6 $\neq$ "Stayed the same" or "Don't know.")*

Q7 How do you expect the **number of unemployed people** to change over the next 12 months?

- Increase sharply, Slightly, Stay the same, Fall slightly, Fall sharply, Don't Know

Q8 Is now the right time for **major purchases** (e.g., furniture, appliances)?

- Yes, Neither right nor wrong, No, Don't Know

Q9 Compared to the last 12 months, do you expect to spend more or less on major purchases?

- Much more, A little more, About the same, A little less, Much less, Don't Know

Q10 Is now a good time to save?

- Very good, Fairly good, Not good, Very bad, Don't Know

Q11 How likely are you to save money over the next 12 months?

- Very likely, Fairly likely, Not likely, Not at all likely, Don't Know

Q12 Which best describes your household's current financial situation?

- Saving a lot, Saving a little, Just making ends meet, Drawing on savings, Running into debt, Don't Know

B. Confidence intervals for LASSO shares

Since LASSO does not provide traditional standard errors, and we aim to derive non-standard confidence intervals for the variance shares explained by each regressor, we compute these shares using the estimated LASSO coefficients and the variances of the regressors, while neglecting covariance terms. Confidence intervals are then obtained via bootstrap resampling:

1. Perform 1,000 LASSO regressions, each time randomly splitting the data for cross-validation (CV). We use 10 CV samples per run.
2. For each iteration, select the optimal λ_{1SE} and compute the regression coefficients. Determine the share explained by each covariate using the estimated LASSO coefficients.
3. Construct empirical confidence intervals using the 2.5th and 97.5th percentiles of the estimated LASSO share distributions.

Shrinkage factor To quantify the degree of shrinkage in LASSO relative to OLS, we define the shrinkage factor as:

$$s = \frac{\sum_{j=1}^{k} |\hat{\beta}_j|}{\sum_{j=1}^{k} |\hat{\beta}_j^{ols}|}, \tag{4}$$

where $s < 1$ indicates variable shrinkage due to LASSO regularization.

[Figure A1](#) and [Figure A2](#) show the LASSO coefficients and the prediction errors, respectively, for the pre-inflation surge period 2009:01 to 2019:12, corresponding to [Figure 3](#). [Figure A1](#) confirms the robustness of food as the main driver of inflation expectations across different shrinkage levels (s).

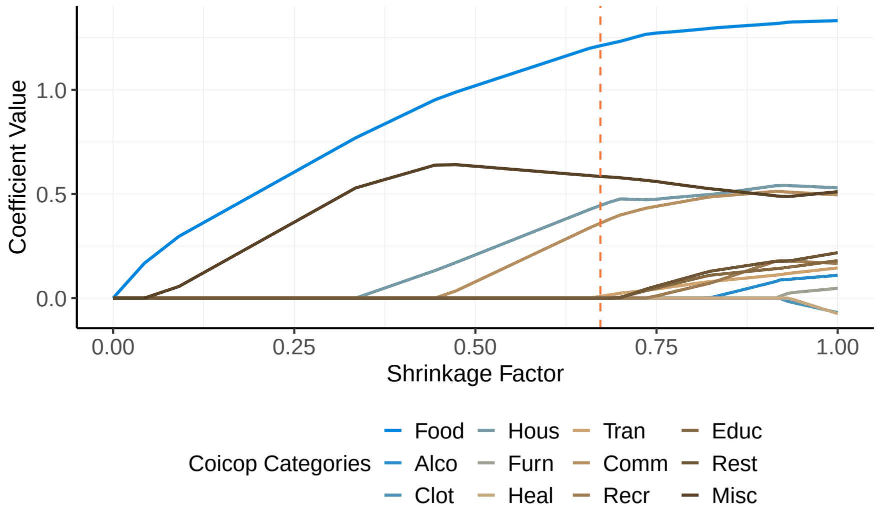

Figure A1: Profiles of LASSO coefficients for the pre-inflation surge period 2009:01 - 2021:05

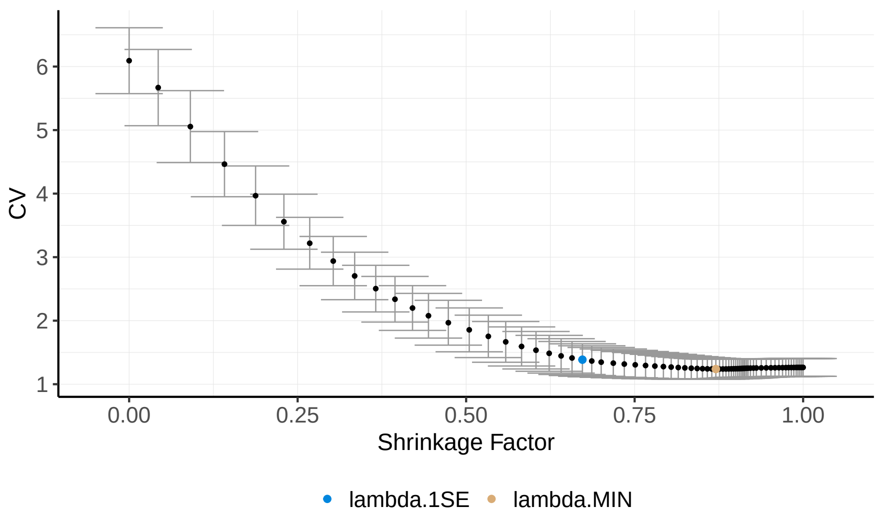

Figure A2: Estimated prediction error curve with standard errors for the pre-inflation surge period 2009:01 - 2021:05

C. HICP AND COICOP

The Harmonized Index of Consumer Prices (HICP) is a measure of inflation that compares the price changes of a basket of consumer goods and services over time. It is harmonized across European Union member states to ensure comparability of inflation rates.

A consumption basket refers to a representative set of goods and services that households typically purchase over a given period. Each item in the basket is assigned a weight based on its relative importance in household expenditures. The weight reflects how much consumers typically spend on a particular category. The weights differ across countries due to variations in consumption patterns, income levels, cultural differences, and economic structures.

The HICP is structured according to the Classification of Individual Consumption According to Purpose (COICOP), an international classification system developed by the United Nations Statistics Division. COICOP categorizes individual consumption expenditures incurred by households, non-profit institutions serving households, and general government according to their purpose.

COICOP follows a hierarchical structure:

1. **Level 1: Divisions (2-digit codes)**
   - Broad categories of expenditure, e.g., Food and Non-Alcoholic Beverages, Transport, Housing, etc.
2. **Level 2: Groups (3-digit codes)**
   - Further breakdown of divisions, e.g., Food, Non-alcoholic beverages, Purchase of vehicles, Transport services etc.
3. **Level 3: Classes (4-digit codes)**
   - More specific categories within each group, e.g., Meat, Bread and cereals, Milk, cheese and eggs.
4. **Level 4: Subclasses (5-digit codes)**
   - Detailed subcategories, e.g., Beef, Pork, Poultry under Meat etc.
5. **Level 5 and Level 6 (optional, country-specific)**

- Additional granularity, distinguishing between different product qualities, brands, or packaging sizes.

A more detailed description of COICOP categories can be found in United Nations and Social Affairs (2018).

COICOP class	**Description**
CP01	Food and non-alcoholic beverages
CP02	Alcoholic beverages, tobacco and narcotics
CP03	Clothing and footwear
CP04	Housing, water, gas, electricity and other fuels
CP05	Furnishings, household equipment and routine maintenance of the house
CP06	Health
CP07	Transport
CP08	Communications
CP09	Recreation and culture
CP10	Education
CP11	Restaurants and hotels
CP12	Miscellaneous goods and services

Table A1: COICOP classes description

D. LASSO COEFFICIENTS UNDERLYING THE MAIN RESULTS

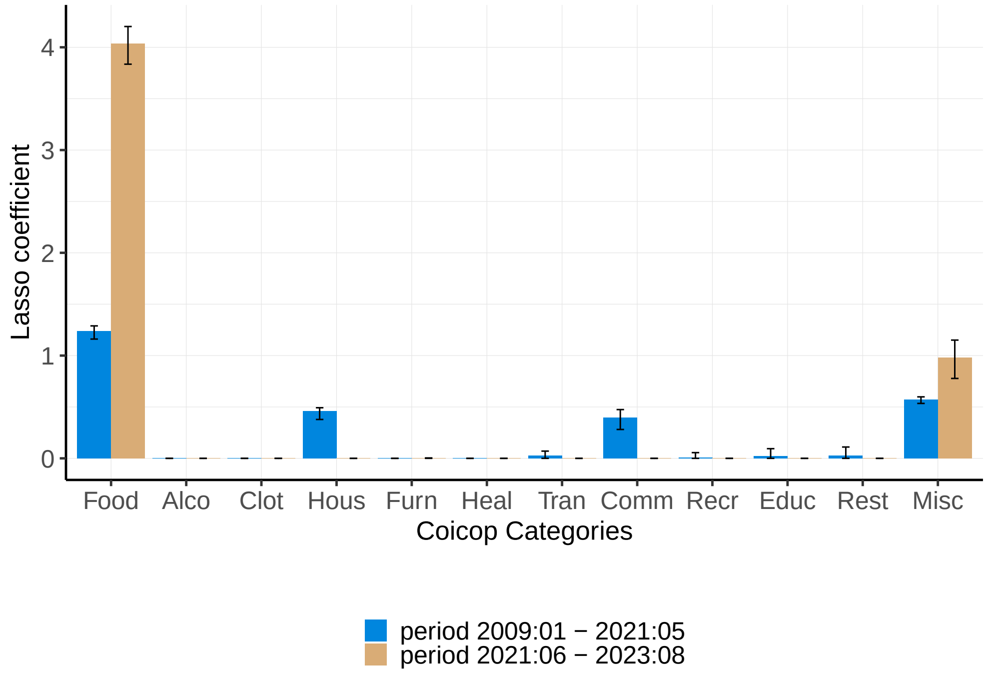

Figure A3: Lasso loadings on sectoral inflation rates in the pre-surge and surge periods

E. RESULTS USING LAGGED VALUES OF SECTORAL INFLATION RATES

Figure A4 presents the same estimates as Figure 4, but based on a model where the predictors are lagged by one month. The motivation for lagging the values is that consumer surveys are usually conducted in the first two weeks of the month, and therefore strictly speaking when referring to publicly available information at the time of the survey respondents could only base their answers on official statistics from the previous month. This specification serves as an additional robustness check. It shows that the results are not skewed because of using not yet available values for the analysis. This suggests that households' expectations take into account current, not yet officially reported, price movements.

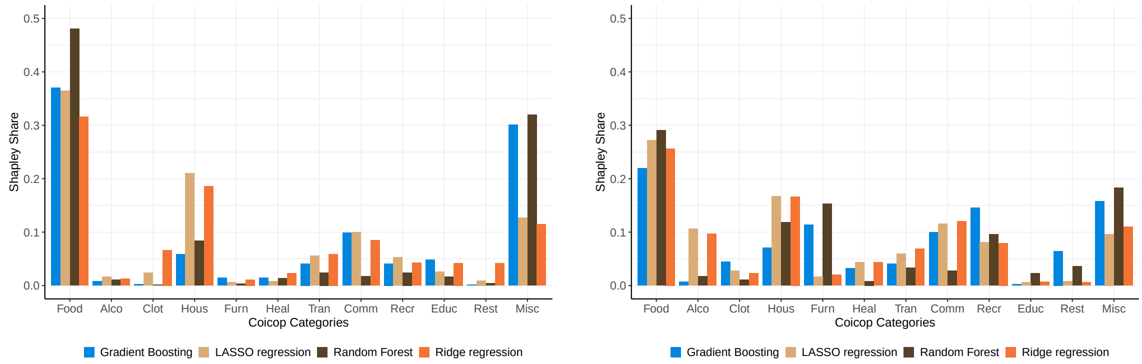

Figure A4: Results using lagged values of sectoral inflation rates

F. Granular categories and heterogeneity across socio - demographic groups

F.1. Socio-demographic heterogeneity

This section investigates whether different socio-demographic groups expect inflation differently and which product categories drive their expectations. If inflation expectations are shaped by personal consumption habits, we expect lower-income or older individuals to focus more on staple goods (e.g., food, rent, basic healthcare), while higher-income and younger groups may emphasize non-essential goods and services.

We use the LASSO-based variance decomposition method introduced in the main text, applied separately to each socio-demographic subgroup to identify the most influential product categories. We provide more details about the socio-demographic subgroups in Appendix Appendix G. The key drivers of inflation expectations vary across demographic groups, but food categories consistently dominate across all categories.

Figure A5 shows, interestingly, that during the surge period the contribution of food prices to explaining inflation expectations is at largest for the highest quartile of the income distribution.

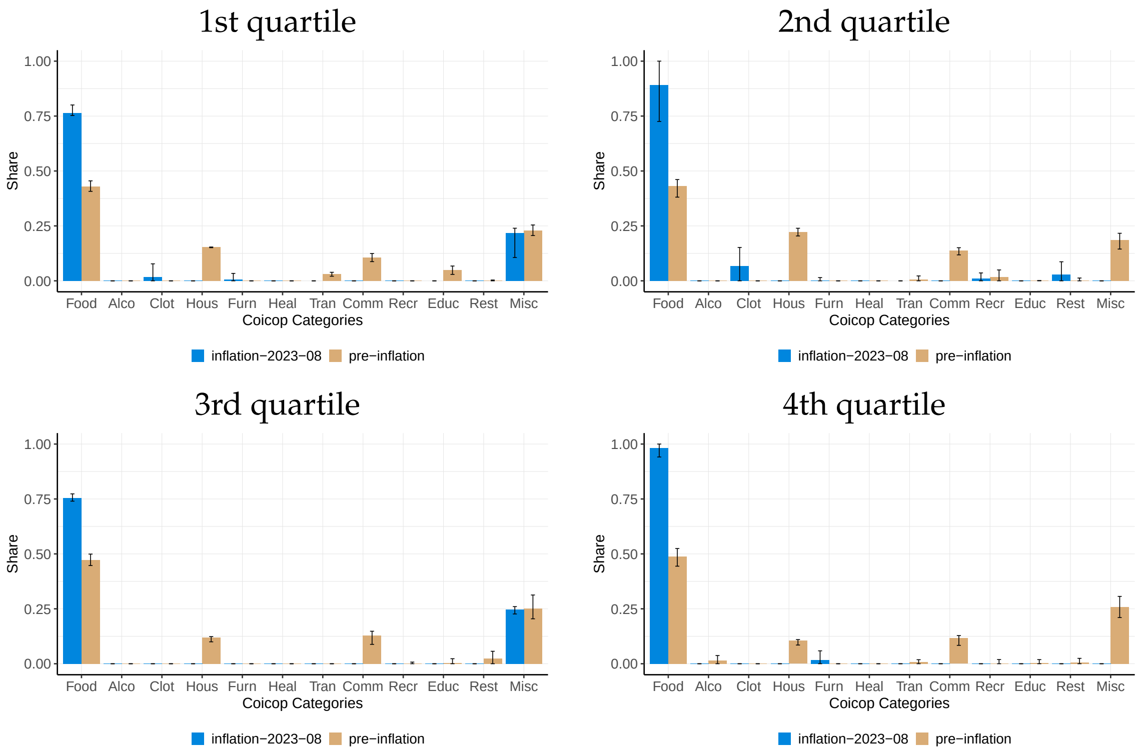

Figure A5: Income distribution

Next, Figure A6 illustrates that also across the age distribution, the contribution of groceries is significantly larger during the surge than in the pre-surge period.

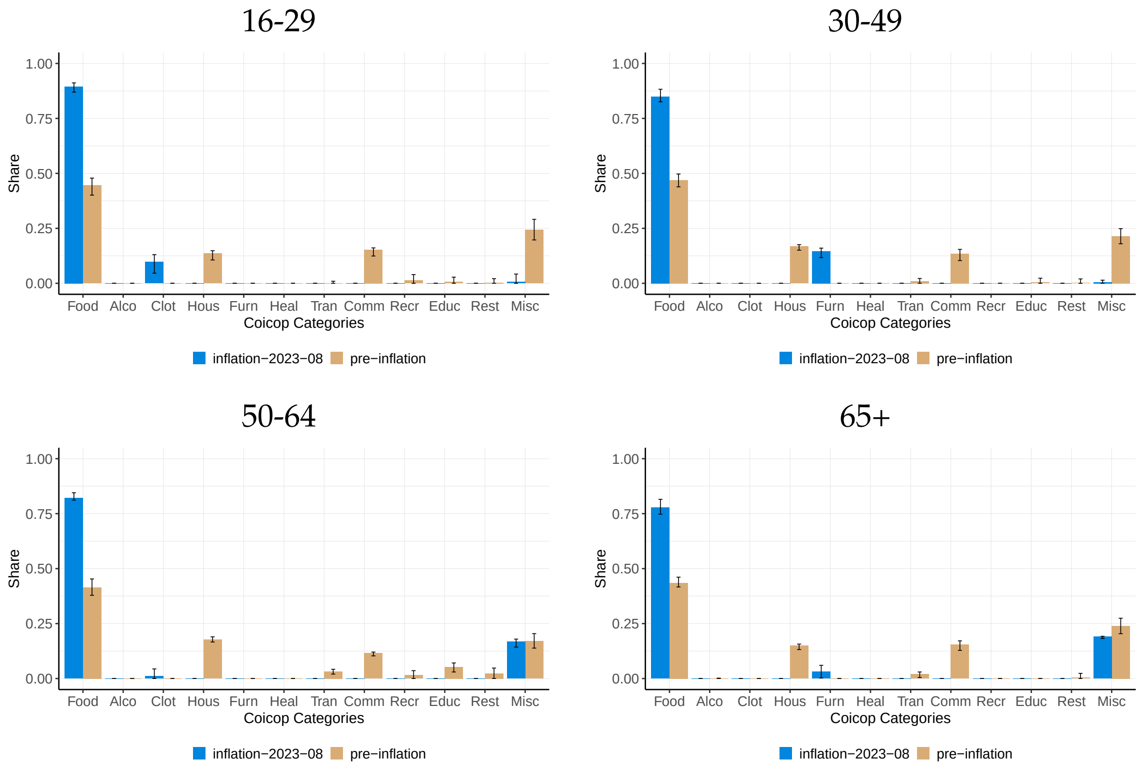

Figure A6: Age distribution

While in the pre-surge period, categories food, housing, communication and miscellaneous good and services were almost equally driving expectations of male and female respondents during the surge period, food became virtually the only explanatory category for women while the share for men increase also significantly from slightly below 50% to almost 75% (Figure A7).

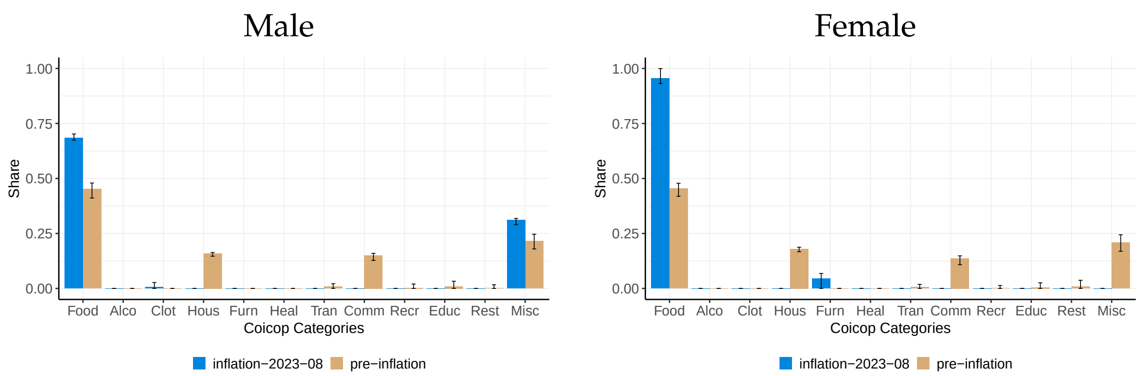

Figure A7: Gender

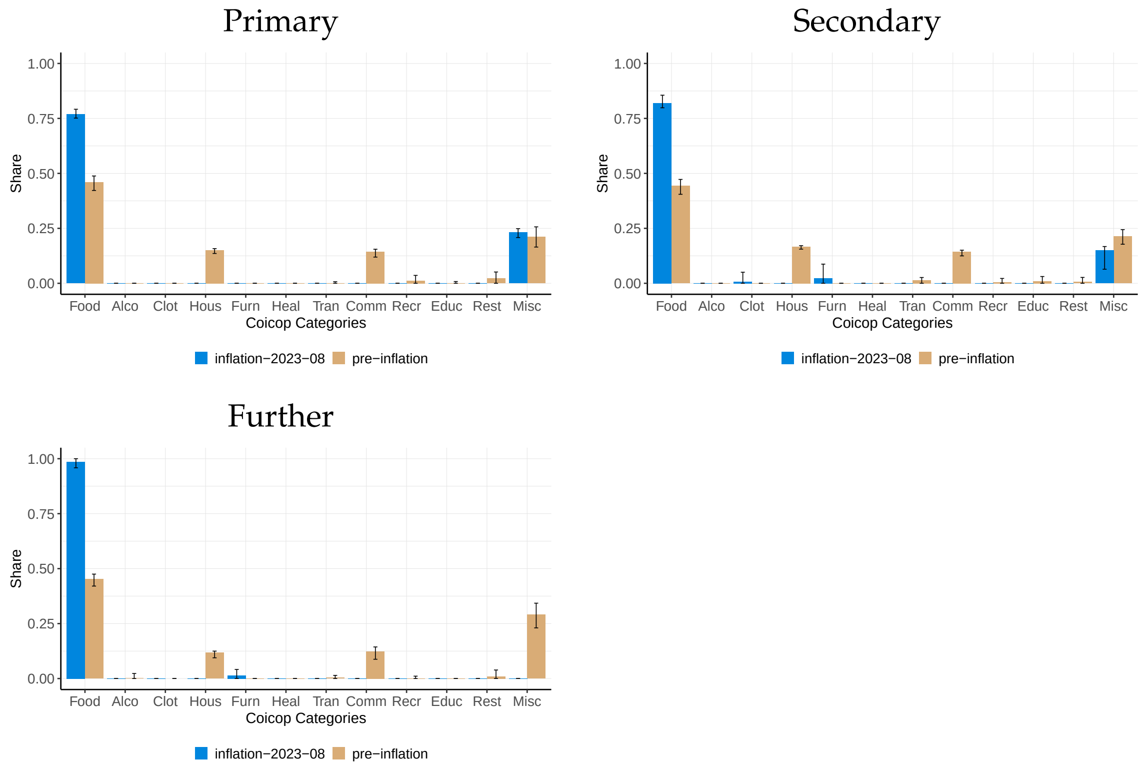

Figure A8: Education

The results for the heterogeneous impact across the educational attainment is in line with the results for the income distribution showing that for respondents with higher that secondary school food prices explain all the variation in inflation expectations (Figure A8).

F.2. COICOP 3 CATEGORIES

In this section we examine a more granular categorization of items in the consumption baskets at the COICOP 3 instead of the COICOP 1 level. Table Table A2 summarizes the key categories shaping inflation expectations across socio-demographic groups. It shows shifts in dominant goods from the pre-inflation period to the high-inflation period.

In line with the previous evidence at the COICOP 1 level, the key drivers of inflation expectations vary slightly across demographic groups, but food categories consistently dominate across all segments. Bread and cereals, meat, and dairy products (milk, cheese, and eggs) are the most significant contributors to inflation expectations across the entire sample and various subgroups. During the high-inflation period, dairy products become the most influential category, highlighting their sensitivity to inflation shocks. In contrast, before inflation surged, meat was the leading driver. Among demographic groups, older individuals (65+) and lower-income quartiles tend to assign higher importance to staple food items, whereas younger groups (16-29) and higher-income individuals also consider non-food items like garments and household maintenance materials.

Group	Whole Sample	Pre-Inflation Period	High-Inflation Period
Whole Sample	Bread and cereals (0.623)	Meat (0.613)	Milk, cheese and eggs (0.711)
Female	Bread and cereals (0.65)	Meat (0.628)	Milk, cheese and eggs (0.806)
Male	Materials for maintenance (0.734)	Meat (0.626)	Milk, cheese and eggs (0.671)
65+	Bread and cereals (0.828)	Meat (0.494)	Milk, cheese and eggs (0.65)
50-64	Bread and cereals (0.625)	Meat (0.594)	Milk, cheese and eggs (0.703)
30-49	Bread and cereals (0.713)	Meat (0.616)	Milk, cheese and eggs (0.771)
16-29	Garments (0.628)	Meat (0.656)	Milk, cheese and eggs (0.757)
Further Educ.	Bread and cereals (0.74)	Meat (0.692)	Milk, cheese and eggs (0.743)
Secondary Educ.	Bread and cereals (0.651)	Meat (0.632)	Milk, cheese and eggs (0.696)
Primary Educ.	Materials for maintenance (0.494)	Meat (0.593)	Milk, cheese and eggs (0.751)
4th Quartile	Bread and cereals (0.812)	Meat (0.682)	Milk, cheese and eggs (0.777)
3rd Quartile	Garments (0.477)	Meat (0.704)	Milk, cheese and eggs (0.609)
2nd Quartile	Bread and cereals (0.472)	Meat (0.564)	Milk, cheese and eggs (0.645)
1st Quartile	Bread and cereals (0.545)	Bread and cereals (0.534)	Milk, cheese and eggs (0.494)

Table A2: Key Categories Driving Inflation Expectations

Notes: Values in parentheses represent the share of explained variance of inflation expectations of the given socio-demographic category by the top selected COICOP 3 category.

G. Socio-demographic groups

Table A3 displays the socio-demographic groups from the harmonized European Commission (EC) Consumer Survey for Slovakia..

Income distribution	1st quartile 2nd quartile 3rd quartile 4th quartile
Education	Primary Secondary Further
Age distribution	16-29 30-49 50-64 65+
Gender	Male Female

Table A3: Socio-demographic groups