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Household Inflation Expectations Uncertainty: A Case for Pakistan

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Abstract: This study examines the uncertainty of consumer inflation expectations in Pakistan using the data collected by the State Bank of Pakistan (SBP) through the Consumer Confidence Survey (CCS). CCS has been conducted every second month since January 2012. The research employs round numbers to calculate inflation expectation uncertainty and finds it countercyclical and positively correlated with inflation. Further, it also displays a weakly positive correlation with inflation disagreement, inflation volatility, and the Economic Policy Uncertainty (EPU) index. The study also reveals that inflation expectation uncertainty is higher for female, less educated, and young respondents compared to businessmen, males, older people, and educated. The study suggests asymmetric behavior of inflation expectations uncertainty for high and low inflation levels, where uncertainty is high when inflation is high. The study also suggests that inflation uncertainty is significantly related to food inflation. Lastly, the study establishes that inflation expectation uncertainty affects the consumption of durable goods by influencing consumer spending attitudes.

Keywords: Inflation Expectations, Uncertainty, Consumer, Consumer Confidence.

JEL Classification: D18, E31.

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Household Inflation Expectations Uncertainty: A Case for Pakistan[1]

1. Introduction

The inflation expectations (IE) of economic agents are increasingly becoming an essential part of economic policy formulation across economies (Duca et al., 2018). Numerous central banks now collect inflation expectations data from consumers, businesses, and professional forecasters for the purpose of monetary policy formulation (Kose et al., 2019). However, there is a growing debate on how these expectations are formed and how effective the "expectations channel" is.

As the primary demand driver in any economy, the inflation expectations of consumers can significantly impact the realized or actualized inflation: an increase in inflation expectations about the future will encourage consumers to increase demand for goods and services in the present. As a result, actual inflation would go up. Another channel through which increased expectations can affect inflation is the demand for a rise in wages from workers: if expectations increase, workers demand higher wages, resulting in higher inflation. A study by the Federal Reserve Bank of New York found that households' inflation expectations have a statistically significant effect on core inflation, which suggests that inflation expectations can play a role in shaping actual inflation outcomes (Armantier et al., 2020).

Economists have, especially over the last three decades, devised different techniques to estimate the inflation expectations of economic agents. The measurement of inflation expectations can be broadly categorized into survey-based and market-based measures: survey-based measures have the advantage of incorporating views of heterogeneous groups of economic agents in the economy, whereas market-based measures (measures based on comparisons of specific yields in financial markets) have the advantage of being readily available and at a higher frequency, covering more extensive periods than survey-based measures (Kose et al., 2019).[2]

[1] The author is responsible for any errors or omissions. Views expressed in this research should not be taken as those of the Research Department or the State Bank of Pakistan.

[2] For background on market- and survey-based measures of inflation expectations, see Coibion et al. (2018) and Grothe & Meyler (2015) for the United States and the Euro Area, and Sousa & Yetman (2016) for EMDEs.

In this study, we will explore the uncertainty of consumer inflation expectations as it can help policymakers better understand the workings of the expectations channel in Pakistan. As stated above, an increase in expectations can cause an increase in realized inflation. The relationship is more complex than it appears, however, and many factors are simultaneously at play. One factor that highly affects this relationship is 'uncertainty.' If the consumers' inflation expectations are high, but there is high uncertainty among consumers about their expectations, then the effect of this expectation on realized inflation would be mild. If consumers are highly certain about their expectations, however, the impact of expectations on realized inflation would be significant. More specifically, we will look into understanding the Household Inflation Expectation (HHIE) formation through the lens of uncertainty in a developing economy.[3] We are interested in the level of uncertainty that prevails among consumers' expectations and the different demographic and social factors associated with the level of uncertainty.

Our research contributes to the increasing literature on how consumer inflation expectations are formed and what factors contribute to the heterogeneity of expectations. According to economic theory, the expectations channel is the key determinant of overall effective monetary policy, as a result, factors that shape inflation expectations become crucial for policymakers. Recent survey-based data across different countries have revealed that households' inflation expectations are persistently higher than inflation, which defies the rational expectations hypothesis.[4] (Jia et al., 2020). One primary reason for such behavior is that when forming expectations, consumers give much more weight to their frequently bought items (such as food and petrol) and do not consider the overall CPI basket. Furthermore, the subjective inflation expectation of consumers is highly dependent on time and sociodemographic variables (D'Acunto et al., 2021). Parallel to the previous, inflation expectation is higher for females, less educated, and younger populations in the advanced and developing worlds. (Kose et al., 2019)

[3] Recent studies, mostly done for advanced economies, have identified several factors that shape the uncertainty of inflation expectations. These include the inflation level, inflation expectation, and social and demographic variables. (Binder, 2017; Haidiri & Nolan, 2022; Reichi & Myler 2022; Rumler & Valderrama 2015).

[4] The rational expectation is called the sixth revolution in economics, and its representative, Robert E. Lucas, won the 1995 Nobel Prize in Economics. Since the 1970s, the rational expectation, as a significant amendment to Keynesianism, has been regarded as one of the theoretical sources of long-term liberalism in major European and American countries. However, after the global financial crisis 2008, the theory of the free market, including rational expectation, was seriously questioned at the practical level.

In the case of Pakistan, we have a Michigan-style survey called the Consumer Confidence Survey (CCS), conducted by the Institute of Business Administration (IBA), Karachi, Pakistan, and the State Bank of Pakistan (SBP). The CCS, starting from January 2012, is conducted with a two-month frequency and is a telephone-based survey that resulted in 110,260 responses until its 64th wave in July 2022. Furthermore, in each survey wave, two-thirds of the respondents are new i.e. they had not been previously contacted, while one-third are from the survey done six months ago. Consumers are asked how they anticipate the "prices of things you buy" will change over the next six months, along with sociodemographic data (such as sex, age, income, occupation, education, and location). Most of the questions are asked as per the Likert scale. Our primary interest variable for this study is Q6[5], however, which asks the consumers regarding their six-month-ahead inflation expectation and records responses in integer values.

The only problem that we face is calculating uncertainty from these point estimates. This would have been an easy task if consumers had given their expected inflation range, but estimating variation in expectation from a single-point response is somewhat tricky. However, one way of calculating inflation uncertainty from consumer point estimates has been proposed by Binder (2015)[6], who argued that individuals who are highly uncertain about their inflation expectations give more rounded responses. Their logic is based on the intuitive linguistic observation that Round Numbers Suggest Round Interpretations (RNRI) (Krifka, 2009). They have taken data from the Michigan Survey of Consumers (MSC) and divided the responses into round responses (multiple of five) and non-round responses. Non-round responses are categorized as not highly uncertain.

Further, instead of marking individuals with round responses as highly uncertain, the author has refined the round responses into highly uncertain versus not highly uncertain, depending on the value of the response and the time of the survey. For example, when comparing two individuals with inflation expectations of 10 percent and 100 percent, the latter is likely to be more highly uncertain than the former. In addition, only some round numbers can be categorized as a measure of uncertainty;

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[5] Consumer Confidence Survey Questionnaire https://www.sbp.org.pk/ccs/Survey%20Information/Questionnaire%20Urdu.pdf

[6] We thank Dr. Carola C Binder for sharing her code with us. It is important to put a disclaimer here that most of the analysis we have done in our study parallels the work done by Binder (2015). We have focused on whether the index developed by Binder (2015) for the US can suitably be used for measuring inflation expectations uncertainty for a developing country like Pakistan.

a person having an inflation expectation of 10 percent may or may not be uncertain about their inflation expectations.

In CCS, around 76 percent of responses are in multiples of 10 (M10), which, as per Binder (2015), suggests high uncertainty among households regarding their inflation expectations. We will further refine these responses into highly uncertain versus not highly uncertain categories, following the methodology set out by Binder (2015). The percentage of round numbers is comparatively smaller for other developed economies; the percentage of round numbers in multiples of 5 (M5) is approximately 50 percent in Australia, rising during periods of uncertainty, touching 70 percent during the global financial crisis and notably rising at the beginning of the COVID-19 pandemic (Haidari & Nolan, 2021).

One argument against using round numbers to calculate uncertainty is the respondents' disengagement and carelessness during the survey. We can dismiss this argument by showing that the round responses are high at times of economic and policy uncertainty, indicating that uncertainty is the reason behind round responses.

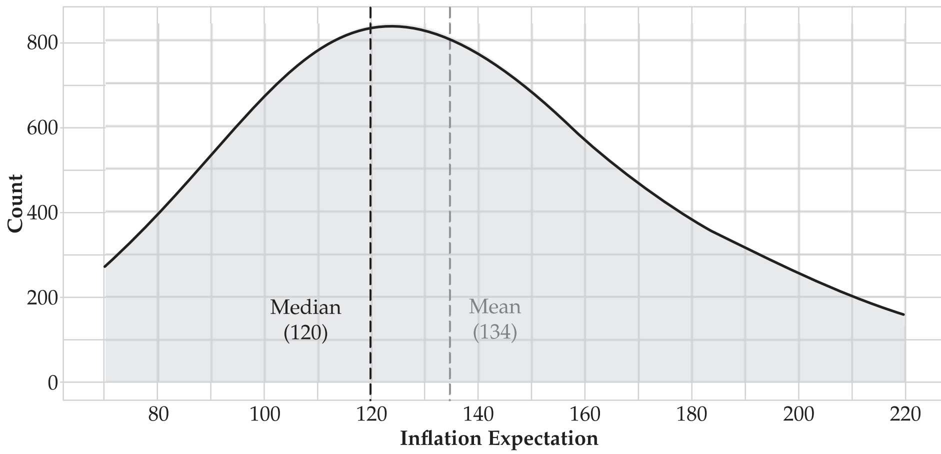
Once we get the uncertainty proxy ζ_{it} for an individual i at time t, we see the strong positive correlation of ζ_{it} with inflation expectation and the current level of inflation. ζ_{it} is also high for females, less educated, and younger individuals. Moreover, ζ_{it} is lower for heads of households and business owners.

The rest of the study is organized as follows: Section 2 explores the inflation expectations data available through the CCS; Section 3 looks into the construction of an inflation expectation uncertainty proxy; Section 4 explores the properties of inflation uncertainty, and Section 5 concludes.

2. Data Pre-processing and Exploration

As stated above, we have 110,260 responses from January 2012 to July 2022. After removing N/A values in Q6 of the survey, we are left with 96671 responses. Further, we identified the outliers and removed all responses below 70 and above 220 (goods priced at PKR 100 will be priced at PKR 220 after six months.)[7] After filtering out the outliers, the final 88,070 responses can be represented by the density curve in Figure 1.[8]

Figure 1: Density curve for trimmed inflation expectation data from January 2012 till July 2022.



Price level expectation (100 + inflation expectation)

First, we try to see any co-movement between the inflation and the Household Inflation Expectation (HHIE). Figure 2 clearly shows that household inflation expectations are greater than the actual inflation; the finding aligns with the existing literature (Binder, 2017; Haidiri & Nolan, 2021). Some asymmetries can also be seen in the graphs. From 2015 to 2019, actual inflation increased, but the mean inflation expectation decreased. Also, when inflation increased rather sharply, starting from mid-2020 untill 2022, inflation expectations increased much faster and peaked in March 2022. The inflation expectations decreased sharply in surveys that followed the general elections even though inflation continuously increased (shaded rectangles in Figure 2). These patterns suggest that non-economic variables significantly impact the formation of household inflation expectations.

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[7] $[LU] = [Q1 - g * (M - Q1)Q3 + g * (Q3 - M)] where g = 3.1, L = Lower Limit, U = Upper Limit, Q1 = Lower Quartile, M = Median \wedge Q3 = Upper Quartile$

[8] Please note that in Figure 1, the x-axis is price level expectation, i.e., 100 + inflation expectations. This is because the questions asked in the survey were worded as such. However, this does not affect our analysis because taking price level expectations or inflation expectations is the same for our analysis. For example, a price level value of 110 equals an inflation expectation value of 10. The question in the survey was designed keeping in mind that asking about percentages can be confusing at times for respondents, so to keep the question as simple as possible, the question was rephrased as "What will be the price after 6 months of a product which is Rs.100 today?" to get respondent's inflation expectations.

Figure 2: Six months ahead actual prices (dotted); HHIE mean (dashed)

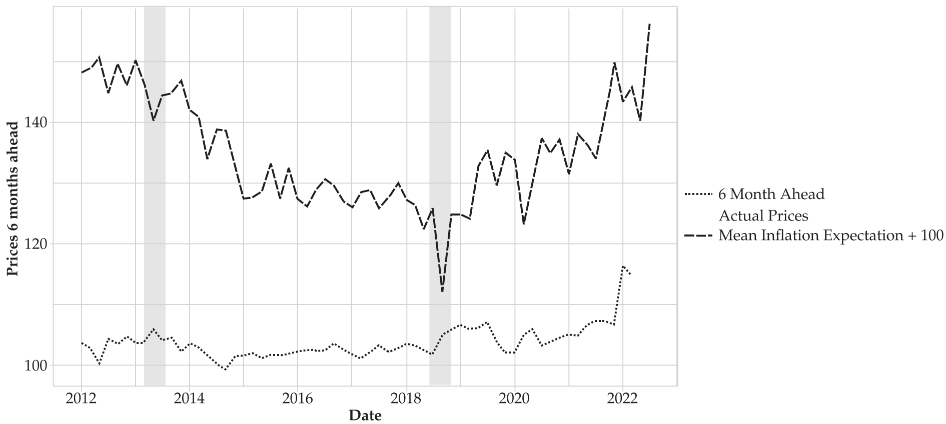
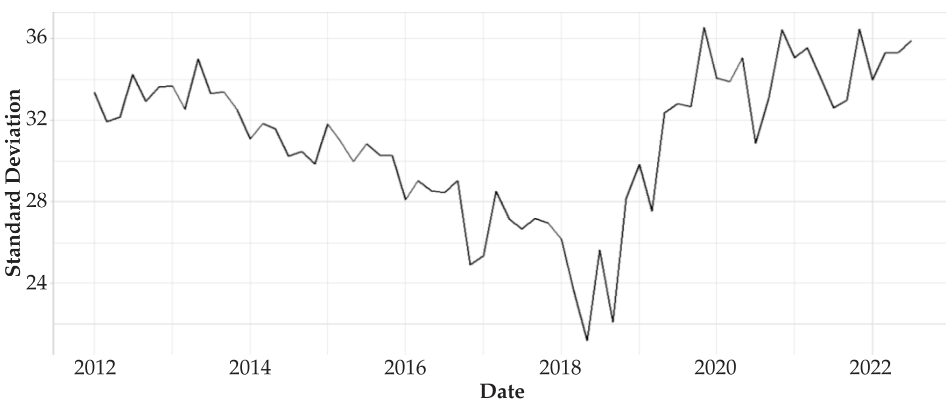


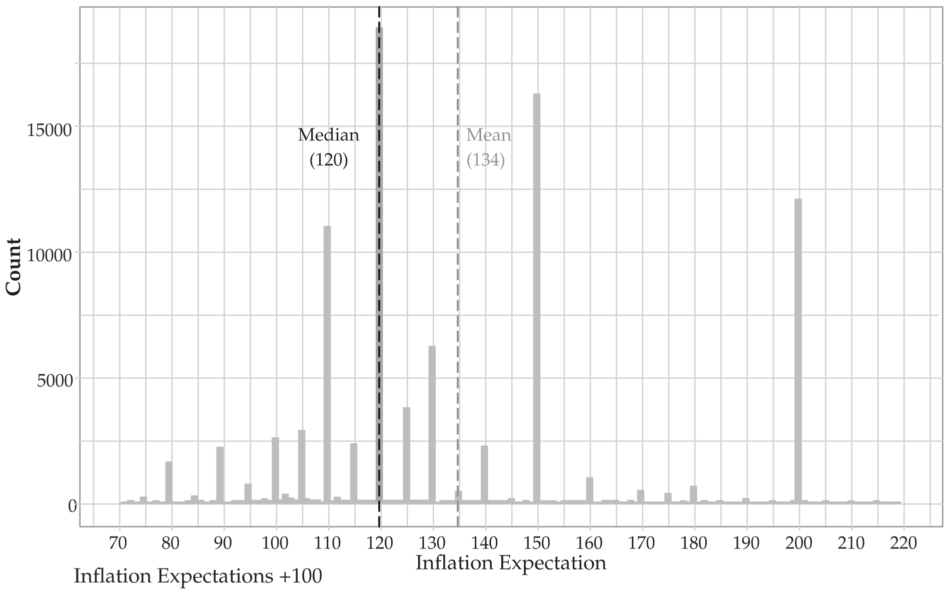
Figure 3 shows the standard deviation of responses over time. The graph clearly shows that for 2014-2019, the uncertainty was declining, and the chances of getting household inflation expectations anchored were high. However, after 2019, the standard deviation of household inflation expectations again started rising, indicating increasing uncertainty among households regarding the inflation outlook. This could be due to multiple reasons, including Covid-19 lockdowns and the high global inflation that followed.

Figure 3: Standard deviation of Household Inflation Expectation



As stated earlier, another feature of any survey data is the presence of round numbers. Likewise, our data of expectations have heaping at multiples of 10; in fact, 76 percent of the responses are in multiples of 10. The histogram in Figure 4 depicts this situation. This can be used as a starting point for investigating the uncertainty in the point estimates provided by the respondents. We will apply the technique of Binder (2015) to calculate the underlying uncertainty from these point estimates. Further, we will check the robustness of this uncertainty index within the context of Pakistan.[9].

Figure 4: Histogram depicting heaping of responses at multiples of 10.



3. Inflation Expectations Uncertainty

3.1 Uncertainty vs. Inattention

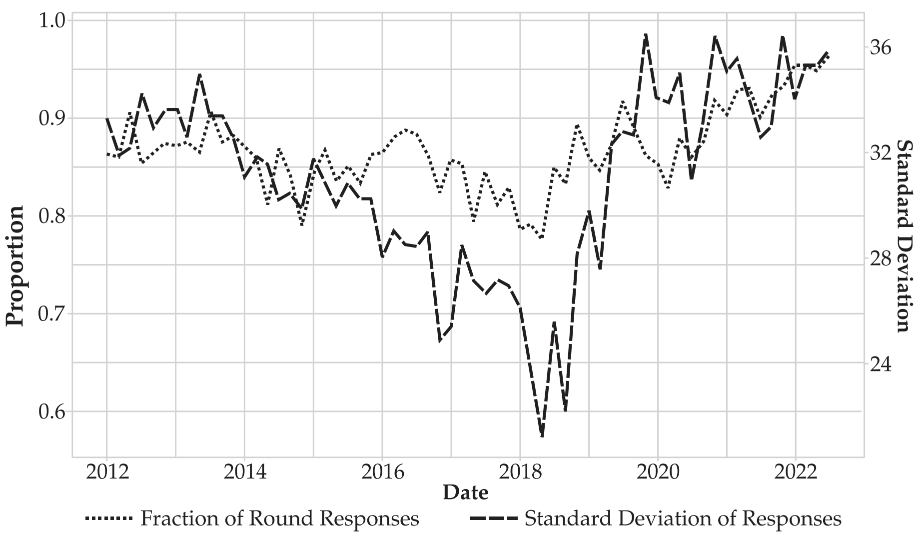
The round responses may indicate disengagement or carelessness on the part of the respondents, rather than uncertainty. This section will demonstrate that round responses reflect uncertainty about outcomes instead of demonstrating consumer indifference. Although rounding and uncertainty have received considerable attention in other fields, it is new in terms of inflation expectations. Remarkably, research in cognition, linguistics, and communication suggests that round numbers are frequently used in survey responses to indicate more significant uncertainty than non-round numbers (such as digits and decimals) (Krifka 2009). In an experimental study, Ruud et al. (2014) also demonstrated that a rise in the

[9] Please see Appendix C at the end of the document for disaggregated survey details.

exogenous level of uncertainty corresponds to a rise in the variance of the beliefs of the subjects, which causes more rounding.

To indicate this, we graph the fraction of responses in multiples of 10 for inflation expectations along with the standard deviation of inflation expectations. We see responses in the multiples of 10 directly related to the standard deviation of inflation expectations (correlation coefficient= 0.61). May 2018, as a point of fact, saw the standard deviation of responses and the proportion of round responses at their lowest. The graph below compares the standard deviation and the fraction of responses in multiples of ten for inflation expectation over time. The fraction of responses in multiples of 10 (frac10) time series is more stable than the standard deviation, but some relation is visible from the two graphs. This establishes that people tend to give more round responses when there is uncertainty.

Figure 5: Mean Inflation Expectation over time over different population characteristics



Similarly, outliers and "Don't Know" (DK) responses indicate uncertainty among the population regarding any variable. To test this, we can establish the correlation between the indicators of uncertainty and the fraction of outliers. Using the inflation-expectations standard deviation, a fraction of round responses, and the fraction of DK responses from the respondents, we see a moderate to strong correlation between the standard deviation, frac10, and frac_outliers. However, DK has a weak correlation with the other variables.

Table 1: Pearson correlation coefficients between standard deviation, fraction of round responses, fraction of outliers and fraction of DK responses

	frac10	frac_outlier	frac_DK
Standard deviation	0.618	0.693	0.08
	(0.00)	(0.00)	(0.53)
frac10		0.426	0.229
		(0.00)	(0.068)
frac_outlier			0.139
			(0.272)

Note: P-values are in brackets.

3.2 Construction of Uncertainty proxy using rounded-off data

Next, we construct the Household Inflation Expectation Uncertainty Index (HHIE-UI) using the approach followed by Binder (2015). We will take values in multiples of 10 (M10) as it has already been established that there is some correlation between the frac10 and other proxies of variation in responses. We aim to refine the data using statistical techniques to filter out responses from uncertain individuals using the micro-data available from the survey. Binder (2015) has used M5 instead of M10 while using the Michigan Survey for US households. In a developing economy like Pakistan, inflation hits double digits more often, so M10 would be a better option to measure uncertainty than M5.

The fraction of respondents with reported inflation expectations in multiples of 10 can be used as a simple proxy for uncertainty. However, not all responses in multiples of 10 are from uncertain individuals. There must be some respondents who are not highly uncertain, but their expected inflation can be in multiples of 10. Hence, those individuals who gave responses in multiples of 10 can be divided into two bins: high uncertainty type(h) and low uncertainty type (l). On the contrary, we assume that those who did not give a response in multiples of 10 are certain about their expectations, and hence, they are type l individuals. Further, individuals who responded with "Don't Know" or responded with outlier values are definitely highly uncertain and are type h.

For each individual at time t, therefore, the response R_{it} is the M10 value or the integer value for type h and type l individuals, respectively. The probability ζ_{it} of any individual $i$being type h can be calculated using the maximum likelihood estimate.[10] Note that the probability of being highly

[10] Please look into Appendix C

uncertain is zero ($\zeta_{it} = 0$) for individuals giving integer responses that are not multiple of 10. Furthermore, the probability of being highly uncertain is one ($\zeta_{it} = 1$) for individuals giving a "Don't Know" response or outlier value. Figure 8 displays some estimates of uncertainty proxy ζ_{it} over time for responses 110 (10 percent inflation expectation) and 170 (70 percent inflation expectation). Individuals giving a 10 percent forecast are less likely to be categorized as type h when compared to individuals giving a 70 percent forecast. This is understandable, as higher inflation expectations are associated with more uncertainty since they are much farther away from actual inflation.

Once we get the probability of type$h$respondents, we can move ahead with the Household Inflation Expectation Uncertainty Index (HHIE-UI) using these probabilities. The total fraction of uncertain individuals can be calculated as follows:

$$\frac{1}{N_t}\sum_{i=1}^{N_t}\zeta_{it} \tag{1}$$

Where N_t is the total number of respondents at time t.

Moreover, some respondents responded "Don't Know" when asked about their inflation expectations, which can also be treated as highly uncertain type (Type h). This means that if individual i gave a DK response, $\zeta_{it} = 1$. So, equation 1 can be decomposed as below:

$$U_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\zeta_{it} = \frac{1}{N_t^h + N_t^l + N_t^{DK}}\sum_{i=1}^{N_t}\zeta_{it} \tag{2}$$

Figure 6: The graphs of the proportion of responses with Don't Know responses and estimated Type h and Type l responses over time

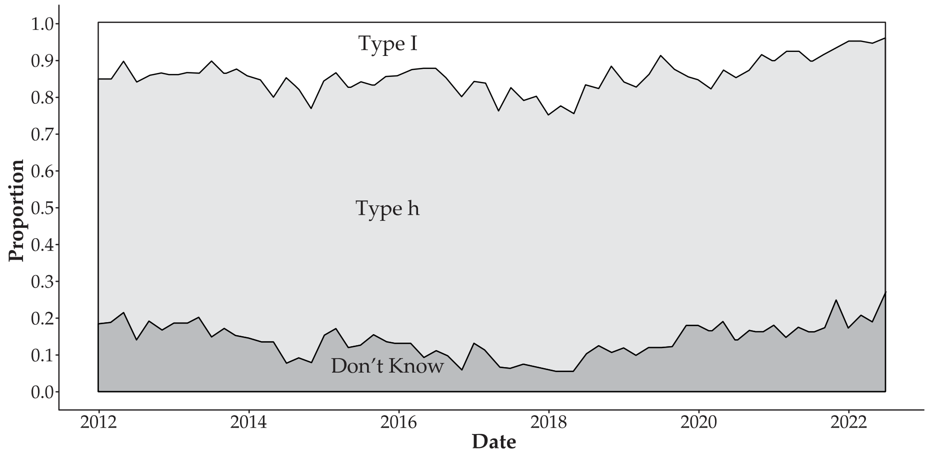


Figure 7 shows the difference between the Household Inflation Expectation Uncertainty Index (HHIE-UI) and the fraction of responses in multiples of 10 (frac10). The graph of UI is lower than the frac10 graph, indicating the fact that every round response is not a result of uncertainty. Figure 8 further clarifies that in our statistical model, the rounded figures far from the true inflation have a higher probability of being highly uncertain compared to the round values closer to the actual inflation.

Figure 7: Uncertainty index in comparison with round responses over time

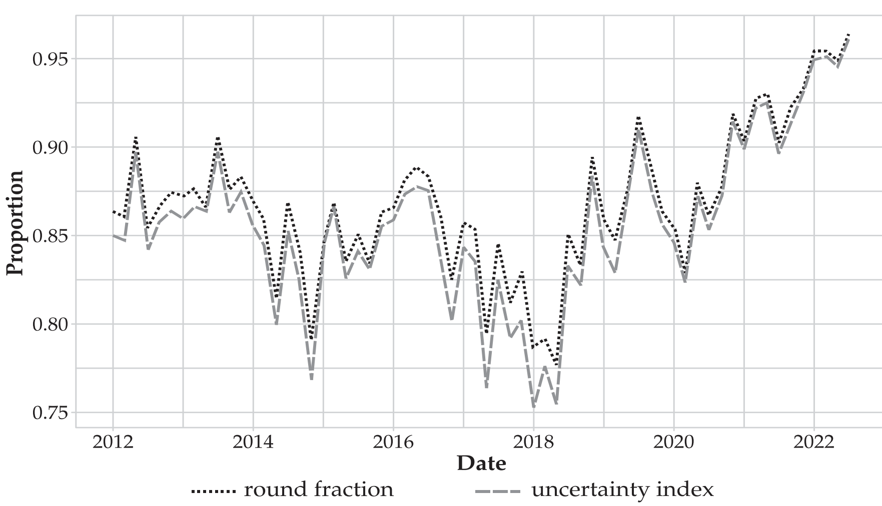
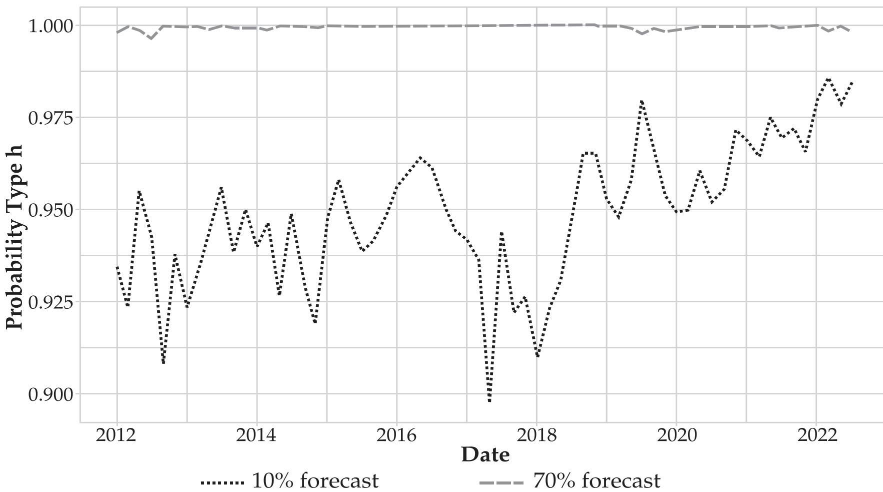


Figure 8: Plots the inflation uncertainty proxy for 10% and 70% responses over time

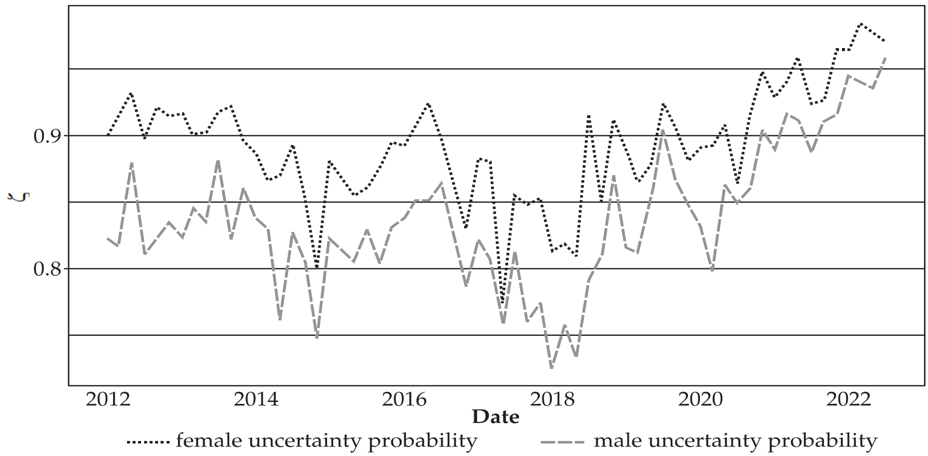


4. Properties of Uncertainty Proxy

4.1 Gender-segregated Uncertainty Proxy

The average uncertainty $\overline{\zeta}$ for males is 0.84, lower than the average uncertainty for females at 0.89, and the difference of mean is significant at a 1 percent significance level using a pair-wise t-test. This is in line with theory, which suggests that the uncertainty of inflation expectation is lower for males than for females. Figure 9 plots the mean probability $\overline{\zeta_t}$ for males and females over time. The graph clearly shows that the probability for females to be uncertain about their expectations is always higher than the probability for males.

Figure 9: Segregation of HHIE-UI based on gender

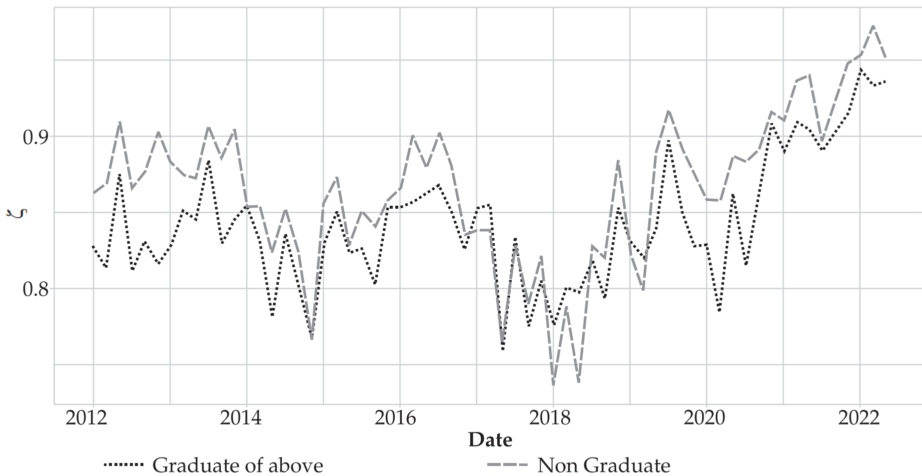


4.2 *Segregation of Uncertainty Proxy based on Education level attained*

Individuals can be divided into two groups depending on their education: Non-Graduate and Graduate[11] or above. Theory suggests that uncertainty should be high for the less educated group. The mean uncertainty over time is 0.87 and 0.84 for non-graduate and graduate individuals, respectively. Also, the difference in the means is significant at a 1 percent significance level using a pair-wise t-test. From the graph below, we can see that the uncertainty proxy for more educated individuals is lower than the other group most of the time. The graph also suggests that the deviation in uncertainty is higher for the lower-educated group.

[11] Graduate respondents are those who have completed a bachelor's degree

Figure 10: Segregation of HHIE-UI based on the highest education level attained



Further, the inflation expectation uncertainty proxy (ζ_{it}) has a mean of 0.86 and a standard deviation of 0.32 with 100863 observations. The regression of ζ_{it} on time-fixed effects has an R^2 of 0.02, indicating that in addition to cross-sectional variation, the time-fixed effect significantly impacts the uncertainty. This observation differs from Binder (2015) for the US, possibly due to relatively stable economic conditions in developed countries as compared to developing countries. If we compare the model with and without the time effect, it is clear that in the case of Pakistan the time-fixed effect significantly impacts the uncertainty.

Next, we test our uncertainty index for common characteristics observed in the literature. Binder (2015) argues that more uncertain individuals will likely make larger prediction adjustments and errors. Similarly, uncertainty should also persist for respondents who take the survey twice because people who have better access to information or more precise models of the inflation process should have less uncertainty in the second round of the survey; Lahiri & Liu (2006) and van der Klaauw et al. (2008) also find individual-level persistence in inflation uncertainty.

Table 2 shows three regressions, columns 1, 2, and 3 regress square error, absolute revision, and ζ_{it+6} on ζ_{it}; where Sq. Error is $(\pi^e_{it} - \pi_{t+6})^2$, Abs. revision is the absolute forecast revision of a rotating panel respondent who takes the survey twice with a six-month interval, $|\pi^e_{it+6} - \pi^e_{it}|$ and ζ_{it+6} is the uncertainty of rotating panel respondent after six months. Results from columns one and two verify that uncertain individuals, on average, make more revisions and errors, which aligns with the available literature (Binder, 2015). Further, the result in column 3 shows that uncertainty is persistent for individuals, and uncertainty today is predictive of the uncertainty after six months.

Table 2: The regression output incorporates a time-fixed effect in the model R^2

	Dependent variable:		
	Sq. Error	**Abs. Revision**	ζ_{it+6}
	(1)	**(2)**	**(3)**
ζ_{it}	2,133.884***	6.852***	0.026***
	(16.688)	(0.534)	(0.008)
Constant	1,351.265***	26.265***	0.774***
	(90.321)	(1.462)	(0.020)
Observations	85,650	20,446	20,446
R^2	0.107	0.026	0.026

Note: The cross-section models without time-fixed effects have R^2 of 0.06, 0.008, and 0.001 for regression (1), (2), and (3), respectively.
Note: *p<0.1.**p<0.05,***p<0.01

Table 3 shows a few demographically segregated properties from the data. The first two columns show the percentage of the population giving responses in multiples of 10 and "Don't Know" (DK). The third column displays the RMSE for the population, and the fourth displays the mean of ζ over the given group. Table 3 clearly shows that the mean uncertainty is lower for people with higher income and higher education. This is in agreement with the literature that states that uncertainty is lower for high-income, high-education males and those optimistic about government policies (Van der Klauuw et al., 2008; Armantier et al., 2013; Binder, 2017; Haidiri & Nolan, 2022; Reiche & Meyler, 2022). There is also growing evidence in the literature (Malmendier & Nagel, 2016; Cavallo et al., 2017) that people factor in the price signals they receive in their daily lives while forming inflation expectations, suggesting that the head of household should have a more certain opinion about inflation than others. This is also demonstrated in ζ where the mean uncertainty for the head of household is lower than that for other household members. The patterns emerging for ζ suggest that the round number responses are not merely a result of inattention at the respondent's end. Although much higher, the uncertainty proxy is behaving more or less the same way as suggested by the theoretical and empirical literature. This solidifies our assumption that the uncertainty proxy, calculated through round numbers, represents the true uncertain behavior of respondents at the micro-level in developing economies such as Pakistan.

Table 3: Fraction of responses in multiples of ten, a fraction of don't know responses, root mean square of the error between expected and actual inflation, and inflation expectations uncertainty proxy is presented with disaggregation by demographic characteristics

Expectations and uncertainty by demographic groups				
	Mult_10	**DK**	**RSME**	**ζ**
All	74.81%	13.99%	44.32	0.865
Bottom Income Group	75.57%	12.90%	47.24	0.865
Middle Income Group	77.57%	10.78%	41.72	0.865
Top Income Group	76.83%	10.86%	39.31	0.846
Non Grad	74.79%	14.96%	46.44	0.865
Grad	75.31%	12.14%	44.41	0.846
Male	75.19%	11.97%	41.48	0.846
Female	74.17%	18.00%	50.15	0.884
Age 18-29	75.57%	13.78%	46.78	0.865
Age 30-64	75.45%	13.06%	44.98	0.846
Age > 64	73.75%	13.16%	44.63	0.846
Head of Household	74.85%	12.28%	42.97	0.846
Not Head of Household	75.02%	14.96%	47.43	0.865
Satisfied with Govt. Policies	74.79%	12.58%	35.51	0.828
Not Satisfied with Govt. Policies	74.89%	14.26%	48.34	0.865

The differences among different demographic groups are further clarified by regressing ζ_{it} on demographic variables, expectation variables, and time-fixed effects (see Table 4). The result is significant for age, income, education, gender, and region. The uncertainty decreases with age, and the most probable cause for this could be the increase in the information set as age increases. Coefficients of income, gender, and education are in line with the extant literature. Female respondents have a higher uncertainty than males as, on average (Lusardi, 2008). The regression also suggests that respondents from urban areas have lower uncertainty about inflation than those from rural areas, even though the mean inflation expectations in urban areas was relatively higher. Another vital finding from this regression is that the respondents who run their own businesses have lower uncertainty than others. Since business owners have to keep in touch with changing economic conditions, they are more aware of the current economic conditions and, hence, less uncertain in their predictions. This is in line with Kumar et al. (2015), which suggests that those managers who consider national news important for their decision-making and follow them closely have less uncertainty in their decisions.

Furthermore, the impact of inflation on the inflation expectation uncertainty can be further explained in columns two and three of Table 4. Instead of taking headline inflation, if we take food, housing, and energy inflation, only the coefficient of food inflation is significant, indicating that food prices are a major factor affecting household inflation expectation uncertainty. We can also check for asymmetric behavior of household inflation expectation uncertainty for high and low inflation levels. Suppose we classify periods with inflation above 8.69 percent (mean since 2002) as a high inflation period and low inflation period otherwise. In that case, the coefficient of high inflation is significantly positive, indicating the asymmetric behavior of uncertainty during high and low inflation periods.

Table 4: Regression results of expectation, demographic, and macroeconomic variables on inflation uncertainty with time-fixed effects

	Dependent variable: ζ_{it}		
	(1)	**(2)**	**(3)**
Economic Perception- Neutral	-0.008	-0.008	-0.008
	(0.005)	(0.005)	(0.005)
Economic Perception-Positive	-0.008	-0.008	-0.008
	(0.005)	(0.005)	(0.005)
Economic Expectation-Neutral	-0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)
Economic Expectation-Positive	-0.015***	-0.015***	-0.015***
	(0.005)	(0.005)	(0.005)
Food inflation expectation – No change	-0.021***	-0.021***	-0.021***
	(0.006)	(0.006)	(0.006)
Food inflation expectation – Decrease	-0.011	-0.011	-0.011
	(0.008)	(0.008)	(0.008)
Gas inflation expectation – No change	-0.010*	-0.010*	-0.010*
	(0.005)	(0.005)	(0.005)
Gas inflation expectation – Decrease	-0.002	-0.002	-0.002
	(0.007)	(0.007)	(0.007)
Head of Household	-0.013***	-0.013***	-0.013***
	(0.004)	(0.004)	(0.004)
Business Owners	-0.009**	-0.009**	-0.009**
	(0.004)	(0.004)	(0.004)
Graduate	-0.023***	-0.023***	-0.023***
	(0.004)	(0.004)	(0.004)
Female	0.035***	0.035***	0.035***
	(0.004)	(0.004)	(0.004)
Inflation Expectation	0.0004***	0.0004***	0.0004***
	(0.00002)	(0.00002)	(0.00002)

	Dependent variable: ζ_{it}		
	(1)	(2)	(3)
Age	-0.0002*	-0.0002*	-0.0002*
	(0.0001)	(0.0001)	(0.0001)
Income 50k-100k	-0.009*	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)
Income >100k	-0.017**	-0.017**	-0.017**
	(0.007)	(0.007)	(0.007)
Urban	-0.010**	-0.010**	-0.010**
	(0.004)	(0.004)	(0.004)
Food Inflation		0.010***	
		(0.002)	
Housing and Energy Inflation		0.002	
		(0.002)	
High Inflation			0.118***
			(0.018)
Inflation	0.016***		
	(0.002)		
Constant	0.751***	0.776***	0.809***
	(0.019)	(0.019)	(0.014)
Observations	33,904	33,904	33,904
R2	0.053	0.053	0.053

Note: Robust standard errors are given in parentheses. Column 2 decomposes inflation into its subcomponents, and column 3 uses a dummy for high inflation as opposed to a quantitative value of inflation to measure asymmetry
*p<0.1 **p<0.05 ***p<0.01

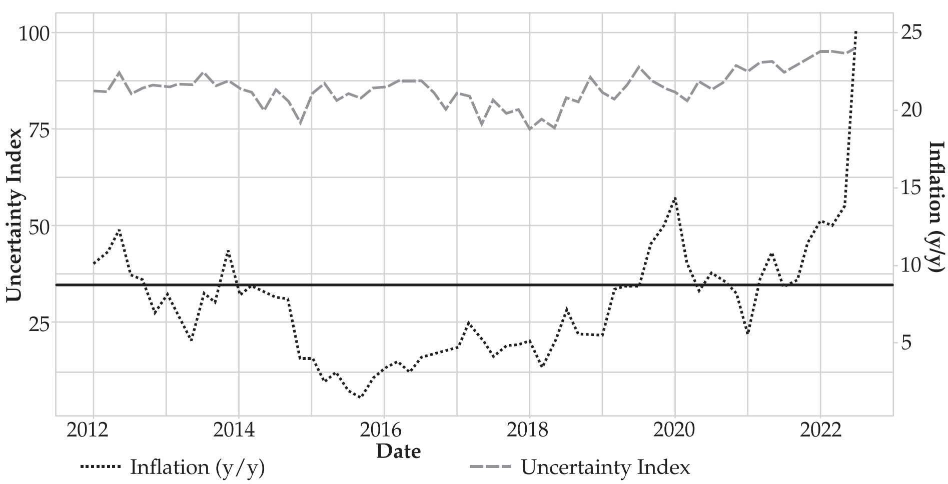
4.3 *Time Series Properties*

The HHIE-UI has a mean of 0.856 and a standard deviation of 0.04. The correlation coefficient between HHIE-UI and inflation is 0.57($p<0.00$), which aligns with general economic theory that states that higher inflation expectations uncertainty is often preceded by periods of high inflation. For example, this idea is a central theme in Okun's (1971) "The Mirage of Steady Inflation" and Friedman's (1977) Nobel Lecture. Ball (1992) has established that a rise in inflation raises uncertainty in expectations. This is because when inflation is low, people do not expect any intervention from the monetary authority; however, when inflation is high, there is disagreement in public opinion about whether the government will intervene to bring inflation down. This means that during periods of high inflation, HHIE-UI should be high, and during periods of low inflation, HHIE-UI should be relatively lower. The average level of year-on-year inflation since 2002 is 8.69 percent. We have taken the inflation level over this as a high inflation period and the inflation level lower than this value as a low inflation period. Since Jan 2012, Pakistan has seen 20 periods of high inflation and 44 periods of low inflation. When we calculate the Pearson correlation coefficient between the

HHIE-UI and inflation for both periods of high inflation and periods of low inflation, we get the desired results. The average value of HHIE-UI for a high inflation period is 87.5 percent, and the average value of HHIE-UI for a low inflation period is 83.1 percent.

Furthermore, the Pearson correlation coefficient between inflation and HHIE-UI is 0.47 (0.035) during the high inflation period, as compared to the correlation coefficient of 0.29 (0.058) between inflation and HHIE-UI during the low inflation period. During low inflation, the correlation coefficient is not significant at the 5 percent level, which indicates a weak relationship between inflation and HHIE-UI during the low inflation period. (also see Figure 11).

Figure 11: HHIE-UI with inflation level where the red line represents the twenty-year average inflation since 2002



Since the HHEI-UI is trying to capture the uncertainty in the expectations, expectations are formed by multiple factors, including the economic-related news in print and news media. To test this, we will use the Economic Policy Uncertainty Index (EPUI) developed for Pakistan by Choudhary et al. (2020) to see if some correlation exists between our HHIE-UI and economic uncertainty. For our comparison, we have used the EPU-4 index.[12]; the figure below shows that the EPU-4 index is much more

[12] To construct their EPU index, Choudhary et al. (2020) first obtain monthly counts of articles that contain terms about uncertainty (or uncertain, unpredictable, unclear, unstable), and economics (or economy) and one or more of the following policy-relevant terms: regulation, monetary policy, fiscal

erratic than HHIE-UI, but the Pearson correlation coefficient is 0.49, which indicates some relationship between the two series.

Further, inflation uncertainty is positively but mildly correlated, with a coefficient of 0.4, with inflation disagreement.[13] Economic theory proposes that inflation disagreement is closely related to uncertainty but is not the same (Lahiri & Sheng, 2010). The extant literature provides conflicting findings on whether inflation disagreement can be used as a proxy for inflation uncertainty (Binder, 2015). Our data suggests that when inflation disagreement is high,[14] the correlation between inflation disagreement and inflation uncertainty is low ($\rho = 0.4$), and when inflation disagreement is low, the correlation between inflation disagreement and inflation uncertainty is high ($\rho = 0.7$). This asymmetric relation between inflation disagreement and inflation uncertainty suggests that inflation disagreement might not fully capture inflation uncertainty. Another important variable that is positively correlated to inflation expectation uncertainty is inflation volatility.[15] The two variables are positively correlated with a correlation coefficient of 0.65 (see Figure 12).

4.4 Inflation Uncertainty and Consumption

The uncertainty in inflation expectations can affect many economic variables; we focus on consumption here: Inflation uncertainty can impact consumption decisions in two ways: Firstly, it can impact consumption by creating uncertainty about real income. Higher uncertainty about future income may result in "buffer-stock saving," and hence, the consumption would go down. Secondly, inflation uncertainty will result in uncertainty about the real rate of return on savings. As a result, risk-averse individuals might reduce savings and ultimately increase consumption. Since both effects work in different directions, the impact of inflation uncertainty on consumption is theoretically ambiguous. Empirical studies have also shown mixed results, with some establishing a negative relation between inflation

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policy, central bank (or SBP), FBR (or tax authorities), policymakers, parliament, deficit, government, reserves, taxes, tariffs, legislation. After obtaining these raw counts, they scale by the number of articles published in the same newspaper and month. They standardize each newspaper's scaled frequency counts to have a unit standard deviation from January 2015 to April 2020 (EPU-4) and then compute the simple average across newspapers by month. Finally, they multiplicatively normalize the series to have a mean of 100 for the given time period.

[13] Inflation disagreement is calculated as the interquartile range of a household's inflation expectation in a given survey.

[14] Inflation disagreement above mean inflation disagreement.

[15] Inflation volatility is calculated as the variance of the 3-year rolling window of the inflation time series.

uncertainty and consumption and others establishing either a positive or no relation (Binder, 2015). The CCS survey asks individuals about their current and expected consumption of durable goods. The link between uncertainty and spending on durable goods can be studied through respondents' spending attitudes. The theoretical framework for this has already been established by Bachmann et al. (2015), which established the relationship between the inflation expectations and spending attitudes of respondents of the MSC Survey. Further, Binder (2015) has incorporated uncertainty into the model of Bachmann et al. (2015) to analyze the impact of uncertainty on spending attitudes toward consumer durables.

Our goal in this section is to check whether the said relationship exists for a developing economy. Since the only data available to us is of car and bike sales, we will try to establish a relation between mean reported spending attitudes and the actual aggregated sales of cars and bikes through the following equations:

$$ln(CarSales_t) = \alpha + \beta CAR_t + \gamma t \tag{3}$$

$$ln(BikeSales_t) = \alpha + \beta CAR_t + \gamma t \tag{4}$$

Where CAR_t is respondents' mean spending attitude for time period t. CAR_{it} is the binary response variable with 0 if the consumer says it is a good time to buy a car or a bike and 1 if the consumer says it is not a good time to buy a car or a bike. Please note that CAR_t is countercyclical. Table 5 establishes the relationship between consumer spending attitudes and the sales of cars and bikes. As expected, the negative coefficient indicates that when consumers anticipate that it is not a good time to buy, sales decline. Furthermore, the R^2 for cars is much lower than for bikes, which indicates that the expectations have a more pronounced effect on bike sales than car sales. One underlying reason for this is that the affordability of bikes is much more prevalent in society than cars. So, a direct impact of expectations can be seen in the bike sales data and not in the car sales data, as the affordability of cars is only limited to a relatively "rich" segment of society in Pakistan.

Furthermore, from Table 6, we can ascertain that inflation expectations and uncertainty significantly shape consumer spending attitudes. This analysis establishes a crucial link between inflation uncertainty and the consumption of durable goods in the economy. It can be seen that an uncertain individual is almost 2 percent less likely to buy motor vehicles, durable goods, or houses than an individual who is highly certain about his inflation expectations. We have used the logit model to explore the impact of inflation expectations and inflation uncertainty with controls for the demographic characteristics of respondents and other macroeconomic variables. (For further details, see Appendix B.)

Table 5: Spending attitudes and Sales of Automobiles and Motorbikes

	Dependent variable:	
	ln(Car Sales)	**ln(Bike Sales)**
	(1)	**(2)**
CAR_t	-1.014*** (0.213)	-1.092*** (0.153)
Constant	9.885*** (0.131)	11.664*** (0.093)
Observations	64	64
R^2	0.206	0.648
Adjusted R^2	0.179	0.636
Residual Std. Error (df = 61)	0.309	0.240
F Statistic (df = 2; 61)	7.890***	56.065***

Note: Robust time clustered error in parenthesis
*p<0.1 **p<0.05 ***p<0.01

Table 6: Marginal Effect of Changes in Inflation Uncertainty and Inflation Expectations on spending attitudes of consumers regarding the purchase of durables, motor vehicles, and homes

	DURABLE	**CAR**	**HOME**
Marginal Effect of Inflation Uncertainty	0.021664**	0.018153**	0.015807*
Marginal Effect of Inflation Expectation	0.00033606***	0.00042051***	0.00027789***

Note: Marginal Effects are calculated while taking mean values of demographic control variables and macroeconomic variables after applying logit regression on the microdata available from CCS. For further details, please refer to Appendix B
*p<0.1 **p<0.05 ***p<0.01

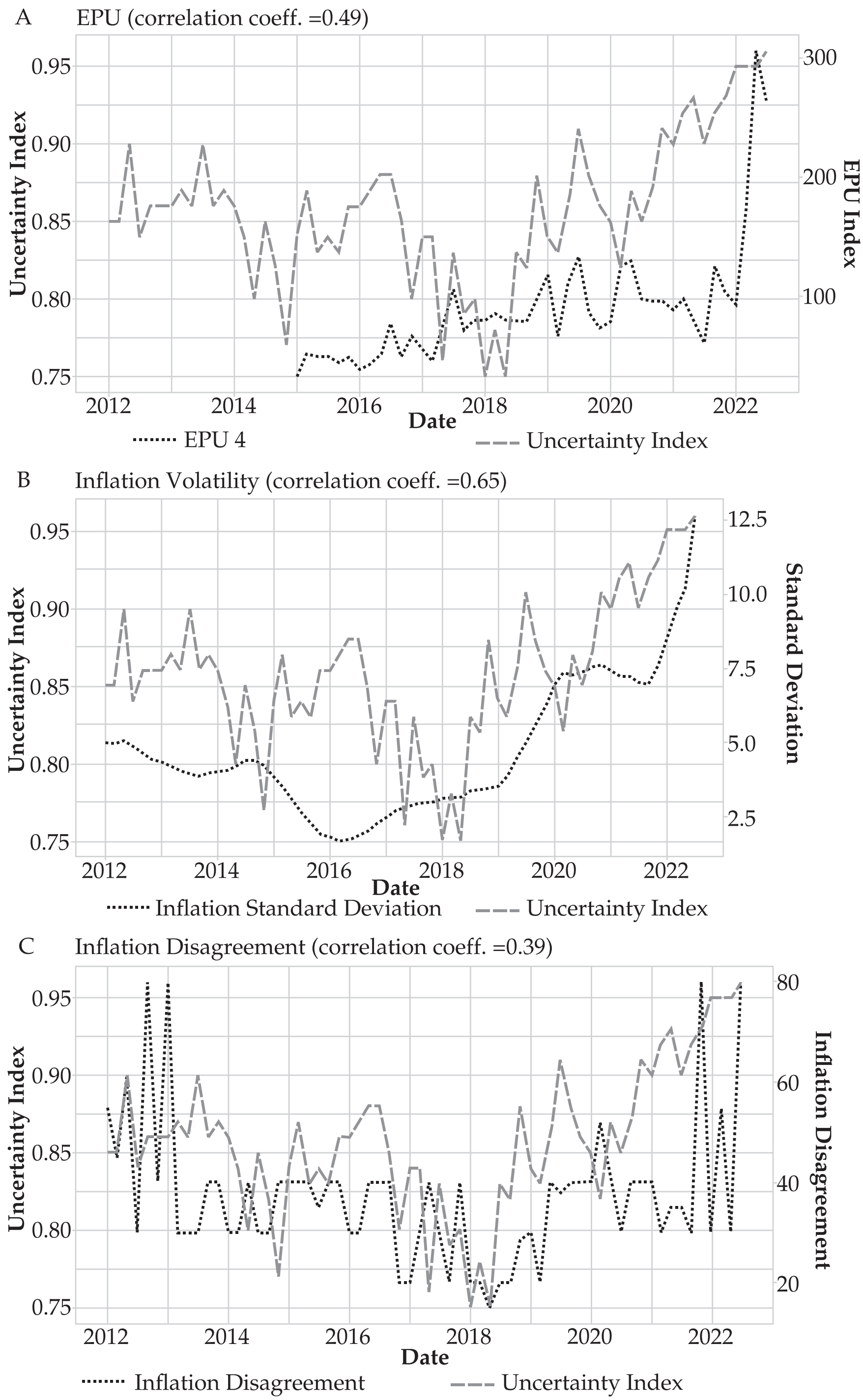
5. Conclusion

In conclusion, this study has examined the concept of inflation expectation uncertainty in Pakistan, its main determinants, and how it impacts the consumption of durable goods. The findings reveal that inflation uncertainty is highly linked with demographic characteristics and inflation expectations, as well as with inflation asymmetrically. Uncertainty tends to be high when inflation is high and is mainly driven by food inflation as opposed to energy and housing inflation. The study also shows that inflation uncertainty is linked to other aggregated macroeconomic variables of uncertainty, such as inflation disagreement, inflation volatility, and the EPU index.

In terms of policy implications, this study suggests that policymakers should focus on reducing inflation uncertainty to promote economic growth stability, as we have established that uncertainty has an indirect impact on durable sales and, ultimately, on consumption and aggregate demand in the economy. To achieve this, policymakers can take several measures, including improving communication with the public about monetary policy, using credible and consistent policy frameworks, and addressing structural issues that contribute to inflation uncertainty. For instance, policies can be designed to reduce food price volatility, a significant driver of inflation expectation uncertainty in Pakistan.

Further research can be directed towards establishing links between consumer inflation expectations uncertainty and other macroeconomic variables. In addition, consumer uncertainty can be studied in tandem with inflation uncertainty from businesses and professional forecasters. This would give some valuable insights into the rational expectations theory and its validity in a developing economy.

Figure 12: Inflation Expectation Uncertainty Index with related time series



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Appendix A

Date	Mean	Median	Standard Deviation	Don't Know Responses	HHIE-UI	Inflation (Y/Y)	High Inflation
Jan-12	148.23	150	33.34	13%	0.85	10.11	1
Mar-12	148.83	150	31.92	44%	0.85	10.84	1
May-12	150.75	150	32.15	55%	0.90	12.28	1
Jul-12	144.77	140	34.23	30%	0.84	9.37	1
Sep-12	149.76	150	32.90	41%	0.86	9.02	1
Nov-12	146.11	150	33.62	40%	0.86	6.91	0
Jan-13	150.12	150	33.68	20%	0.86	8.14	0
Mar-13	146.31	150	32.54	38%	0.87	6.67	0
May-13	140.29	130	35.00	58%	0.86	5.1	0
Jul-13	144.46	150	33.30	36%	0.90	8.2	0
Sep-13	144.89	140	33.39	44%	0.86	7.56	0
Nov-13	146.91	148	32.50	23%	0.87	10.92	1
Jan-14	142.04	130	31.07	27%	0.86	7.99	0
Mar-14	140.93	130	31.83	24%	0.84	8.57	0
May-14	133.93	125	31.56	15%	0.80	8.33	0
Jul-14	138.91	130	30.21	24%	0.85	7.92	0
Sep-14	138.70	130	30.45	20%	0.82	7.78	0
Nov-14	132.96	125	29.86	23%	0.77	3.95	0
Jan-15	127.46	120	31.80	42%	0.84	3.95	0
Mar-15	127.65	120	30.99	50%	0.87	2.45	0
May-15	128.58	120	29.97	31%	0.83	3.18	0
Jul-15	133.26	120	30.83	21%	0.84	1.86	0
Sep-15	127.40	120	30.27	31%	0.83	1.44	0
Nov-15	132.58	120	30.26	43%	0.86	2.7	0
Jan-16	127.30	120	28.08	58%	0.86	3.34	0
Mar-16	126.07	120	29.03	41%	0.87	3.78	0
May-16	128.81	120	28.52	42%	0.88	3.09	0
Jul-16	130.70	120	28.45	48%	0.88	4.03	0
Sep-16	129.54	120	29.02	29%	0.85	4.2	0
Nov-16	126.97	120	24.90	26%	0.80	4.45	0
Jan-17	126.10	120	25.34	41%	0.84	4.68	0
Mar-17	128.46	120	28.51	48%	0.84	6.26	0
May-17	128.89	120	27.16	35%	0.76	5.21	0
Jul-17	125.91	120	26.65	14%	0.83	4.09	0
Sep-17	127.63	120	27.18	26%	0.79	4.82	0
Nov-17	129.95	120	26.94	3%	0.80	4.86	0
Jan-18	127.36	120	26.16	26%	0.75	5.12	0
Mar-18	126.46	120	23.60	16%	0.78	3.37	0
May-18	122.40	120	21.20	35%	0.75	5.05	0
Jul-18	125.96	120	25.63	33%	0.83	7.09	0
Sep-18	112.07	110	22.11	31%	0.82	5.53	0
Nov-18	124.75	120	28.15	21%	0.88	5.44	0
Jan-19	124.90	120	29.82	22%	0.84	5.42	0
Mar-19	124.01	120	27.53	35%	0.83	8.47	0
May-19	132.88	120	32.36	25%	0.86	8.63	0

Date	Mean	Median	Standard Deviation	Don't Know Responses	HHIE-UI	Inflation (Y/Y)	High Inflation
Jul-19	135.51	125	32.78	22%	0.91	8.61	0
Sep-19	129.64	120	32.66	27%	0.88	11.4	1
Nov-19	135.05	125	36.53	19%	0.86	12.48	1
Jan-20	133.77	125	34.04	20%	0.85	14.42	1
Mar-20	123.29	120	33.88	24%	0.82	10.14	1
May-20	130.52	120	35.06	25%	0.87	8.36	0
Jul-20	137.34	130	30.86	22%	0.85	9.5	1
Sep-20	134.86	125	33.10	27%	0.87	9.05	1
Nov-20	137.32	125	36.42	36%	0.91	8.19	0
Jan-21	131.47	120	35.05	36%	0.90	5.5	0
Mar-21	138.06	125	35.53	33%	0.92	9.04	1
May-21	136.54	120	34.07	36%	0.93	10.78	1
Jul-21	134.02	120	32.58	34%	0.90	8.53	0
Sep-21	141.01	130	32.97	21%	0.92	9	1
Nov-21	149.80	150	36.46	42%	0.93	11.42	1
Jan-22	143.20	130	33.98	22%	0.95	12.86	1
Mar-22	145.77	140	35.28	32%	0.95	12.53	1
May-22	140.23	130	35.32	34%	0.95	13.75	1
Jul-22	156.20	150	35.88	40%	0.96	25.06	1

Appendix B

We have used the logit model with expectations about purchase of durable goods as the binary dependent variable, with 0 as the good time to purchase durable goods and 1 as a bad time to purchase durable goods. We have used socio-economic demographic characteristics, inflation expectation and uncertainty, along with other macroeconomic control variables and time fixed effects as independent variables. The marginal effect is the change in probability (in percentage points) of having an unfavorable spending outlook for a unit increase in uncertainty or a percentage point increase in inflation expectation. When calculating marginal effects, remaining variables are fixed at their average. The same logit regression and subsequent marginal effect calculation is then done for expectations about purchase of home and cars/bikes.

Table 7: This table looks into the marginal effect of the given variables on the spending attitudes of consumers towards durable goods, housing and motor vehicles. Marginal effects are calculated with other variables fixed at their mean value

Marginal Effect	Durables	Home	Car
Uncertainty Proxy	0.021664**	0.015807*	0.018153*
Expected Inflation	0.00033606***	0.00027789***	0.00042051***
Head of Household	0.011606*	0.0099729	0.022774***
Business Owners	0.014853**	0.0081925	0.0063227
Other Professions	0.013674*	0.017862**	0.035318***
College Graduate	0.0024973	-0.000032297	0.019412***
Female	-0.0017711	0.010994	0.0082428
Age	0.0013619***	0.0017434***	0.0010773***
Income 50k-100k	-0.026211***	-0.005015	-0.0023042
Income >100k	-0.065093***	-0.033389***	-0.032443***
Income Others	-0.047245***	-0.060603***	-0.050821***
Urban	-0.012502*	0.02066***	0.0047231
Inflation	0.0064067	0.22418**	0.17339
EPUI	-0.00060291	0.002443	0.0023353
KIBOR Rate	0.030992	-0.073605	-0.077074
Exchange Rate	0.0016267	-0.024625**	-0.017894

Note: *p<0.1 **p<0.05 ***p<0.01

Appendix C: Calculation of Uncertainty Proxy[16]

(C. Binder, 2015)

Let f_{it} be the inflation forecast of respondent i at time t. His forecast f_{it} would be distributed $N(\mu_{ht}, \sigma_{ht}^2)$ and $N(\mu_{lt}, \sigma_{lt}^2)$ if he is $type\ h$ or $type\ l$ respectively. The pmfs ϕ_t^h and ϕ_t^l of cross sectional responses are discretized normal distributions:

$$\phi_t^h = P(R_{it}|i\ is\ type\ h) = \int_{j-5}^{j+5} \frac{1}{\sigma_{ht}\sqrt{2\pi}} e^{\frac{(x-\mu_{ht})^2}{2\sigma_{ht}^2}} dx, j = 70,80, \dots ,210,220$$

$$\phi_t^l = P(R_{it}|i\ is\ type\ l) = \int_{j-0.5}^{j+0.5} \frac{1}{\sigma_{lt}\sqrt{2\pi}} e^{\frac{(x-\mu_{lt})^2}{2\sigma_{lt}^2}} dx, j = 70,71,72, \dots ,219,220$$

In each survey at time t, responses come from a mixture distribution ϕ_t of these two pumps where ϕ_t is defined as:

$$\phi_t = \lambda\phi_t^h + (1-\lambda)\phi_t^l$$

Now, from above three equations we have five unknown parameters $\lambda_t, \mu_{ht}, \mu_{lt}, \sigma_{ht}, \sigma_{lt}$ at time t, where λ_t is the fraction of respondent of $type\ h$.

Now, if the response R_{it} is not a multiple of ten, we know respondent is $typel$ but if the response is a multiple of ten we don't know if the respondent is $typeh$ or $typel$. Let there be total numerical responses be N_t, at given time. Then the likelihood for responses $\{R_{it}\}_{i=1}^{N_t}$ is given by:

$$L\left(\{R_{it}\}_{i=1}^{N_t}|\lambda_t, \mu_{ht}, \mu_{lt}, \sigma_{ht}, \sigma_{lt}\right) = \Pi_{j=1}^{N_t}\phi_t(R_{it}|\lambda_t, \mu_{ht}, \mu_{lt}, \sigma_{ht}, \sigma_{lt})$$

By applying Maximum Likelihood Estimations, we can estimate the parameters $\lambda_t, \mu_{ht}, \mu_{lt}, \sigma_{ht}, \sigma_{lt}$ at any given time t.Once we have parameter estimates, we can estimate the probability ζ_{it} that at any given time t respondent i is $typeh$ using the Bayes Rule as follows:

$$\zeta_{it} = \zeta_t(R_{it}) = P(typeh|R_{it}) = \frac{P(type\ h)\times P(R_{it}|type\ h)}{P(R_{it})} = \frac{\lambda_t\times\phi_t^h(R_{it})}{\lambda_t\times\phi_t^h(R_{it})+(1-\lambda_t)\times\phi_t^l(R_{it})}$$

[16] These calculations are taken from C. Binder (2015) and have been adjusted for multiples of ten. For further details please refer to C. Binder (2015).

Appendix D: Details of Survey

We have 110,260 responses for the period from January 2012 till July 2022. After removing N/A values in Q6 of the survey we are left with 96,671 responses. Further, we identified the outliers and removed all responses that are below 70 and above 220 (goods with price of PKR 100 will be priced at PKR 220 after six months.)[17] After removing the outliers, we are left with 88,070 responses.

Male vs Female

The average inflation expectation for males over the full period of survey is 132, while for females the value is 141. Furthermore, the standard deviation of responses from male is 31, while for responses from female the value is 34. These two statistics, combined with the figure 13D below, suggest that the female respondents have high inflation expectations and higher disagreement as well, compared to male respondents. Reiche & Myler 2022 would suggest that higher variation, along with higher inflation expectation, is an indicator for higher uncertainty. Hence, the data suggests that female respondents are more uncertain about their inflation expectations than male respondents.

Graduate vs Non-Graduate

When comparing household inflation expectation between education brackets, the clear difference is between graduate respondents and non-graduate respondents. The graduate respondents have a mean inflation expectation of 134 over time, compared to the value of 136 for non-graduate respondents over time. This can be further clarified from figure 13A, which shows that the mean inflation expectation of graduate respondents in lower than that of non-graduate respondents. Furthermore, the standard deviation of non-graduate is also higher than that of graduate respondents. This signifies the fact that there is more disagreement among non-graduate respondents compared to graduate respondents.

Urban vs Rural

When comparing the mean value of Inflation Expectation between urban respondents and rural respondents, the urban inflation expectation is

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[17] $[LU] = [Q1 - g * (M - Q1) Q3 + g * (Q3 - M)] where g = 3.1, L = LowerLimit, U = UpperLimit,$
$Q1 = LowerQuartile, M = Median \wedge Q3 = UpperQuartile$

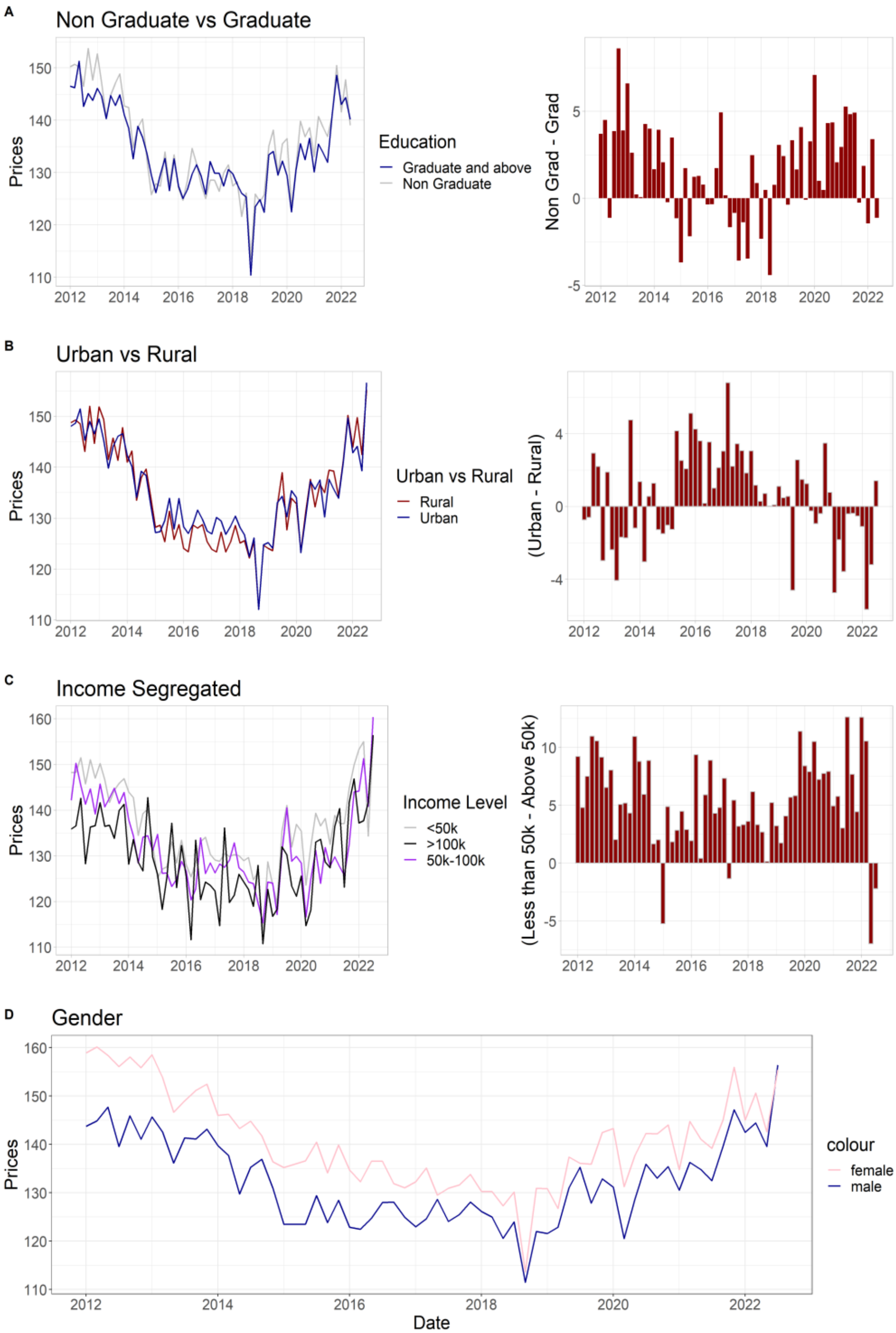
slightly more that the rural inflation expectation at 134.8 and 134.5 respectively. Figure 13B also displays this relation over time and it is clearly visible that mean inflation expectation is slightly higher for urban respondents in most of the surveys; similar pattern also appear in standard deviation. The possible reason for such a difference could be the difference in the standard of living between urban and rural areas. For instance, a car may be considered a necessity in an urban household while it may not be considered a necessity for rural household. This may result in high expenditure in urban household than rural household and hence the inflation expectation.

High Income vs Low Income

The inflation expectations is significantly different for different income groups with mean 137.5, 134.9 and 132.9 for lowest, middle and highest income groups respectively[18]. The inflation expectation is decreasing with the rise in income. The phenomenon is quite visible in figure 13C. This is in line with the recent literature on Inflation expectation that states that inflation expectation is inversely related to the income (Reiche & Myler, 2022).

[18] Lowest: Income < PKR 50K ; Middle: Income between PKR 50K and PKR 100K ; Highest: Income > PKR 100K

Figure 13: Mean Inflation Expectation for different demographics over time



Appendix E: Non-normal distribution

(C. Binder, 2015)

In section 3, we assumed that the forecasts followed a normal distribution for both type of individuals: high uncertainty type and low uncertainty type. Here we will show that our uncertainty index is not sensitive to that normality assumption. Now we will use the assumption that consumers' forecasts follow logistic distribution and see if the results are similar to the uncertainty index that we developed in section 3. Logistic distribution has fatter tails with the following density function:

$$f(x;\mu,s) = \frac{e^{\frac{-x-\mu}{s}}}{s\left(1+e^{\frac{-x-\mu}{s}}\right)^2}$$

with mean μ and the variance is $\sigma^2 = s^2\,\pi^2/3$.

Figure 14 shows the final uncertainty index under both assumptions and it can be clearly see that the final output under both assumptions is similar indicating the non—sensitivity of our index to the normality. Furthermore, figure 15 and table 8 give the details of estimated parameters and their relation with each other under both distributions.

Figure 14:Uncertainty Index under normal distribution and logit distribution

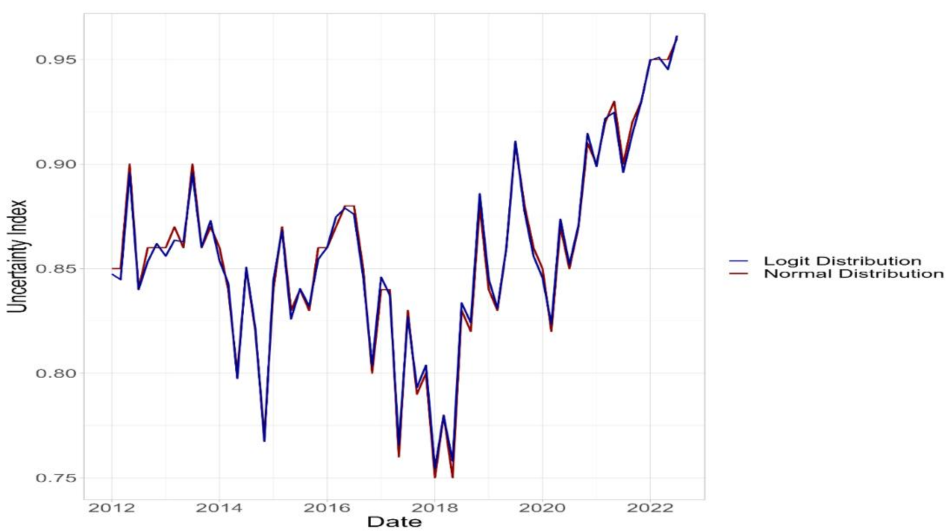


Table 8: Maximum likelihood estimates with normal and logistic distributions

Estimate	Mean with Normal Distribution	Mean with Logit Distribution	Correlation between normal and logistic
λ	0.838	0.838	0.99
μ_l	116.2	115	0.99
μ_h	138.5	135.6	0.99
σ_l	16.18	7.9	0.95
σ_h	31.8	17.9	0.98
Uncertainty index	0.857	0.857	0.99

Figure 15: Estimated parameters under assumption of normal distribution(red) and logit distribution(blue)