Does Sentiment Predict Consumption Growth of Indian Households?*

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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 due to its significantly greater cross-sectional heterogeneity with richer information content compared to developed countries. We demonstrate that household sentiments, explained by geographical location, income level, education attainment, and different demographic characteristics, exhibit stronger predictive power on consumption growth than raw sentiment measures themselves. The resulting excess sensitivity of consumption to sentiments represents a violation of the rational expectations-based Permanent Income/Life Cycle Hypothesis for Indian households. It indicates that households' sentiments regarding future financial positions and business conditions should be appropriately incorporated when forecasting household consumption, and overall business cycle dynamics of India. We also argue that, consistent with pre-pandemic patterns, sentiments should remain crucial for business cycle forecasting in post-pandemic periods, even though COVID-19 has fundamentally altered spending patterns and their underlying determinants for Indian households. Our results broadly parallel evidence from developed economies, 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. 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)[1]. This paper makes three distinct contributions to the literature[2]. First, it provides a comprehensive analysis of consumption sensitivity to sentiment in an emerging market setting, extending the predominantly developed-market 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, it generates new empirical evidence on how extraordinary economic circumstances - particularly pandemic-induced uncertainty - influence household spending decisions and precautionary savings behavior. Our analytical framework, grounded in the Euler equation, serves dual purposes: it assesses the predictive capacity of sentiment while simultaneously providing a natural setting to test for excess sensitivity of consumption to sentiments. This approach enables us to evaluate the rational expectations-based Permanent Income/Life Cycle Hypothesis (PIH), which posits that current consumption fully incorporates all information relevant for predicting future consumption. Hence, the predictive power of sentiment within the Euler equation framework directly challenges the prediction of PIH.

Note that the PIH is violated if sentiment predicts consumption growth within the Euler equation framework. Our paper finds evidence of excess sensitivity of consumption to sentiment and a violation of the PIH for Indian households. Moreover, by comparing the OLS estimate of the Euler equation with that of GMM estimation we show that, instead of the raw sentiments, the part of the household sentiments explained by the their geographical location, income, education, and demographics is a much better predictor of consumption growth of the Indian households. We also show that, since the Covid-19 pandemic has significant and lasting impact on the household income risk. It causes

[1]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 households are surveyed under CPHS to measure the household well-being in India. This large longitudinal dataset is widely acknowledged as representative of the Indian economy. For details see; https://consumerpyramidsdx.cmie.com/

[2]To analyze the impact of sentiment on business cycle, Solı́s (2023) analyzes the effects of monetary policy statements on quantity and price level for Mexico. Similarly, Dinh (2025) analyze the asymmetric role of short-term and long-term consumer sentiments on the transmission of the monetary policy.

changes in the pattern and the determinants of their spending decisions, and considerably reduces the predictive capacity of household sentiments falls significantly in the Covid-periods[3].

After establishing the excess sensitivity of consumption to sentiment, a crucial question emerges: what mechanisms drive sentiment's predictive power over consumption growth? The literature suggests that sentiment operates through its influence on precautionary savings motives within the Euler equation framework. Blanchard & Mankiw (1988) provides a theoretical foundation of the precautionary savings motive through a second-order Taylor series expansion of the Euler equation, expressing expected consumption growth as a function of three components: the real interest rate-discount factor differential, the conditional variance of consumption (consumption risk), and individual borrowing or liquidity constraints. Since, consumption risk is highly correlated with income risk, and a large body of literature identifies voluntary and/or involuntary job loss due to layoffs and/or voluntary resignation, variations in labor supply, and changes of productivity/wage stemming from health shocks or job mobility as key determinants of individual income uncertainty. , these same determinants of income risk also shape individual sentiment formation. Building on this connection, Pistaferri (2016) envisage sentiments as a "catch-all" of individual income prospects, and precautionary savings in an Euler equation based analysis of excess sensitivity of consumption to sentiments. This "catch-all" nature of sentiment presents both methodological advantages and limitations in regression analysis. While it enables a parsimonious specification, it precludes the isolation of specific factors driving excess sensitivity and precautionary savings behavior.

While highlighting the advantage of survey data in addressing the excess sensitivity of consumption to sentiment, Jappelli & Pistaferri (2017) and Christelis et al. (2020) demonstrate that survey-based calculation of consumption growth and its variance, when used in the regression based on Euler equation framework, yield consistent estimates by mitigating endogeneity concerns stems from the correlation between forecast errors of consumption and the consumption risk. Complementing this methodological insight, Lahiri & Zhao (2016) argue that household sentiment transcends mere reflections of aggregate macroeconomic conditions. Rather, it encapsulates substantial idiosyncratic information shaped by households' subjective interpretations of aggregate economic con-

[3]Albuquerque & Green (2023) analyzes the impact of financial concern arising from the uncertainty of the Covid-19 pandemic on the consumption behavior of the US households. Using a survey data through a hypothetical transfer £500, they find that the household expectations play a key role in determining differences in MPCs across households

ditions. This perspective underscores the importance of preserving and appropriately leveraging the rich information embedded in micro-level sentiment data - particularly its time-varying cross-sectional heterogeneity - when forecasting consumption patterns. Moreover, after analyzing the demographic specific information content of the University of Michigan Survey of Consumer Attitudes and Behavior (CAB), Toussaint-Comeau & McGranahan (2006) show that the disaggregated level survey data serves the dual purpose - (i) it helps to better predict the expenditure pattern that often differs for various sub-groups of people, and (ii) it helps to identify the welfare of different demographic groups that can allow to undertake appropriate policy initiatives aimed at assisting the vulnerable group of people[4].

Realizing the potential benefits of the micro level survey data, Christelis et al. (2016) employs survey-based estimates of consumption growth and risk to calculate the index of prudence and examine precautionary savings for Netherlands through the Euler equation framework. Building on this approach,Immordino et al. (2024) investigates household spending decisions during the COVID-19 pandemic using data from 3,016 Italian households. They find a positive relationship between the expected consumption growth, and the expected disposable income growth, but did not find any significant relationship between income risk and the expected consumption growth in their analysis. Surprisingly, health factors did not emerge as primary drivers of Italian household spending decisions during the pandemic. In contrast, Choi et al. (2024) examine the asymmetric impact of consumer confidence on economic outcomes across 29 U.S. states using a VAR framework. Their findings indicate that consumer confidence innovations positively affect output while negatively impacting inflation, suggesting that sentiment primarily captures supply-side rather than demand-side influences on economic behavior[5]. Matasuka & Sbordone (1995) on the other hand explain the positive Granger causality of consumer confidence to consumption by means of strategic complementarities and multiple equilibria, identified after appropriately controlling for the economic fundamentals in their VAR estimation based on the aggregate data of the US. Additionally, Pistaferri (2016) demonstrates that consumer confidence, alongside leverage ratios, significantly explains the sluggish recovery of U.S. consumption following the Great Recession[6].

[4]Dominitz & Manski (2004) also argue that, the survey data at the disaggregated level enhances the informative power of the sentiment indexes. Also see; Lahiri et al. (2016).

[5]In their analysis, Choi et al. (2024) follow the spirit of Barsky & Sims (2012), who using a quarterly data of the US analyze the differential impact of animal spirits, and news on consumption, inflation, output, and labor supply through VAR. Corrado et al. (2022) also follow Barsky & Sims (2012) to analyze the impact of news on consumption for the US.

[6]Even before the disaggregated micro level sentiments data was available, Acemoglu & Scott (1994) analyzes the relationship between aggregate sentiments, and consumption growth for the UK through

Souleles (2004) on the other hand, investigates the excess sensitivity of consumption to sentiments through the Euler equation framework by using the household level data of the US. His methodology involved matching consumption data from the Consumer Expenditure Survey (CEX) with sentiment data underlying Michigan's Index of Consumer Sentiment (ICS) through demographic characteristics. Given the distinct data sources, Souleles (2004) applies two-sample IV estimation method of Angrist & Krueger (1992) to ensure appropriate standard errors and valid statistical inference. While finding evidence of excess sensitivity and PIH violation for U.S. households, Souleles (2004) uniquely documents a negative relationship between household-level sentiments and consumption growth.

Against this backdrop, our paper investigates whether sentiments predict consumption growth for Indian households. We use the Euler equation framework provides for our analysis which provides a natural setting to examine both consumption's excess sensitivity to sentiments and the validity of the PIH in the Indian context. This study represents the first comprehensive examination of household sentiment's predictive capacity and consumption excess sensitivity for Indian households[7]. We select India for our analysis due to its significantly greater cross-sectional heterogeneity and hence the richer information content compared to developed economies. However, accurately estimating sentiment's predictive power requires preserving the substantial cross-sectional heterogeneity within Indian data, which contains valuable information as emphasized by 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 Euler equation framework. They find that the evidence of excess sensitivity of consumption to sentiments, and argue that sentiments has can predict consumption growth for the UK. Moreover, while analyzing the relationship between consumption growth and University Michigan's Index of Consumer Sentiments (ICS) through the Euler equation framework, Carroll et al. (1994) find that current as well as the lagged sentiments positively affect consumption growth even for the US. Alongside precautionary savings they argue that the habit formation of individuals plays important role to explain the interrelationship between consumption, and sentiments.

[7] Priya & Sharma (2024) have used the data of sentiments of Indian households to estimate a consumption function. Their primary objective was to test the role of animal spirits in the propagation of the oil price and the monetary policy shock for the Indian economy.

the complete 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 time-varying cross-sectional heterogeneity in real consumption. We employ this expenditure-minimizing consumption bundle as our measure of real consumption throughout our analysis[8]. 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. These bundles serve as our real consumption measures.

We use both OLS, and GMM to estimate the Euler equation for the period April, 2016 to October 2022. We employ two distinct sentiment measures: 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. The coefficient of the sentiments obtained from OLS indicates the proportion of the variance of consumption growth of Indian households can be explained by their raw sentiments. It is important to mention here that, Blendon et al. (1997) argues that individuals form their sentiments mostly by processing information obtained during the conversation with their neighbors at the backyard of their house. Following this insight and Souleles (2004), we implement GMM estimation using geographical location, income level, educational attainment, and other demographic characteristics as instruments for household sentiment. This approach enables us to assess whether the part of sentiment explained by these socioeconomic factors provides superior predictive power compared to raw sentiment measures[9]. We find that the part of the household sentiments explained by their geographical location, income, education, and demographics is a superior predictor of their consumption growth than the raw sentiments itself. Our results reported in Table 3 also show that, the fuel

[8]For identical reason, we calculate real household specific real income by deflating their nominal income using the corresponding household specific price indices. It preserve the true cross-sectional heterogeneity of household specific real income.

[9]Souleles (2004) used geographical location, income level, educational attainment, and relevant demographic characteristics to match the sentiments of US households obtained from University of Michigan Survey of Consumer Attitudes and Behavior (CAB) with their spending obtained from Survey of Consumption Expenditure (CEX). Note, literature mostly used various subsets of the variables used by Souleles (2004) mentioned above in the regression to control for the unobserved cross-sectional heterogeneity and aggregate shocks to achieve consistency. We use these variables as instruments of sentiments, and show that household sentiments explained by their geographical location, income level, and educational has more predictive power on consumption growth. Moreover, by assuming educational attainment, income level, and geographical location as determinants of individual neighborhood, our results endorse the claim of Blendon et al. (1997), who claim that individual sentiments plays important role to shape their sentiments.

consumption of Indian households is more sensitive to their sentiments than the food consumption.

To examine the COVID-19 pandemic's impact on household spending decisions, we estimate our model separately for the pre-COVID period (April 2016-February 2020) and the COVID period (March 2020-October 2022). We find that only expectations regarding households' own future financial position predict food bundle consumption growth. For the combined food & fuel bundle, both personal financial expectations and business condition sentiments predict consumption growth, with the latter demonstrating superior predictive power. Notably, sentiment's predictive capacity diminishes substantially during the COVID period. Our results further reveal that the COVID-19 pandemic has exerted lasting effects on job prospects, health, and income risk. In the absence of comprehensive social security systems, these effects have fundamentally altered both spending patterns and their determinants among Indian households, as evidenced by the reduced predictive power of sentiment during this period. To address potential spurious excess sensitivity, we incorporate household forecast errors as a control variable in our estimation, following Souleles (2004). The results remain qualitatively identical to specifications without systematic control for forecast errors, confirming the robustness of our findings. The results of our paper broadly parallel evidence from developed economies, contributing to the broader literature on sentiment-driven consumption and business cycle dynamics[10].

The rest of the paper proceeds as follows. Section 2 describes the data, and Section 3 briefly discusses the PIH and the excess sensitivity of consumption. Section 4 presents the results, and Section 5 concludes.

2 Data Description

We collect data of household sentiments from Consumer Pyramid Household Survey (CPHS). 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,

[10]See, Vuchelen (2004) and references therein for a comprehensive analysis on sentiment and business cycle.

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 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. 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.

[**Table 1**]

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[11]. 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) SnacksUsing 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

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

3 The 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,

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

where, $p^j_{i,t}$ is the price of the i^{th} sub-category of consumption at, time t for the household, h located at the j^{th} geographical area. $c^j_{i,h,t}$, 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.

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

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,

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

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.

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

where, $a^j_{h,t}$ 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

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

where, $E_t\left(\delta^j_{h(t+1)}\right) = 0$. Equation 3 implies the absence of excess sensitivity of consumption – factors included in the information set of the households at t^{th} period cannot forecast the consumption growth of the (t+1) period. Note, the absence of excess sensitivity of consumption implies that the current consumption contains all the relevant information to forecast future consumption. Note, $E_t\left(\delta^j_{h(t+1)}\right) = 0 \Rightarrow E_t\left(\Delta ln\left(c^j_{h(t+1)}\right)\right) = E\left(\Delta ln\left(c^j_{h(t+1)}\right)\middle| I^j_{ht}\right) = 0$; where, I^j_{ht} is the information set of household h belonging to the location j at the t^{th} period. This yields, $E_t\left(ln\left(c^j_{h(t+1)}\right)\right) = ln\left(c^j_{ht}\right)$, implying current consumption contains all the relevant information to forecast future consumption. Suppose, $x^j_{ht} \in I^j_{ht}$ but, $x^j_{ht} \neq c^j_{ht}$. The PIH implies that, x^j_{ht} cannot predict, $c^j_{h(t+1)}$. If x^j_{ht} predicts $c^j_{h(t+1)}$, the excess sensitivity of consumption to x^j_{ht} exists, and the PIH is violated.[12]

[12]Therefore, to test the excess the excess sensitivity of consumption to x^j_{ht}, we include x^j_{ht} in the Euler equation as one of the control variables, and test the significance of its estimated coefficient (see, Equation 4 and Equation 5 in the text). A significant estimated coefficient of x^j_{ht} implies the presence of excess sensitivity of consumption to x^j_{ht}, and the violation of PIH (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 dataof 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 -

$$\pi^j_{h(t+1)} = \ln\left(p^j_{h,(t+1)}\right) - \ln\left(p^j_{h,(t+1)-12)}\right)$$

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.

[13]The relative importance of different commodities in the consumption basket varies over time, and across individuals belonging to the different socioeconomic strata of the society. As a result, the incidence of inflation also varies across individuals and also over time. However, although the weight/importance of different items included in the CPI basket changes with the base year, it remains unchanged across individuals. This results in the well-known substitution bias of the aggregate CPI. Again to obtain CPI, we aggregate the expenditure shares of different items in the CPI basket for individuals belonging to the different socioeconomic strata of the society. Such an aggregation of expenditure shares of heterogeneous individuals to obtain a homogeneous price index yields the Plutocratic bias of the CPI (Izquierdo et al., 2003; Ley, 2005; Nachane & Chaubal, 2019). A disaggregated household specific price level calculated from Equation 2, and the expenditure minimizing consumption bundle from Equation 1 by incorporating the weight/importance of different items that changes over time, and across individuals serves the dual purpose: (i) it allows to address the substitution, and the plutocratic bias; and (ii) it preserves the true cross-sectional heterogeneity of the real consumption expenditure by taking care of the cross-sectional heterogeneity of the household specific nominal consumption expenditure, and that of the household specific price index. Another group of literature tries to obtain an index of household/individual specific price differently by using a consumption index based on non-homothetic implicit CES aggregator. Expenditure minimisation based such an consumption index generates price index, and hence the inflation rate that varies across individuals depending on their value of consumption index. For details see, Matsuyama (2023), and Duernecker et al. (2023).

[**Figure 1**]

Since, households changes occupation over time, we calculate the inflation rate after classifying the households according to the educational qualification, and the age of the household head. Figure 2 and 3 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 2 and 3 also portray the significant variation of the average inflation rate across different types of households.

[**Figure 2**]

[**Figure 3**]

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 4. Along with the disaggregated level of consumption expenditure for different types of households, Figure 4 also plots the average aggregate real consumption growth for all the households too. While the upper panel of Figure 4 plots the average consumption growth for the food bundle, the lower panel depicts the same for the food & fuel bundle. Figure 4 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 4 also shows the slow recovery of the consumption of Indian households in the periods after the Covid-19 pandemic.

[Figure 4]

Figure 5 and 6 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 5 and 6 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 Figures 4 to 6 show that, the average consumption growth for the Indian households has 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).

[Figure 5]

[Figure 6]

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 is equals to the proportion of the pessimistic household, the balance statics 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 100, representing an overall optimistic sentiments for the economy, and vice-versa[14] .

Upper panel of Figure 7 plots the aggregate balance statistics for questions III, and IV from May 2017 to October 2022, along with the ICS. The ICS is the average of the balance statistics of question III, and question IV. Upper panel of Figure 7 shows that the balance statistics both for the questions III, and IV as well as the ICS were more than 100 for India till May 2020. It represents an overall optimistic sentiments for Indian households in the pre-Covid period. However, all measures of household sentiments significantly falls below their baseline value 100, due to the Covid-19 pandemic in May 2020. It represents the extent of overall pessimism and uncertainty as soon as the Covid-19 pandemic hits the Indian economy. The upper panel of Figure 7 also shows that the household sentiments, although rising, remains significantly below their baseline value till October 2022.

[**Figure 7**]

While, the upper panel of Figure 7 plots the sentiments, the lower panel of Figure 7 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 Figure 7 portrays 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 affects their consumption, from which the Indian households are yet to fully recover. Observing their co-movement, we calculate the correlation between the aggregate consumption growth with – (a) the balance statics of question III, (b) the balance statistics of question IV, and (c) the ICS to assess their interrelationship. We find, correlation coefficients are positive, and significant at the 1% level[15]. Note, both Figure 7 as well as the lower panel of Table 1 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 next section.

[14]See, Lahiri & Zhao (2016) for the calculation of the balance statistics of sentiments.
[15]See, Correlation Matrix(Table 7) in the appendix.

4.1 The Baseline OLS Estimation

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).

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

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 excess sensitivity parameter implies the presence of the excess sensitivity of consumption to sentiments, and it also represents the violation of the PIH. 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[16]. 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 some additional controls in equation 4 to achieve consistency. We include the time dummy - *time* in equation 4 to control impact of aggregate shocks on the consumption growth of the 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 small time dimension; the inclusion of time dummy helps to achieve consistency when aggregate shocks are assumed to uniformly affect all households Chamberlain (1984). Along with this, we also control for the preference shock by including, $W_{h(t+1)}$ in equation 4 that varies across households and over time. Following Souleles (2004), we use 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[17]. First we estimate Equation 4 by OLS, and report the results in Table 2.

[16] Ludvigson (2004) argues to use the futuristic sentiments for estimating the excess sensitivity of consumption to sentiments.

[17] 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**]

Table 2 shows that, the coefficients of Q_{FP} and Q_{BC} are positive, and significant at 1% level. Table 2 further reveal that, the raw sentiments of Indian household's about their one period 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 their 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, the results of Table 2 imply that, the sentiments of Indian households contains additional information, beyond that is in the current consumption, required to predict the future consumption, which refutes the prediction of PIH as discussed above.

4.2 The GMM Estimation

Toussaint-Comeau & McGranahan (2006) argues that sentiment contains rich demographic specific information of spending pattern for the US households. Similarly, Blendon et al. (1997) argues that individuals form their sentiments mostly by processing information obtained during the conversation with their neighbors at the backyard of their house. This implies that, the geographical location of the individuals, along with their education, income, and other demographic characteristics play important role in the formation of individual sentiments. As a result, we re-estimate Equation 4 through GMM by using, Z=[*age∗time, income∗time, location, marital status, gender of household head, education, nature of occupation, log of real income*]. We have selected, Z, the instruments of Indian households from Souleles (2004) [18]. We report the results of the

[18] Souleles (2004) estimates Equation 4 by using the two-sample IV technique for the US. To do so, he obtains the data of consumption expenditure, and their sentiments from the Survey of Consumption Expenditure (CEX), and the University of Michigan Survey of Consumer Attitudes and Behavior (CAB) respectively. To match the data of two different surveys; Souleles (2004) calculates an estimated value of sentiments of the US households by regressing the their sentiments on a vector of controls, Z=[*age∗time, income∗time, location, marital status, gender of household head, education, nature of occupation, log of real income*] . Next, he estimates Equation 4 by replacing the household raw sentiments, $Q^j_{h(t+1)}$ by its estimated value, $\hat{Q}^j_{h(t+1)}$. Note, $\hat{Q}^j_{h(t+1)}$ is the part of the household sentiments explained by Z.Since, an estimated value of sentiments is used for estimation, Souleles (2004) uses the two-sample IV techniques of Angrist & Krueger (1992) for correcting the standard errors. Note, the analysis of Souleles (2004) intuitively conveys that, the part of household sentiments explained by their location, income, education and demographics matters in predicting consumption growth, instead of their raw sentiments itself. Unlike Souleles (2004), we obtain data of consumption expenditure, and sentiments for Indian households, along with their demographic characteristics from the same survey. Therefore, following Souleles (2004), and Blendon et al. (1997), we use GMM to estimate Equation 4 by using the same instruments, Z as instruments of sentiments

GMM estimation in Table 3. Comparison of the coefficients of sentiments, b_2 obtained from the GMM estimation with that of the OLS estimation of Equation 4 allows us assessing to what extent the part of the household sentiments, explained by the chosen instruments, Z outperforms the raw sentiments in predicting the consumption growth of Indian households.

[**Table 3**]

Table 3 show that, the coefficients of Q_{FP}, and Q_{BC} are positive, and they are significant at 1% level. Like our OLS estimation, the GMM estimation also represents the presence of excess sensitivity of consumption to sentiments, and the violation of the PIH as explained before. Moreover, Table 3 show 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 shows 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. A cursory comparison of the results of Table 3 with that of Table 2 show that the part of the sentiments of Indian households, explained by their geographical location, income, education, and demographics is a superior predictor of their consumption growth than the raw sentiments itself. Our results reported in Table 3 also show that, the fuel consumption of Indian households is more sensitive to the sentiments than the food consumption.

4.3 The Covid-19 Pandemic and the Role of Sentiments as Predictor of Consumption Growth

Figure 7 shows a fantastic co-movement between consumption growth and the sentiments for the pre-Covid periods. However, it is also evident from Figure 7 that such an exquisite interrelationship between consumption growth, and sentiment breaks down in the Covid-periods[19]. From Figure 7, and the lower panel of Table 1 we see that the Covid-19 pandemic has fundamentally altered the spending pattern of Indian households perhaps by influencing their income risk through changing the job prospects, and the health related risks of the households, reflected in the sluggish recovery of household sentiments

of Indian households.

[19]In our analysis, pre-Covid periods is from April, 2016 to February, 2020; and the Covid-periods is from March 2020 to October 2022.

in the Covid-periods[20]. Although consumption growth recovers faster than sentiments in the Covid-periods, both sentiment, and consumption growth remain considerably below than their corresponding pre-Covid values as depicted in Figure 7[21].

Therefore, to disentangle the impact of the Covid-19 pandemic on sentiment, consumption growth, and their interrelationship, we re-estimate Equation 4 through GMM separately for the pre-Covid periods, and the Covid-periods. The results for the pre-Covid periods and Covid-periods are reported in Table 4. For the pre-Covid periods we find that – (i) only Q_{FP} is significant at 1% level, and it explains almost 22% variation of the consumption growth of the food bundle. , (ii) both Q_{FP}, and Q_{BC} are significant at 1% level for the food & fuel bundle. It shows while, Q_{FP} explains 76.6%, Q_{BC} explains almost 75% variation of the food & fuel bundle consumption of the Indian households. Similarly, estimation of Equation 4 through GMM for the Covid-periods reported show – (i) only Q_{FP} is significant at 1% level, and it explains almost 34% variation of the consumption growth of the food bundle , (ii) It also reveal that both Q_{FP}, and Q_{BC} are significant at 1% level. It can be also noted that while, Q_{FP} explains 43%, Q_{BC} explains almost 36% variation of the consumption growth of food & fuel bundle of the Indian households.

To explain the reduced predictive capacity of sentiments note that, Covid-19 pandemic has a lasting impact on the job prospects, health conditions, and the psyche of the households as noted before. The enduring adverse impact of the Covid-19 pandemic becomes more severe for a developing country like India where, households do not enjoy the widespread and permanent safety nets of the social security schemes like the developed countries. In effect, the Covid-19 pandemic significantly changes income risk of the Indian households, which in turn considerably alters the pattern as well as the determinants of their spending decisions in the Covid-periods. The changing pattern and the determinants of the household spending decisions, and correspondingly the precautionary savings motive significantly reduces the predictive capacity of household sentiments in the Covid-periods.

[**Table 4**]

[20]Figure 8 plots the unemployment rate of India. It shows the lasting adverse impact of the Covid-19 pandemic on the job prospects of the Indian households.

[21]Pistaferri (2016) identifies a similar recovery pattern of the US consumption after the global financial crisis. He shows that, alongside sentiments, we need to control for debt and net worth of the households to explain the dynamics of post financial crisis consumption growth of the US.

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

Jappelli & Pistaferri (2017) and Christelis et al. (2016) argue about endogeneity arising from the correlation between the forecast errors of consumption growth in the Euler equation based estimation. To achieve consistency by addressing such endogeneity, they suggest to use 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 use it as one of the covariates in his estimation. Following Souleles (2004), we also calculate the forecast errors for Indian households for his 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 results 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 estimationof Equation 5 for the food bundle, and for the food & fuel bundle are reported in Table 5 and 6.

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

[**Table 5**]

[**Table 6**]

Results reported in Table 5 and 6 validate the robustness of our previous results. It shows that, the household sentiments has significant predicting power and influence business cycles, and it should be properly controlled to forecast consumption. The results of OLS and GMM estimation of Equation 5 separately for the pre-Covid periods, and Covid-periods, reported in Table 5 and 6 are characteristically identical with the results reported in Table 3, re-establishing the robustness of our results.

5 Conclusion

Identifying the determinants of sentiment, and examining its role in forecasting spending has long been 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. 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.

We show that household sentiments explained by geographical location, income level, educational attainment, and demographic characteristics are superior predictors of consumption growth compared to raw sentiment itself. Our results endorse Blendon et al. (1997), who argue that an individual's neighborhood is instrumental in forming and shaping their sentiments. We also demonstrate that (i) both future sentiments regarding household financial position and business conditions can predict consumption growth through influence on precautionary savings motives, and (ii) fuel consumption of Indian households exhibits greater sensitivity to sentiments than food consumption. We argue that, consistent with pre-pandemic patterns, sentiments should remain crucial for business cycle forecasting in post-pandemic periods, despite COVID-19 fundamentally altering spending patterns and their underlying determinants for Indian households by exerting persistent impact on the psyche of consumers. Based on our findings, we conclude that households' sentiments should be appropriately incorporated in econometric models when forecasting India's business cycle. 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 7 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. Following Pistaferri (2016), 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 COVID-period dynamics of consumption growth for India.

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Appendix

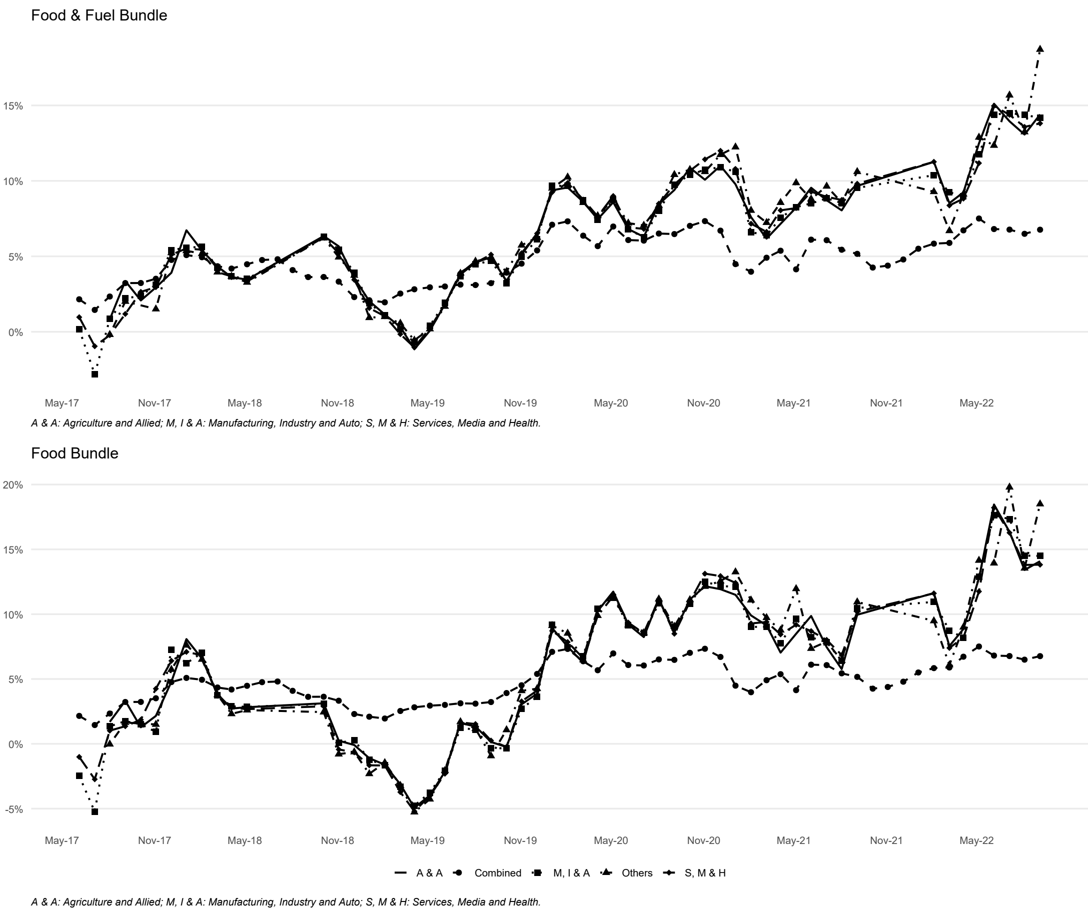

Figure 1: Cross-sectional Heterogeneity of Average Aggregate Inflation Rate, and Household Specific Inflation Rate - Households Classified in terms of Occupations of Household Head

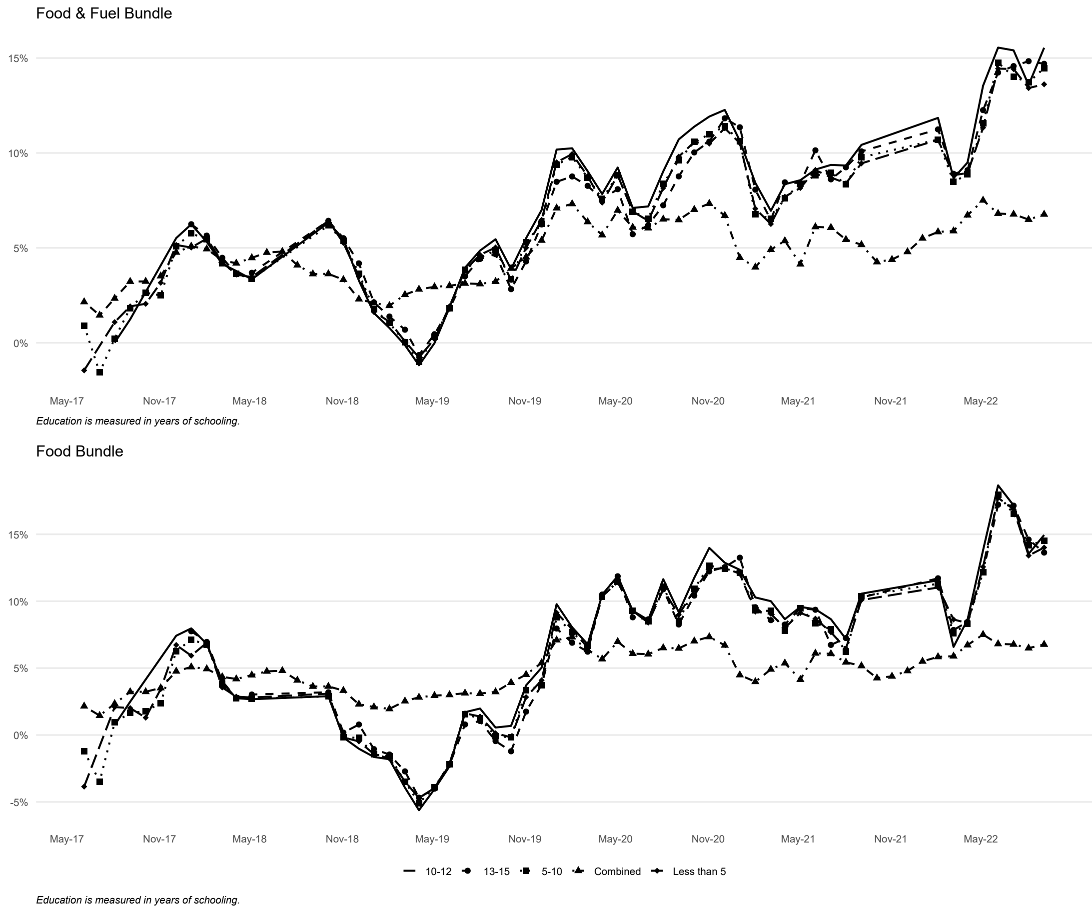

Figure 2: Cross-sectional Heterogeneity of Average Aggregate Inflation Rate, and Household Specific Inflation Rate - Households Classified in terms of Educational Attainment of Household Head

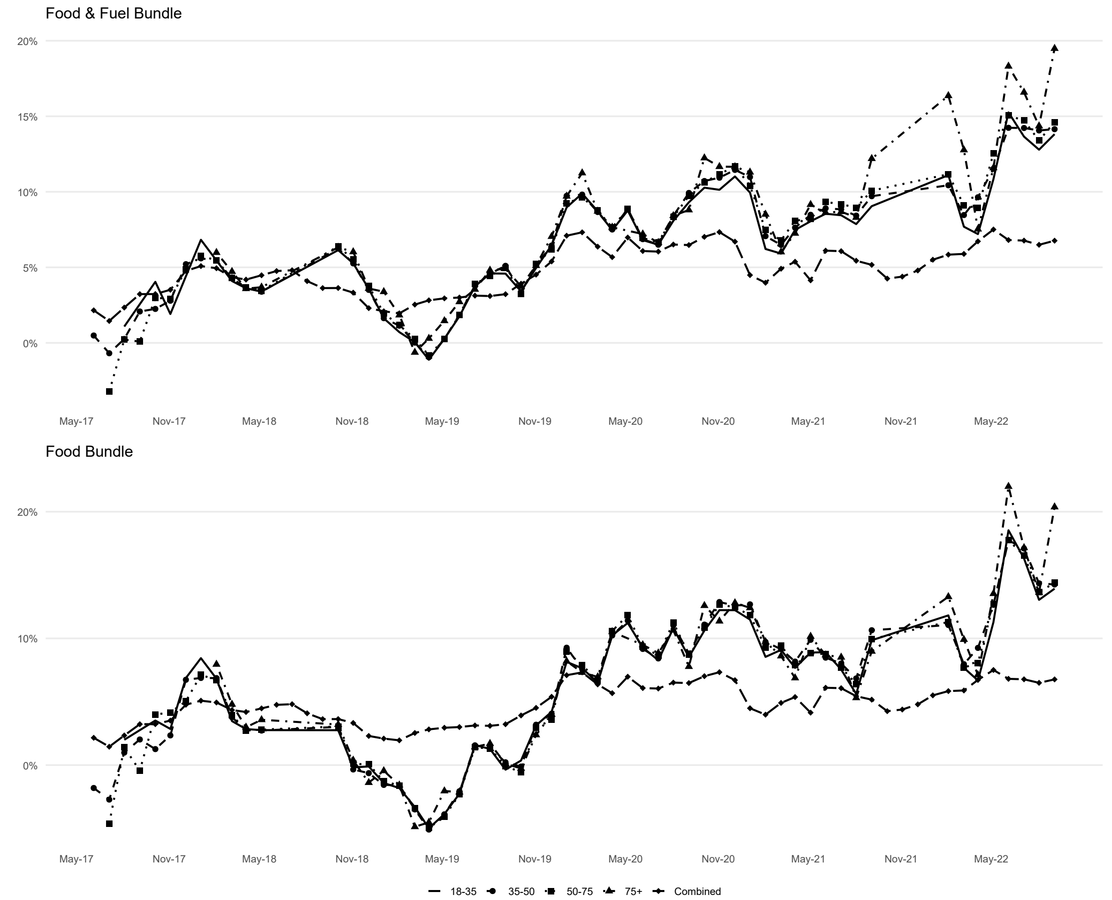

Figure 3: Cross-sectional Heterogeneity of Average Aggregate Inflation Rate, and Household Specific Inflation Rate - Households Classified in terms of Age of Household Head

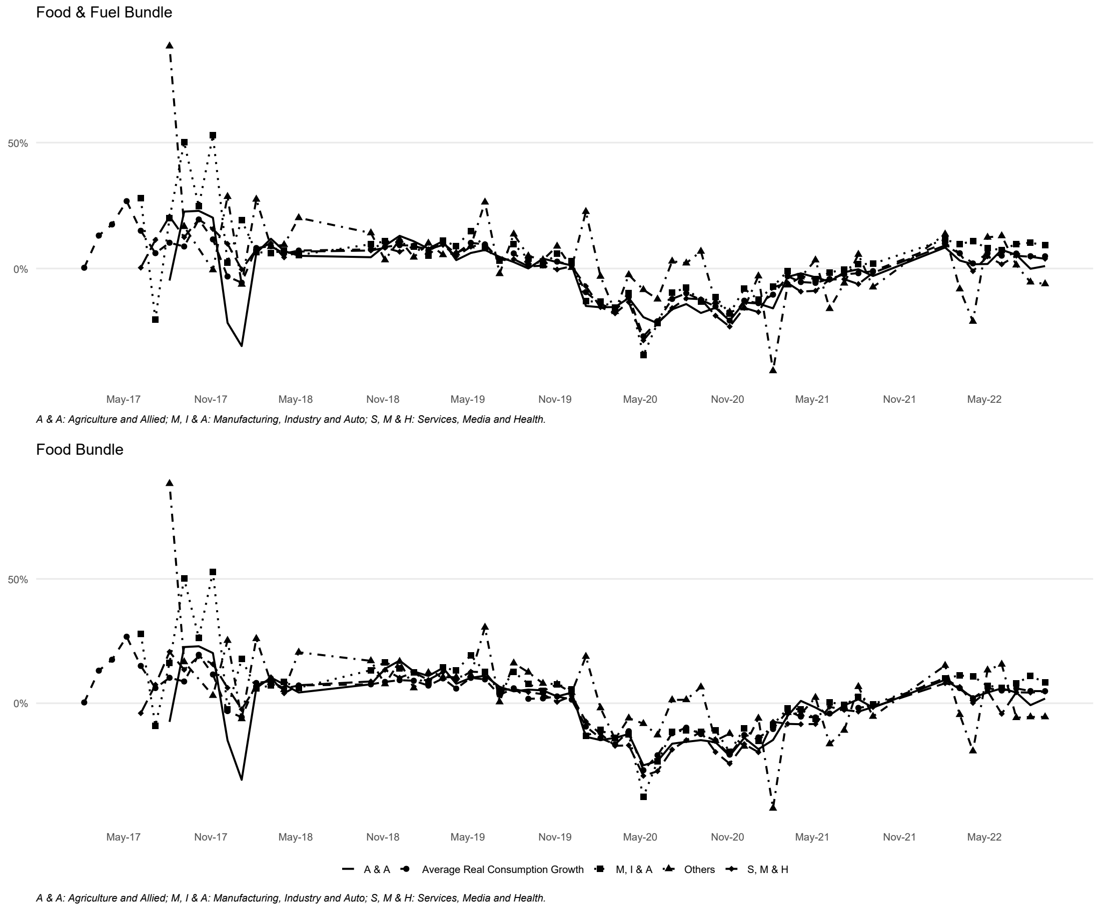

Figure 4: Cross-sectional Heterogeneity of Household Specific Consumption Growth - Households Classified in terms of Occupation of Household Head

Figure 5: Cross-sectional Heterogeneity of Household Specific Consumption Growth - Households Classified in terms of Educational Attainment of Household Head

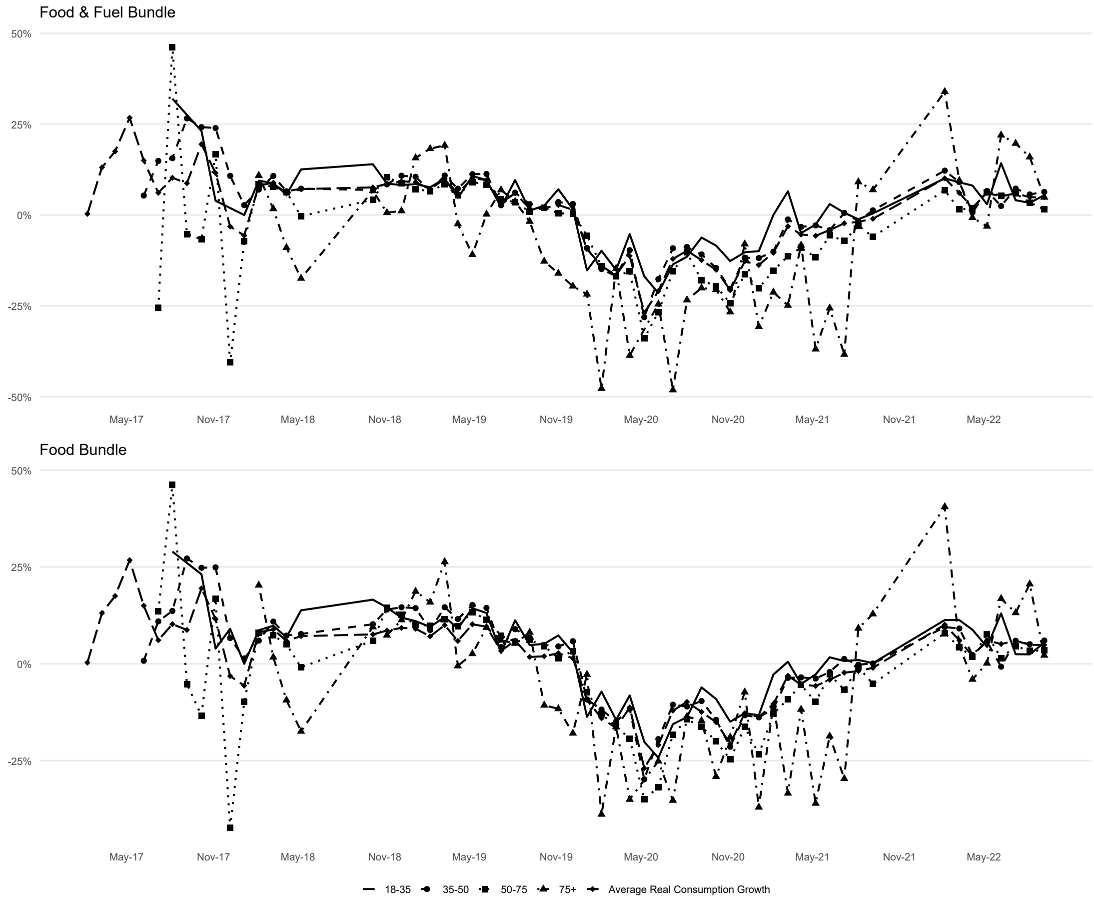

Figure 6: Cross-sectional Heterogeneity of Household Specific Consumption Growth - Households Classified in terms of Age of Household Head

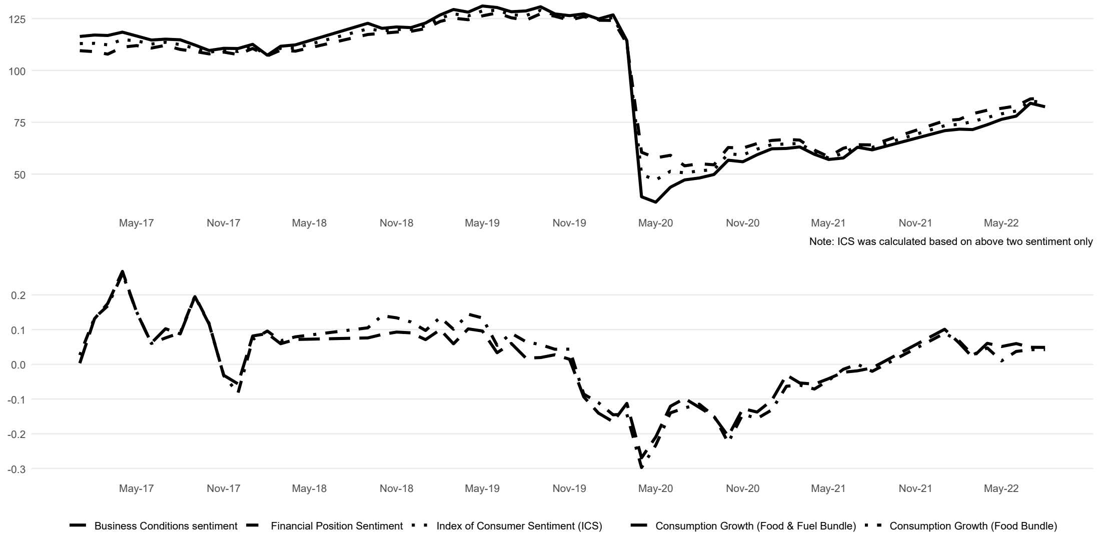

Figure 7: Index of Consumer Sentiment and Aggregate Consumption Growth

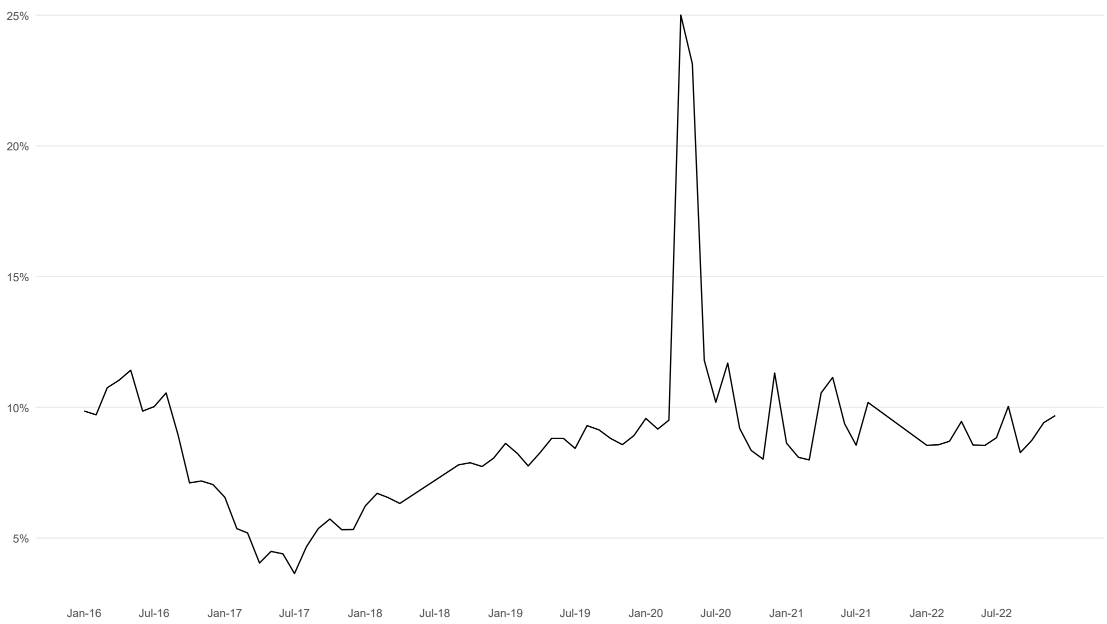

Figure 8: Unemployment Rate

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**		**Covid**	
		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	

Table 2: OLS Estimation for Food and Food & Fuel

	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) FE represents forecast errors of the financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively.

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) FE represents forecast errors of the financial position, (iv) ***, **, * represent significance at 1%, 5%, and 10% level respectively.

Table 4: GMM Estimation for Food and Food & Fuel Bundles - Pre-Covid and Covid Periods

	Pre-Covid Period (2016 April - 2020 February)				**Covid Period (2020 March - 2022 October)**			
	Food		**Food & Fuel**		**Food**		**Food & Fuel**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Q_{FP}	0.22***		0.766***		0.34***		0.43***	
	(0.01)		(0.030)		(0.05)		(0.030)	
Q_{BC}		0.20***		0.749***		0.03		0.36***
		(0.01)		(0.038)		(0.05)		(0.04)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ Kids	0.03	-0.01	0.02	-0.015	0.00	-0.04	0.01	-0.04
	(0.08)	(0.01)	(0.01)	(0.012)	(0.01)	(0.01)	(0.01)	(0.01)
Δ Adults	-0.02	0.03	-0.07	0.03	-0.01	0.00	-0.01	0.00
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,131	38,131	38,131	38,131	17,400	17,400	17,400	17,400

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 5: Estimation for Food Bundle and Food & Fuel Bundle after Controlling for Forecast Error

	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 - Pre-Covid and Covid Periods after controlling for forecast errors

	Pre-Covid (2016 April - 2020 February)		**Covid (2020 March - 2022 October)**	
	Food	Food & Fuel	Food	Food & Fuel
Q_{FP}	0.25***	0.717***	0.31***	0.20***
	(0.002)	(0.030)	(0.06)	(0.06)
FE_{FP}	0.613***	0.613***	0.42***	0.68***
	(0.061)	(0.061)	(0.009)	(0.061)
Age	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Δ Kids	0.017	0.017	-0.03	-0.03
	(0.012)	(0.012)	(0.02)	(0.02)
Δ Adults	-0.009	-0.009**	-0.01	-0.01**
	(0.71)	(0.71)	(0.06)	(0.06)
Time Dummies	Yes	Yes	Yes	Yes
Observations	37,717	37,717	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 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 7: 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***	–