Excess Sensitivity of Consumption to Sentiment of India: Examining the Role of Households' Network*

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Abstract

Leveraging the extensive cross-sectional heterogeneity of the Consumer Pyramid Household Survey (CPHS) - a comprehensive longitudinal dataset representative of the Indian economy - this paper investigates the predictive power of household sentiments on consumption growth through an Euler equation framework. We select India for our analysis to exploit the rich information content arising from the large cross-sectional heterogeneity of the India. To exploit the information content, we calculate expenditure minimizing consumption bundle that fully preserves the cross-sectional heterogeneity of data, and used it for the estimations of the Euler equation. Endorsing the claim of Blendon et al. (1997), we demonstrate that the neighborhood/network plays important role in shaping individual sentient, and the part of household sentiment, explained by neighborhood/network – the network-inferred sentiment - exhibits stronger predictive power on consumption growth than the raw sentiment measures. The presence of excess sensitivity of consumption to sentiment implies that, sentiment should remain crucial for business cycle forecasting for India. Our paper is contributing to the broader literature on sentiment-driven consumption and business cycle dynamics.

Keywords: Consumer Sentiments, PIH, Forecasting, CPHS
JEL Classification: E21, E27

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1 Introduction

Does sentiment predict consumption growth, and if so, why? This question has rekindled substantial scholarly attention since the advent of survey-based sentiment data[1]. Our paper examines the predictive power of sentiment on consumption growth in the context of Indian households, utilizing longitudinal data from the Consumer Pyramids Household Survey (CPHS). This paper makes three distinct contributions to the literature. First, it provides a comprehensive analysis of consumption sensitivity to sentiment in an emerging market setting, extending the predominantly developed country focused literature. Second, it advances the methodological frontier by developing a novel approach to retain the cross-sectional heterogeneity and the corresponding information content, and utilize it in the estimation. Third, we find that the part of the household sentiment explained by their income, educational attainment, occupation, and geographical location is a superior predictor of consumption growth than the raw sentiments itself, signifying the importance of individual neighborhood/network in forming their own sentiment (Blendon et al., 1997).

While analyzing the determinants of sentiment for the US, Lahiri & Zhao (2016) argue that household sentiment transcends the mere reflections of aggregate macroeconomic conditions, and it encapsulates substantial idiosyncratic information shaped by households' subjective interpretations of aggregate economic conditions. Along with this, Souleles (2004) argues about relative importance of the disaggregated, and individual specific information set over that of the aggregate one in rational expectation based forecasting consumption growth. Moreover, Jappelli & Pistaferri (2017); and Christelis et al. (2020) show how the disaggregated survey data becomes useful in producing consistent estimates by addressing the endogeneity concerns stemming from the correlation between forecast errors of consumption and the consumption risk in an Euler equation based forecast of the consumption growth[2]. Realizing the potential benefits and the information content of the disaggregated level data, we select the emerging economy, India

[1]Even before the disaggregated micro level sentiments data were available, Acemoglu & Scott (1994) analyzes the relationship between aggregate sentiments, and consumption growth for the UK through the Euler equation framework. They find that the evidence of excess sensitivity of consumption to sentiments for UK. Moreover, using University of Michigan's Index of Consumer Sentiments, Carroll et al. (1994) find that current as well as the lagged sentiments positively affect consumption growth even for the US. More recently, Malgarini & Margani (2007) analyze the interrelationship between sentiment, and consumption growth using the aggregate data to identify the presence of the rule of thumb consumer for Italy. Along with this, using aggregate data Gelper et al. (2007) find a cointegrated relationship between consumption, and sentiment for the US. After finding the long-run equilibrium relationship between sentiment and consumption, they estimate an error correction model to find the causal relationship between consumption and sentiment for the US.

[2]Toussaint-Comeau & McGranahan (2006), Dominitz & Manski (2004), and Lahiri et al. (2016) also advocate to use the disaggregated level data due to its rich information content, which enhances the informative and predictive power of the sentiment index.

for our analysis due to its significantly greater cross-sectional heterogeneity and hence the richer information content compared to developed economies. Moreover, we use the disaggregated household level data for the Euler equation based forecasting of consumption growth, and testing the excess sensitivity of consumption to sentiments. Our paper is the first comprehensive examination of household of the predictive capacity of sentiment on consumption growth for the Indian households[3].

However, accurately estimating sentiment's predictive power entails preserving the substantial cross-sectional heterogeneity within Indian data, which contains valuable information(Lahiri & Zhao, 2016). The cross-sectional heterogeneity in household real consumption growth stems from two sources: variation in nominal consumption expenditure and household-specific inflation rates. Prior literature has typically overlooked this latter source of heterogeneity by using aggregate CPI to deflate nominal consumption, which lacks cross-sectional variation. Consequently, real consumption growth calculations based on aggregate CPI capture only partial cross-sectional heterogeneity—specifically, the variation in nominal consumption while neglecting differences in household-specific inflation experiences.

To preserve the full cross-sectional heterogeneity, we derive an expenditure-minimizing consumption bundle for Indian households. This approach, which deflates nominal consumption by household-specific price indices, fully maintains the true time-varying cross-sectional heterogeneity in real consumption arising from the household specific nominal consumption, and the household specific price index. We employ this expenditure-minimizing consumption bundle as our measure of real consumption throughout our analysis[4]. Given that food and fuel & lighting constitute approximately 92% of Indian household expenditures, we construct two expenditure-minimizing consumption bundles: (1) a food bundle comprising 8 major food groups, and (2) a food & fuel bundle that incorporates fuel & lighting alongside these food groups. Alongside the above mentioned data of consumption obtained from CPHS, we employ two distinct sentiment measures: households' perceptions of their future financial position and their expectations regarding future business conditions. Note unlike Souleles (2004), since we obtain both the data of consumption, and sentiments from the same survey, it allows us to directly employ the regression analysis for testing their interrelationship[5].

[3]Our paper possibly is the first attempt to test the excess sensitivity of consumption through the Euler equation framework by using the household level data for an emerging economy context. Before us – (i) Priya & Sharma (2024) check the role of animal spirits in the propagation of the oil price and the monetary policy shock for the India by using the CPHS data, and (ii) Juhro & Iyke (2020) show that when consumer and business sentiment are included as covariates, the predictive accuracy of the models forecasting Indonesian consumption rises almost 9%.

[4]Similarly, we calculate real household specific real income by deflating their nominal income using the corresponding household specific price indices to preserve the true cross-sectional heterogeneity of household specific real income.

[5]Note to investigate the excess sensitivity of consumption to sentiments for the US households, Souleles

We use both OLS, and GMM to estimate the Euler equation for the full sample periods (April, 2016-October, 2022), from April, 2016 to October 2022. We employ two distinct short-term sentiment measures for our analysis: households' perceptions of their future financial position and their expectations regarding future business conditions. In the OLS estimation, we use the raw sentiments of the households as the control variable that takes three discrete values – 1, 0, and -1. Results of our OLS estimation show that the coefficient of sentiment is positive, and significant at 1% level, signifying that household sentiments predicts their consumption growth.

It is important to mention here that, Blendon et al. (1997) argues individuals form their sentiments mostly by processing information obtained during the conversation with their neighbors at the backyard of their house. Note, income level of the household along with their educational attainment, occupation, and geographical location largely constitute their neighborhood/network. We use these variables as instruments of sentiment to test the excess sensitivity of consumption to sentiment for the Indian households through our GMM estimation. We find that, the coefficient of sentiment of the GMM estimation is not only positive and significant at 1% level, its magnitude is much higher than that of the OLS estimate even without/with controlling for the household specific forecast error[6]. Endorsing Blendon et al. (1997), our result shows that the part of the household sentiments explained by its neighborhood/network – the network-inferred sentiment - is a superior predictor of consumption growth than the raw sentiments itself for the Indian households. In our analysis, we have captured the effect of neighborhood/network on households' sentiment through their income level, educational attainment, occupational choice, and geographical location of the households.

We obtain above results by estimating the Euler equation for the full sample period (April 2016 - October 2022). In between however, the world experience an unprecedented health related income risk due to the advent of the Covid-19 pandemic, which significantly changes the spending pattern of the households (see, Immordino et al., 2024 and references therein). Consequently, we carried out estimation separately for the pre-Covid periods (April, 2016 to February, 2020), and the Covid-periods (March, 2020 to October, 2022) through GMM. The results of the pre-Covid periods yield a positive coefficient of sentiment which is significant at 1% level with/without controlling after controlling for the household specific forecast error. . It re-establishes the robustness of

(2004) has to match the data of household level consumption (obtained from Consumer Expenditure Survey, CEX) with their sentiment (obtained from the data underlying household level data of Michigan's Index of Consumer Sentiment, ICS) through their demographic characteristics, income, occupation, and the geographical locationTo do that, Souleles (2004) needed to apply two-sample IV estimation method of Angrist & Krueger (1992) to obtain accurate standard errors for drawing appropriate statistical inferences.

[6]Controlling household specific forecast error is required to address potential endogeneity, and achieve consistency (Souleles, 2004)

our findings – the household neighborhood/network matters to shape their sentiment, and the network-inferred sentiment in turn better forecast the consumption growth of the Indian households than the raw sentiment measures itself. Our paper broadly parallel evidence from developed economies, and it is contributing to the broader literature on sentiment-driven consumption and business cycle dynamics (see Vuchelen, 2004 and the references therein for a detailed discussion on sentiment and business cycle)[7].

The rest of the paper proceeds as follows. Section 2 explains the household level data collected from CPHS. Section 3 describes the model, and significant the time-varying cross-sectional heterogeneity of Indian data. Section 4 on the other hand explains the important role of household's neighbourhood/network in the excess sensitivity of consumption to sentiment for India, and and Section 5 concludes.

2 Data Description

We collect data of household sentiments from Consumer Pyramid Household Survey (CPHS)[8]. It is a large longitudinal data set, representative of Indian economy. CPHS collects data of household sentiments of India since April, 2016. To collect the sentiment data, a generic Indian household h is surveyed thrice in a year, e.g.; a household surveyed in April, 2016 is surveyed again in August, 2016 by CPHS for the collection of the sentiments data and so on. To assess the sentiments, CPHS asks questions about the present conditions as well as the future expectations of the household financial position, and the business condition. In the process, to assess the present conditions, CPHS asks the following 2 questions to the households - (I) Compared to a year ago, how is your family faring financially these days?; and (II) Do you think that this is generally a good

[7]Like other professions the CPHS survey underwent a significant disruptions during the Covid-19 pandemic, raising concerns about their mode of data collection, as well as the coverage of the CPHS data. As a result, we separately analyze the excess sensitivity of consumption to sentiment for the Covid-periods (March, 2020 to October, 2022). We have chosen March, 2020 as the starting month of the Covid-periods because from this month the nationwide lockdown started in India due to the Covid-19 pandemic in India. The results for the Covid-periods are reported in the appendix (Table 7). It shows, unlike the results of the full sample and the pre-Covid periods, only the coefficient of household sentiment of overall business condition has significant positive effect on the food & fuel consumption growth in the Covid-periods. But, the magnitude of the coefficient of sentient is much lower than that of the full sample and pre-Covid periods. Such a limited role of sentiment in forecasting consumption growth signifies the persistent impact of the Covid-19 pandemic on the spending pattern and the decisions of the Indian households, and it closely aligns with the spending pattern of the developed countries in the Covid-periods as discussed in the literature.

[8]The Consumer Pyramid Household Survey (CPHS) is conducted thrice every year since 2014 by the Centre for Monitoring Indian Economy (CMIE). Under CPHS, a large panel of sample Indian households are surveyed. This large longitudinal dataset is widely acknowledged as representative of the Indian economy. For details see; https://consumerpyramidsdx.cmie.com/

or bad times to buy things like furniture, refrigerator, television, two-wheeler, and car? Along with this, CPHS asks the following 3 questions to assess the short-run and the long-run future expectations of the households - (III) How do you think that a year from now, financially, your family would be faring?; (IV) How would you describe the financial and business conditions in our country in the next 12 months?; and (V) What do you think would be the financial and business conditions in our country in the next 5 years? The answer to questions (I), and (III) are recorded as Better, Same and Worse, and accordingly a numerical value, 1, 0, -1 is assigned. On the other hand, answers to questions (II), (IV) and (V) are recorded as Good time, uncertain time and Bad time, and accordingly a numerical value, 1, 0 and -1 is assigned to the answer.

Along with sentiments, we also collect data of household's monthly expenditure on 8 major food groups, and fuel & lighting from CPHS from April 2016. The 8 major food groups include - (1) cereals; (2) oils and fats; (3) fruits; (4) pulses and products; and (5) milk and milk products; (6) meat, fish and egg; (7) vegetables and spices; and (8) sweets and snacks. Along with the above mentioned 8 food groups, we also collect data on household expenditure share for food & fuel. We find that the 8 food groups and the fuel and lightning contribute almost 92% of the expenditure for the Indian households. Table 1 reports the descriptive statistics of the data collected from CPHS[9]. Using this data, and by using the methodology described below, we calculate two types of expenditure minimizing consumption bundles for the Indian households – (i) food bundle: consisting of the 8 food groups mentioned above; and (ii) food & fuel bundle: consisting of the fuel & lighting along with the 8 food groups mentioned above.

[9]The lower panel of Table 1 shows the impact of Covid-19 on household sentiments. The significant rise in the proportion of pessimistic households, and the corresponding decline in the proportion of optimistic households as depicted in the lower panel of Table 1 shows the negative impact of the Covid-19 on the psyche of Indian households. By using the difference of the optimistic households and the pessimistic households, we calculate the balance statistics to give a graphical representation of the pessimistic impact of Covid-19 on the psyche of Indian households. For details, see Figure 3 and the discussion in Section 4.

Table 1: Descriptive Statistics

(a): Demographic Variables

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	7.0
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

(b): Sentiment Variables

Variable	**Response**	**Full Sample**		**Pre-Covid Periods**		**Covid Periods**	
		N	**%**	**N**	**%**	**N**	**%**
QFP	Bad	12,610	21.4	5,097	12.9	7,513	38.8
	Same	34,245	58.2	24,010	60.8	10,235	52.9
	Good	12,016	20.4	10,407	26.3	1,609	8.3
QBC	Bad	13,671	23.2	5,544	14.0	8,127	42.0
	Same	30,628	52.0	20,894	52.9	9,734	50.3
	Good	14,572	24.8	13,076	33.1	1,496	7.7
Total N		58,871		39,514		19,357	

Along with this, we also collect data on the price index of the aforementioned eight food groups, as well as fuel and lighting, from MoSPI[10]. MoSPI directly reports the price index for the first five food groups—(1) to (5) listed above. However, it separately provides the price index for the following food items:(i) Meat and fish (ii) Egg (iii) Vegetables (iv) Spices (v) Sweets (vi) Snacks. Using the price indices of these food items and their corresponding weights, we calculate the monthly price index for the remaining three food groups:(6) Meat, fish, and eggs (7) Vegetables and spices (8) Sweets and snacks

3 The Rational expectation based Permanent/Life Cycle Hypothesis (PIH) and the Excess Sensitivity of Consumption – The Model

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

$$\begin{aligned} \text{minimize} \quad & e^j_{h,t} = \sum_{i=1} p^j_{i,t} c^j_{i,ht}\,; \quad h = 1, 2, \dots, H; \quad j = \ rural, urban \\ \text{subject to} \quad & c^j_{h,t} = \prod_{i=1}^{n} \left(c^j_{i,ht}\right)^{\alpha^j_{i,ht}}\,; \quad \sum_{i=1}^{n} \alpha^j_{i,ht} = 1; \quad 0 < \alpha^j_{i,ht} < 1 \end{aligned}$$

where, $p^j_{i,t}$ is the price of the i^{th} sub-category of consumption at, time t for the household, h located at the j^{th} geographical location[11]. $c^j_{i,h,t}$, 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 yields an expenditure minimizing consumption bundle for the household, h; located at the j^{th} geographical location at time, t, as written as written in Equation 1. It is a measure of real consumption of the household, h located at the j^{th} geographical area at time, t. We use real consumption, and consumption synonymously in this paper.

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

[10]See; mospi.gov.in for the data of price index.

[11]Our paper has two types of geographical location, *j=rural, urban*

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[12],

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

and,

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

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

$$\begin{aligned}
&\underset{\{c^j_{h,t}\}_{t=0}^{\infty}}{\text{maximize}} && E_0 \sum_{t=0}^{\infty} \beta^t u\left(c^j_{h,t}\right) \\
&\text{subject to} && a^j_{h,t} - c^j_{h,t} = \frac{a^j_{h,t+1}}{R}, \quad \text{for all } t \geq 0, \\
& && a^j_{h,0} \quad \text{given}, \\
& && \lim_{T \to \infty} R^{-(T+1)} a^j_{h,(T+1)} = 0 \quad \text{(No Ponzi Game Condition (NPG))}
\end{aligned}$$

where, $a^j_{h,t}$ is the real income/asset of household h, belonging to the j^{th} geographical location at t, R is the gross real interest rate and $0 < \beta < 1$ is the discount factor. The utility function is concave - $u'(c_t) > 0; \quad u''(c_t) < 0$

The Euler equation gives,

$$E_t \left[\frac{u'(c^j_{h,t+1})}{u'(c^j_{h,t})} \right] = \beta R$$

When, $\beta R = 1$, and $u\left(c_t\right) = \ln\left(c_t\right)$, the Euler equation gives,

[12]We obtain, $e^j_{i,ht}$ from CPHS, and calculate – (i) $e^j_{h,t} = \sum_{i=1}^{n} e^j_{i,ht}$; and (ii) $\alpha^j_{i,ht} = \frac{e^j_{i,ht}}{e^j_{h,t}}$ from the data for food bundle, and food & fuel bundle. This implies,$0 < \alpha^j_{i,ht} < 1$. Note, constructing disaggregated real consumption indices using household-specific price weights might perhaphs be a well-established practice in micro-level consumption literature. However for the very first time, we use such a methodology in the literature of excess sensitivity of consumption to sentiment. The purpose of using such a methodology is to calculate household specific real consumption expenditure that preserves the true information content of the data; arising from the time-varying true cross-sectional heterogeneity of the household specific nominal consumption $\left(e^j_{h,t}\right)$, price $\left(p^j_{h,t}\right)$ and the relative importance of various items in the consumption bundle $\left(k^j_{h,t}\right)$

$$\Delta \ln \left(c^j_{h,(t+1)}\right) = \delta^j_{h,(t+1)} \tag{3}$$

where, $\delta^j_{h,(t+1)}$ is the forecast error of the household h, residing at the j^{th} geographical location for the period $(t+1)$, with $E_t\left(\delta^j_{h(t+1)}\right) = 0$. Equation 3 implies that factors included in the information set of the households at t^{th} period, except the current consumption, cannot forecast the consumption growth for the period $(t+1)$ (Hall, 1978; Jappelli & Pistaferri, 2017).

3.1 The Time-varying Cross-sectional Heterogeneity

Extant literature calculates the household specific real consumption by deflating their nominal consumption through the aggregate CPI. Since, aggregate CPI only changes with time, and does not change across households; such a measure of real consumption only partially captures the cross sectional heterogeneity of the real consumption. It leads to the loss of potentially rich information content of the data especially for a country like India with a vast cross-sectional heterogeneity[13]. To comprehend the information loss, we calculate the household specific price index from Equation 2 using the monthly data of CPI for the food bundle, and food & fuel bundle. Consequently, we calculate the household specific y-o-y inflation rate for food bundle, and food & fuel bundle as follows -

$$\pi^j_{h,t} = \ln\left(p^j_{h,t}\right) - \ln\left(p^j_{h,t-12}\right)$$

Next, we classify the households in 4 categories according to the occupation of their household heads, calculate the average inflation rate from May 2017 to October 2022, and plot them in Figure 1. Alongside the average inflation rate, Figure 1 also plots the average inflation rate based on the aggregate CPI. While the upper panel of Figure 1 plots the average inflation rates for the food bundle, the lower panel depicts the average inflations for the food & fuel bundle. Figure 1 shows that, the average inflation rate significantly varies across different types of households and also over time.

Since, households often change occupation over time, we calculate the inflation rate after classifying the households according to the educational qualification, and the age

[13]The relative importance of different commodities in the consumption basket varies over time. It also varies across individuals belonging to the different socioeconomic strata of the society. As a result, the incidence of inflation varies across individuals and over time too. Ignoring the changing relative importance of different commodities, and for different groups of people yields a Plutocratic bias of the price index (Nachane & Chaubal, 2019). A disaggregated household specific price level can possibly address the Plutocratic bias as well.

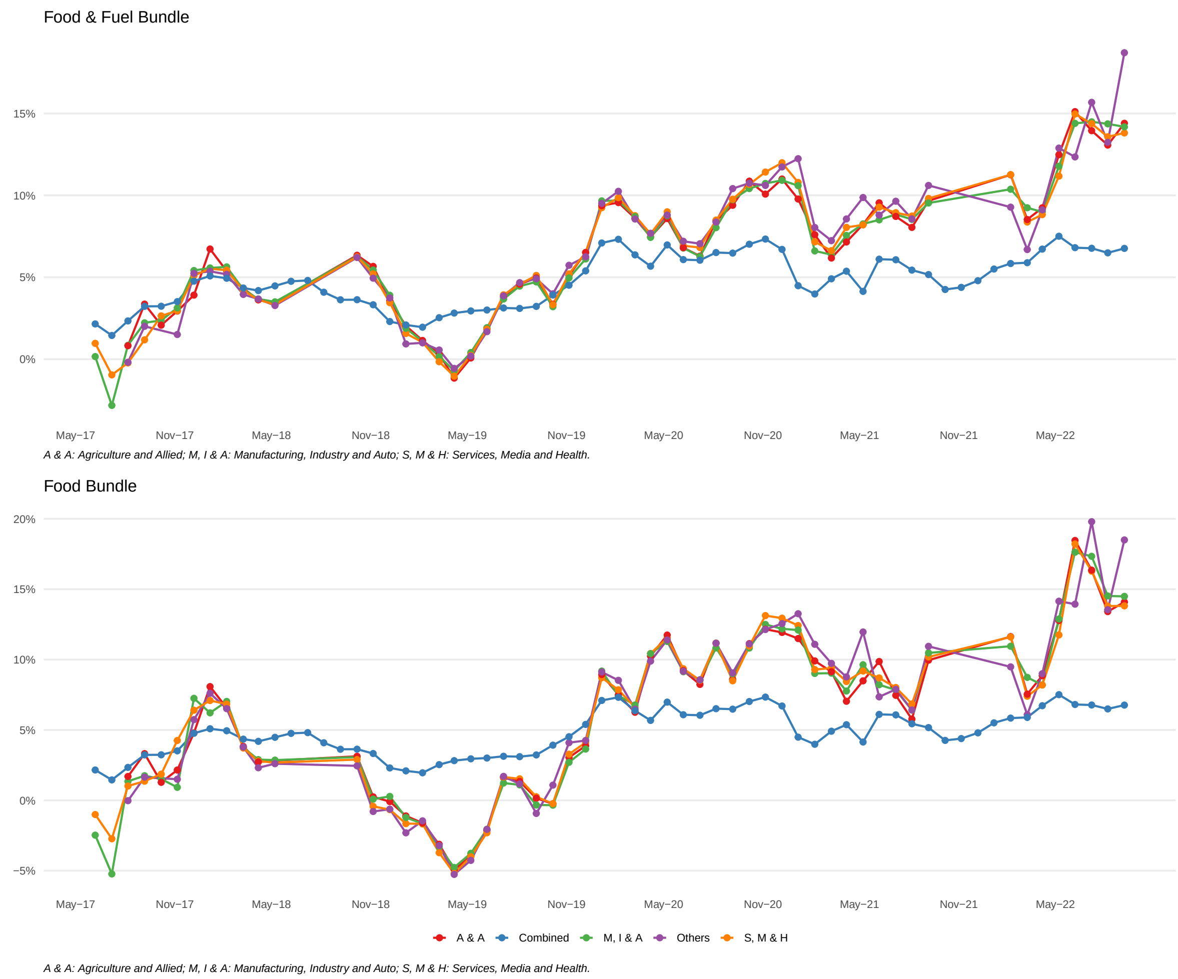

Figure 1: Cross-sectional Heterogeneity of Average Aggregate Inflation Rate, and Household Specific Inflation Rate - Households Classified in terms of Occupations of Household Head

of the household head. Figure 4 and Figure 5 plot the average inflation rate from May 2017 to October 2022 for the Indian households classified according to the educational qualification, and the age of the household head respectively. Like Figure 1, Figure 4 and Figure 5 also portray the significant variation of the average inflation rate across different types of households.

Next, to understand the cross-sectional heterogeneity in real consumption, we calculate a monthly household-specific expenditure-minimizing consumption bundle for food bundle, and for food & fuel bundle using Equation 1. The expenditure-minimizing consumption bundles represent the household-specific real consumption in our paper. Note, such a measure of real consumption of the households incorporates the time-varying cross-sectional heterogeneity of both nominal consumption, and the price level, and thereby fully preserves the information content of the data relevant for forecasting (Lahiri & Zhao, 2016).

Using the measure of real consumption described above, we calculate its growth rate as follows:

$$\Delta \ln \left(c^{j}_{h(t+1)}\right) = \Delta \ln \left(e^{j}_{h(t+1)}\right) + \Delta \ln \left(k^{j}_{h(t+1)}\right) - \pi^{j}_{h(t+1)}$$

To understand the cross-sectional heterogeneity of consumption, we plot the average real consumption growth for the 4 categories of households, classifieds according to the occupation of their household head in Figure 2. Along with the disaggregated level of consumption expenditure for different types of households, Figure 2 also plots the average aggregate real consumption growth for all the households. While the upper panel of Figure 2 plots the average consumption growth for the food bundle, the lower panel depicts the same for the food & fuel bundle. Figure 2 shows- (i) the significant variation in consumption growth across the five types of households, and also over time, and (ii) the reduction in the average consumption growth for all types of households due to the Covid-19 pandemic. Figure 2 also shows the slow recovery of the consumption of Indian households in the periods after the Covid-19 pandemic.

Figure 6 and Figure 7 on the other hand, portray the average consumption growth from May 2017 to October 2022 when the households are classified according to the educational qualification, and the age of the household head. Figure 6 and Figure 7[14] also depict significant time-varying cross sectional heterogeneity, and the slow recovery of the consumption growth from the Covid-19 pandemic shock for the Indian households. The significant time-varying cross sectional heterogeneity depicted in Figure 2, Figure 6 and Figure 7 show that, the average consumption growth for the Indian households has

[14] See Appendix for Figure 4, Figure 5, Figure 6 and Figure 7

Figure 2: Cross-sectional Heterogeneity of Household Specific Consumption Growth - Households Classified in terms of Occupation of Household Head

a definite pattern, and it is not random as predicted by the PIH as mentioned above in Equation 3. Note in our expenditure minimizing consumption bundle, the time-varying cross-sectional heterogeneity of real consumption arises from the time-varying cross-sectional heterogeneity of the nominal consumption, and the household specific price level. Therefore, the expenditure minimizing consumption bundle used by us as a measure of real consumption, fully preserves the information content arising from the cross-sectional heterogeneity in household specific nominal consumption, and the household specific price level, which is relevant for better forecasting (Lahiri & Zhao, 2016).

4 Does Sentiment Predict Consumption Growth?

This section examines the relationship between the aggregate consumption growth, and the aggregate sentiments for India from May 2017 to October 2022. To do so, we calculate an Index of Consumer Sentiments (ICS) for India using the average of the balance statistics of the sentiments associated with – (i) the year ahead household's own future financial positions (question III of CPHS), and (ii) the overall business condition of the economy (question IV of CPHS). The balance statistics of sentiments is calculated by adding 100 with the difference between the proportion of optimistic respondents and the pessimistic respondents for a given question. Note, when the proportion of optimistic respondents exactly matches with the proportion of the pessimistic respondents , the balance statistics of sentiments takes its baseline value 100. Similarly, when the proportion of optimistic respondents is more than the proportion of pessimistic respondents, the balance statistics of sentiments is higher than its baseline value and vice-versa. Therefore, a balance statistics with more than its baseline value, 100 represents an overall optimistic sentiment for the economy and vice-versa[15].

The upper panel of Figure 3 plots the aggregate balance statistics for questions III and IV from May 2017 to October 2022, along with the ICS where, ICS is the average of the balance statistics of question III and question IV. The upper panel of Figure 3 shows that the balance statistics calculated on the basis of questions III, and IV; and the ICS calculated on the basis of questions III and IV were more than 100 till May 2020. These higher balance statistic, higher than the neutral baseline of 100, indicate the prevailed optimistic sentiment among Indian households during the pre-COVID-19 period. However, ICS as well as both balance statistics fall well below their baseline value, 100 due to the Covid-19 pandemic in May 2020 as depicted in Figure 3. Figure 3 also shows that the household sentiments, although rising, remain significantly below the baseline

[15]See, Lahiri & Zhao (2016) for the calculation of the balance statistics of sentiments.

value till October 2022. Such a time path of the ICS represents the highly persistent pessimistic impact of the Covid-19 pandemic on the psyche of Indian households[16].

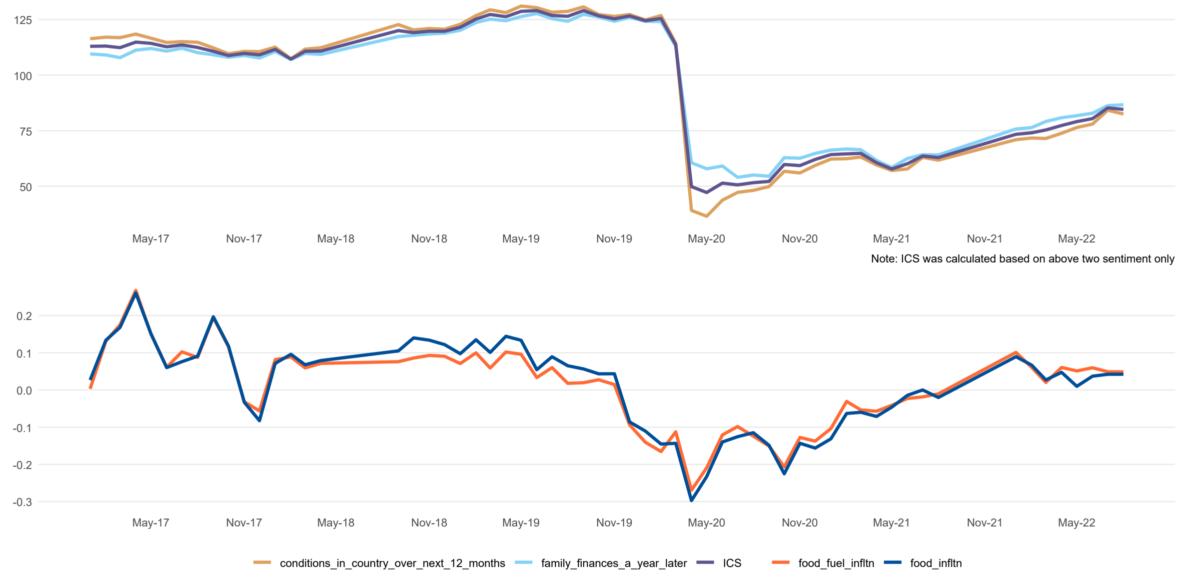

Figure 3: Index of Consumer Sentiment and Aggregate Consumption Growth

While the upper panel of Figure 3 3 plots the sentiment, the lower panel depicts the aggregate consumption growth of India from May 2017 to October 2022, calculated on the basis of the food bundle and the food & fuel bundle, respectively. Note, the upper and the lower panel of the Figure 3 3 portray a significant co-movement between the household sentiments and their consumption growth. It also shows that, along with the household sentiments, the Covid-19 pandemic also badly affected their consumption, from which the Indian households are yet to fully recover. Observing the co-movement from Figure 3 3, we calculate the correlation between the aggregate consumption growth with – (a) the balance statistics of question III, (b) the balance statistics of question IV, and (c) the ICS to assess their interrelationship. We find that the correlation coefficients are positive and significant at the 1% level[17]. Note, both the figure above as well as the lower panel of the correlation matrix table portrays the lasting impact of the Covid-19 pandemic on the psyche and the spending decisions of the Indian households. To fully uncover their interrelationship, and to examine the predictive power of sentiments, we use a full-blown regression analysis based on the Euler equation framework in the next section.

[16]Using the pre-vaccination data Zervoyianni et al. (2023) also find the declining sentiment for the EU-27 countries, and the UK due to the Covid-19 pandemic. Malgarini & Margani (2007) also find that beyond economic fundamentals sentiment is highly responsive to the political cycle, and exceptional circumstances.

[17]See, Correlation Matrix(Table 8) in the appendix.

4.1 The OLS Estimation

Following the extant literature and after observing the positive association between consumption growth, and sentiments, we estimate Equation 4 by OLS using the data of Indian households from May 2017 to October 2022. Equation 4 is adopted from Souleles (2004)[18].

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

The dependent variable of Equation 4, $\Delta ln\left(c^{j}_{h(t+1)}\right)$ is the consumption growth for the household h, belonging to the j^{th} geographical location at period, $(t+1)$. We have calculated consumption growth either on the basis of the food bundle, or the food & fuel bundle for as explained above. Our coefficient of interest is, b_2 – the excess sensitivity parameter. A statistically significant b_2 implies the presence of the excess sensitivity of consumption to sentiments. Following Ludvigson (2004), we use the futuristic sentiments of the households h, belonging to the j^{th} geographical location at time $(t+1)$, $Q^{j}_{h(t+1)}$ as determinants of consumption growth in Equation 4. To estimate Equation 4, we use two such futuristic measures of household sentiments – (i) one period ahead future sentiments for the household's own financial position (Q_{FP}); and (ii) one period ahead sentiments about the future business condition (Q_{BC}).

Along with sentiments, we also include following additional controls in Equation 4 - (i) time dummy that controls the impact of aggregate shocks on the consumption growth that uniformly affect all households. The time dummy takes the value 1 for the said time period, and 0 otherwise. For a panel data with large cross sectional units, and smaller time dimension; the inclusion of time dummy helps to achieve consistency when aggregate shocks are assumed to uniformly affect all households (Chamberlain, 1984). and (ii) we also control for the preference shock, determined by the change in number of kids, change in number of adults, and the age of the household head in $W_{h(t+1)}$ as proxies of the preference shocks (Souleles, 2004)[19]. Table 2 reports the results obtained from estimating Equation 4 by OLS.

Table 2 shows that, the coefficients of Q_{FP} and Q_{BC} are positive, and significant at 1% level. Table 2 that, the sentiment of Indian households about their own one period

[18]Note, Equation 4 assumes that the forecast error of Equation 3 is not random but systematically depends linearly on aggregate shock (represented by the time dummy), preference shock (represented by $W_{h(t+1)}$), and the household specific sentiment (Q^{j}_{ht}).

[19]Section 3 shows that, PIH holds when the homogeneous discount is equal to the inverse of the gross interest rate, $\beta = R^{-1}$. However, the discount factor can also vary across households. Alongside the preference shock, variables included in $W_h(t+1)$ in Equation 4 captures the cross-sectional heterogeneity of the discount factor as well.

Table 2: OLS Estimation for Food and Food & Fuel – Full Sample (April 2016-October 2022)

	Food		Food & Fuel	
	(1)	(2)	(3)	(4)
Q_{FP}	0.009***		0.054***	
	(0.002)		(0.002)	
Q_{BC}		0.003***		0.003***
		(0.002)		(0.002)
Age	-0.000***	-0.000***	-0.000***	-0.000***
	(0.002)	(0.000)	(0.002)	(0.000)
Δ kids	0.011***	0.011***	0.07***	0.07***
	(0.012)	(0.012)	(0.002)	(0.002)
Δ adults	0.038***	0.038***	0.028***	0.002***
	(0.002)	(0.002)	(0.002)	(0.002)
Time Dummies	Yes	Yes	Yes	Yes
Number of Observations	58,871	58,871	58,871	58,871

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)***, **, * represent significance at 1%, 5%, and 10% level respectively.

ahead financial position Q_{FP} can explain only 0.9% variation of the consumption growth of the food bundle, and 5.4% variation of the food & fuel bundle. On the other hand, we find that the raw sentiments of Indian household's about one period ahead business condition Q_{BC}, can explain only 0.3% variation of the consumption growth of both the food bundle, and the food & fuel bundle. In effect, Table 2 implies the presence of excess sensitivity of consumption to sentiment for India. The excess sensitivity of consumption to sentiment in turn shows that, the sentiment of Indian households contains additional information, beyond that is in the current consumption, required to predict the future consumption[20].

4.2 The GMM Estimation

Toussaint-Comeau & McGranahan (2006) argue that sentiment contains rich demographic-specific information of spending patterns for US households. Similarly, Blendon et al. (1997) argues that individuals form their sentiments mostly by processing information obtained during conversations with their neighbors at the backyard of their house, implying that the neighborhood/network of the households, captured by geographical location, educational attainment, income level, and occupational choice plays important role to shape individual sentiment. To check the predictive power of the network-inferred sentiment of the Indian households, we re-estimate Equation 4 through GMM by using, $\mathbf{Z}$ = [age of household head × time, income × time, location, marital status of the household head, gender of household head, education of household head, nature of occupation of household head, log of real income] as instruments of Indian households, and estimate Equation 4 by GMM[21]. Table 3 reports the results of the GMM estimation.

Table 3 show that the coefficients of Q_{FP} and Q_{BC} are positive and significant at the 1% level implying the presence of excess sensitivity of consumption to sentiment. Table 3 also show that while Q_{FP} explains 55.5% variation of the consumption growth for the food bundle, it explains almost 70% variation of the food & fuel bundle. Similarly, results of our GMM estimation reported in Table 3 also show that while Q_{BC} explains 34.5% variation of the consumption growth for the food bundle, it explains almost 66% variation of the food & fuel bundle. The substantially higher magnitude of the excess sensitivity parameter, b_2 obtained under GMM estimation as compared to the OLS estimation highlights the role of the network-inferred sentiment in predicting

[20]Anthony Bryant & Macri (2005) develop a theoretical model to analyze the positive relationship between sentiments and consumption observed for Australia.

[21]Souleles (2004) used the vector Z mentioned in the text for the US to match the sentiment of the US household with their consumption. We are using the vector Z as determinants of households' neighborhood/network for the Indian households.

Table 3: GMM Estimation for Food and Food & Fuel

	Food		Food & Fuel	
	(1)	(2)	(3)	(4)
Q_{FP}	0.555***		0.695***	
	(0.00)		(0.030)	
Q_{BC}		0.345***		0.661***
		(0.038)		(0.037)
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Δ kids	0.009	-0.007	0.010	-0.015
	(0.37)	(0.009)	(0.012)	(0.012)
Δ adults	0.018	0.041**	-0.342	-0.010
	(0.46)	(0.021)	(0.026)	(0.026)
Time Dummies	Yes	Yes	Yes	Yes
Number of Observations	56,211	56,211	56,211	56,211

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)***, **, * represent significance at 1%, 5%, and 10% level respectively.

consumption growth. Our results show that, the part of household sentiment, explained by their neighborhood/network – the network-inferred sentiment - is a superior predictor of consumption growth than the raw sentiment measures. Hence, our results reported in Table 3 not only corroborate the claim of Blendon et al. (1997) about the role of individual neighborhood to form their sentiments as mentioned above, it also reveals its superior prediction power of the business cycle too.

Next, we estimate Equation 4 separately for the pre-Covid periods (April, 2016 to February, 2020). The results for the pre-Covid periods are reported in Table 4.

Table 4: GMM Estimation for Food Bundle and Food & Fuel Bundle - Pre-Covid Periods (April, 2016-February, 2020)

	Food		Food & Fuel	
	(1)	(2)	(3)	(4)
Q_{FP}	0.22***		0.766***	
	(0.01)		(0.030)	
Q_{BC}		0.20***		0.749***
		(0.01)		(0.038)
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Δ Kids	0.03	-0.01	0.02	-0.015
	(0.08)	(0.01)	(0.01)	(0.012)
Δ Adults	-0.02	0.03	-0.07	0.03
	(0.02)	(0.03)	(0.03)	(0.03)
Time Dummies	Yes	Yes	Yes	Yes
Observations	38,131	38,131	38,131	38,131

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) ***, **, * represent significance at 1%, 5%, and 10% level respectively. (iv) Standard Error in paranthesis.

The estimates of Equation 4 for the pre-Covid periods are characteristically identical with that of the full sample estimation of Equation 4. The positive and highly significant coefficient of sentiment identifies the sentiment as one of the important predictors of consumption growth for India, signifying the presence of excess sensitivity of consumption to sentiment.

4.3 Consistency and the Spurious Excess Sensitivity - The Role of Forecast Error

Jappelli & Pistaferri (2017) and Christelis et al. (2020) argue about endogeneity often arising from the correlation between the forecast errors of consumption growth in the Euler equation-based estimation. Hence to achieve consistency by addressing such endogeneity, they suggest using survey data-based estimates of expected consumption growth and expected consumption risk for the estimation. On the other hand, to address the spurious excess sensitivity of consumption to sentiments, Souleles (2004) calculates the forecast error of household sentiments from the survey data and uses it as one of the covariates in his estimation. Following Souleles (2004), we also calculate the forecast errors for Indian households for their own financial position and use it as one of the covariates in our estimation to address the spurious excess sensitivity of consumption to sentiments and to achieve consistency as well.

We calculate the forecast errors by taking the difference of question II and question III mentioned in Section 2. As a result, the forecast error, FE_{FP}, takes discrete values between -2 to +2 in our analysis. Using this measure of forecast errors, we estimate Equation 5 through OLS and also through GMM. Results of the OLS estimation and GMM estimation of Equation 5 for the food bundle and for the food & fuel bundle are reported below:

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

Table 5: Estimation for Food Bundle and Food & Fuel Bundle after Controlling for Forecast Error– Full Sample (April 2016-October 2022)

	OLS		GMM	
	Food	Food & Fuel	Food	Food & Fuel
Q_{FP}	0.03***	0.023***	0.476***	0.461***
	(0.003)	(0.003)	(0.00)	(0.00)
FE_{FP}	0.027***	0.023***	0.53***	0.497***
	(0.002)	(0.002)	(0.00)	(0.00)
Age	-0.000***	-0.000***	-0.001	-0.000
	(0.000)	(0.000)	(0.96)	(0.92)
Δ kids	0.011***	0.06***	0.017	0.003
	(0.012)	(0.003)	(0.012)	(0.02)
Δ adults	0.039***	0.029***	0.009	0.011
	(0.002)	(0.002)	(0.71)	(0.62)
Time Dummies	Yes	Yes	Yes	Yes
Observations	53,312	53,312	53,312	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 6: GMM Estimation for Food and Food & Fuel Bundles after Controlling for Forecast Errors- Pre-Covid Periods (April, 2016-February, 2020)

	Food	Food & Fuel
Q_{FP}	0.25***	0.717***
	(0.002)	(0.030)
FE_{FP}	0.613***	0.613***
	(0.061)	(0.061)
Age	-0.001***	-0.001***
	(0.000)	(0.000)
Δ Kids	0.017	0.017
	(0.012)	(0.012)
Δ Adults	-0.009	-0.009**
	(0.71)	(0.71)
Time Dummies	Yes	Yes
Observations	37,717	37,717

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

Results reported in Table 5 and Table 6 show that the network-inferred household sentiments have significant predicting power on consumption growth and business cycle even after controlling the forecast errors.

To explain the interrelationship between sentiment, and consumption growth, Pistaferri (2016) envisage sentiments as a "catch-all" of individual income prospects, and precautionary savings in Euler equation based analysis of excess sensitivity of consumption to sentiment. Therefore, using sentiment in the Euler equation setting to predict consumption growth has its own pros-and cons. While, it enables a parsimonious specification of the regression equation, it also restricts us to – (i) identify the exact source of the excess sensitivity of consumption, and precautionary savings, (ii) test the validity of the PIH[22].

5 Conclusion

Identifying the determinants of sentiment, and examining its role in forecasting spending has long intrigued econometricians and policy makers. While early research relied primarily on national or state-level aggregate data to examine this relationship, the field has evolved methodologically with the increasing adoption of microeconomic survey data. This methodological shift offers enhanced analytical power for assessing the predictive capacity of sentiment indicators on consumption dynamics. Our paper represents the first comprehensive attempt to examine the predictive power of sentiment on consumption growth and to test the implications of the rational expectation based Permanent Income/Life Cycle Hypothesis using household-level data from India.

To examine whether sentiment can forecast household consumption growth in India, we employ the comprehensive longitudinal microdata from the Consumer Pyramid Household Survey (CPHS). Our novel methodological approach involves constructing two distinct expenditure-minimizing consumption bundles: (i) food bundle, and (ii) food & fuel bundle. These bundles serve as household-specific real consumption expenditure measures, effectively preserving the rich cross-sectional heterogeneity of the Indian economy.

[22]Note, through a second order Taylor series expansion of the Euler equation, Blanchard & Mankiw (1988) shows that, consumption growth is also influenced by the expected consumption risk. In the context of the, it implies consumption risk is a sufficient statistic, and one does need to take into account the risks related to income and/or health to forecast consumption growth once the consumption risk is appropriately controlled (Christelis et al., 2016; Jappelli & Pistaferri, 2017). This further implies that, the excess sensitivity of consumption to income represents a violation of the PIH. However, since sentient is a "catch-all"; beside income risk, even expected consumption risk might influence individual sentiment too. If so, the excess sensitivity of consumption to sentiment cannot not be unequivocally interpreted as the violation of the PIH.

We utilize two forward-looking sentiment indicators: households' expectations regarding their future financial position and their perceptions of future business conditions. By using these sentiment measures within an Euler equation framework, we simultaneously test whether household sentiment indicators possess significant predictive power for consumption growth and whether consumption exhibits excess sensitivity to sentiment fluctuations—findings that would test the validity of the Permanent Income Hypothesis (PIH) in the Indian household context.

Endorsing Blendon et al. (1997), we show that households' neighborhood/network represented by geographical location, income level, educational attainment, and occupation choice in our paper plays important role not only to shape their sentiment, but the network-inferred sentiment – the part of household sentiment explained by their neighborhood/network has better predictive power consumption growth and business cycle than the raw sentiment measures themselves. We argue that, consistent with pre-pandemic patterns, sentiments should remain crucial for business cycle forecasting in post-pandemic periods, and our results broadly parallel evidence from developed economies, contributing to the broader literature on sentiment-driven consumption and business cycle dynamics.

Finally, to outline our future research agenda, we note that the sluggish recovery pattern of consumption for Indian households depicted in Figure 3 closely mimics the dynamics of US consumption growth in the post-Great Recession period. Pistaferri (2016) demonstrates that alongside sentiments, household debt and net worth should be controlled for when explaining post-Great Recession consumption growth dynamics in the US.Depending on the availability of data, we plan to explore models that incorporate health-related risks faced by Indian households due to the COVID-19 pandemic, alongside their sentiments, liabilities, and net worth to explain the consumption dynamics of Indian households in the post-Covid periods.

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Appendix

Figure 4: Cross-sectional Heterogeneity of Average Aggregate Inflation Rate, and Household Specific Inflation Rate - Households Classified in terms of Educational Attainment of Household Head

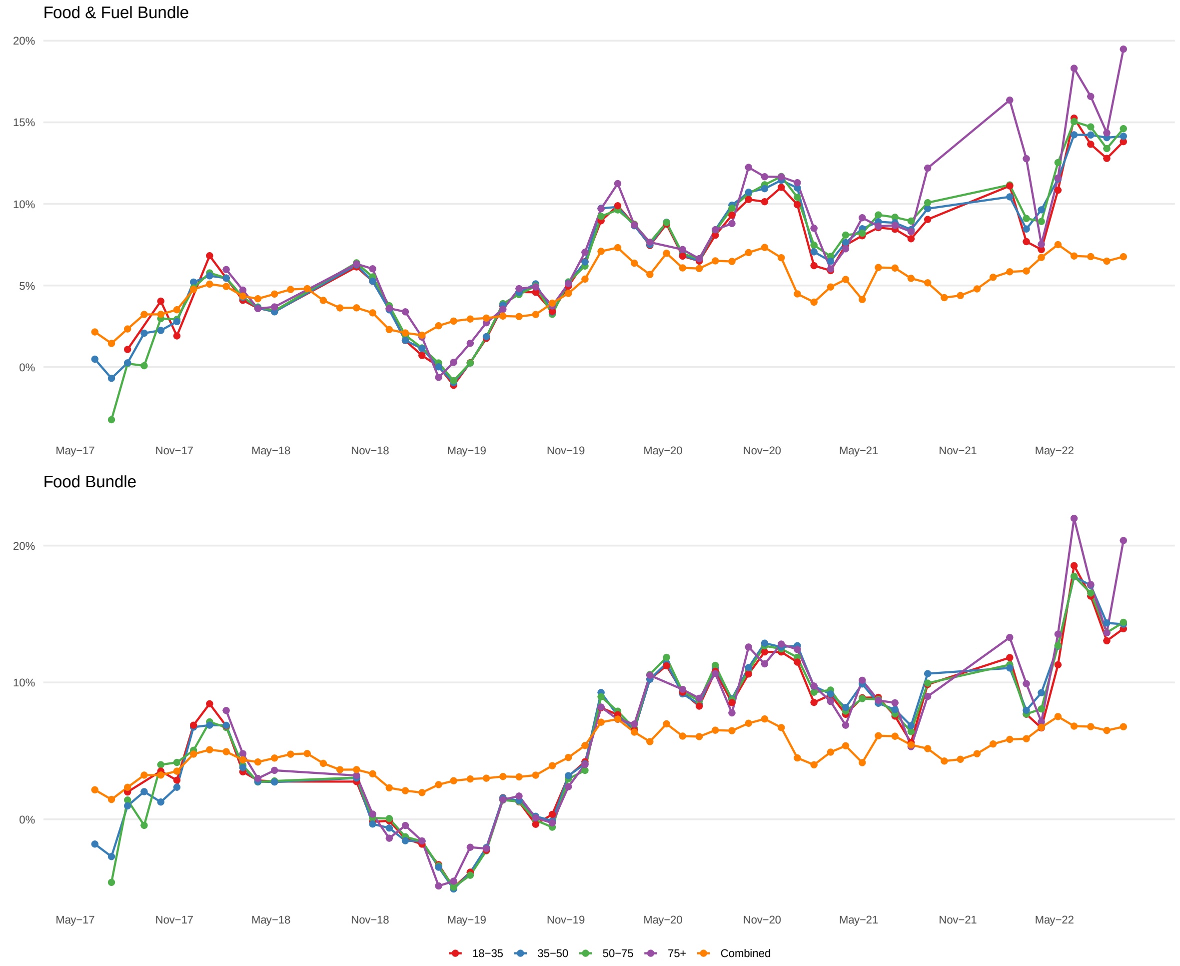

Figure 5: Cross-sectional Heterogeneity of Average Aggregate Inflation Rate, and Household Specific Inflation Rate - Households Classified in terms of Age of Household Head

Figure 6: Cross-sectional Heterogeneity of Household Specific Consumption Growth - Households Classified in terms of Educational Attainment of Household Head

Figure 7: Cross-sectional Heterogeneity of Household Specific Consumption Growth - Households Classified in terms of Age of Household Head

Table 7: GMM Estimation for Food and Food & Fuel Bundles - Covid-periods (March, 2020-October, 2022)

	Without Controlling Forecast Errors		**With Forecast Errors as Controls**	
	Food	Food & Fuel	Food	Food & Fuel
Q_{FP}	0.34***	0.43***	0.31***	0.20***
	(0.05)	(0.030)	(0.06)	(0.06)
Q_{BC}	0.03	0.36***		
	(0.05)	(0.04)		
FE_{FP}			0.42***	0.68***
			(0.009)	(0.061)
Age	-0.002***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Δ Kids	0.00	-0.04	-0.03	-0.03
	(0.01)	(0.01)	(0.02)	(0.02)
Δ Adults	-0.01	0.00	-0.01	-0.01**
	(0.03)	(0.03)	(0.06)	(0.06)
Time Dummies	Yes	Yes	Yes	Yes
Observations	17,400	17,400	12,615	12,615

Note: (i) Age represents the age of the household head, (ii) Δ kids and Δ adults represent change in number of kids and adults respectively, (iii) FE_{FP} is forecast error of financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively, (v) Standard Errors in parentheses.

Table 8: Correlation Matrix

	Consumption Growth (Food Bundle)	Consumption Growth (Food & Fuel Bundle)	Business Conditions	Financial Position	ICS
Business Conditions	0.66***	0.59***	–	–	–
Financial Position	0.62***	0.54***	0.99***	–	–
ICS	0.65***	0.57***	1***	1***	–