1 Introduction

The Canonical permanent income/life cycle hypothesis (PIH) predicts consumption as a random walk process, whose growth rate is unpredictable (see, Hall, 1978). This implies, only current consumption captures all available information to predict the future consumption. However, as soon as the survey data of consumer sentiments become available, a large body of literature starts using sentiments to test the implications of PIH. While doing it, their primary objective was to test if sentiments possess additional information, beyond that in the current consumption, which helps predicting the future consumption, and if so why?

Using the Euler equation framework, Carroll et al. (1994) finds lagged sentiments (measured by the Index of Consumer Sentiments, ICS) positively affects the consumption growth rate of the US. Carroll et al. (1994) explains the excess sensitivity of consumption to the lagged sentiments by means of consumption frictions; arising primarily from the habit formation of the individuals. Acemoglu & Scott (1994) find the excess sensitivity of consumption to sentiments, and the violation of the PIH for the UK. They explain the positive relationship between consumer confidence and consumption through the precautionary savings motive of the individuals. They show that, the higher consumer confidence is not only associated with average income, but is is also associated with the uncertainty, arising from the higher income volatility. According to Acemoglu & Scott (1994), such a positive association between the sentiments, and uncertainty induces the individuals to save more, yielding the positive relationship between consumer confidence, and the consumption growth as observed in their estimation.

Observing the importance of sentiments in forecasting consumption growth, a growing number of literature studies it's determinants. While, analyzing the determinants of household sentiments, Blendon et al. (1997) finds that the household sentiments is not necessarily a mirror image of current macroeconomic conditions because individuals often form their sentiments during the discussion with their neighbor at the backyard of their apartment. Lahiri & Zhao (2016) performed a detailed analysis of ICS, and it's underlying sub-components. They find, household sentiments, mostly driven by the perceptions of their own financial conditions, and unemployment contains significant information, which is highly heterogeneous, asymmetric, and cyclical in nature. They also argued that, such a rich important information content, embodied in household sentiments are often lost in aggregation. Additionally, Lahiri et al. (2016) shows that, the time-varying asymmetry in the cross sectional distribution of household's expected financial condition, unemployment, and non-economic wave of optimism and pessimism cause household sentiments significant in forecasting consumption growth.

Souleles (2004) also highlights the importance of the household level information sets, and expectations while testing the implications of rational forecasts by directly using the household level data of sentiments for the US. Alongside the rational expectations, the paper also tests the excess sensitivity of consumption to sentiments for the US households through an Euler equation framework. Note, the Euler equation framework not only tests the excess sensitivity of consumption to sentiments, but it also gives us natural setting to test the validity of the PIH by using the highly informative micro level data of the household sentiments as already identified in the literature, discussed above. Note, Souleles (2004) sourced the data of household sentiments, and consumption from two different surveys for his estimation. While, the data of household sentiments are taken from CAB, the data of household consumption are obtained from CEX. Souleles (2004) first matched these two datasets through a rich set of the demographic characteristics of the households, and consequently used their estimated sentiments as one of the control variables in his estimation. As a result, Souleles (2004) had to use a two-sample instrumental variables technique to obtain a correctly adjusted standard error of the coefficient of the estimated sentiments. The paper finds that, the excess sensitivity of consumption to sentiments holds, and hence PIH is violated for the US. The paper also finds the evidence of the precautionary savings motive for the US households. Souleles (2004) established the robustness of their results by including households estimated forecast errors as an additional control variables to the log-linearized Euler equation alongside the sentiments, which eliminates the possibility of the spurious excess sensitivity.

The extant literature has already identified that, the cross sectional heterogeneity of the micro level data contains important information, which gets lost in aggregation. Lahiri & Zhao (2016), and Souleles (2004) identified the importance of household level sentiments for predicting consumption growth of the US. In this context, it is important to note, India is a big country, and the extent of demographic diversities of the country are significantly higher than that of any developed country. As a result, using the household level sentiments obtained from the CPHS, CMIE, we examine the excess sensitivity of consumption to sentiments, and the validity of the PIH for India by fully utilizing the large informative content of the Indian data. In this context, it important to note that a few papers have used the data of sentiments provided by CPHS, CMIE to estimate a consumption function for the Indian households. The main objective of the papers to test the presence of animal spirits, and its role in the propagation of the oil price and the monetary policy shock to consumption (see, Priya & Sharma, 2024). Our paper is the first genuine attempt to examine the presence of the excess sensitivity of consumption to sentiments for the India households. We have employed an Euler equation approach for estimation so that we can simultaneously test the PIH for the Indian households along with the role of sentiments in the prediction of household level consumption of India.

It is important to note that, we lose a significant extent of cross sectional heterogeneity when, following the existing literature, we calculate the household level real consumption, and income by deflating their corresponding nominal consumption, and the nominal income through an aggregate CPI. We find that, the incidence of inflation considerably differs across households, influencing their demand for goods and services. As a result, instead of using an aggregate price index, a household specific price index is required for calculating real income, and consumption to preserve the cross sectional heterogeneity, and the associated information content of the data. Hence, we calculate an expenditure minimizing consumption bundle for each Indian household by deflating their nominal consumption, and income through a household specific price index, and used it in our analysis. Following this methodology, we calculate two types of consumption bundles for the Indian households - (i) the consumption bundles consisting of only 8 important food groups, and (ii) the consumption bundle that includes fuel and lighting along with the 8 important food groups. Using these consumption bundles, we examine the excess sensitivity of consumption to sentiments for the India households through the Euler equation approach as done by Souleles (2004) for the US.

Note, unlike Souleles (2004), we obtain the data of household consumption, income, sentiments, and other relevant demographic characteristics from a single survey - CPHS, CMIE for India. It gives a large longitudinal data household consumption, sentiments, income, and other relevant demographic variable, which is representative of the Indian economy. As a result, instead of using the two sample instrumental variables technique, we have used GMM in our paper. Note, the GMM estimation used by us, where the part of the household sentiments explained by their income, and other demographic characteristics as suggested by Souleles (2004) is used as an excess sensitivity regressor for estimation is identical in spirit with the two sample instrumental variables technique used by Souleles (2004). It is also important to mention here that, we have also performed a baseline OLS estimation to test the excess sensitivity of consumption to sentiments where, unlike the GMM, we directly use the raw household sentiments entered in the regression equation. We find that, the impact of sentiments on consumption growth is significantly higher under GMM than that of OLS. This implies that, the part of the sentiments, explained by the income, and other relevant demographic characteristics of the Indian households is a better predictor of their consumption growth than the raw sentiments itself.

We have used two types of household sentiments as the excess sensitivity regressors in our paper - (i) the perception of the households about their own year ahead financial position, and

(ii) the perception of the households regarding the year ahead business condition. Moreover, to eliminate the possibility of the spurious excess sensitivity, we have also controlled the household's forecast error related to their own financial position, alongside the household sentiments, and their demographic characteristics as suggested by Souleles (2004). We find, like the US, the excess sensitivity of consumption to sentiments exists for India. This implies that the household sentiments of India holds important information, beyond that in current consumption that helps predicting their future consumption. This further implies that, PIH does not hold for India. Our results also show - (i) since the sentiments of the households are associated with uncertainty, the motive of precautionary savings also exists for the Indian households, and (ii) fuel and lighting is an important component of the consumption of Indian households. The prediction of consumption growth by sentiments significantly rises once we include fuel and lighting in the consumption bundle of the household along with the food groups.

2 Data Description

CPHS collects sentiments data of Indian households from April, 2016. To do it, a generic household h is surveyed thrice in a year in an interval of every four months by CPHS. For example, a household surveyed in April, 2016 will be surveyed again in August, 2016 for the collection of the sentiments data and so on. To collect the data of sentiments, the CPHS asks the following questions to the households – (I) compare to a year ago, how is your family faring financially these days? ; (II) How do you think that a year from now, financially, your family would be faring?; (III) How would you describe the financial and business conditions in our country in the next 12 months?; (V) What do you think would be the financial and business conditions in our country in the next 5 years?; (V) Do you think that this is generally a good or bad times to buy things like furniture, refrigerator, television, two-wheeler, car? While, the answer to questions (I), and (II) mentioned above are recorded as Better, Same and Worse, and accordingly assigned a numerical value, 1, 0, -1 respectively, answer to questions (III), (IV) and (V) are recorded as Good time, Uncertain time and Bad time, and accordingly take numerical value, 1, 0 and -1 is assigned respectively. We have used the answer of the questions (II), and (III) from April, 2016 to October, 2022 as the measure of sentiments for our analysis, which takes the values -1, 0, 1 for negative response, neutral response, and positive response respectively. Note, the sentiments related to question (II) represents the perception of the households about their own year ahead financial position, denoted by Q_{FP} in our analysis. On the other hand, sentiments related to question (III) represents the perception of the households about year ahead business conditions, denoted by Q_{BC} in our analysis. Moreover, using the difference in response to question (I) and (II), we also calculate the forecast error related to household's financial position, and used it in our estimation as a separate control variable to eliminate the possibility of spurious excess sensitivity (see; Souleles (2004)). For a generic household h, this forecast error can take discrete integer values between -2 to 2[1] . We denote the forecast error by FE in our analysis.

From the CPHS survey, we also collect the data of monthly consumption expenditures of households for 8 food groups; and fuel and for our estimation. To do it, we collect relevant price index of different food items from MoSPI. The price index for 5 food groups - (1) cereals; (2) oils and fats; (3) fruits; (4) pulses and products; and (5) milk and milk products are directly available in MoSPI[2]. But, MoSPI reports price index separately for the food items like (i) meat and fish; (ii) egg; (iii) vegetables; (iv) spices; (v) sweets; and (vi) snacks. Using the price index, and the corresponding weights of the 6 food items mentioned above, we calculate the monthly price index of the following food groups- (1) meat, fish and egg; (2) vegetables and spices; and (3) sweets and snacks. We also collect monthly price index of fuel and lighting from MoSPI.

Using the monthly data of various sub-categories of consumption expenditures as mentioned above, and the appropriate price index, we calculate to calculate 2 types of consumption bundles for each household - (i) consumption bundle, consisting of 8 food groups, and (ii) consumption bundle, consisting of 8 food groups, and fuel and lighting. The methodology of constructing the consumption bundle, and a household level aggregate price index is described Section 3.

Along with the household level consumption expenditures, we also collect data of monthly income of the households from the CPHS survey, and calculate monthly real income after deflating their nominal income by the monthly household level aggregate price index. Next, to execute our estimation, we take 4 months average of the consumption bundles, and the real income to match their frequency with the corresponding household level sentiments, which is available for every 4 months interval as mentioned above.

Alongside this, following Souleles (2004), we also collect data of - (i) age of the household head, (ii) change in number of kids, and the change in number of adults (ii) location of the household (rural and urban), (iii) marital status and gender of the household head, (iv) educational qualification and the nature of occupation of the household head for our analysis.

[1]See; Figure (9) in Section 5 for the plot of the forecast error.
[2]https://cpi.mospi.gov.in/TimeSeries_BackSeries_2012.asp

Table 1: Descriptive Statistics

[]

Variable		Mean/Proportion
Income		19,834.12
Age		46.34
Education	Less than 5	27.5
	5-10	56.4
	10-12	8.7
	13-15	7
	15+	0.4
Gender	Male	88
	Female	12
Marital Status	Married	85
	Unmarried	15
Geographic Location	Rural	25
	Urban	75
Occupation	Agriculture and Allied	15.4
	Manufacturing, Industry and Auto	34.1
	Services, Media, Health	50.3
	Others	0.2

Table (1) gives the descriptive statistics of the relevant variables collected by us from the CPHS survey to execute our estimation.

3 Model

A generic household h, belonging to the geographical location j in our model calculates the minimum expenditure required to obtain a certain consumption bundle by solving the following static problem in each period t,

$$
\begin{aligned}
&\text{minimize} \quad e^j_{h,t} = \sum_{i=1} p^j_{i,t} c^j_{i,ht}\,; \quad h = 1, 2, \ldots, H; \quad j = \ rural, urban \\
&\text{subject to} \quad c^j_{h,t} = \prod_{i=1}^{n} \left(c^j_{i,ht}\right)^{\alpha^j_{i,ht}} \ ; \quad \sum_{i=1}^{n} \alpha^j_{i,ht} = 1;
\end{aligned}
$$

where, $p^j_{i,t}$ is the price of the i^{th} sub-category of consumption at, t for the household, h belonging to the j^{th} geographical location. $c^j_{i,h,t}$, and $\alpha^j_{i,h,t}$ are the real respectively the demand, and the expenditure share of the i^{th} sub-category of goods by household, h; belonging to the j^{th} geographical location at t. $e^j_{h,t}$ is the nominal expenditure of household, h; belonging to the j^{th} geographical location at time, t. The optimization exercise yields a (real) consumption bundle for the household, h; belonging to the j^{th} geographical location at time, t, as written below,

$$
c^j_{h,t} = \frac{k^j_{h,t} \ e^j_{i,h,t}}{p^j_{h,t}} \tag{1}
$$

where, $p^j_{h,t}$ is a measure of aggregate price index for household h, belonging to the j^{th} geographical location at t as written below,

$$
p^j_{h,t} = \prod_{i=1}^{n} \left(p^j_{i,t}\right)^{\alpha^j_{i,ht}} \ ; \tag{2}
$$

and,

$$
k^j_{h,t} = \prod_{i=1}^{n} {\alpha^j_{i,ht}}^{\alpha^j_{i,ht}}
$$

The real income of household, h belonging to the j^{th} geographical location at time, t is calculated by deflation their nominal income by the price index, $p^j_{h,t}$. It is denoted by, $a^j_{h,t}$ in our model.

Next, the generic household h solves an intertemporal problem to decide the time path of consumption.

$$
\begin{aligned}
\text{maximize} \quad & E_0 \sum_{t=0}^{\infty} \left(\beta_h^j\right)^t \log\left(c_{h,t}^j\right) \\
\text{subject to} \quad & a_{h,t}^j - c_{h,t}^j = \frac{a_{h,t+1}^j}{R_{t+1}}, \\
& a_{h,0}^j = \text{given} && \text{(Initial condition)} \\
& \lim_{t\to\infty} R^{-(t+T)} a_{h,t}^j \geq 0 && \text{(Transversality Condition (TVC))}
\end{aligned}
$$

where, $a_{h,t}^j$ is the real income, of household h, belonging to the j^{th} geographical location at t, $R_t$is the gross real interest rate at time, t, and $0 < \beta < 1$ is the discount factor. Under logarithmic utility function, and $\beta = R^{(-1)}$, the Euler equation gives

$$
\Delta ln(c_h(t+1)^j\ ) = \delta_h(t+1)^j \tag{3}
$$

where, $E_t\left(\delta_{h(t+1)}^j\right) = 0$. The PIH assumes, $\delta_{h(t+1)}^j$ is sunspots, and independent of economic fundamentals. As a result, equation (3) implies, log transformed consumption follows a random walk process, and growth rate of consumption is unpredictable (Hall, 1978) However, to check the excess sensitivity of consumption to sentiments for the US, Souleles (2004) assumes, $\delta_{h(t+1)}^j$ is not random, but it is systematically dependent on household sentiments, and their demographic characteristics. Hence, following Souleles (2004), we estimate Equation (4) to test the excess sensitivity of consumption to sentiments for the Indian households.

$$
\Delta ln\left(c_{h(t+1)}^j\right) = b_0 time + b_1 W_{h(t+1)} + b_2 Q_{ht}^j + \eta_{h(t+1)} \tag{4}
$$

where, $E_t\left(\eta_{h(t+1)}\right) = 0$, and $\Delta ln\left(c_{h(t+1)}^j\right)$ is the growth rate of the consumption between time t to $(t+1)$ of household, h belonging to the j^{th} geographical location. Here, *time* represents the time dummy that takes a value 1 for a given month, and 0 otherwise. $W_{h(t+1)}$ is the demographic components of household h, which includes - change in number of kids, change in number of adults, and the age of household head in our estimation.

Q_{ht}^j in Equation (4) is the excess sensitivity repressor for a household, h belonging to the j^{th} geographical location at time, t. Q_{ht}^j is calculated by using questions (ii), and (iii) given in Section 2, and it takes discrete integer values $(-1, 0, 1)$. When the excess sensitivity regressor,

Q^j_{ht} is calculated based on the household's year ahead perception about their own financial position, as given in question (ii), it is denoted by Q_{FC} in our estimation (see, Tables (2) to (5)). On the other hand, when the excess sensitivity is calculated based on household's perception about the year ahead business condition of the economy, as given in question (ii), it is denoted by, Q_{BC} in our estimation (see, Tables (2) to (5)). The advantage of using household sentiments as an excess sensitivity rgressor is that, it parsimoniously encapsulates a lot of factors, e.g.; household's perception about their own financial condition, overall economic conditions, unemployment; borrowing constrains, income uncertainty, etc. that might affect household consumption growth as suggested by previous literature.

Intuitively, Equation (4) suggests that, the aggregate shock, $\delta^j_{h(t+1)}$ has two different components through which it is mediated to consumption growth – (a) a symmetric component of shock that equally affects every households through the time dummy, time. The time dummy captures the impact of macroeconomic aggregates, as well as the shocks like demonetization, Covid-19, etc.; and (b) an asymmetric component of shock that affects households differently through their sentiments, and demographic characteristics.

4 The Time-Varying Cross-Sectional Heterogeneity of Inflation Rate

Using Equation (2), we calculate the household specific price level. The log difference of the household specific price level yields the Y-o-Y household specific inflation rate from May, 2017 to October, 2022. Next, depending on the occupation of the household head, we classify the households into 4 classes – (i) Agriculture and Allied, (ii) Manufacturing, Industry and Automobile, (iii) Services, media, and health, and (iv) Others. Consequently, we identify the average inflation rate for each occupational classes for two types of expenditure minimizing consumption bundles – (i) consumption bundles with 8 food groups, an(ii) consumption bundle with food and fuel. Figure (1) plots the average inflation rate for the occupational classes mentioned above from May, 2017 to October, 2022. Along with the inflation rate corresponding to each occupational classes, Figure (1) also plots the aggregate inflation rate based on CPI from May, 2017 to October, 2022.

Figure (1) shows – (i) households belonging to each occupational classes experience significantly different inflation rate from each other, and (ii) inflation rate of households belonging to different occupational groups significantly differs from the aggregate inflation rate based on CPI. In other word, Figure 1 reveals the existence of time-varying cross sectional heterogeneity of inflation rate for the Indian households, which gets lost in aggregation. Moreover, to identify the information content, we calculate the average standard deviation of the inflation rate for the households belonging to different occupational classes from May, 2017 to October, 2022, and plot it in Figure (2). The significant variations in the standard deviation of the inflation rate depicted in Figure (2) shows the rich information content in the household specific inflation rate of India, which we lose in aggregation.

To further understand the importance of the cross sectional heterogeneity, and the corresponding information content, we classify the inflation rate of the Indian households according to the age, and the educational qualification of the head of the Indian households. Figure (3) and (4)respectively plot the average inflation rate, and average standard deviation of the inflation rate when the households are classified according to the age of the head of the households. Similarly, Figure (5) and (6) respectively plot the average inflation rate, and average standard deviation of the inflation rate when the households are classified according to the educational level of the head of the households. Akin to Figure (1) and (2), Figures (3) to (6) also reveal the rich information content in the in the household specific inflation rate, originating from the time-varying cross sectional heterogeneity of the data.

Figure 1: Average Inflation Rate among occupational class vis-a-vis CPI

To identify the source of the time-varying cross sectional heterogeneity, and the associated information content in the household specific inflation rate note, the weights of different goods, included in the basket of CPI are fixed across households from 2016 to 2022. But, the expendi-

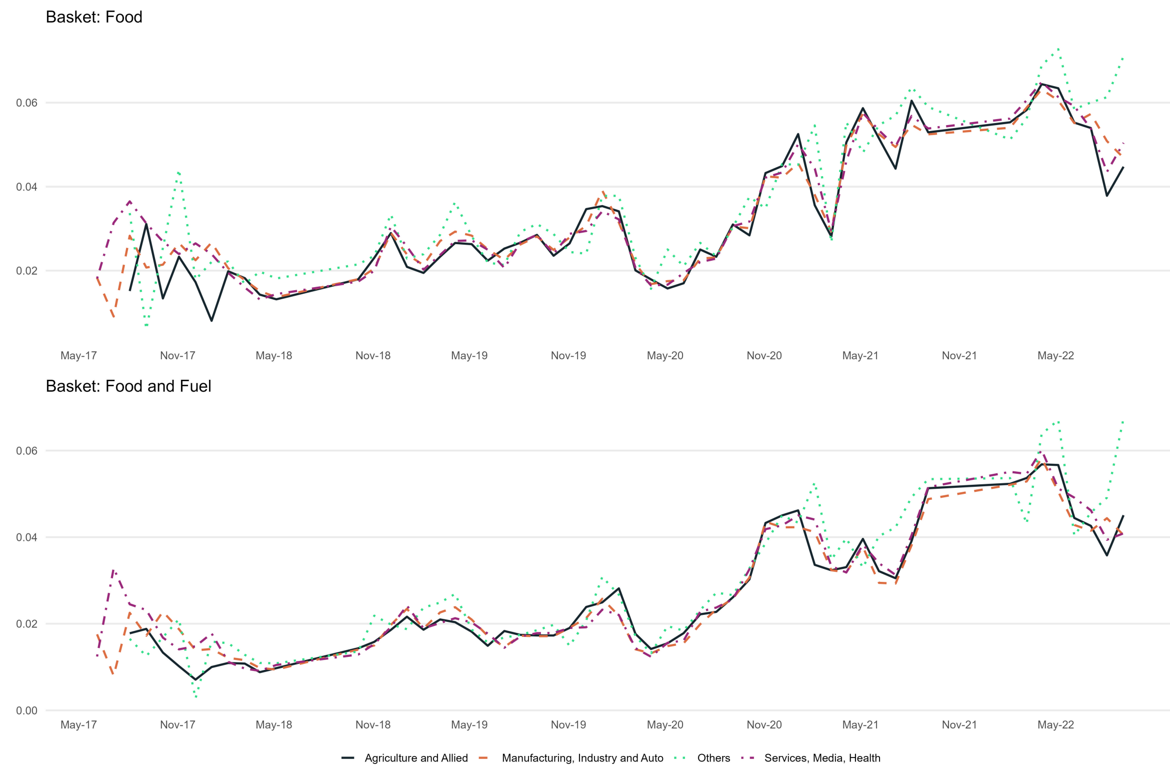

Figure 2: Standard Deviation of Inflation Rate among occupational class vis-a-vis CPI

ture shares of goods included in the consumption bundle, $\alpha^j_{i,ht}$ vary both across households, and over time. We have used these time-varying household specific expenditure shares as weights to calculate the household specific price index from equation (2). These expenditure shares of goods, $\alpha^j_{i,ht}$ included in the consumption bundle, which vary both across time and households yields the time-varying cross sectional heterogeneity, and the associated information content of inflation rate for the Indian households, as depicted in the Figures (1) to (6).

Figure 3: Average Inflation Rate among age groups vis-a-vis CPI

Note, since the aggregate CPI is fixed across households, we partially lose important information if we use it to deflate household's nominal consumption expenditure to calculate their real consumption expenditure. A plethora of existing literature have obtained the real consumption expenditure in this fashion for different households. However, to preserve the information content of the data and to fully utilize it in the estimation, we calculate an expenditure minimizing consumption bundle (for food, and also for food and fuel) for Indian households from equation (1) by using the household specific price index given in equation (2). Note, the expenditure minimizing consumption bundle obtained from equation (1) yields a measure of real consumption expenditure. Such a measure of real consumption expenditure fully preserves

Figure 4: Standard Deviation of Inflation Rate among age groups vis-a-vis CPI

Figure 5: Average Inflation Rate among educational groups vis-a-vis CPI

Figure 6: Standard Deviation of Inflation Rate among educational groups vis-a-vis CPI

the time-varying cross sectional heterogeneity, and the associated information content of the household specific nominal consumption expenditure, and the household specific price level. Similarly, by deflating the nominal income by the corresponding household specific price index, we calculate the household specific real income; and use it in our estimation of equation (4).

5 Estimation and Results

Before presenting ours for India, let us briefly explain the results of Souleles (2004) for the US. Since, the data of household consumption, and their sentiments are sourced from two different surveys, Souleles (2004) estimates equation (4) for the US through a two-sample instrumental variables techniques of (see, Angrist & Krueger, 1992). To do it Souleles (2004) matched the sentiments of the households included in CAB, with the households surveyed in CEX using the information of their demographic profile as follows - (i) regress the sentiments of the households included in CAB on a vector, Z=[*age∗monthly dummies, income∗monthly dummies, location, marital status, gender of household head, education, nature of occupation, log of real income*]; (ii) calculate an "estimated sentiments" of the households included in CEX by using their demographic information, and estimated coefficients obtained from step (i), and (ii) estimate equation (4) by using the estimated sentiments of the households obtained from step (ii) [3].

Note, the relevant parameter of interest is b_2, the coefficient of the excess sensitivity regressor $\left(Q^j_{ht}\right)$ in equation (4). Souleles (2004) finds, b_2 is negative, and significant at 5% level. A significant b_2 implies that, the excess sensitivity of consumption to sentiments exists, and sentiments helps predicting consumption growth. This further implies that, the PIH does not hold for the US. Moreover, a flatter consumption profile, represented by the negative value, b_2 implies that, the precautionary savings motive exists for the US households.

Since, unlike the US, the data of household consumption, their sentiments, and other relevant demographic variables for India are obtained from CPHS, CMIE, we initially estimate equation (4) by OLS to check the excess sensitivity of the consumption of the Indian households. The results of the baseline OLS estimation, which captures the direct impact of sentiments on the growth rate of household consumption bundles; consisting only the 8 food groups (see; Section 2) are reported in Column 2 of Table (2). Column 2 of Table (2) reports the results

[3] Note, since an estimated household sentiments are used in the second step for the estimation of Equation (4), it requires to adjust the standard errors of the estimated coefficients of Equation (4) for drawing appropriate statistical inferences. To handle it, Souleles (2004) used the two-sample instrumental variables techniques of Angrist & Krueger (1992) in his estimation.

of the OLS estimation reports the results of the OLS estimation when household's perception about their year ahead own financial condition, Q_{FP} is used as the excess sensitivity regressor, along with the demographic variables - change in number of kids, change in number of adults, and the age of the household age as the control variables to estimate equation (4) by OLS. The results of the OLS estimation, reported in Column 2 of table (2) shows that, the coefficient of the excess sensitivity regressor $(Q_{FP}) - b_2$ is significant at 1% level. This implies, like the US, the excess sensitivity of consumption to sentiments exists, and sentiments helps predicting consumption growth for the India too. This further also implies that, the PIH does not hold for India as well. On the other hand, we find that, b_2 is positive for the Indian. The results of our OLS estimation implies that, better sentiments yields a steeper consumption profile for the Indian households – a unit rise in Q_{FP} increases the consumption growth of the Indian households by only 0.9%.

Note, after food, the second most important component in the basket of Indian household consumption, is fuel[4]. As a result, following the methodology described in Section 3, we reconstruct a new consumption bundle for the Indian households with 8 food groups, and fuel and lighting. Using this new consumption bundle, we re-estimate equation (4) by OLS for the Indian houeholds. We have reported this results in Column 2 of Table (3). Our results show that, the coefficient of the excess sensitivity parameter $(Q_{FP}) - b_2$ remains positive, and significant at 1% level. Results of OLS estimation, reported in Table (3) shows that, a unit rise in Q_{FP} increases the consumption growth of the Indian households by only 5.4%. Note, the results reported in Table (2) and (3) show that, consumption growth rate of the Indian households are more sensitive when fuel and lighting is included in the consumption bundle of the household along with the food groups.

It is important to mention here that, the two step estimation technique, adopted by Souleles (2004) as described above intuitively assumes that, the part of the household sentiments, explained by their income, and other demographic characteristics, Z= [age∗monthly dummies, income∗monthly dummies, location, marital status, gender of household head, education, nature of occupation, log of real income] affects their consumption growth. In other words, Souleles (2004) assumes that, the demographic variables of the households, includes in Z does not directly affects their consumption growth, they influence their consumption growth indirectly through their sentiments.

Following the spirit of Souleles (2004), we re-estimate equation (4) for the Indian house-

[4]The average share consumption expenditure for food and fuel is almost 92% in the last 5 years for the Indian households While, the average share of the food during last 5 years is almost 67%, the same for the fuel is almost 25%.

Table 2: OLS Estimation for Food

	(1)	(2)	(3)
Q_{FP}	0.009***		0.03***
	(0.002)		(0.003)
Q_{BC}		0.003***	
		(0.002)	
FE_{FP}			0.027***
			(0.002)
Age	-0.000***	-0.000***	-0.000***
	(0.002)	(0.000)	(0.000)
Δ kids	0.011***	0.011***	0.011***
	(0.012)	(0.012)	(0.012)
Δ adults	0.038***	0.038***	0.039***
	(0.002)	(0.002)	(0.002)
Time Dummies	Yes	Yes	Yes
Number of Observations	58,871	58,871	53,312

Note: : (i) Age represents the age of the household head, (ii) Δ kids, and Δ adults represent change in number of kids, and change in number of adults respectively, (iii) FE represents forecast errors of the financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively.

Table 3: OLS Estimation for Food and Fuel

	(1)	(2)	(3)
Q_{FP}	0.054***		0.023***
	(0.002)		(0.003)
Q_{BC}		0.003***	
		(0.002)	
FE_{FP}			0.023***
			(0.002)
Age	-0.000***	-0.000***	-0.000***
	(0.002)	(0.000)	(0.000)
Δ kids	0.07***	0.07***	0.06***
	(0.002)	(0.002)	(0.003)
Δ adults	0.028***	0.002***	0.029***
	(0.002)	(0.002)	(0.002)
Time Dummies	Yes	Yes	Yes
Number of Observations	58,871	58,871	53,312

Note: : (i) Age represents the age of the household head, (ii) Δ kids, and Δ adults represent change in number of kids, and change in number of adults respectively, (iii) FE represents forecast errors of the financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively.

holds through GMM by using, Z=[age∗monthl dummies, income∗monthly dummies, location, marital status, gender of household head, education, nature of occupation, log of real income], as an instrument for the excess sensitivity regressor, Q_{FP} [5]. The results of the GMM estimation of equation (4) for the consumption bundle; consisting of 8 food groups, and for the consumption bundle; consisting of food and fuel along with the 8 food groups are reported in Table (4) and (5) respectively. Note, like the OLS estimation, the results of the GMM estimation, reported in Column 2 of Table (4) and Column 2 of Table (5) also yields a positive, and highly significant coefficients of the excess sensitivity regressor (Q_{FP}) - b_2, establishing the robustness of our results.

Besides, Q_{FP}; we have also estimated equation (4) through OLS by using the household's perception of the year ahead business conditions of the economy as an excess sensitivity regressor. It is denoted by, Q_{BC} in Table (2) and (3). We find that, the estimated coefficient of Q_{BC}, obtained from the OLS estimation is positive but non-significant (see, Column 3 of Table (2) and (3)). However, our GMM estimation yields a highly significant (significant at 1% level), and positive coefficient of the excess sensitivity regressor, Q_{BC} as reported in Table (4) (for consumption bundle; consisting of 8 food groups), and Table (5) (for the consumption bundle; consisting of 8 food groups, and fuel and lighting). The results of our GMM estimation, where only the part of the household sentiments explained by their income and the demographic characteristics enters into the estimation show that, a unit rise in the excess sensitivity regressor, Q_{FP} (Q_{BC}) predicts the consumption growth to rise by 69.5% (66.1%) when the consumption bundle includes fuel and lighting too in the consumption bundle with the food groups (see; Table (5)). Note, our results reported in Tables (2) to (5) show that, alongside sentiments, even the demographic variable like the change in number of kids, change in number of adults, and the age of the household also contain additional information beyond that in current consumption that helps to predict consumption of the Indian households.

To elucidate the positive coefficient of the excess sensitivity regressor, b_2 in equation (4) seems counterintuitive with respect to the precautionary savings motive of the households. To explain the positive coefficient of the excess sensitivity regressor note that, the advantage of using household sentiments as an excess sensitivity regressor is that, it parsimoniously captures a variety of shocks and the economic conditions for the Indian households in equation (4) like –

[5]Souleles (2004) use a two-sample instrumental variables technique to estimate equation (5) because the data of household consumption and their sentiments for the US are sourced from two different surveys as mentioned in the text. We obtain data of household consumption, sentiments, and other control variables used in equation (5) from a single survey – CPHS, CMIE. Hence, instead of the two-sample instrumental variables technique, we estimate equation (5) by GMM, which is same in spirit with the two-sample instrumental variables technique used by Souleles (2004) as mentioned in the text.

Table 4: GMM Estimation for Food

	(1)	(2)	(3)
Q_{FP}	0.555***		0.476***
	(0.00)		(0.00)
Q_{BC}		0.345***	
		(0.038)	
FE_{FP}			0.53***
			(0.00)
Age	-0.001***	-0.001***	-0.001
	(0.000)	(0.000)	(0.96)
Δ kids	0.009	-0.007	0.017
	(0.37)	(0.009)	(0.012)
Δ adults	0.018	0.041**	0.009
	(0.46)	(0.021)	(0.71)
Time Dummies	Yes	Yes	Yes
Number of Observations	58,871	58,871	53,312

Note: : (i) Age represents the age of the household head, (ii) Δ kids, and Δ adults represent change in number of kids, and change in number of adults respectively, (iii) FE represents forecast errors of the financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively.

shock of Covid-19 pandemic, demonetization, household specific constraints like liquidity, and borrowing constraints, etc. that creates a widespread cloud of uncertainty and restrictions, and hinder households to fully smooth their consumption.

To obtain a measure of uncertainty for India, following Lahiri et al. (2016), we calculate a balance statistic for India. The yearly average of the balance statistic is calculated by using the questions (II), and (III) related to household's perception about their own year ahead financial conditions, and business condition. It is calculated by adding 100 with difference of the proportion of responses codded as good/better response, and the proportion of responses coded as bad/worse. Note, the value of the balance statistic less (more) than 100 represents more households with the bad (good) perception about their future financial condition, and the business condition. Figure (7) and (8) show that, the value of the balance statistic is - (i) always below the neutral value 100; and (ii) hits the nadir during the period of Covid-19, and yet to recover from it. Figure (7) and (8) succinctly represents the perception of uncertainty prevailing in the mind of Indian households during 2016-2022.

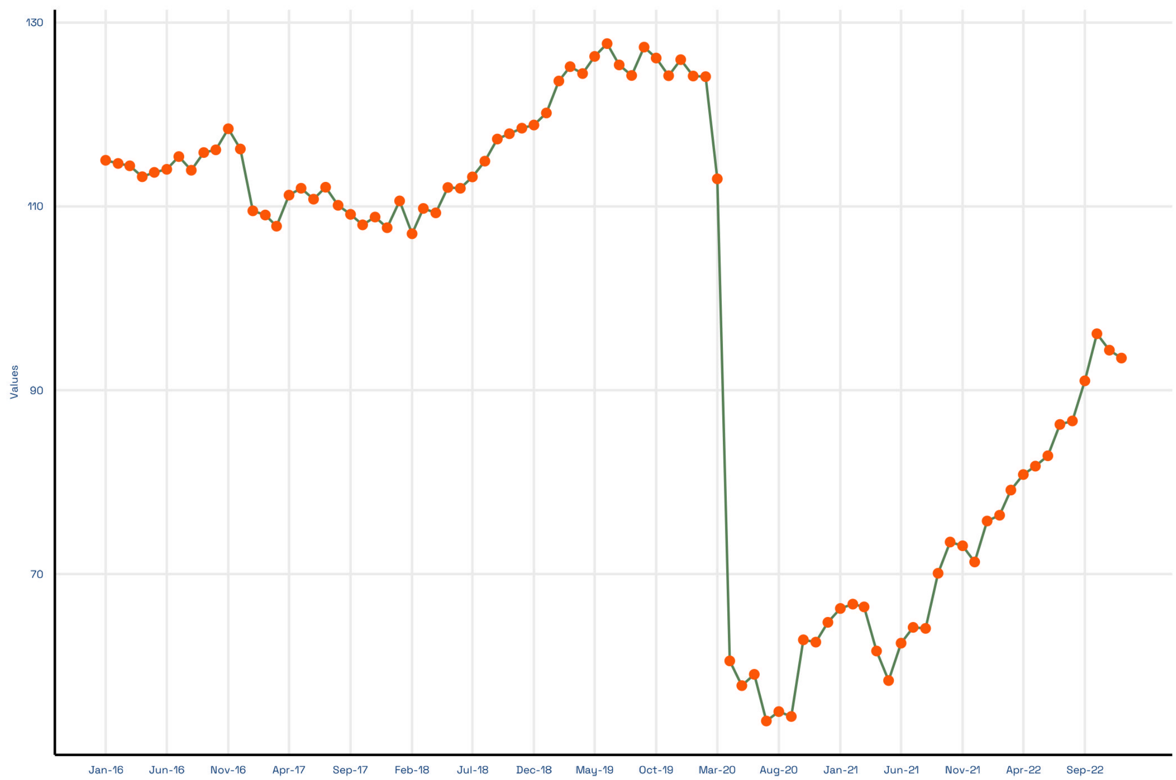

Figure 7: financial conditions

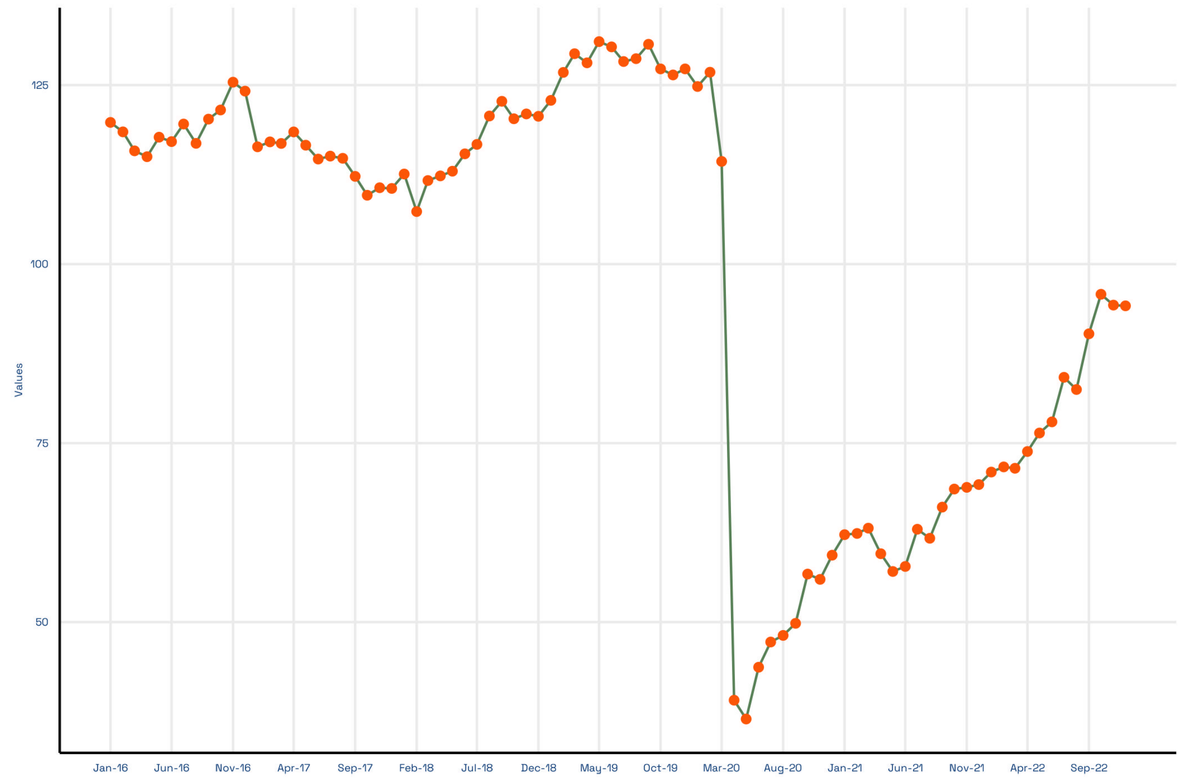

Figure 8: business conditions

We believe that, absence of the wide spread social security net like the developed countries, Indian households mitigate the perception of a growing uncertainty by increasing their savings as a precaution. Hence, the positive coefficient of the excess sensitivity regressor, b_2 also represents the presence of the precautionary savings motive among Indian households. The explanation of the precautionary savings motive given above is identical in spirit with the explanation of by Acemoglu & Scott (1994) given for the US.[6]

[6]Using aggregate data, Acemoglu & Scott (1994) also find sentiments positively affects consumption growth of the UK. They show that, the higher consumer confidence is not only associated with higher average income, but is also associated with the higher income uncertainty; yielding the positive coefficient of the excess sensitivity regressor for the US.

Table 5: GMM Estimation for Food and Fuel

	(1)	(2)	(3)
Q_{FP}	0.695***		0.602***
	(0.030)		(0.030)
Q_{BC}		0.661***	
		(0.037)	
FE_{FP}			0.613***
			(0.061)
Age	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Δ kids	0.010	-0.015	0.017
	(0.012)	(0.012)	(0.012)
Δ adults	-0.342	-0.010	-0.056**
	(0.026)	(0.026)	(0.027)
Time Dummies	Yes	Yes	Yes
Number of Observations	58,871	58,871	53,312

Note: : (i) Age represents the age of the household head, (ii) Δ kids, and Δ adults represent change in number of kids, and change in number of adults respectively, (iii) FE represents forecast errors of the financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively.

Note, as cautioned by Souleles (2004), we have to be careful about the presence of spurious excess sensitivity in our estimation; originating from the various components, and the characteristics of the random error of equation (4) - η. Souleles (2004) explains that, if a particular type of households consistently experience adverse shock (for example, on income), it gets reflected in their forecast error, hidden in the random error term, η. Souleles (2004) also explains that, such forecast errors can highly influence the household sentiments as well. Note, such a correlation between the random error, η and sentiments produces inconsistent estimates, and also the spurious excess sensitivity of consumption had we not controlled for the household's forecast errors. To check the possibility of correlation between the random error term and the sentiments of equation (4), we calculate the forecast error of the households related to their own financial position using the difference in answer of a household to questions (I) and (II) reported in CPHS, CMIE, and plot it in Figure (9). The co-movement of the forecast error, plotted in Figure (9), with the balance statistics, plotted in Figure (7) and (8) reveals a possibility of correlation between the sentiments and the forecast error for the Indian households.

Figure 9: Forecast Errors

As a result, to eliminate the possibility of spurious excess sensitivity, we re-estimate equation (5) through OLS, and GMM by including the forecast error of the households regarding their own financial position, $FE_{PC,ht}$ as an additional control variable.

$$\Delta ln\left(c^j_{h(t+1)}\right) = b_0 time + b_1 W_{h(t+1)} + b_2 Q^j_{ht} + b_3 FE_{PC,ht} + \omega_{h(t+1)} \tag{5}$$

While, column 4 of Table (2) and (3) reports the results of the estimation of equation (3) by OLS, column 4 of Table (4) and (5) report the results of the GMM when Q_{FP} is taken as the excess sensitivity regressor. Our results show that the coefficient of the excess sensitivity regressor, b_2, remains positive, and significant at 1% level, along with the coefficient of the forecast error, b_3 when we estimate equation (5) by GMM. Our results show that, once we control for the forecast error of the households regarding their own financial position, a unit rise in Q_{FP} predicts the consumption growth of the Indian households to rise by, 47.6% when the consumption bundle includes only food groups (see; table (4)). However, a unit rise in Q_{FP} predicts a significantly higher consumption growth, 60.2% once fuel and lighting is included in the consumption bundle of the household with the food groups.

Using appropriate econometric models suggested by literature, our analysis robustly establish, like the US - (i) the household sentiments contains additional information beyond that in current consumption that helps to predict the consumption of the Indian households, leading to the violation of the PIH for India, (ii) the precautionary savings motive holds for the Indian households, (iii) even the information contained in the demographic variables like, change in number of kids, change in number of adults, and the age of the household age are important to predict the consumption growth of India; and (iv) food and fuel is a very important component of the consumption bundle of the Indian households. Their consumption growth becomes highly sensitive to sentiments when fuel and lighting is included in the consumption bundle of the households along with the food groups.

6 Conclusion

Rational expectations based permanent/life cycle hypothesis predicts consumption growth is random, and unpredictable, implying the information about the current consumption possesses all the relevant information to predict consumption growth. Literature tests this hypothesis for the developed countries with aggregate data, and find evidence against it. Existing literature further shows that, aggregate sentiments is important, and captures additional information beyond that in the current consumption to predict consumption growth. Souleles (2004) tests the PIH using household level data of the US, and he also finds presence of excess sensitivity of consumption to their sentiments for the US. Alongside the violation of the PIH, he also finds existence of the precautionary savings motive among the US households. Following Souleles (2004), our objective of this paper is to test the excess sensitivity of consumption to sentiments for India using the Euler equation approach.

To do it, we have used the large longitudinal data given by CPHS, which is representative of the Indian economy. Alongside the household level consumption, income, and demographic data, we also use the data of prices of different food groups, and fuel and lighting - the largest two components of household consumption for India to calculate a household level price index for India. Then, in contrary to the existing literature, instead of using the aggregate CPI, we use this household level price index to calculate real consumption and the real income of the Indian households. This allows us keeping the rich information content intact in estimation, arising from the large time-varying cross sectional heterogeneity of the micro level data. Note, using the CPHS data, Priya & Sharma (2024) have estimated the consumption function for Indian households using the data of the household level sentiments to test the presence of animal spirits, and it's role in the propagation of the oil price shock. Our paper on the other hand, is the first attempt to test the rational expectations based PIH using the household level data for India.

Like the US, our paper finds the presence of the excess sensitivity of consumption to sentiments for the Indian households. It further shows that the household sentiments are important to forecast the consumption growth for Indian as well. Our results imply, like the US, PIH does not hold for India as well. To test the robustness of our results, following Souleles (2004), we also control for the household specific forecast errors in our estimation to eliminate the possibility of the endogeneity and the consequent spurious excess sensitivity. We find that, the spurious excess sensitivity does not exists in our estimation. Absence of spurious excess sensitivity shows that, the excess sensitivity of consumption to sentiments found by us for India is robust. Note, the consumption of foods and fuel used in our estimation holds approximately 92% of household consumption of India. Our results imply that, household sentiments, and the significant information content embedded in the time-varying cross sectional heterogeneity of the micro-level data intact as much as possible in estimation, if we need to appropriately forecast consumption growth for the Indian households.

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