The Drivers of Household Inflation Uncertainty *

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February 20, 2025

Applying the round-number methods proposed in Binder (2017), we infer an individual's cognitive uncertainty about product groups. We use the responses of individuals to point expectations about gasoline, food, medical, education, rent, and gold prices in the FRBNY Fed Survey of Consumers Expectations. We incorporate existing literature on cognition with expectations and employ the round-number methods Binder (2017). Of these individual product groups, food prices are found to be the main driver of an individual's aggregate uncertainty about future inflation. We then show that monetary policy is effective at reducing food price uncertainty.

Keywords: uncertainty, expectations, inflation
JEL Codes: D01,

*Any views expressed are solely those of the author and so cannot be taken to represent those of the Bank of England or members of its committees.

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1 Introduction

An increase in uncertainty accompanied the return of above-target inflation in the aftermath of the pandemic affecting households, firms, and policymakers[1] alike. Uncertainty and higher inflation levels also reduced the precision with which households predict future prices. This kind of uncertainty about inflation prevents households from making optimal choices and is thus costly to welfare (Friedman, 1977; Ball et al., 1990; Grier and Perry, 1998; Elder, 2004; Binder et al., 2024). The inflation uncertainty of households is usually studied as uncertainty about the price growth of an aggregated consumption basket. Due to a lack of data, the literature has so far not studied whether uncertainty in the price growth of specific product groups in the basket drives the aggregate inflation uncertainty of households. For the same reason we know little about the effect monetary policy has on the uncertainty about the price growth of product groups in the basket.

In this paper, we infer inflation uncertainty about product groups from the Federal Reserve Bank of New York's Survey of Consumer Expectations (SCE). We use the round-numbers method established in Binder (2017) to infer the cognitive uncertainty of respondents in the SCE about subgroups of the consumption basket. The method relies on the fact established by scientists studying human behaviour that respondents answer questions about which they are uncertain with an increased likelihood with multiples of 5. Applying this positive association to the open questions in the survey about the expected price growth of gas, food, medical treatment, education, and rent we can estimate the likelihood that each of the respondents has a low or high uncertainty about prices in each of these consumption groups. We then use the estimated uncertainty of individuals about each consumption group to estimate the extent to which each product group drives uncertainty about aggregate price level growth. Further, we construct an index for the uncertainty of each consumption group. We then estimate the response of these indices to identified monetary policy shocks.

Our contribution in this paper is threefold. First, we provide a method to estimate uncertainty about price changes for sub-components of the price index in the SCE. Second, this enables us to identify food price uncertainty as the most important sub-component driving an individual's aggregate inflation uncertainty. Food prices drive on average XX% of aggregate inflation uncertainty. Third, our novel uncertainty measures for groups going into the consumption basket to construct uncertainty indices for these groups. We then find that while food price uncertainty is the most important driver of inflation uncer-

[1] Mann (2024); Lane (2024); Ramsden (2024); Bowman (2024)

tainty, it is also the most responsive to monetary policy and a monetary policy tightening reduces food prices uncertainty.

Inflation uncertainty has received increased interest due to the post Covid inflation period, which also increased inflation uncertainty as the Friedman-Ball hypothesis would predict. Coibion et al. (2024), Kostyshyna and Petersen (2024), and Fischer et al. (2024) estimate the causal effect inflation uncertainty has on household behaviour. Our analysis builds on the work of Binder (2017) who introduces the round number methods to measuring inflation uncertainty. Her seminal paper focuses on measures of inflation uncertainty about the CPI basket from responses the Michigan Survey of Consumers and the SCE. We here look at subcomponents of the basket and to which extent they drive aggregate inflation uncertainty. We also build on Binder et al. (2024) to verify the plausibility of our estimates of uncertainty. We show that that agents display reduced expected price change uncertainty for a product group with increasing survey tenure as one would expect for a reliable measure.

In the remainder of this paper we discuss our data in section two. We present our estimates of inflation uncertainty and the decomposition of aggregate uncertainty in section three. In section four we discuss the impact of identified monetary policy shocks on our estimated uncertainty about product groups. In section five we conclude.

2 Data

We use the Survey of Consumer Expectations from the Federal Reserve Bank of New York (FRBNY). The SCE is a monthly survey that collects information on consumer expectations along with demographic information. It is a rotating panel where individuals are interviewed for up to 12-16 consecutive months. Our core survey covers from June 2013 to December 2023. This covers 127 months and approximately between 1200 to 1300 respondents each month. We focus on expectations for inflation, gasoline, food, medical, education, rent, and gold. Respondents are asked to provide a point estimate and a distribution of the growth rate for inflation over the next 12 months and 36 months.

2.1 Measuring Uncertainty

Inflation uncertainty is measured based on individual 12-month inflation expectations, derived from the subjective probability distributions reported by survey respondents. Each individual provides probabilities over 10 symmetrical bins, representing possible inflation outcomes ranging from -12% to +12%. To quantify uncertainty, we fit a generalized beta distribution (GBD) to each respondent's probability distribution, following the methodology outlined by Engelberg et al. (2009) and Armantier et al. (2017). The standard deviation of the fitted subjective distribution serves as our uncertainty measure for inflation expectations.

To ensure robustness, we remove outliers by winsorizing point forecasts at the top 95th and bottom 5th percentiles. Additionally, we verify the internal consistency of point estimates by checking whether an individual's reported forecast falls within the support of their subjective probability distribution. If a reported point estimate lies outside this range, we set it to missing to maintain data integrity.

3 Product Price Growth Uncertainty

To construct uncertainty proxies for expected price changes in gasoline, food, medical expenses, education, and rent, we adopt the methodology of Binder (2017)[2]. The key insight from this approach is that individuals with greater uncertainty tend to round their numerical responses to common reference points, such as multiples of five (Round Number Round Interpretation (RNRI)). Leveraging this insight, we classify individuals into low-uncertainty and high-uncertainty types based on their price expectations across these five commodity categories.

For each respondent, we observe their subjective point forecast R_{it}. The monthly distribution of responses consists of a mix of round-number responses (multiples of five, denoted as M5) and non-round responses.

- Low-uncertainty agents ("type l") are those who report non-M5 responses (e.g., 3, 4, 7, 9, etc.), as their forecasts suggest greater numerical precision and confidence.
- High-uncertainty agents ("type h") are those who report M5 responses (e.g., -5, 5, 10, 15, etc.), indicating greater uncertainty in their price expectations.

However, an M5 response does not definitively indicate high uncertainty—some individuals may round due to convenience rather than genuine uncertainty. Therefore, we estimate the conditional probability of each respondent belonging to the high or low uncertainty type, given their reported forecast $R_{i,t}$. This probability, denoted as ν_{ijt} , is estimated using Maximum Likelihood Estimation (MLE).

[2]This paper constructs an inflation uncertainty index using data from the Michigan Consumer Survey.

Since each cross-section consists of a mixture of M5 and non-M5 responses, we estimate the discretized normal probability mass function (PMF) for two separate distributions—one for low-uncertainty agents and another for high-uncertainty agents. The corresponding PMFs are given by:

$$\phi_{l,t} = P(R_{i,t} = r|\text{i is of type l}) = \int_{r-0.5}^{r+0.5} p_{low}(x)dx \tag{1}$$

$$\phi_{h,t} = P(R_{i,t} = r|\text{i is of type h}) = \int_{r-2.5}^{r+2.5} p_{high}(x)dx \tag{2}$$

In Figure 1, we illustrate the distribution of commodity price expectations. A clear clustering of responses at multiples of five confirms the presence of rounding behavior, which we use as a proxy for inflation uncertainty.

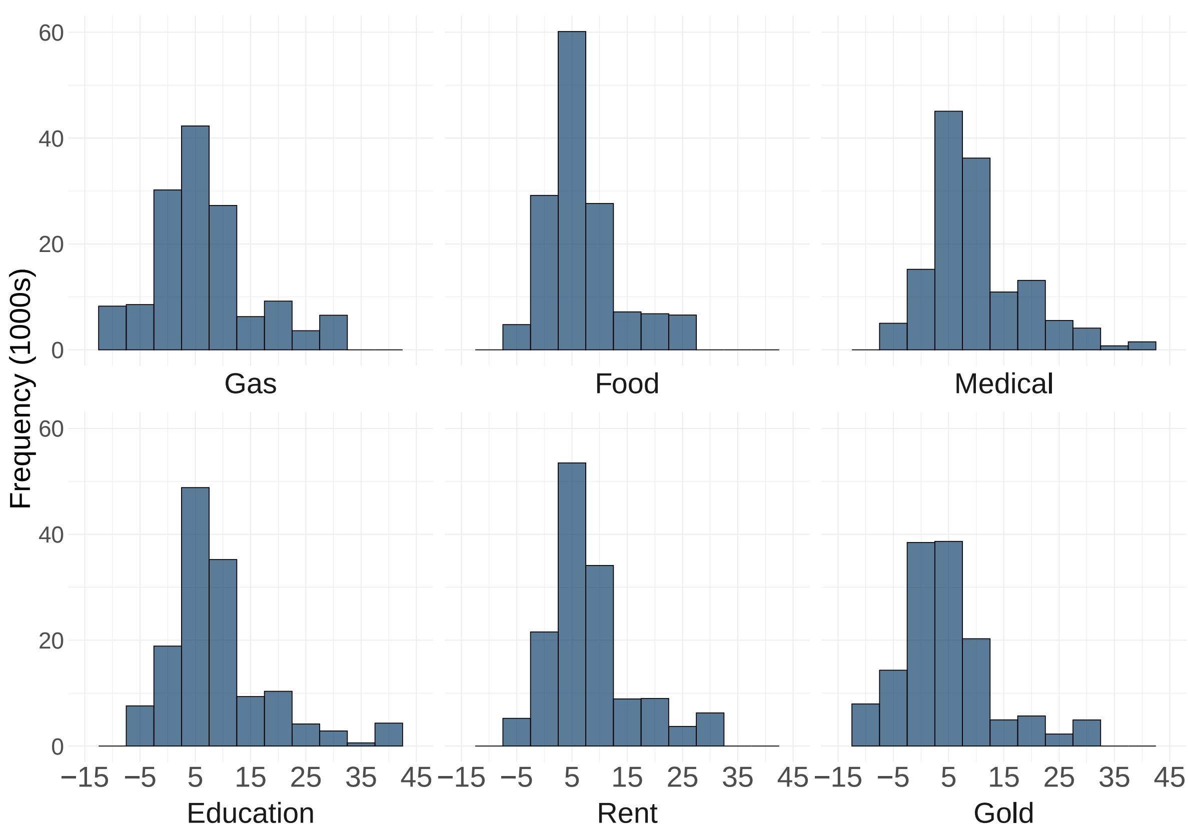

Figure 1: Commodity Price Expectations

We estimate the probability ν_{ij} for each commodity category 'j' (where 'j' includes gasoline, food, medical, education, and rent) using MLE over the mix of survey responses R_{ijt}. The MLE likelihood function is given by:

$$L(R_{jit}i = 1^N | \lambda jt, \mu_{jlt}, \mu_{ht}, \sigma_{jlt}, \sigma_{jht}) = \Pi_{k=1}^{N} \phi_{jt}(R_{jit} | \lambda_{jt}, \mu_{jlt}, \mu_{jht}, \sigma_{jlt}, \sigma_{jht})) \tag{3}$$

After obtaining the MLE estimates, we calculate the posterior probability ν_{jit} as follows:

$$\nu_{jit} = \frac{P(typehigh)P(R_{it}|\text{type h})}{P(R_{it})} = \frac{\lambda_t \phi_t^h(R_{it})}{\lambda_t \phi_t^h(R_{it}) + (1-\lambda_t)\phi_t^l(R_{it})} \tag{4}$$

In Figure 2, we show the mean of ν_{jt} over time, capturing uncertainty dynamics from June 2013 to December 2023. Notably, a sharp spike in March 2020 coincides with the onset of COVID-19 lockdowns, followed by a gradual decline in uncertainty, although levels remain elevated compared to pre-pandemic periods.

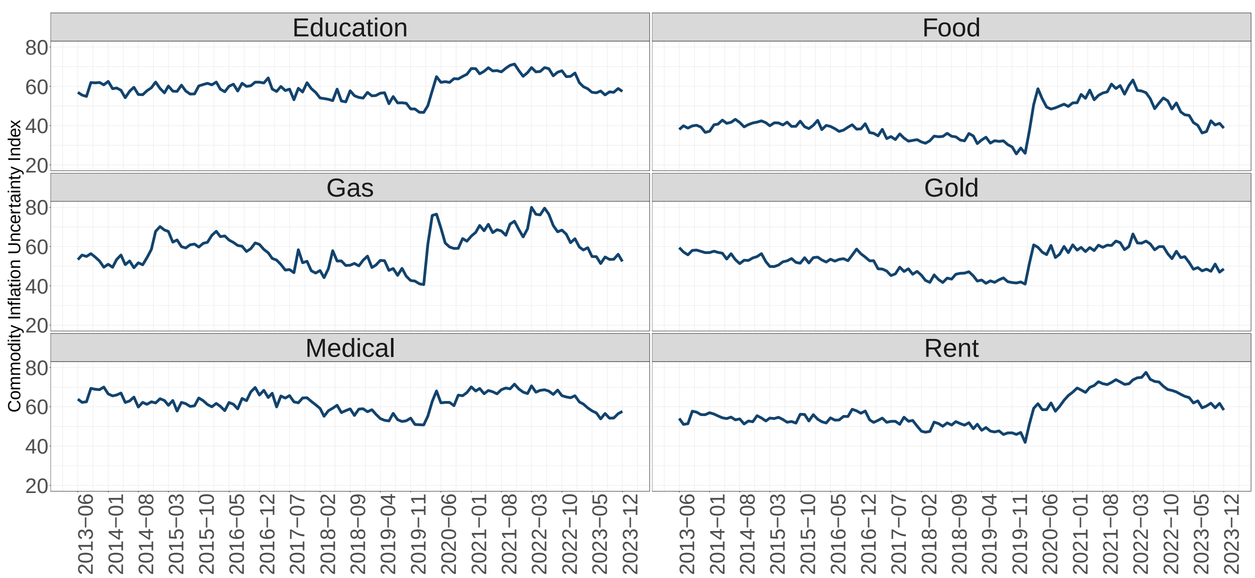

Figure 2: Estimates of uncertainty proxy ζ_{ijt}

Note: This figure presents the estimated uncertainty proxy ν_{ijt} for different commodities from June 2013 to December 2023. Survey responses are winsorized at the bottom 3rd and top 97th percentiles.

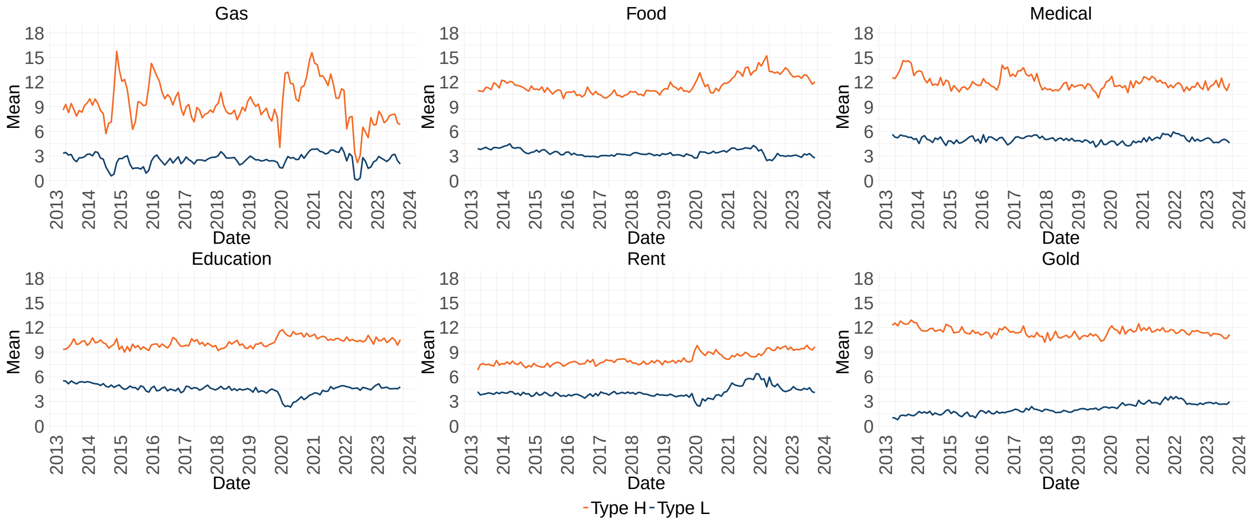

Figure 3: Estimated mean for high and low

Note: In the above Panel we show the maximum likelihood estimates of μ_{lt} and μ_{ht} bootstrapped.

Figure 4: Estimated sigma for high and low

Note: In the above Panel we show the maximum likelihood estimates of σ_{lt} and σ_{ht} bootstrapped.

Figures 3 and 4 present the MLE estimates for the mean and variance of high and low uncertainty agents, highlighting systematic differences across commodity categories.

4 Decomposing drivers of inflation uncertainty

Using these probabilities around six different products in this section we study how individual uncertainty probability affects overall inflation uncertainty. First, we study how a dummy around these products affects uncertainty. We create dummy ($M5^j$) which equals 1 if it's a multiple of 5 and otherwise zero.

$$M5^j = \begin{cases} 1, & \text{if } j \text{ is a multiple of 5} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

In equation 6, we estimate the following to reduce form OLS fixed effects.

$$\sigma_{it}^{\pi} = \alpha + \beta_1 \,\mathrm{M5}_{\text{gas}}^{it} + \beta_2 \,\mathrm{M5}_{\text{food}}^{it} + \beta_3 \,\mathrm{M5}_{\text{medical}}^{it} + \beta_4 \,\mathrm{M5}_{\text{education}}^{it} + \beta_5 \,\mathrm{M5}_{\text{rent}}^{it} + s_{it} + \chi_{it} + \mu_t + \epsilon_{it} \tag{6}$$

where σ_{it}^{π} is the uncertainty over expected inflation and the independent variables are dummy as a multiple of five over the above mentioned commodities. Ideally we would like to identify the causal effect of independent variables on inflation uncertainty. We address this potential source of endogeneity by controlling for individual level, survey date, and tenure-id fixed effects. Individual level fixed effect mitigates the problem of unbiasedness to great extend as it absorbs all the unobservable. Survey date effects reflects the exact date on which respondent filled out the survey so this is a more precise time-fixed effect as compared to year-month fixed effects and finally tenure id fixed effects Kim and Binder (2023) controls for the fact the respondents learn the survey over time and hence this mitigates some biasedness coming from learning.

Second, in 7 we estimate the continuous probability of being a low or high uncertainty agent on how it affects inflation uncertainty. We replace the independent X variables with the probability of the type of agent as calculated from the above-mentioned methodology. We also control for individual level, survey date, and tenure-id fixed effects

$$\sigma_{it}^{\pi} = \alpha + \beta_1 \,\zeta_{\text{gas}}^{it} + \beta_2 \,\zeta_{\text{food}}^{it} + \beta_3 \,\zeta_{\text{medical}}^{it} + \beta_4 \,\zeta_{\text{education}}^{it} + \beta_5 \,\zeta_{\text{rent}}^{it} + s_{it} + \chi_{it} + \mu_t + \epsilon_{it} \tag{7}$$

The estimates of 6 and 7 are presented in tables below.

In Table 1, we report the effects of commodity uncertainty dummy on inflation uncertainty (over the next 12 months) in col (1) and (2). The difference between col(1) and col(2) is just the addition of tenure-id fixed effects. This improves our R2 slightly. But from the two columns, we can see that food has the highest effect on inflation uncertainty followed by the gasoline dummy. In cols(3) and (4) we replace the dummies with the continuous probability type. We see that not only it increase the R2 from just using dummies but also the magnitude of food increases and also the rent.

In table 2 we conduct the same analysis as above but with uncertainty over expected inflation for the next three years (36 months). The effect's magnitude decreases but is still significant and mostly contributed by food, rent, and gasoline.

Lastly, in table 3 we look at whether uncertainty around commodities affects inflation expectations and inflation uncertainty before and after COVID-19. Even though the overall uncertainty over expected inflation surged after COVID-19 but except for gasoline there is no significant difference as to what drives inflation uncertainty. Uncertainty over inflation is pre- and driver by the salience nature of gasoline and food price inflation expectations.

Table 1: Effect of uncertainty commodity on Inflation uncertainty (one year ahead)

Dependent Variable:	Inflation Uncertainty (12m)			
Model:	(1)	(2)	(3)	(4)
$M5^{gas}_{t+12\|t}$	0.13***	0.10***		
	(0.01)	(0.01)		
$M5^{food}_{t+12\|t}$	0.13***	0.13***		
	(0.01)	(0.01)		
$M5^{medical}_{t+12\|t}$	0.05***	0.05***		
	(0.01)	(0.01)		
$M5^{education}_{t+12\|t}$	0.08***	0.07***		
	(0.01)	(0.01)		
$M5^{rent}_{t+12\|t}$	0.10***	0.09***		
	(0.01)	(0.01)		
$\zeta^{gas}_{t+12\|t}$			0.13***	0.10***
			(0.01)	(0.01)
$\zeta^{food}_{t+12\|t}$			0.24***	0.24***
			(0.02)	(0.02)
$\zeta^{medical}_{t+12\|t}$			0.08***	0.07***
			(0.01)	(0.01)
$\zeta^{education}_{t+12\|t}$			0.11***	0.10***
			(0.01)	(0.01)
$\zeta^{rent}_{t+12\|t}$			0.16***	0.15***
			(0.01)	(0.01)
User id FE	Yes	Yes	Yes	Yes
Tenure FE	Yes	Yes	Yes	Yes
Survey Date FE		Yes		Yes
Observations	140,015	140,015	139,607	139,607
R^2	0.73183	0.74153	0.73249	0.74201

Clustered (user-id) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. We have inflation uncertainty calculated from individual density forecast of inflation one year ahead as the dependent variable. In cols (1) and (2) after controlling for user-id and tenure-id Kim and Binder (2023) and additionally survey-date effects we have the dummy on commodities i.e. gas, food, medical, education, and rent which is equal to 1 if it a multiple of 5, 0 otherwise. In, columns (3) and (4) we report the effect of probability with high or low type agents on commodity uncertainty measured by the above methodology. For fixed effects, we control for survey date and tenure id The analysis time frame is from June 2013 to December 2023.

Table 2: Effect of uncertainty commodity on Inflation uncertainty (3 years ahead)

Dependent Variable:	Inflation Uncertainty (36m)			
Model:	(1)	(2)	(3)	(4)
$M5^{gas}_{t+12\|t}$	0.12***	0.11***		
	(0.01)	(0.01)		
$M5^{food}_{t+12\|t}$	0.12***	0.12***		
	(0.01)	(0.01)		
$M5^{medical}_{t+12\|t}$	0.05***	0.05***		
	(0.01)	(0.01)		
$M5^{education}_{t+12\|t}$	0.07***	0.07***		
	(0.01)	(0.01)		
$M5^{rent}_{t+12\|t}$	0.11***	0.10***		
	(0.01)	(0.01)		
$\zeta^{gas}_{t+12\|t}$			0.13***	0.12***
			(0.01)	(0.01)
$\zeta^{food}_{t+12\|t}$			0.22***	0.22***
			(0.02)	(0.02)
$\zeta^{medical}_{t+12\|t}$			0.08***	0.07***
			(0.01)	(0.01)
$\zeta^{education}_{t+12\|t}$			0.10***	0.10***
			(0.01)	(0.01)
$\zeta^{rent}_{t+12\|t}$			0.16***	0.16***
			(0.01)	(0.01)
user-id FE	Yes	Yes	Yes	Yes
Tenure ID FE	Yes	Yes	Yes	Yes
Survey Date FE		Yes		Yes
Observations	140,085	140,085	139,675	139,675
R^2	0.73757	0.74640	0.73812	0.74686

Clustered (user-id) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. We have inflation uncertainty calculated from individual density forecast of inflation 3 years ahead as the dependent variable. In cols (1) and (2) after controlling for user-id and tenure-id Kim and Binder (2023) and additionally survey-date effects we have the dummy on commodities i.e. gas, food, medical, education, and rent which is equal to 1 if it a multiple of 5, 0 otherwise. In, columns (3) and (4) we report the effect of probability with high or low type agents on commodity uncertainty measured by the above methodology. For fixed effects, we control for survey date and tenure id The analysis time frame is from June 2013 to December 2023.

Table 3: Effect of uncertainty commodity on Inflation uncertainty Pre and Post Covid

Dependent Variables:	Inflation Expectations	Inflation Uncertainty	
Model:	(1)	(2)	(3)
$E_t\pi^{gas}_{t+12\|t}$	0.01***		
	(0.003)		
$E_t\pi^{food}_{t+12\|t}$	0.07***		
	(0.006)		
$E_t\pi^{medical}_{t+12\|t}$	0.008***		
	(0.003)		
$E_t\pi^{education}_{t+12\|t}$	0.02***		
	(0.004)		
$E_t\pi^{rent}_{t+12\|t}$	0.04***		
	(0.004)		
$D^{highuncert} \times E_t\pi^{gas}_{t+12\|t}$	-0.004		
	(0.005)		
$D^{highuncert} \times E_t\pi^{food}_{t+12\|t}$	0.05***		
	(0.009)		
$D^{highuncert} \times E_t\pi^{medical}_{t+12\|t}$	-0.01*		
	(0.006)		
$D^{highuncert} \times E_t\pi^{education}_{t+12\|t}$	-0.02***		
	(0.007)		
$D^{highuncert} \times E_t\pi^{rent}_{t+12\|t}$	0.02***		
	(0.007)		
$M5^{gas}_{t+12\|t}$ ($\zeta^{gas}_{t+12\|t}$)		0.15***	0.14***
		(0.01)	(0.02)
$M5^{food}_{t+12\|t}$ ($\zeta^{food}_{t+12\|t}$)		0.14***	0.26***
		(0.01)	(0.02)
$M5^{medical}_{t+12\|t}$ ($\zeta^{medical}_{t+12\|t}$)		0.08***	0.11***
		(0.01)	(0.02)
$M5^{education_{t+12\|t}}$ ($\zeta^{education}_{t+12\|t}$)		0.10***	0.15***
		(0.01)	(0.02)
$M5^{rent_{t+12\|t}}$ ($\zeta^{rent}_{t+12\|t}$)		0.14***	0.23***
		(0.01)	(0.02)
$D^{highuncert} \times M5^{gas}_{t+12\|t}$ ($\zeta^{gas}_{t+12\|t}$)		0.03	0.06*
		(0.03)	(0.03)
$D^{highuncert} \times M5^{food}_{t+12\|t}$ ($\zeta^{food}_{t+12\|t}$)		0.02	0.02
		(0.03)	(0.04)
$D^{highuncert} \times M5^{medical}_{t+12\|t}$ ($\zeta^{medical}_{t+12\|t}$)		0.001	0.008
		(0.03)	(0.04)
$D^{highuncert} \times M5^{education}_{t+12\|t}$ ($\zeta^{education}_{t+12\|t}$)		0.03	0.007
		(0.03)	(0.03)
$D^{highuncert} \times M5^{rent}_{t+12\|t}$ ($\zeta^{rent}_{t+12\|t}$)		-0.01	-0.06*
		(0.03)	(0.03)
User ID FE	Yes	Yes	Yes
Observations	140,015	140,015	139,607
R^2	0.60837	0.72503	0.72610

Clustered (userid) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

4.1 Variance Decomposition

In this section, we try to identify how much variability in the outcome variable, inflation uncertainty, is explained by the all of the explanatory variables (gasoline, food, medical, education, and rent). We therefore measure how the observed factors explain the variability in inflation uncertainty. But some of the unobserved factors, like other economic uncertainty, account for the unobserved variability. Hence we have Explained variability given as the Sum of Squares Explained (SSE) explained by the explanatory variables, i.e. the x-variables in your regression. It is given as:

$$SSE = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2 \tag{8}$$

The Sum of Squares Residual (SSR) (sometimes referred to as the Sum of Squares Error) is a measure of the variability in the outcome variable that is not explained by your regression, and therefore is due to all the other factors that affect inflation uncertainty. It is given as:

$$SSR = \sum_{i=1}^{n} (y_i - \hat{y}_i^2) = \sum_{i=1}^{n} e_i^2 \tag{9}$$

Analysis of Variance (ANOVA) is a common way to summarize these measures of variability. The ANOVA table does not report the sum of squares explained (SSE), which is the measure of explained variability using all the regression coefficients. Rather, it reports the sum of squares explained by each explanatory variable. To obtain the total sum of squares explained, you could add up the values in the column labeled Sum Sq. The variance of the error, σ^2 plays a fundamental role in the inference for the model coefficients and in prediction. is decomposed into two parts, each corresponding to the regression and to the error, respectively. This decomposition is called the Analysis Of Variance (ANOVA). The anova function takes a model as an input and returns the following sequential ANOVA:

Predictor	**Degrees of Freedom**	**Sum Squares**	**Mean Squares**	**F-value**	**p-value**
Predictor 1	1	SSR_1	$SSR_1/1$	$\frac{(SSR_1/1)}{SSE/(n-p-1)}$	p_1
Predictor 2	1	SSR_2	$SSR_2/1$	$\frac{(SSR_2/1)}{SSE/(n-p-1)}$	p_2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Predictor p	1	SSR_p	$SSR_p/1$	$\frac{(SSR_p/1)}{SSE/(n-p-1)}$	p_2
Residuals	$n-p-1$	SSE	$\frac{SSE}{n-p-1}$		

Table 4: ANOVA Explanation

In Figure 5 we compute the variance decomposition for Inflation uncertainty based on the variability of five commodity inflation expectations. For the time period June 2013 to December 2023, we see that food and gasoline expected inflation contributes to the maximum variability towards inflation uncertainty.

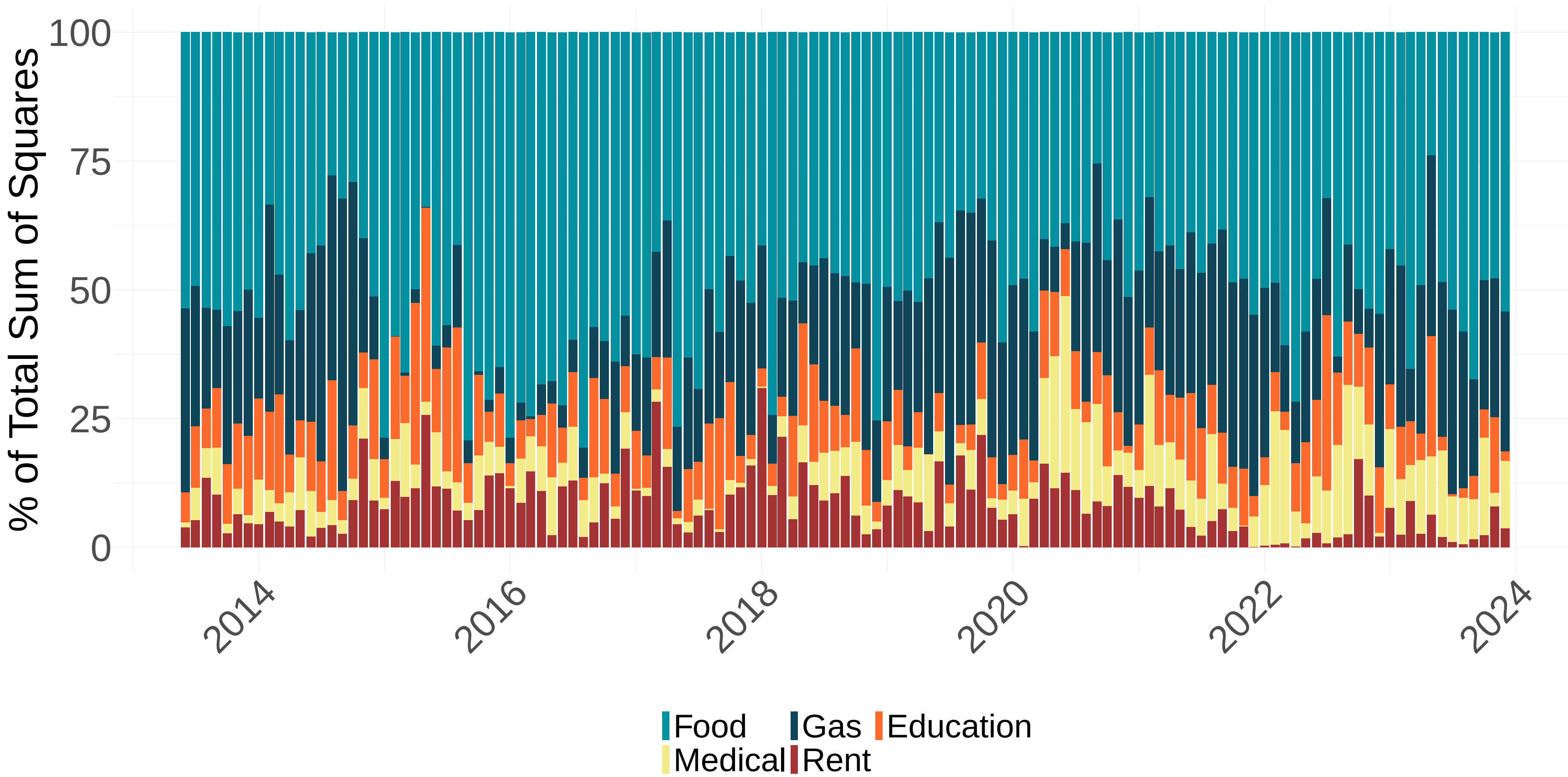

Figure 5: Product Price Uncertainty decomposition

5 Monetary Policy impacting Product Price Growth Uncertainty

In this section, we finally look at how much a monetary policy shock effectively reduces inflation or commodity-specific uncertainty using local projections Jordà (2005) and Adämmer (2019). Using Jarociński and Karadi (2020) to get identified monetary policy shocks to study the relationships between expectations and uncertainty around inflation and commodity inflation and other macro variables. For monetary policy shock, from June 2013 to December 2023 and estimate the monetary policy shock ϵ_t at horizon h, we estimate the relationship between our dependent variable and controls and four lags of target variable which is given as:

$$y_{t+h} = \alpha_h + \sum_{j=1}^{p} \gamma_h y_{t-j} + \delta\omega_t + \epsilon_{t+h} \tag{10}$$

and then look at the impulse response functions given as:

$$IR_h^{y,\omega_t} = E(y_{t+h|\epsilon_t=1}, \omega_t) - E(y_{t+h|\epsilon_t=0}, \omega_t) \tag{11}$$

where ω_t is a vector of control variables (interest rate and actual inflation rate)

In figure 6 we look at the effect of MP policy shock on both inflation uncertainty and inflation expectations at both 68 and 90 percent confidence intervals. With an MP shock, we see a rather stable or a slight decrease in inflation uncertainty but mean inflation expectations decrease sharply after 1st period.

In Figure 7 we look at the impact of MP shock on 5 different commodities price expectations. We see a decline in food prices, gas prices, medicine, and rent price expectations.

In Figure 8 we look at the impact of MP shock on 5 different commodities price expectations uncertainty indexes (ζ_{jt}) created by using the methodology in Binder (2017). We see a decline in food price uncertainty, and gas price uncertainty.

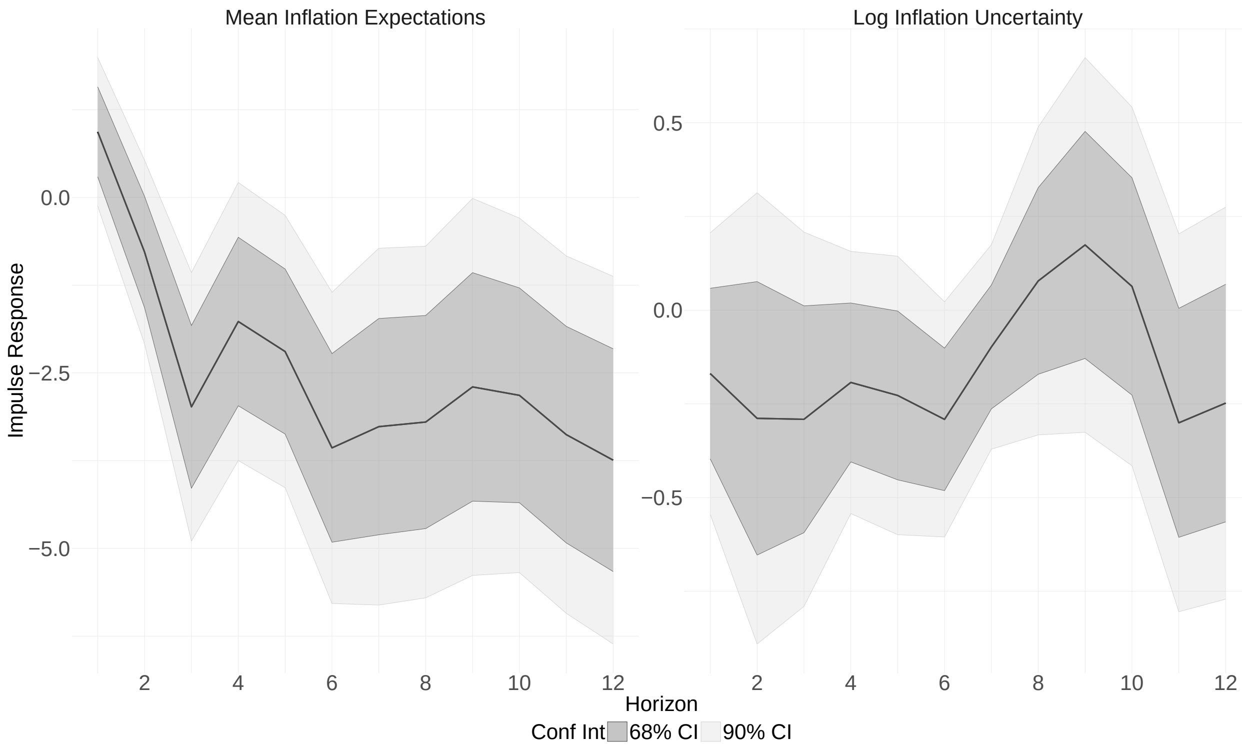

Figure 6: MP shock effect on expected inflation and inflation uncertainty

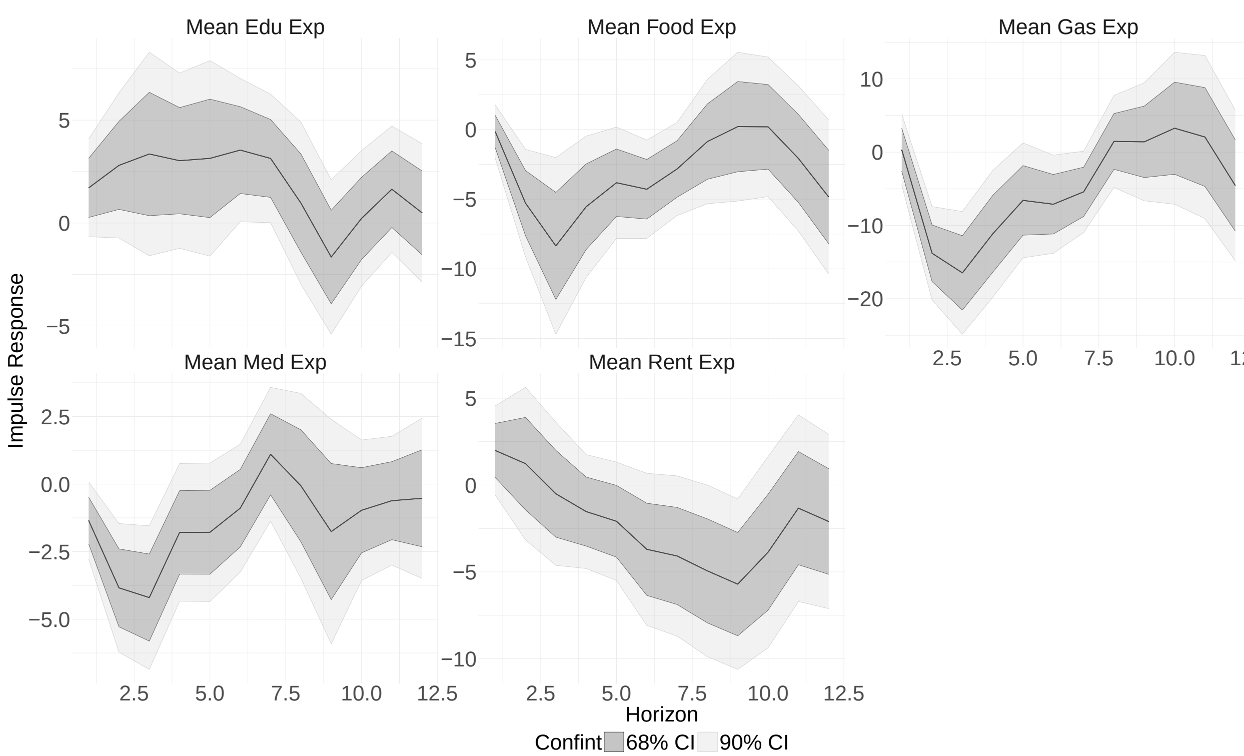

Figure 7: MP shock effect on expected commodity price expectations

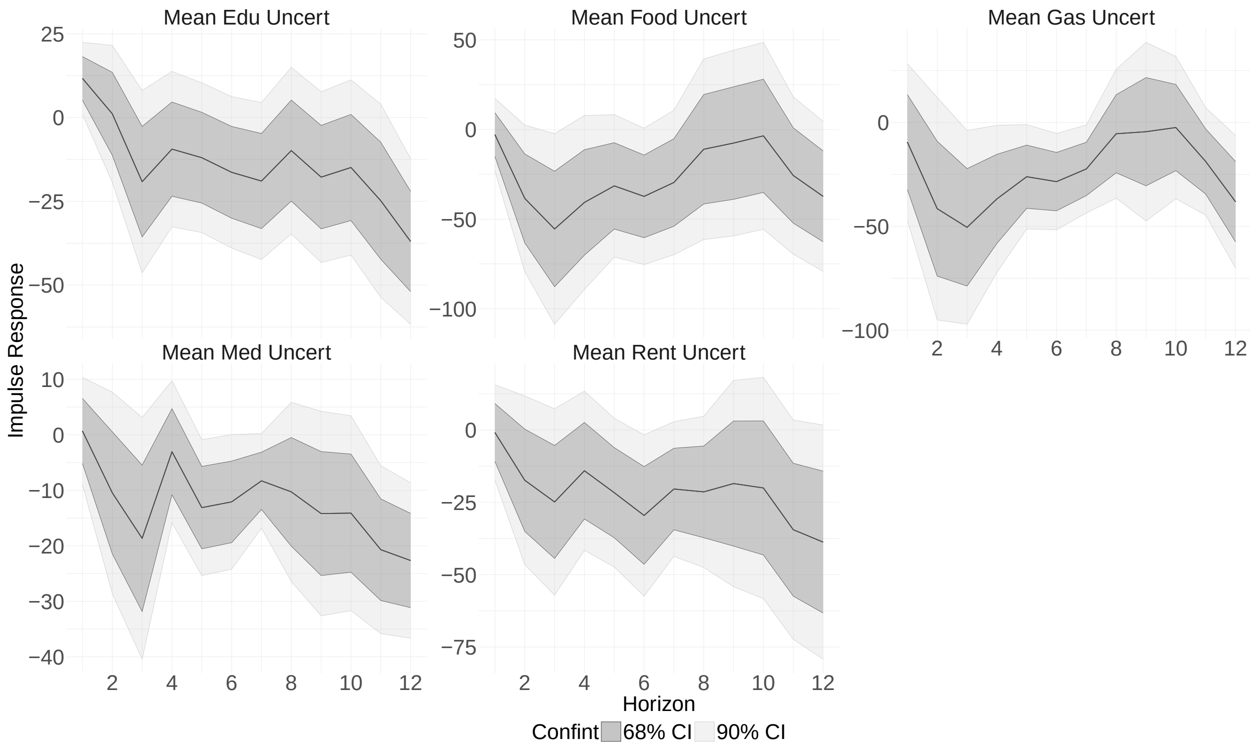

Figure 8: MP shock effect on expected commodity price uncertainty

6 Conclusion

This paper extends the methods of measuring uncertainty using the survey respondents on various variables (inflation expectations, gasoline, food, rent, medical, and education). We estimate the parameters of the mixed distribution using maximum likelihood. This gives us the individual probability ζ_{it} for each commodity. We then use these uncertainty proxies to decompose over all individual subjective inflation uncertainty. We find that food and gasoline expected price uncertainty are the biggest driver of an individual inflation uncertainty. Moreover we show how monetary policy can be effective in lowering food price uncertainty which reduced over inflation uncertainty.

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7 Appendix

In this section, we present the robustness of our estimates using other proxies for expectations and uncertainty. We conduct the same analysis by replacing the point inflation forecast with the mean of the subjective probability distribution.

In Table 5 we have a point forecast for inflation in cols (1) and cols(2). In cols(3) and (4) we have the same analysis but using the density implied mean on 12 months ahead inflation expectations

Table 5: Effect of commodity inflation on inflation expectations

Dependent Variables:	$E_t\pi_{t+12}$		$E_t\pi^{density}_{t+12}$	
Model:	(1)	(2)	(3)	(4)
$E_t\pi^{gas}_{t+12\|t}$	0.01***	0.01***	0.008***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
$E_t\pi^{food}_{t+12\|t}$	0.09***	0.08***	0.07***	0.06***
	(0.005)	(0.005)	(0.004)	(0.003)
$E_t\pi^{medical}_{t+12\|t}$	0.004	0.005**	0.005***	0.007***
	(0.003)	(0.003)	(0.002)	(0.002)
$E_t\pi^{education}_{t+12\|t}$	0.006**	0.007**	0.003	0.003
	(0.003)	(0.003)	(0.002)	(0.002)
$E_t\pi^{rent}_{t+12\|t}$	0.05***	0.04***	0.04***	0.03***
	(0.004)	(0.004)	(0.003)	(0.003)
userid	Yes	Yes	Yes	Yes
tenure_id	Yes	Yes	Yes	Yes
survey_date		Yes		Yes
Observations	140,015	140,015	140,015	140,015
R^2	0.60825	0.62394	0.63441	0.65001

Clustered (user-id) standard errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. We have inflation expectations as the dependent variable. In cols (1) we control for user-id and tenure-id fixed effects Kim and Binder (2023). In col (2) we additionally control for survey date fixed effects. For the independent variables, we have one year ahead expectations over gas, food, medical, education, and rent. The analysis time frame is from June 2013 to December 2023.

In Table 6, we analyze how product price uncertainty affects individual subjective inflation uncertainty. Here our dependent variable is inter quantile range instead of the standard deviation of variance. In cols(1) and cols(2) we have the inflation IQR over the next 12 months and in cols(3) and (4) over the next 36 months.

Table 6: Effect of uncertainty commodity on Inflation uncertainty (IQR)

Dependent Variables:	IQR (12m)		IQR (36m)	
Model:	(1)	(2)	(3)	(4)
$M5^{gas}_{t+12\|t}$	0.19***	0.16***	0.19***	0.18***
	(0.02)	(0.02)	(0.02)	(0.02)
$M5^{food}_{t+12\|t}$	0.20***	0.19***	0.18***	0.17***
	(0.02)	(0.02)	(0.02)	(0.02)
$M5^{medical}_{t+12\|t}$	0.07***	0.07***	0.07***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
$M5^{education}_{t+12\|t}$	0.12***	0.11***	0.09***	0.09***
	(0.02)	(0.02)	(0.02)	(0.02)
$M5^{rent}_{t+12\|t}$	0.14***	0.13***	0.15***	0.14***
	(0.02)	(0.02)	(0.02)	(0.02)
userid	Yes	Yes	Yes	Yes
tenure id	Yes	Yes	Yes	Yes
survey date		Yes		Yes
Observations	140,015	140,015	140,085	140,085
R^2	0.71027	0.72070	0.71696	0.72640

Clustered (userid) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Effect of uncertainty commodity on Inflation uncertainty (IQR): Product uncertainty

Dependent Variables:	IQR(12m)		IQR(36m)	
Model:	(1)	(2)	(3)	(4)
ζ^{gas}	0.20***	0.15***		
	(0.02)	(0.02)		
ζ^{food}	0.38***	0.37***		
	(0.03)	(0.03)		
$\zeta^{medical}$	0.10***	0.09***		
	(0.02)	(0.02)		
$\zeta^{education}$	0.16***	0.16***		
	(0.02)	(0.02)		
ζ^{rent}	0.23***	0.21***		
	(0.02)	(0.02)		
$M5^{gas}$			0.19***	0.18***
			(0.02)	(0.02)
$M5^{food}$			0.18***	0.17***
			(0.02)	(0.02)
$M5^{medicine}$			0.07***	0.07***
			(0.02)	(0.02)
$M5^{education}$			0.09***	0.09***
			(0.02)	(0.02)
$M5^{rent}$			0.15***	0.14***
			(0.02)	(0.02)
userid	Yes	Yes	Yes	Yes
tenure id	Yes	Yes	Yes	Yes
survey date		Yes		Yes
Observations	139,607	139,607	140,085	140,085
R^2	0.71093	0.72117	0.71696	0.72640

Clustered (userid) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

7.1 Tenure Effect on Uncertainty

Lastly in this section, we show how individuals learn throughout the period of filling the survey.

Using Kim and Binder (2023) we also test for tenure effect on people's subjective commodity price expectations and then inflation uncertainty. We estimate the tenure effect on individuals who appeared 12 times for measuring inflation expectations and inflation uncertainty. For commodity price expectations we look at all individuals who appeared 11 consecutive times from tenure id from 2 to 12. We then estimate the following equation:

$$y_{its} = \sum_{3}^{12} \beta_s \tau_s + \alpha_i + \gamma_t + \epsilon_{it} \tag{12}$$

where $\{\beta_s\}_{s=3}^{12}$

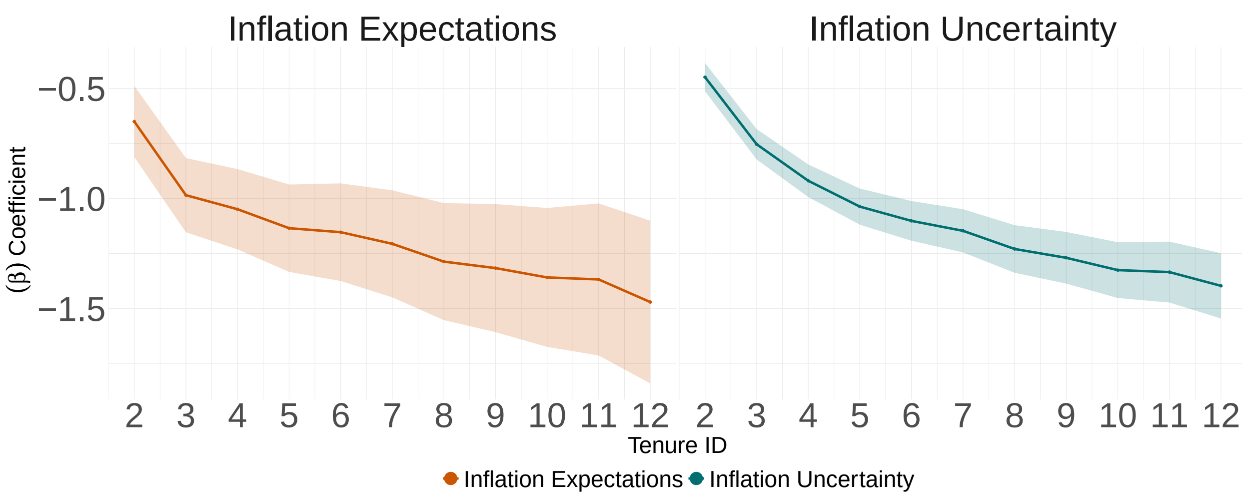

Figure 9

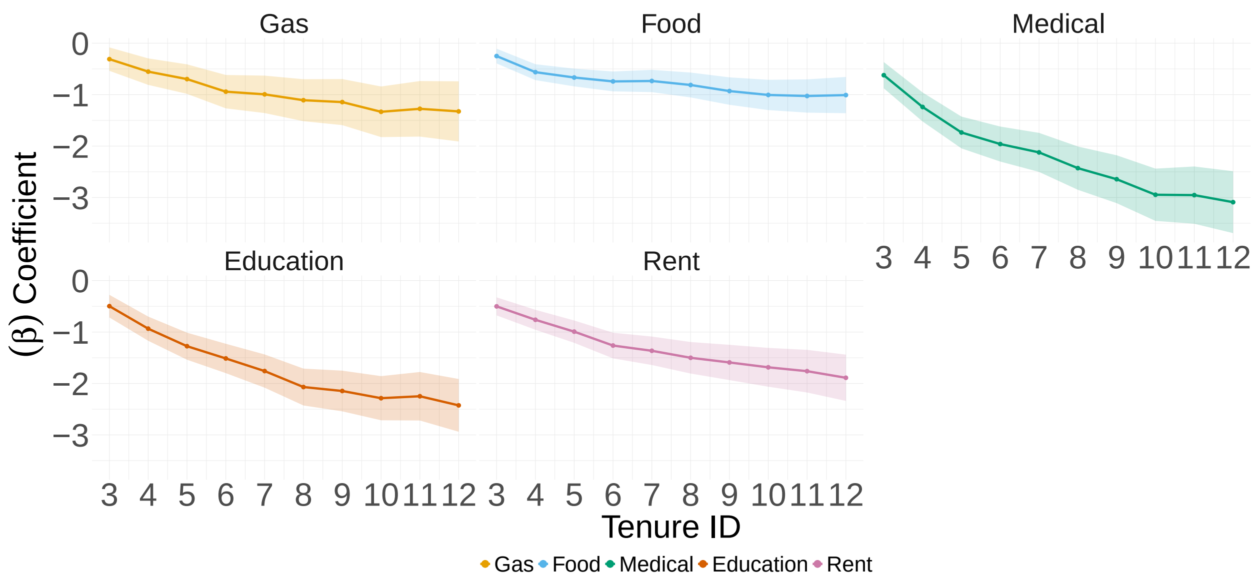

Figure 10: Commodity Point Forecast Tenure Effect

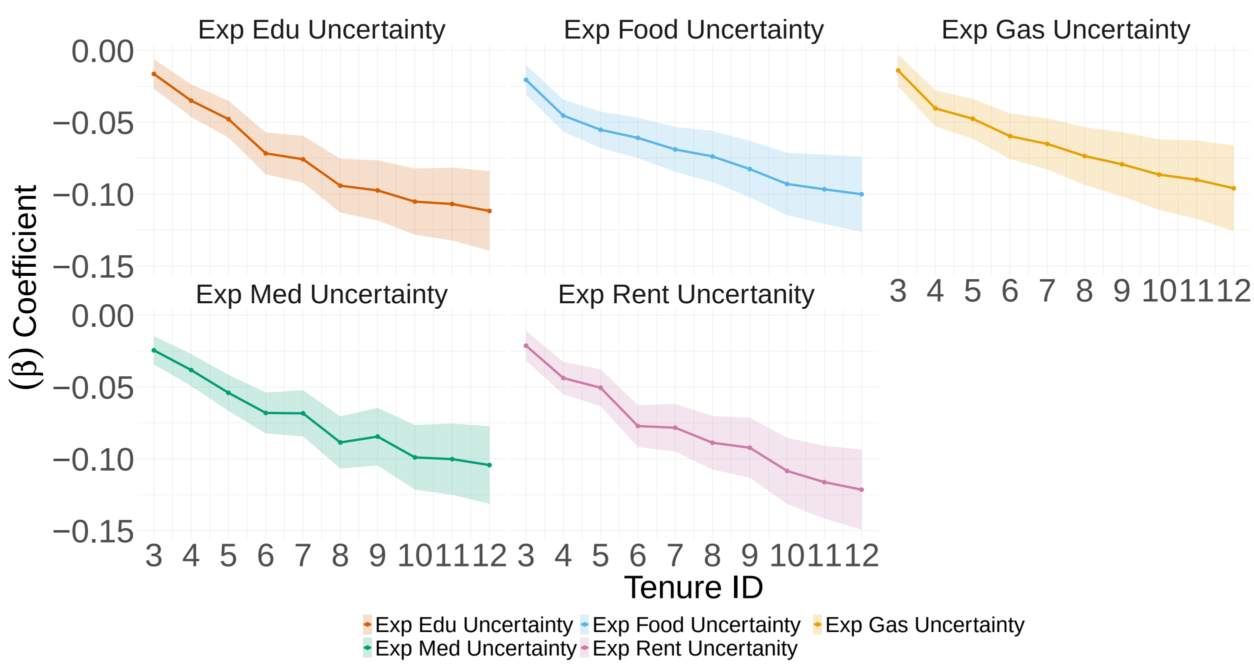

Figure 11: Commodity Uncertainty Probability

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Figure 12: MP shock effect on expected inflation and inflation uncertainty - Low Income

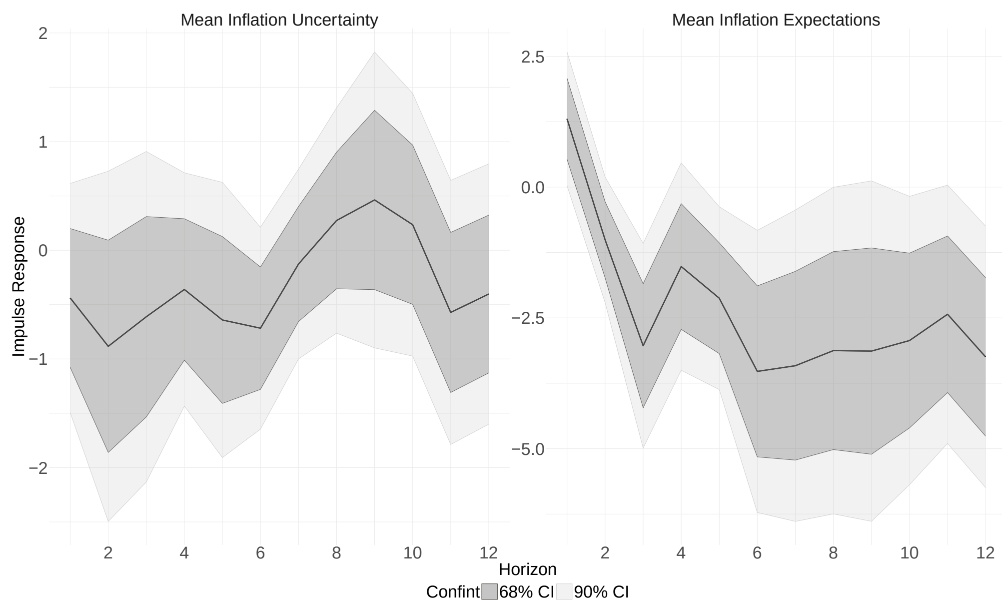

Figure 13: MP shock effect on expected inflation and inflation uncertainty - High Income

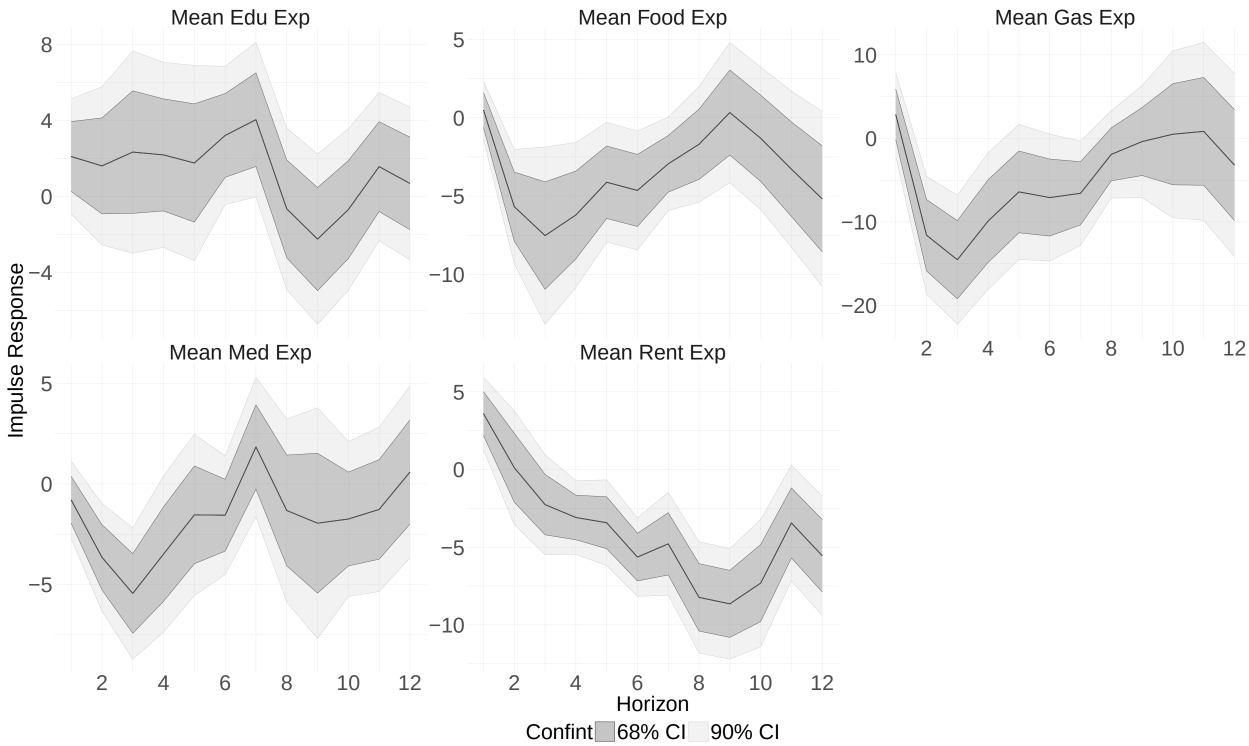

Figure 14: MP shock effect on expected commodity price expectations - Low Income

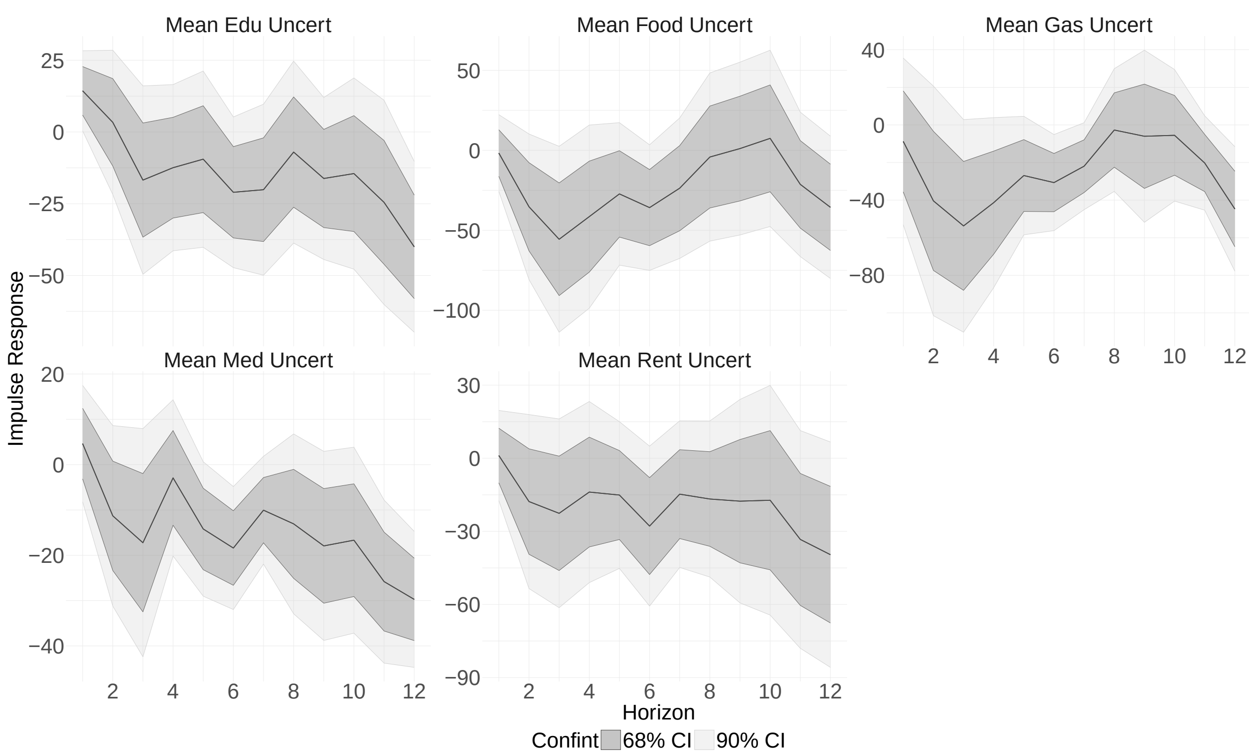

Figure 15: MP shock effect on expected commodity price uncertainty - High Income

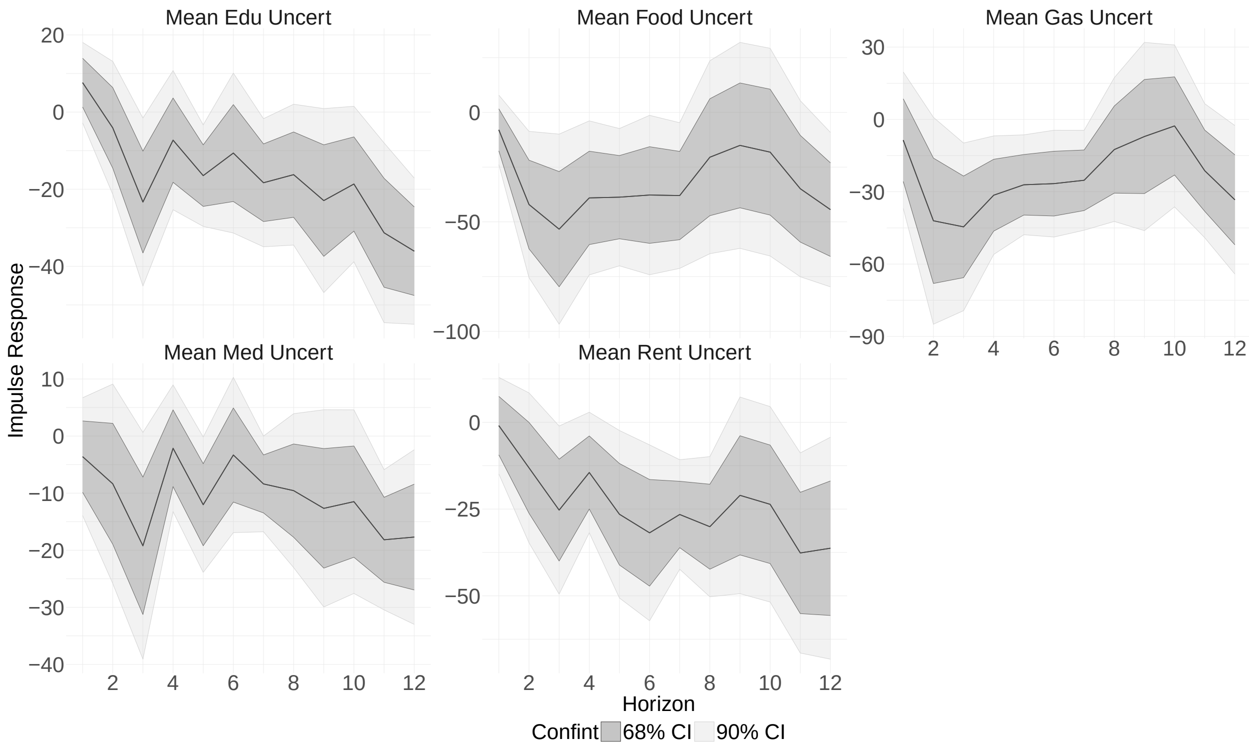

Figure 16: MP shock effect on expected commodity price uncertainty - Low Income

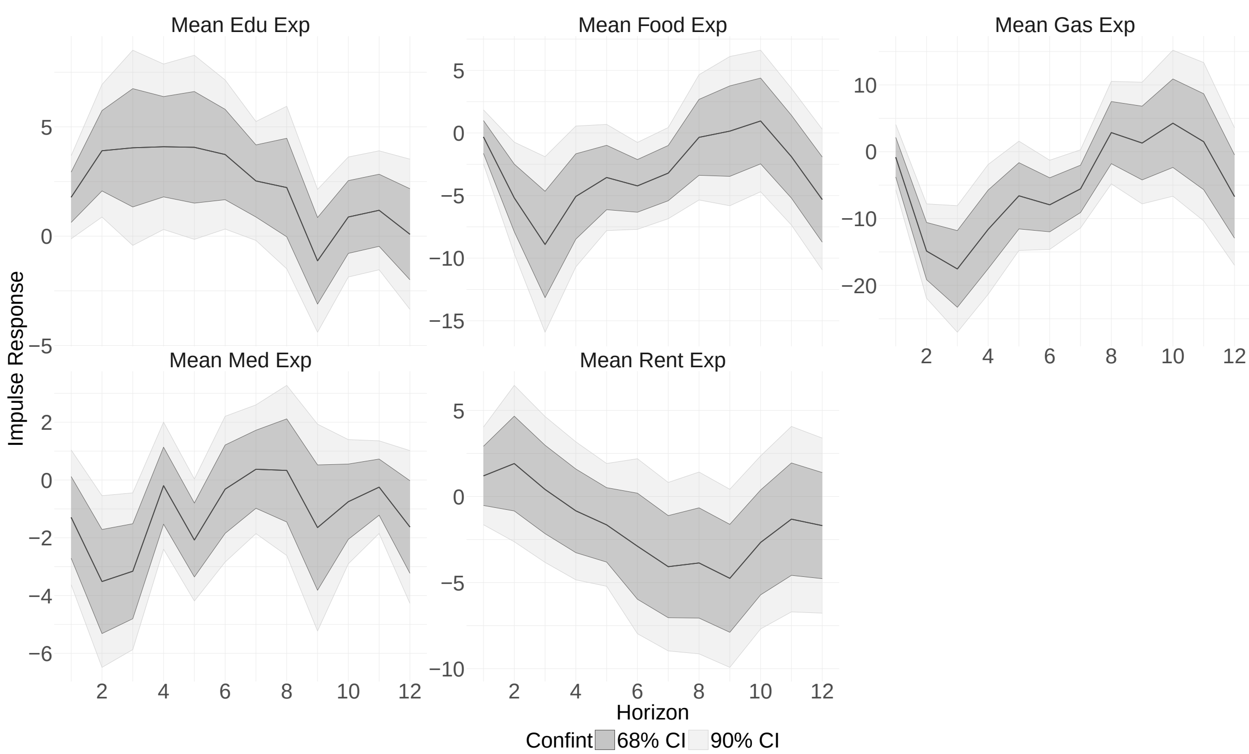

Figure 17: MP shock effect on expected commodity price expectations - High Income