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Neha Bairoliya, Areendam Chanda, Jingyi Fang and Fang Yang

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Household Consumption and Savings over the Life Cycle: The Roles of Demographics and Durables*

Neha Bairoliya†, Areendam Chanda‡, Jingyi Fang§ and Fang Yang‡

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Abstract

The canonical prediction of life-cycle models, that individuals smooth consumption over their lifetime, has been mostly tested for developed countries and found little empirical support. We provide a novel, developing country perspective by analyzing patterns of life-cycle consumption, income, and savings rates in India. In contrast to the U.S., Indian households exhibit no growth in nondurable consumption expenditures after adjusting for family size. We present evidence that saving for lumpy investments in consumer durables is a key driver of high savings rates and flat nondurable consumption over the life cycle in India.

Keywords: consumption, savings rate, demographics, life-cycle, durables, asset accumulation, household heterogeneity, panel data, pseudopanel, equivalence scales.

JEL Classification: E21, J10

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†Neha Bairoliya, University of Southern California, Department of Finance and Business Economics, Los Angeles, CA 90089-1422, USA. Email: Neha.Bairoliya@marshall.usc.edu

‡Areendam Chanda, Louisiana State University, Department of Economics, Baton Rouge, LA 70803, USA. Email: achanda@lsu.edu

§Jingyi Fang, Federal Reserve Bank of Minneapolis, USA. Email: jingyi.fang@mpls.frb.org

‡Fang Yang, Federal Reserve Bank of Dallas, USA. Email: fang.yang@dal.frb.org

1 Introduction

The canonical life-cycle model remains central to the study of household consumption and the aggregate economy. In its simplest form, it predicts that forward-looking agents perfectly smooth consumption over time, yet a large empirical literature shows otherwise: a hump-shaped life-cycle profile of consumption is one of the most robust facts, a finding that goes back at least to Thurow (1969). On the theory side, a seminal contribution by Gourinchas and Parker (2002) shows that uninsurable permanent income risk, borrowing limits, and realistic income profiles naturally generate buffer-stock behavior and a hump in consumption without violating rational expectations. On the empirical side, using U.S. Consumer Expenditure Survey data, Fernández-Villaverde and Krueger (2007) document that this hump characterizes total expenditures, nondurables, and durables even after adjusting for family size. Subsequent work enriches the life-cycle framework along several dimensions—the absence of annuities and the role of bequests (Hansen and İmrohoroğlu, 2008), family demographics (Browning and Ejrnæs, 2009), housing collateral and nondurable consumption (Yang, 2009), durables (Fernández-Villaverde and Krueger, 2011), distinctions between work- and non-work-related expenditures (Aguiar and Hurst, 2013), home production (Dotsey et al., 2014), and loss aversion (Pagel, 2017). Beyond the U.S., a lack of consumption smoothing has also been documented in the U.K. (Browning et al., 2016; Browning and Ejrnæs, 2009), the Netherlands (Alessie and de Ree, 2009), and Portugal (Alexandre et al., 2020).

Most existing evidence, however, has focused on either the U.S. or other high-income countries. This dearth of research in low- and middle-income countries can be attributed to a number of factors, one of which is the lack of reliable household survey data. Furthermore, subsistence incomes combined with historically tepid growth led researchers to focus primarily on the short-run implications of weather, policy, and other exogenous shocks on consumption and other outcomes, especially for rural households. An exception is China, where increasing availability of household surveys has enabled a growing literature on consumption, saving, and their interaction with demographics.[1]

We fill this gap for India by providing, to our knowledge, the first estimates of life-cycle profiles of consumption and saving based on a nationally representative household survey, the Consumer Pyramids Household Survey (CPHS). The survey covers 98.5% of the population and interviews more than 150,000 households every four months, recording detailed expenditures, incomes, indicators for a range of assets and liabilities, and demographic data. This makes it possible for the first time to understand these life-cycle behaviors of Indian households and to explore key margins of heterogeneity.

In the first part of this paper, we build on the established research by investigating the extent of consumption smoothing over the life cycle of Indian households. We pay attention to nondurable consumption expenditures, examine their profile, and determine the extent to which they track household income. To provide a comparative perspective, we construct similar profiles for U.S. households using data from the Panel Study of Income Dynamics (PSID) which has served as the foundation for many of the theoretical advancements in this field.

Before adjusting for demographic factors, we find the life-cycle profile of household consumption in India to be hump-shaped, roughly comparable to the U.S., though the hump is slightly

[1] See, among others, Bairoliya et al. (2018); Bairoliya and Miller (2020, 2021); Chamon et al. (2013); Curtis et al. (2015); İmrohoroğlu and Zhao (2018); Wei and Zhang (2011).

smaller. However, once we adjust for demographic factors, this similarity disappears. Unlike the U.S., where households continue to exhibit consumption growth in the early half of the life cycle after adjusting for demographics, Indian households exhibit almost no consumption growth. In short, family demographics play a much larger role in India than in the U.S. These results are robust to a wide range of checks, including alternative definitions of the household head, different equivalence scales, accounting for home production using both our CPHS data and the Indian Time Use Survey, extending the CPHS panel through 2022, and alternative estimation strategies.

These empirical findings pose a central puzzle: family-size–adjusted nondurable consumption in India is essentially flat, even though the mechanisms typically used to explain hump-shaped profiles in rich countries—precautionary saving, liquidity constraints, and income risk—are, if anything, more salient in a developing-country setting. The puzzle is not resolved by income: average household income in India rises substantially over the life cycle—by roughly 106% compared with about 100% in the U.S.—but it grows more slowly and peaks much later (around age 55 versus age 45 in the U.S.).

In the second part of the paper, we use insights from a life-cycle framework with durables and borrowing constraints and offer a potential explanation to this puzzle. Its two workhorse conditions—the nondurable Euler with an occasionally binding borrowing constraint and the durable user-cost condition with lumpy adjustment—yield testable implications that are supported by the data.

First, using comprehensive information on major and minor purchases (cars, tractors, cattle, and other durables), we construct a measure of durable stock and show that it rises steeply—about 120%—over the life cycle, consistent with lumpy, self-financed adjustment. Second, stated purchase intentions predict higher subsequent saving, and event-time profiles show savings rates increasing before purchases and declining afterward; very few households borrow from banks to finance these goods. Third and finally, we document heterogeneity consistent with credit access: urban and nuclear households display faster growth in family-size–adjusted nondurables and earlier durable accumulation than rural and extended households.

The interaction of later income growth and credit frictions thus reallocates the life-cycle surplus—realized late—toward durables rather than toward higher per-adult-equivalent nondurable spending. Measured nondurables remain flat even as living standards improve through the service flow from durables (better housing, transport, and appliances). By contrast, U.S. households reach peak income earlier and face deeper credit markets. They can borrow against steeper near-term income growth, finance durables on credit, and allow adjusted nondurables to rise through midlife. Taken together, durable indivisibilities, tight credit, and late income peaks—combined with buffer-stock motives—provide a plausible explanation for why adjusted nondurable consumption in India exhibits little growth over the life cycle despite large increases in income and saving.

To summarize, we provide a perspective that is not only different from that observed in high-income countries but also sheds new light on how lack of access to credit markets might interact with the timing of consumption, especially in the case of lumpy durables in creating a flat consumption profile despite growth in income. The rest of the paper is organized as follows: Section 2 discusses some of the related literature for India, China, and other developing countries and section 3 describes the data used in our analysis. In section 4, we explore life-cycle patterns of consumption, income and savings rates in detail. Section 5 presents a theoretical setup and supporting empirical analysis. Returning to life-cycle profiles, in section 6 we undertake a variety of robustness exercises. Finally, section 7 discusses unresolved issues, outlines future research directions,

and provides concluding remarks.

2 Background and Related Literature

In the context of research on developing economies, our study complements a substantial body of work on China. Chamon and Prasad (2010) provide a seminal analysis documenting the absence of consumption smoothing even after controlling for demographic factors and the close correlation between income and consumption for all cohorts over the life cycle. A distinctive feature of the Chinese experience is the inverted U-shaped profile of the savings rate, which has been attributed to rising income uncertainty, policy reforms, gender imbalances, and the marriage market (Chamon et al., 2013; Du and Wei, 2013; Nie, 2020; Wei and Zhang, 2011). Curtis et al. (2015) provide evidence that simple demographics along the life cycle can explain the U-shape. Unlike China, we do not find any evidence of a U-shape for India. Beyond China, the literature is limited. De Magalhães and Santaeulàlia-Llopis (2018) examine panel data from Malawi and note that households have relatively flat consumption profiles and do not accumulate wealth over the life cycle. The contrasting results between China, a high growth country where households depress consumption at the beginning of the life cycle to accumulate assets, and Malawi, a low growth country, where consumption stays relatively flat with little or no asset accumulation, provides additional motivation for our analysis.

When it comes to India, there is a large literature on how households insure against income shocks and also the determinants of consumption-based measures of poverty. Much less attention, if any at all, has been paid to life-cycle behavior. This is both by design and due to data limitations. Rosenzweig (2001) notes that households in developing countries generally tend to save more for precautionary (high-frequency, i.e., seasonal shocks) rather than for life-cycle reasons. Large short-term income volatility combined with lack of access to formal credit and insurance markets historically means that any asset accumulation is also quickly depleted.[2] The inter-generational nature of households also makes computing life-cycle savings challenging (Deaton and Paxson, 2000). Furthermore, households substitute high fertility rates for old-age savings. From a data standpoint, widely used surveys on consumption expenditures such as the National Sample Survey Office (NSSO) do not record income measures, and are not longitudinal. While some of these concerns remain valid, the emergence of a large middle class (or at the very least, a large section of the population emerging out of poverty), provides additional rationale for our research.[3]

As far as a macro perspective is concerned, the research is much thinner. Badarinza et al. (2017) exploit a 2013 NSSO cross-sectional survey on investment and debt among Indian households to provide a comprehensive overview of the nature of assets and liabilities. They note that the average household holds 77% of its total assets in real estate — a number higher than the 62% in China — and only 5% in financial assets. They also note that these numbers stay remarkably stable over the life cycle and households have little or no retirement assets. A recent official summary of the 2019 round of the same survey indicates even higher numbers. Real estate comprises 77% of assets in urban India and 91% in rural India.[4]

[2]The extent – and the methods used – to which farming households are able to insure against such shocks has been extensively debated going back to Rosenzweig and Wolpin (1993).

[3]See Kapur et al. (2017) on the middle class in India.

[4]The results from the 2019 survey are compiled in Government of India (GOI) (2021). Formal sector employees

3 Data

3.1 Consumer Pyramids Household Survey

The CPHS is a nationally representative longitudinal survey where each household's information is recorded triannually (once every four months). Approximately 158,000-165,000 households were interviewed in each wave during the period of our analysis, 2014-2019. Households are asked detailed questions about their monthly expenditure and income, or in the case of durables, assets, and liabilities – indicators about ownership, intentions, and purchases – over the previous four months. Additionally, the survey records demographic and income information for each household member, along with employment status, expectations about the economy, and perceived financial well-being. Over the past few years, researchers have increasingly relied on the data to study household responses to important macro events in India such as demonetization in 2016 (e.g. Chanda and Cook (2022); Chodorow-Reich et al. (2020); Karmakar and Narayanan (2020), and Lahiri (2020)). More recently, the data has been used to investigate the effects of the COVID-19 pandemic (Anand et al., 2021; Gupta et al., 2021; Malani and Ramachandran, 2022; Mohanan et al., 2021). Researchers have also employed the data to study a range of topics from financial inclusion (Agarwal et al., 2021) to labor-market participation (Deshpande and Singh, 2021). Roy and Van Der Weide (2025) synthesize the CPHS with earlier releases of government conducted household expenditure surveys to create recent estimates of poverty. The survey represents 98.5% of the total population in India, and about two-thirds of the respondents live in urban areas and one-third live in rural areas. While this is the opposite of the actual composition of the Indian population, survey weights are designed so that the aggregate values are representative of the entire country.[5]

How comparable are the CPHS survey estimates to other measures of consumption expenditures and incomes? While detailed survey data on incomes are hard to come by, we can compare consumption expenditures.[6] A 2014-15 survey of durable goods and services also asks a question on total household consumption expenditures (Government of India (GOI), 2016). The monthly household consumption expenditures from the 2014 CPHS surveys can be compared to these. The latter values for India as a whole, rural, and urban households were INR 7,951 (USD 550), INR 6,802 (USD 471) and INR 10,270 (USD 711) respectively. These are 97%, 102%, and 91% of the government survey counterparts – surprisingly close numbers.[7] Another way to evaluate reliability is to look at growth rates. The per-capita real consumption expenditure growth was 6.7%, which

in India are required to contribute 12% of their salaries to their "provident fund," analogous to a funded social security system. However, 90% of the labor force remains in the informal/unorganized sector.

[5]The rationale for surveying more urban households is due to the larger heterogeneity in this population. Vyas (2020) provides a useful introduction to the survey.

[6]The Indian government withheld the release of the 2017-18 round of the consumption expenditure survey due to concerns regarding the estimated expenditures being lower than their earlier 2011-12 survey. Researchers have also relied on Rural Economic & Demographic Survey (REDS), a rural panel of households. Apart from being rural and a relatively smaller sample (about 9000), REDS was last conducted in 2006. Another survey is the IHDS by the University of Maryland. It was conducted in both 2004-05 and 2011-12, and has a panel component.

[7]While a precise mapping of sub-categories is difficult, we find that the nondurable expenditures were also 97%, 99%, and 91% respectively. This is especially reassuring given some questions raised regarding the survey recently by Somanchi (2021). One of the concerns is that estimated consumption of rural households might be too high, while income might be too low. Even if this concern is valid, it would actually reinforce our finding of high savings rates. Gupta et al. (2021) and Roy and Van Der Weide (2025) also address some of the concerns.

was only a little higher than the national accounts per-capita private consumption expenditure growth of 6.2%.

The CPHS is comprised of several modules. This study draws on the Expenditures, Incomes (household and individual), Assets and Liabilities, and the People of India (household member demographics and socioeconomic characteristics) modules. From the expenditure categories, we construct a measure of nondurable consumption that includes expenditures on food, intoxicants, clothing & footwear, cosmetics & toiletries, recreation, restaurants, rent & bills, power & fuel, transport, health, education, and miscellaneous expenses.[8] The idea is to stay as close as possible to the PSID equivalent of nondurable expenditures. Households also report total income as well as income contributed by each household member in every wave. Later in the paper, we use wealth indicators like reported intentions to purchase major durables such as houses, cars, two-wheelers, tractors, cattle, etc., as well as actual reported purchases to analyze their implications for savings behavior. Finally, we use information from the "People of India" module of the survey to understand the demographic structure and living arrangements of Indian households. In particular, we utilize information on total family size, age, and each individual's relationship to the head of the household.

In order to construct our sample, we first merge all wave-year files (2014 to 2019) for household income and expenses.[9] In each wave, households are required to report income and expenditure information for the previous four months, giving us household-month-year level data. Since previous literature using this data has found little variation in expenditures at the month level for a given wave, we only use average monthly expenditures for each wave, giving us a household-wave-year level dataset. Next, we merge all the wave-year files for the "People of India" module containing demographic information for each household member in each wave-year.[10] Table 1 provides some summary statistics that we discuss further below, after explaining the U.S. PSID data.

3.2 Panel Study of Income Dynamics

PSID is a well-known longitudinal dataset which started in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 households in the U.S., and who were followed annually through 1997 and biennially thereafter.[11] The survey contains detailed information on earnings, expenditures, and employment. Historically, PSID only collected information on food and housing expenditures. However, starting in 1999, it also started adding questions about spending on transportation, healthcare, education, utilities, and childcare. Expenditures are reported weekly, monthly, or yearly depending on the spending categories. The non-response rate is fairly low in the PSID, and together with its long panel structure, has made it an attractive dataset for studying life-cycle facts about American households. For our analysis, we use data in the 2005 to 2017 surveys, consistent with our India surveys.

[8] Two categories are excluded - appliances and equal monthly installments. The appliance category, despite its name, also records expenditures on a host of durable electronic goods. EMIs mostly reflect payments on loans for homes, vehicles, and other durables.

[9] Although our subscription to the data extended through 2022, we restrict our main analysis to 2014–2019 to avoid confounding from the COVID-19 pandemic and related measurement disruptions. We report robustness exercises using the full sample through 2022 in Section 6.

[10] Non-response rate averages about 15%. Attrition with such a large and frequent survey is certainly a problem, though approximately 100,000 households answered the survey for at least 14 out of the 17 waves that we cover.

[11] The survey was conducted annually between 1968 and 1997 and biennially since then.

Table 1 compares summary statistics of household expenditures and income for both India and the U.S. Columns 2 and 4 provide annual expenditures and income (converted to USD PPP for India) for both countries and columns 3 and 5 compare the share of major consumption categories as a fraction of total nondurable consumption expenditures. A few important differences become obvious. In India, food takes up a little more than half of all nondurable expenditures, whereas for the U.S., this is only 22%. Interestingly, non-mortgage housing-related expenditure shares that include rent, utilities, and communications are roughly the same in both countries. Transportation and health care, unsurprisingly, account for much larger shares in the U.S. Appendix Section A provides a detailed discussion about each expenditure category for both countries.

With respect to demographics, the age of the household head is higher in our Indian sample. Given that India is a younger population, this reflects the importance of extended households. Within extended households, the nominal head might be a patriarch and not the main earner or the financial decision maker. In our robustness section, we re-examine life-cycle profiles by redefining the head of household to be the primary male earner. Lastly, the family-size and OECD adult-equivalent scales differences between the two countries are as expected.

Table 1: Comparison of PSID and CPHS datasets

	CPHS		PSID	
	Mean	Fraction	Mean	Fraction
Age of household head	50.02		47.14	
Annual income	12,216.55		76,665.31	
Annual expenditures	8,476.09		38,388.44	
Food	3,472.57	0.54	7,860.95	0.22
Non-mortgage housing	1,473.57	0.21	8,377.49	0.27
Transport	1,869.79	0.03	9,722.70	0.24
Health	176.52	0.02	3,326.08	0.08
Education	279.83	0.03	1,399.44	0.02
Clothing	779.55	0.11	1,554.67	0.04
Recreation	37.88	0.00	2,613.33	0.06
Family size	4.09		2.31	
OECD scale	2.34		1.49	
Adjusted expenditures	3,955.65		26,243.38	
Observations	974442	974442	61005	61005

Notes: The expenditure data for CPHS is in USD PPP converted values. Non-mortgage housing expenses in PSID include rent, utilities, internet charges etc.; the housing category in CPHS includes housing, power, and communication fees. Others in PSID include repairs and furnishing expenses; others in CPHS include miscellaneous expenditures. Adjusted expenditures are annual expenditures divided by the OECD adult equivalent scale.

4 Life-Cycle Patterns

4.1 Identification and estimation of the age effects

In order to use the identification strategy proposed by Deaton (1985), we treat each panel of the CPHS data as repeated cross sections and build a pseudo–panel that mitigates attrition and obviates individual fixed effects by aggregating across agents. Households are assigned to birth–cohort bins using the age of the household head. We use ten five–year bins, chosen to balance granularity with precision. Cell sizes are large enough that sample means are reliable estimates of population moments. For each cohort c, period t (year $\times$ wave), and the implied age a_{ct}, we form population–weighted cell means to obtain a balanced pseudo–panel $\{c_{ct}, a_{ct}\}$, where c_{ct} is the cohort–period mean of the variable of interest (log consumption, savings rate, or log earnings). Let u_{ct} denote a mean–zero disturbance.

The above three ingredients in our setting — age, calendar period and birth cohort (APC) —are linked by an exact identity: the age of a cohort in period t equals 'period minus cohort', that is, $a_{ct} = t - \text{cohort}_c$. If one were to include a fully flexible age effect, a full set of period indicators, and a full set of cohort indicators in a single regression, these regressors would be perfectly collinear (the so–called APC identification problem). To break this linear dependence in a transparent way, we follow Fernández-Villaverde and Krueger (2007) and impose simple normalizations: (i) attribute the aggregate linear drift in outcomes to calendar time, and (ii) the remaining period indicators are stripped of any overall level and linear trend. Concretely, let t be a scalar time index, and we construct a vector of period deviations $\tilde{\mathbf{d}}_t$ by projecting each period dummy onto $\{1, t\}$ and taking the residual. We also include cohort indicators $\mathbf{1}\{c = k\}$ with one base cohort k_0 omitted to anchor levels. We then estimate the following partially linear specification:

$$c_{ct} = \underbrace{g(a_{ct})}_{\text{nonparametric age}} + \underbrace{\beta\, t}_{\text{linear time drift}} + \underbrace{\tilde{\mathbf{d}}_t' \boldsymbol{\lambda}}_{\substack{\text{period effects orthogonal} \\ \text{to level and trend}}} + \underbrace{\sum_{k \neq k_0} \gamma_k \, \mathbf{1}\{c = k\}}_{\text{cohort differences (base } k_0)} + u_{ct}, \qquad (1)$$

where $g(\cdot)$ is an unknown smooth function. The orthogonality restrictions for each column j of $\tilde{\mathbf{d}}_t$ are $\sum_t \tilde{d}_{tj} = 0$ and $\sum_t t\, \tilde{d}_{tj} = 0$ (weighted by cell size), so that β exhausts the linear time drift and $\tilde{\mathbf{d}}_t$ captures only mean–zero, trend–free fluctuations. We omit one cohort to fix the overall level; all cohort coefficients are interpreted relative to the omitted cohort. With these restrictions, $g(\cdot)$ is identified up to an additive constant, which we fix by evaluating at a reference period; we report the age profile at the sample–mean period $\bar{t}$ and the base cohort.

We estimate (1) using the Robinson (1988) double–residual (partially linear) estimator: we non-parametrically partial out age via kernel regression and estimate the parametric block $(\beta, \boldsymbol{\lambda}, \boldsymbol{\gamma})$ by OLS on residuals; the age function is then recovered as $\hat{g}(a) = \widehat{E[c \mid a]} - \widehat{E[X \mid a]}\hat{\beta}$, where X collects the parametric controls. In practice we implement this with `semipar` in STATA, using pseudo–panel cell sizes as analytic/frequency weights when forming conditional means and the period–deviation normalization. We validate the results with several robustness exercises: (i) replacing the kernel smoother for $g(\cdot)$ with flexible cubic splines (varying knot number and placement), (ii) re–estimating via the Speckman (1988) two–step partially linear estimator, and (iii) using a longer panel to estimate these effects. These checks yield substantively similar age profiles.

In the next sub-section, we discuss our key empirical findings related to life-cycle patterns in consumption, compare them to the U.S., and explore three major sources of heterogeneity – family type (nuclear/extended), region (urban/rural), and occupation. We then move on to income and savings rates for Indian households to get a comprehensive understanding of how the evolution of income and consumption spending differs from that of a developed country like the U.S.

4.2 Consumption

Figure 1 compares the evolution of life-cycle consumption in Indian and American households.[12] Panel (a) shows that while total household consumption grows by roughly 50% (as compared to age 25) for U.S. households, it grows by roughly 42% for Indian households.[13] Next, we adjust total household expenditures using OECD equivalents to understand the importance of changes in family size and age composition in determining the growth in consumption. In other words, we would like to understand how much of the growth in total household consumption is due to the fact that households may get bigger in size over the life cycle (as proxied by the age of the household head) due to the presence of spouse, children, parents, and other family members. We find that U.S. household consumption grows by more than 30% after adjusting for demographics. These findings are consistent with previous literature that has looked at consumption growth for U.S. households using the CEX and the PSID. However, a surprising finding for India is that almost all the growth in life-cycle consumption seems to be driven by changes in household size and composition. After adjusting for that, consumption growth declines from 42% to 8.3%, as seen in panel (b) of Figure 1. These results, as well as the subsequent ones in this sub-section, are summarized in Table 2.

Table 2: Life-Cycle Growth in Consumption and Savings in India

		Region		Family Type		Occupation		
	Average	Urban	Rural	Nuclear	Extended	Farmers	Self-Emp.	White Collar
Consumption								
Unadjusted (%)	42.09	44.43	35.52	51.03	29.35	29.75	43.40	42.27
Adjusted (%)	8.32	10.48	5.02	15.82	8.30	0.76	11.04	5.63
Saving rate (p.p.)	26.57	29.45	23.24	27.12	15.49	27.29	29.77	30.76

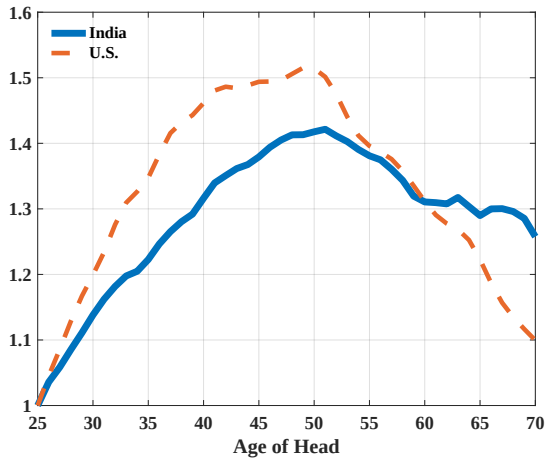
Notes: For consumption, the table reports the percent growth in life-cycle consumption or the statistic $\left[\frac{y_{peak}}{y_{25}} - 1\right] * 100$ where y is household's consumption of non durable goods and services, y_{peak} is the peak value of y over the life cycle (between ages 25 and 70), and y_{25} is the value of y at age 25. Adjusted consumption refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16. For savings rates, the percentage points difference between the peak savings rate (between ages 30 and 70) and the savings rate at age 30 is reported.

[12] Refer to column 1 of Appendix Tables D.1 and D.2 for time and birth cohort effects for Indian and U.S. households, respectively.

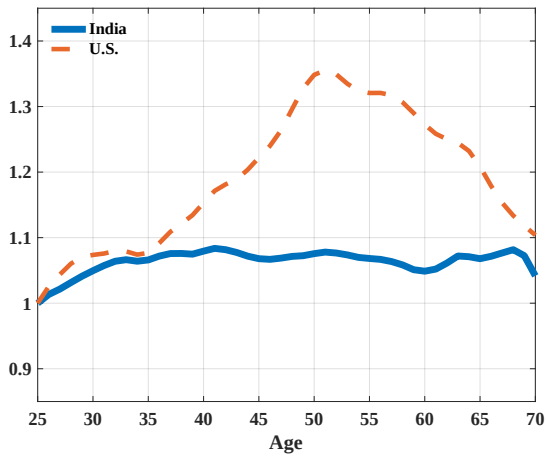
[13] We net out payments towards property taxes and mortgage from the PSID to have a more comparable measure with that of Indian household consumption. Figure D.1 in the appendix provides estimates of growth in consumption in the U.S. using total reported household expenditures in the PSID and the measure of expenditures constructed in this analysis by netting out mortgage payments, property taxes, etc.

Figure 1: Life-Cycle Consumption
by Age of Household Head

(a) Unadjusted



(b) Adjusted



Notes: Household consumption relative to age 25 (household head) is reported for both the U.S. and India. Data for the U.S. comes from the PSID. "Adjusted" refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child aged 16 or younger, and 0.5 to each adult over the age of 16. Expenditure categories include total expenditures on food, transportation, education, childcare, healthcare, clothing, household repairs and furnishing, trips and recreational activities, and housing (rent, utility, telephone and internet).

In order to understand these striking differences between India and the U.S., we look further into the demographic structure of households in both countries. Panels (a) and (b) of Figure 2 shows a comparison in terms of both the total family size and the number of children, both of which affect how household consumption gets scaled. There are interesting differences between the two countries that are worth noting. First, Indian households are on average larger than U.S. households all through the life cycle (average family size in the former is roughly double that of the latter between ages 50 and 59). Second, changes in family size are more pronounced for the latter as compared to the former. Finally, the distribution of children over the life cycle of the household differs in non-trivial ways for the two countries. While U.S. households, after an initial increase in the number of children between ages 20 and 40, experience a constant decline over the remaining life, Indian households experience a second, somewhat less prominent hump in the later part. This is due to the presence of grandchildren in extended families. Extended families, including parents and children from outside the nuclear family, are common in Asia, the Middle East, Central/South America, and sub-Saharan Africa, but not in other regions of the world such as North America or Western Europe (Scott et al., 2015).[14]

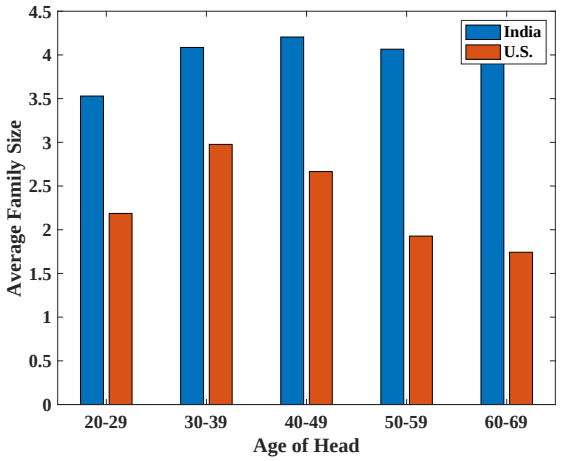
These structural differences have direct implications for converting household consumption to adult-equivalent consumption. Panel (c) of Figure 2 plots the size of the adult equivalent using

[14]In this paper, we adhere to the common practice of defining a nuclear family as a basic social unit including a couple and their dependent children only. Appendix tables D.3 and D.4 provide details about the likelihood of the presence of different types of family members as well as their average number, respectively, for Indian households.

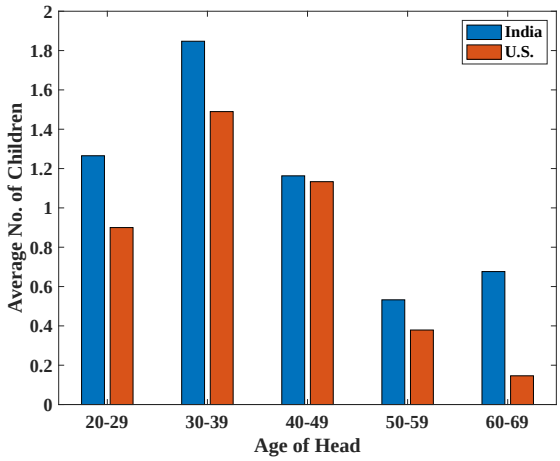
the OECD equivalence scale (relative to ages 20–29). In the United States the scale peaks around ages 30–40 and then declines sharply; in India it continues to rise at later ages because presence of intergenerational families keeps household size elevated.

Figure 2: Household Composition
by Age of Household Head

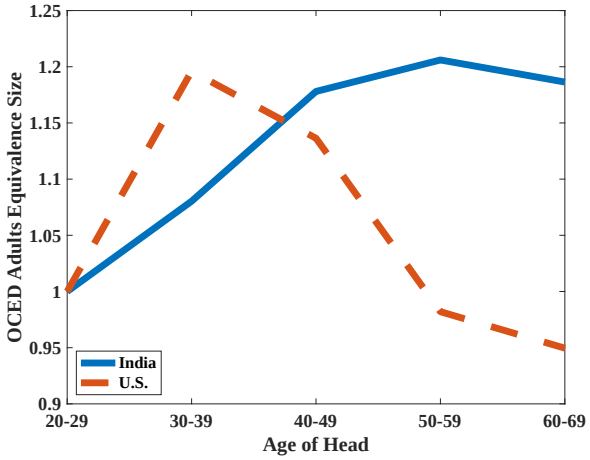
(a) Family Size



(b) Children



(c) OECD scale



Notes: Data for the U.S. comes from the PSID. Children are defined as members living within a household under the age of 18. The OECD adult equivalence scale in panel (c) assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16.

4.2.1 Heterogeneity Across Sub-Groups

To understand if the Indian results are driven by specific sub-groups, we look at differences across households along three key dimensions: nuclear vs. extended families, rural vs. urban

households, and occupational differences. These margins of heterogeneity are important from two different standpoints: demographics (like in extended vs. nuclear families) and level of financial inclusion (like in urban/rural or farming/non-farming households).

Panel (a) of Figure 3 displays the evolution of nondurable consumption for nuclear and extended families. In contrast to our finding that for the representative household, consumption peaks around age 50, we see that there exists substantial differences in the pattern of consumption growth between the two family types. Nuclear families exhibit a markedly steeper lifecycle profile: peak consumption is about 51% above the age-25 level, compared to 29.3% for extended families. The timing also diverges. For nuclear families, the peak occurs around age 50 (similar to the aggregate), whereas for extended families the profile rises more gradually and peaks much later. In the latter case, consumption increases monotonically over the observed ages, consistent with the dynamics of large multi-generational households. To further investigate this, we repeat the exercise after adjusting for family size using the OECD scale. We present the results in Figure 3b. Adjusted consumption now shows a perceptible decline that bottoms out at middle age before increasing again. This may reflect the possibility that an extended family with a head of household at age 45 has parents who are no longer earners, while those households with heads at age 60 or more may still be earning while so are their cohabiting adult children.[15] It may also reflect some increasing returns to being in a joint family. However, note that expenditures here include only nondurables and services. Other than utility expenses, most of the benefits of joint consumption are likely to come from durables.

Beyond inter-generational families, households in India also insure against income shocks by relying on local networks in the absence of formal institutions. Particularly important are caste networks (Munshi and Rosenzweig, 2016). While informal networks can exist in both rural and urban areas, the likelihood is much stronger for the former, where seasonal fluctuations in incomes are also more salient. In the next set of figures, we examine whether consumption smoothing is different for rural and urban households. Figure 3c displays the consumption paths for the two groups along the life cycle. As expected, urban households experience much faster growth (44.4%) compared to rural households (35.5%) with the former almost comparable to the peak values for the U.S. However, once we adjust for family size, the relatively flat profile resurfaces (Figure 3d). In the case of urban households, there is still a slight but noticeable increase in the early years, while in the case of rural households, there is initially a flat, followed by a declining consumption profile toward the later years.

Finally, we look at the heterogeneity in consumption growth across different occupations of the household head. In particular, we explore life-cycle consumption patterns for three distinct groups: farmers, self-employed, and white-collar workers.[16] As the nature of income growth might be very different across these different groups, so would the extent of consumption smoothing. Figures 3e and 3f show the unadjusted and adjusted consumption, respectively, for these groups.[17] We find that across these households, farmers experience the least growth in consumption (both unadjusted and adjusted). The peak consumption growth for both self-employed and white-collar worker households looks very similar.

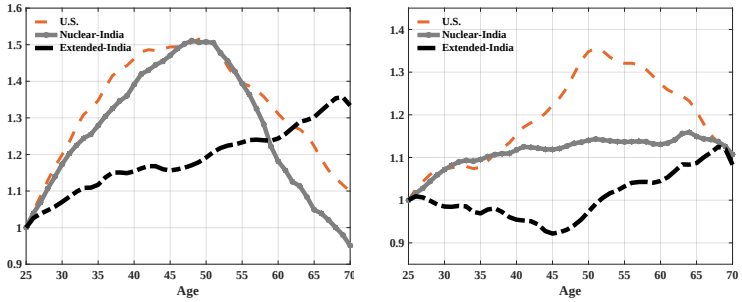
[15] In Section 6.1 we discuss the issue of head of household further.

[16] Appendix Section C provides details on how we construct these.

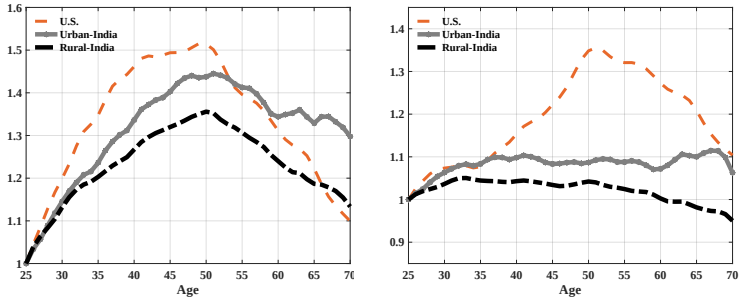
[17] Appendix Figure D.4 provides estimates of both adjusted and unadjusted life-cycle consumption by education status of the head.

Figure 3: Life-Cycle Consumption
by Family Type, Region, and Occupation

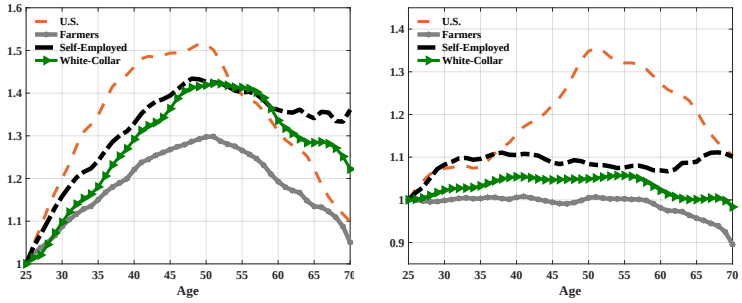
(a) Family Type - Unadjusted (b) Family Type - Adjusted



(c) Region - Unadjusted (d) Region - Adjusted



(e) Occupation - Unadjusted (f) Occupation - Adjusted



Notes: Nuclear families are defined as those comprised only of the household head, their spouse, and children. Extended families include all other members like siblings or parents of the household head, son-in-laws or daughter-in-laws, other relatives, etc. Adjusted refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16.

4.2.2 Heterogeneity Across Expenditure Categories

An important distinction between U.S. and Indian households lies in the composition of non-durable expenditures. U.S. households are likely to spend far more on their own or their children's higher education, as well as on health expenditures. In the case of India, old-age health expenditures are often borne by adult children even if they are not part of an extended household. Beyond that, home production of important categories such as food are likely to differ considerably between the two countries. Transportation is an example of another category that is likely to be more salient for U.S. households. Some of these differences, in terms of shares, are apparent in Table 1. To gain further insight, Appendix Figure D.2 compares the evolution of total household consumption spending on food, non-mortgage housing, education, health, and transportation. We plot data for the U.S., India as a whole, and for urban and rural India. We find that while growth in food and transportation expenditures in urban India is similar to that of the U.S., there are stark differences in education and health expenditure growth, which remains negligible for Indian households. Housing expenditures (net of mortgage payments) grow substantially more for Indian households. Appendix Figure D.3 confirms that the stark differences in consumption spending between Indian and U.S. households are not driven by differences in education and medical spending alone. Even after we eliminate these spending sources and re-estimate our life-cycle profiles, we find substantial differences in growth rates between the two countries.

Taking stock: Our analysis of consumption evolution for Indian households so far suggests a smooth age consumption profile, once the changes in household size and age composition are taken into account. This finding is at odds with the existing literature based on the experience of the developed world. Conventional economic thought suggests that if households' income growth over the life cycle is uncertain, then some of this growth translates into growth in consumption. Even if growth is predictable, market incompleteness makes consumption smoothing difficult. The absence of growth in adjusted consumption for Indian households hints towards three different possibilities. First, Indian households are able to perfectly smooth consumption over the life cycle and there are no market imperfections or uncertainty in wage growth. This seems very unlikely. Even though a sizeable fraction of Indian households reported some debt in 2019 – 35% for rural and 22% for urban, the actual amount of debt relative to total assets was low at 3.8% and 4.4%, respectively (GOI (2021)). In comparison, 77% of U.S. households carried some debt in 2019, and the debt to asset ratio was 15%.[18] This rules out the possibility that relatively younger households are borrowing against their future income growth to smooth consumption. A second possibility is the polar opposite – Indian households are severely borrowing constrained, consuming their income every period, which in turn exhibits no growth (on an adult equivalent basis). Third, they may face seasonal fluctuations in income that lead to either precautionary savings that dissipate quickly or cycles of indebtedness leading to no growth in consumption. In order to test this hypothesis, we estimate household income profiles in India and compare them to those in the U.S. in the next section.

[18]The first U.S. statistic comes from the Survey of Consumer Finances. The U.S. debt to asset ratio was calculated from OECD.

4.3 Income

We use the same methods as described in Section 4.1 to estimate age-income profiles for both countries. Figure 4 shows that growth in total household income in India is comparable to that of the U.S.[19] While U.S. households experience a roughly 100% growth in income (as compared to age 25), Indian counterparts experience about 106% growth.[20] However, income grows more slowly and peaks much later (around age 55 versus age 45 in the U.S.). The fact that Indian households exhibit income growth close to that of the U.S., but lower consumption growth is *prima facie* evidence that it is not income per se that constrains nondurable consumption. The variation in adult equivalents over the life cycle, which would affect both series similarly, would not change this. In addition to total household income, we also look at "adjusted income" – per-earner household income.[21] Another important difference between India and the U.S. is now apparent. In the case of the latter, almost all income growth is due to growth in individual earnings. In the case of India, of the 106% growth, only 40% can be attributed to individual earnings growth; the rest is due to changes in labor force participation, i.e., along the extensive margin of various family members.

Figure 5 compares the life-cycle income profiles of different types of Indian households – nuclear vs. extended families, urban vs. rural, and across different occupations – to U.S. households.[22] Interestingly, we find that income growth in urban India as well as nuclear families and that experienced by self-employed households exceeds that of the U.S. – 117%, 116 % and 130%, respectively compared to 100%. The growth is lower for other household types, with the lowest being extended families (60%). The peak for all household types is also reached later, and in the case of extended families, it never quite drops off. Irrespective of the grouping, the fact remains that peak income (relative to age 25) is higher than peak consumption. These findings, to a great extent, rule out the second hypothesis that households may be completely borrowing constrained, consuming their income every period which exhibits no growth. In the next sub-section, we look into this in more detail through the lens of savings rates.

Appendix Figure D.5 displays the income per earner vs. the total household income for each sub-group. After controlling for the number of contributing members, life-cycle income grows by roughly 60% for nuclear and urban households, 43% for the self-employed, and 36% for white-collar workers. Despite productivity growth, about 50-90% of the growth comes from increasing the number of earners. In the case of rural India or farming households, we see very little individual income growth. About 80% and 86% of the growth in total household income, respectively, is due to increasing labor force participation. For extended families, things are quite different. The peak in household income and peak in per-worker income are at different years. The peak household income coincides with more or less a bottoming out of the per-earner income when the head of household is in their mid-fifties. This may reflect the fact that at that age, the second generation

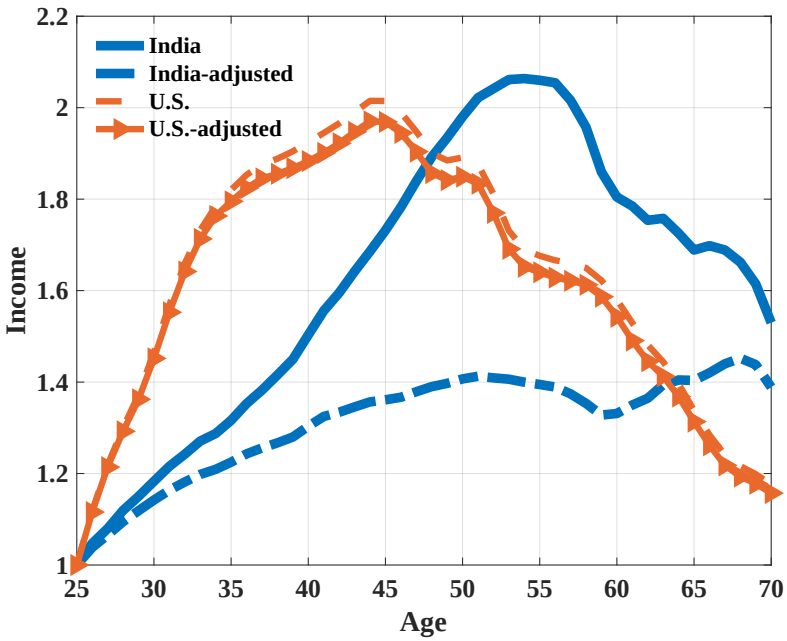
[19] Refer to column 2 of Appendix Tables D.1 and D.2 for time and birth cohort effects for Indian and U.S. households, respectively.

[20] For India, household income refers to income from all sources. This includes remittances, pensions, and government support programs.

[21] For Indian households, total income is divided by total number of earning family members at each point in time. For U.S. households, total income is divided by two in the case where spousal income is positive. While the PSID data allows for the possibility to track income from children and other family members, extended families including cohabitation with adult children, during the working life, is very rare.

[22] Appendix Figure D.6 provides these income profiles by education status of the household head.

Figure 4: Life-Cycle Income
by Age of Household Head



Notes: Total household income relative to age 25 (household head) is reported for both the U.S. and India. Adjusted income refers to income per earning member. Data for the U.S. comes from the PSID. Total family income for the U.S. includes total taxable income, transfer income, and Social Security income of household members for a given year. Total family income for India includes income from all sources including private/public transfers, profits, lotteries, wages, overtime, bonus, imputed income, interest payments, dividends, and insurance payments.

of members have just entered the labor force, and thus their starting income would be much lower than that of the household head. When the household head is older than 60, incomes of individual earners continue to increase as the incomes of the second generation members also increase.[23] To summarize, we find that the contribution of rising productivity to total income growth is highest in nuclear families and those in urban areas, and lowest for farming households.

4.4 Savings rate

A flat family-size adjusted consumption profile with a growing life-cycle earnings profile indicates an increasing savings rate for Indian households. Throughout, we define the savings rate as a "surplus rate": the total household income net of total nondurable consumption as a fraction of total household income. This captures resources allocated to durables and asset accumulation, and may differ from financial saving.

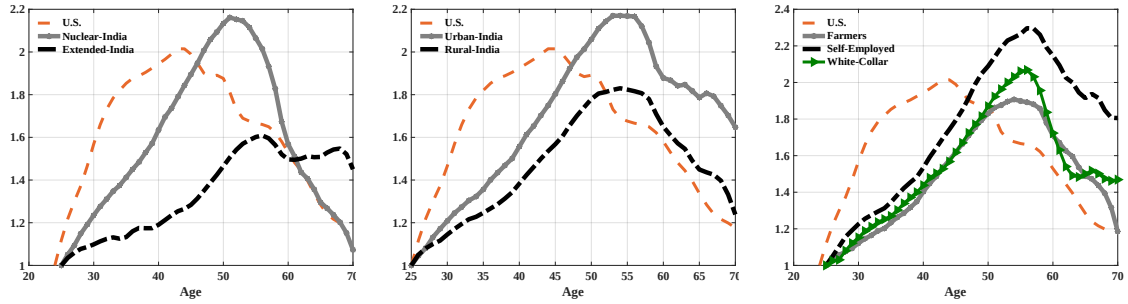
Figure 6 displays patterns in the evolution of savings/surplus rate.[24] For India as a whole, we

[23] It is also possible that the high individual income close to 70 reflects that the household head is a nominal head. We consider the implications of nominal head vs. primary earners in Section 6.

[24] Since the differences between India and the U.S. with respect to consumption and income have been discussed

Figure 5: Life-Cycle Income by Age of Household Head, Family Type, Region, and Occupation

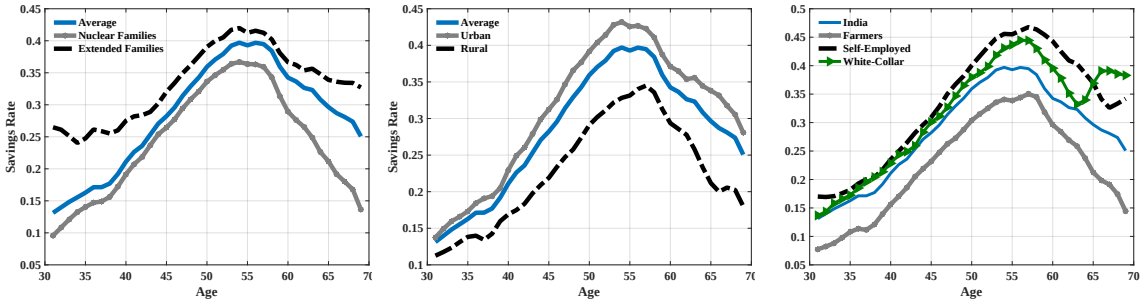
(a) Family Type (b) Region (c) Occupation



Notes: Total household income relative to age 25 (household head) is reported for both U.S. and India. Data for the U.S. comes from the PSID. Total family income for the U.S. includes total taxable income, transfer income, and Social Security income of household members for a given year. Total family income for India includes income from all sources including private/public transfers, profits, lotteries, wages, overtime, bonus, interest payments, dividends, and insurance payments.

Figure 6: Life-Cycle Savings Rate in India
by Age of Household Head, Family Type, Region, and Occupation

(a) Family Type (b) Region (c) Occupation



Notes: Savings rate is computed as total household income net of total nondurable consumption as a fraction of total household income.

find a substantial increase in the savings rate — increasing from 13% to roughly 40% over the life cycle.[25] This pattern holds for all types of households – urban, rural, nuclear, extended, farming, self-employed, and white-collar workers. While urban households experience a peak savings rate of 44%, the rural savings rate peaks at roughly 35%. Interestingly, extended families also exhibit a similar increase. This is despite the non-overlapping life cycles of residents in many such families. This is especially intriguing given that the per-adult consumption also drops to its lowest value around the peak savings age. Moreover, they have a higher savings rate than nuclear families all through the life cycle, and in fact also start off at a higher rate than all the other sub-groups.

at length, we restrict our attention to India for this and the remaining sections of the paper.

[25] Refer to column 3 of Appendix Tables D.1 for time and birth cohort effects.

There are two interesting things to note along the occupation margin.[26] First, the savings behavior of self-employed households and white-collar heads closely resemble each other, especially between ages 30 and 50. Second, farming households start off with the lowest savings rate among all groups studied here (7.8%), though in their case, it also increases over time and reaches a peak of 35%. Put another way, these graphs suggest that income per equivalent adult increases faster than consumption per equivalent adult until around the age of 55. Furthermore, while the savings rate drops after that, it remains positive.

Recall that our measure of savings is total household income net of total household nondurable consumption expenditures. In other words, it captures the accumulation of financial assets, physical assets, and durable goods. Unfortunately, the CPHS data do not allow us to observe the actual amounts spent on assets or durable goods. It could be that most of the surplus presented here is utilized to purchase consumer durables, which we do not observe. It could also be the case that Indian households are saving for other reasons such as retirement, medical expenditure risk, or to insure against life-cycle income risk (the precautionary motive), and so on – factors that have been widely used to explain the drivers of savings for U.S. households.[27] Indeed, a hump-shaped savings profile is consistent with the standard life-cycle model. However, this usually assumes market completeness, with consumption exceeding income during the early years.

5 Motivating Theory and Empirical Evidence

In order to understand the puzzle posed by the estimated life-cycle profiles of consumption, income, and savings behavior of Indian households, we draw insights from a standard life-cycle framework augmented with durables, demographics, and borrowing constraints. The structure is very similar to that of Luengo-Prado (2006).[28] We use the model to highlight potential mechanisms and derive simple predictions that we take to the data.

5.1 Environment

Each household chooses nondurable consumption c_t, durable investment i_t, and next–period financial assets a_{t+1}. The durable stock d_t is a state that evolves via depreciation and investment. Let n_t denote the adult–equivalent (AE) scale (exogenous to the household). Preferences are as follows:

$$\max_{\{c_t, i_t, a_{t+1}\}} \sum_{t \geq 0} \beta^t \, u\Big(\underbrace{c_t/n_t}_{\substack{\text{equiv.-scaled} \\ \text{nondurables}}} , \underbrace{s(d_t, n_t)}_{\substack{\text{durable} \\ \text{services}}} \Big), \qquad \beta \in (0,1)$$

where $s(\cdot)$ captures the (public-good) nature of durable services within the household. The

[26] Appendix Figure D.7 provides these savings rate profiles by education status of the household head.

[27] See, for instance, Bairoliya (2019); De Nardi et al. (2025); French (2005); Kopecky and Koreshkova (2014).

[28] Yang (2009) also considers borrowing constraints and durables, but is specifically focused on explaining home purchases and renovations.

budget constraint and laws of motion are:

$$a_{t+1} = (1+r)\Big[a_t + y_t - c_t - i_t - \kappa\,\mathbf{1}\{i_t \geq 0\}\Big], \tag{2}$$

$$d_{t+1} = (1-\delta)\,d_t + i_t, \qquad i_t \geq 0, \qquad \delta \in (0,1), \tag{3}$$

$$a_{t+1} \geq \underline{a}, \qquad \text{(borrowing constraint)}. \tag{4}$$

where y_t is exogenous labor income, i_t is durable investment, and $\kappa \geq 0$ is a nonconvex adjustment cost that makes purchases lumpy. For simplicity, we allow relative prices to be unity.

Let $\tilde{c}_t \equiv c_t/n_t$, u_c and u_s be marginal utilities with respect to $\tilde{c}_t$ and $s(\cdot)$, respectively. Let λ_t be the multiplier on (2) (marginal utility of wealth) and $\gamma_t \geq 0$ the multiplier on (4).

5.2 Optimality conditions and mechanisms

Asset Euler–KKT. The first–order condition for the risk–free asset with the borrowing constraint yields:

$$\lambda_t \;\geq\; \beta(1+r)\,\lambda_{t+1}, \tag{5}$$

$$a_{t+1} \;\geq\; \underline{a}, \tag{6}$$

$$\big(\lambda_t - \beta(1+r)\lambda_{t+1}\big)\,\big(a_{t+1} - \underline{a}\big) = 0. \tag{7}$$

Thus, if the constraint is slack ($a_{t+1} > \underline{a}$), the Euler equality holds; if it binds ($a_{t+1} = \underline{a}$), the inequality is strict.

Nondurable Euler equation with borrowing constraint. First order conditions imply:

$$u_c\Big(\tilde{c}_t, s(d_t, n_t)\Big) \;=\; \beta(1+r)\,u_c\Big(\tilde{c}_{t+1}, s(d_{t+1}, n_{t+1})\Big) \;+\; \gamma_t. \tag{8}$$

When the constraint binds ($\gamma_t > 0$), marginal utility today exceeds the frictionless benchmark, so current consumption is held down relative to the permanent–income path.

Durable adjustment and inaction. Using the asset Euler–KKT and the envelope condition for d_t yields the standard user–cost condition in today's units, with:

$$UC \;\equiv\; 1 - \frac{1-\delta}{1+r} \;=\; \frac{r+\delta}{1+r}.$$

With a fixed adjustment cost $\kappa > 0$, the problem separates into a discrete "whether to adjust" decision and a continuous "how much to adjust" choice. The fixed cost does not enter the marginal first-order condition conditional on adjusting. Hence:

$$\text{(adjust, } i_t > 0) \qquad u_s\big(\tilde{c}_t, s(d_t, n_t)\big)\, s_d(d_t, n_t) \;=\; \lambda_t \cdot UC, \tag{9}$$

$$\text{(no adjust, } i_t = 0) \qquad u_s\big(\tilde{c}_t, s(d_t, n_t)\big)\, s_d(d_t, n_t) \;\leq\; \lambda_t \cdot UC. \tag{10}$$

In summary, the above equations imply, conditional on adjusting, the marginal utility benefit of one more unit of durable services equals the marginal utility cost of "renting" that unit for one period (the user cost). When the optimum is at the corner $i_t = 0$, a tiny positive adjustment would not be worthwhile, so the marginal benefit is weakly below the user cost. With a pure fixed cost, there are no additional per–unit installation charges once adjustment occurs; the fixed cost governs the whether decision via value matching, creating an inaction band and a trigger at which the household pays κ and makes a lumpy jump to the target (the familiar (s, S) policy)[29].

Mechanism. Two forces might interact to flatten equivalence-scaled nondurables in India: (i) later-peaking income (expected gains arrive relatively late in the life cycle) and (ii) tight credit (limited unsecured and limited durable-specific borrowing), which limits intertemporal smoothing and pushes households to self–finance lumpy durables. When expected income growth is back-loaded, $\gamma_t > 0$ in (8) for a longer stretch (20s–40s), making c_t track current resources rather than lifetime income. At the same time, nonconvex adjustment and user cost considerations in (9)-(10) may lead households to accumulate buffers until wealth crosses a purchase threshold, then convert liquid savings into d_t in lumps. Because many durables provide services with strong scale economies ($\phi < 1$), a single purchase might disproportionately raise services to all members without requiring a commensurate rise in per-adult-equivalent c_t. Survey measures that record expenditures rather than the service flow would then mute growth in measured nondurables.

5.3 Testable implications and evidence

While the model outlined above does not deliver a closed-form solution, it yields clear, testable implications that we evaluate directly in the data.[30]

Implication 1: Muted growth of adult-equivalent nondurables with late-peaking income and tight credit

Rationale: When expected income growth is back-loaded and unsecured credit is limited, younger and middle-aged households cannot pull future resources forward. They accumulate buffers and, when resources allow, allocate surplus to lumpy durables (housing, vehicles, appliances, livestock). This reallocation raises living standards through durable services without requiring a commensurate rise in family-size–adjusted nondurable spending.

Empirical evidence: In India, family-size–adjusted nondurables rise by only about 8% over the life cycle, even as income grows by roughly 106% and peaks around age 55 (Figures 1, 4). Further, savings rates begin near 13% and climb to about 40% by the mid-50s, consistent with buffer accumulation during the long period when credit constraints are salient.

[29] See e.g. Grossman and Laroque (1987) for existence of inaction regions and (s, S)-type policies with durable goods and transaction costs.

[30] See Luengo-Prado (2006) for a discussion regarding the solution methods required to solve problems of this nature.

Implication 2: Lumpy, largely self-financed durable acquisition with rising savings leading to purchase events

Rationale: Fixed/transaction costs create inaction regions for the durable stock and spikes when wealth crosses purchase thresholds (refer to the (s, S) logic discussed above). In the presence of limited durable credit, households self-finance these purchases: saving rises as the threshold approaches and falls afterward when buffers are drawn down. If durables are partially nonrival within the household, a single purchase can boost services for all members without proportionate increases in nondurable outlays per adult equivalent.

Empirical evidence: We show four empirical facts to support this. (i) Accumulation of durables peak later in life when income peaks, (ii) stated durable purchase intentions predict higher subsequent saving, (iii) savings rate peak around durable purchase events and then decline sharply thereafter, and (iv) very few households use bank credit to finance these purchases, consistent with self-financing. [31]

1. Late-life accumulation of durables. Figure 7 provides the estimated age profile (using the same methodology as described in section 4.1 above) of our measure of durable expenditures or the physical asset stock of Indian households.[32] It is obvious that there is substantial growth in this stock over the life cycle (roughly 120% at its peak). What is even more interesting is that the peak is attained around the same time as the peak in savings rate (computed as income net of nondurable expenditures as a fraction of total income). This contrasts with U.S. evidence: Fernández-Villaverde and Krueger (2007) report that durable expenditures grow by about 80% but the peak happens much earlier around age 40 and Yang (2009) finds that households begin to accumulate housing assets early in life. These patterns suggest that Indian households channel a substantial share of their surplus into durables.

2. Durable purchase intentions predict future savings. A distinctive feature of the CPHS is a battery of questions that elicit households' intentions to purchase specific durable goods over the next 120 days. We use these stated intentions to assess their contribution to the high savings rates observed among Indian households.

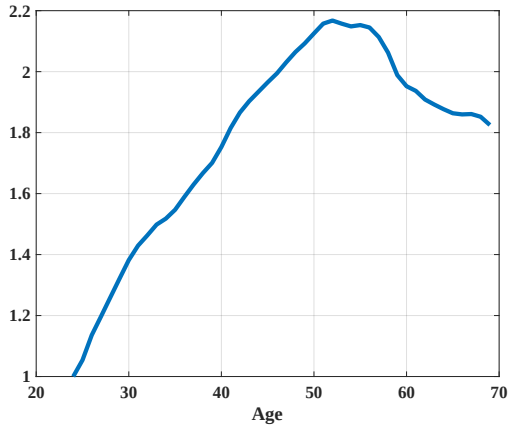
Two concerns naturally arise: the informational content of stated intentions and their causal link to savings. We address the first by showing that stated *intentions* significantly predict *realized* purchases within the survey, indicating nontrivial information content.[33] Regarding reporting bias, note that the savings rate is constructed from underlying survey data rather than elicited as a single self-report; this reduces the concern that households inclined to report intentions also overstate their savings. Specifically, we estimate the following equation:

[31] The figure does not include housing for which we do not have price data. Though there is nothing in our analysis that suggests we should exclude housing, it seems to follow a very different pattern. The CPHS data indicates that 96% of rural and 98% of urban head of households aged 25 own a house. This is in line with real estate ownership found in other studies for India (Badarinza et al. (2019)). Yet, there is very little borrowing for housing purchases (see Appendix Figure D.9), and unlike China there is no early hump to save for housing. This indicates the presence of large inter-vivos, bequest transfers or incremental accumulation. We leave this for future research but present corresponding results for the subsequent exercises in appendix D.

[32] Refer to appendix B for the construction of durable goods measure.

[33] See Appendix Table D.5 for details.

Figure 7: Accumulation of Physical Assets
Over the Life Cycle of Household Head



Notes: The household physical asset stock relative to age 25 (household head) is reported. It is constructed using information on the possession of major and minor durable goods such as televisions, cattle, tractors, refrigerators, cars, two-wheelers, electric generators, washing machines and so on. Note that housing is not included in this index.

$$s_{it} = \sum_{j=1}^{J} \beta^j z_{it}^j + \alpha X_{it} + \gamma_c + \delta_t + \epsilon_{it} \tag{11}$$

where s_{it} is the savings rate of household i at time t (wave), z_{it}^j is reported intentions to purchase durable good j by household i at time t, γ_c and δ_t denote cohort and period fixed effects, X_{it} is a vector of controls, and finally, ϵ_{it} is an independent, mean zero, random error.

Table 3 provides OLS estimates of reported intentions to purchase major durables such as cars, two-wheelers, tractors and cattle on savings rate using the specification discussed above. Since intentions to purchase these assets may overlap, we include each of them separately as a distinct control. Column (1) provides the estimates for a base specification with no other controls, while subsequent columns repeat the estimation with additional controls. In particular, to isolate intentions from any pure life-cycle and income effects on savings rates, we also add controls for the age of the household head (column 3) and measures of household ownership of durable goods and the education status of the head (column 4). Overall, we find that reported intentions of durable purchases have strong and significant effects on household's savings rate. For instance, in column (4) with full controls, reported intentions to purchase a car increases households' savings rate by 2.75 percentage points (p.p.). Intentions to purchase a two-wheeler have a somewhat lesser (1.18 p.p.) albeit significant effect on savings rate as well. Intentions for tractor and cattle purchase increase savings rate by 1.93 and 1.30 p.p., respectively.

Appendix Tables D.6-D.12 provide these estimates separately for urban and rural areas, extended and nuclear families, farmers, self-employed, and white-collar worker households, respectively. It is not surprising that car purchase intentions have significant effects on savings rate in

urban areas and for non-farming households only (after controlling for household assets and education). While intentions for tractor and cattle purchase have insignificant (or smaller) effects on savings for urban households, they increase the rural savings rate by 7.52 and 3.82 p.p., respectively. The effects are similar for farmers. Taken together, these exercises confirm that the desire to purchase these high-value assets is an important motive for savings.

Table 3: OLS Estimates of Intentions to Purchase Durables on Savings Rate in India

	(1)	(2)	(3)	(4)
Intend to Buy Car=1	0.122***	0.103***	0.101***	0.0275***
	(44.65)	(38.68)	(37.87)	(10.80)
Intend to Buy 2-Wheeler=1	0.0109***	0.00540*	0.00477*	0.0118***
	(4.86)	(2.45)	(2.17)	(5.63)
Intend to Buy Tractor=1	0.0349***	0.0302***	0.0281***	0.0193***
	(5.97)	(5.26)	(4.92)	(3.53)
Intend to Buy Cattle=1	0.00113	-0.00648*	-0.00597	0.0130***
	(0.35)	(-2.04)	(-1.89)	(4.29)
Time Dummy		0.00529***	0.00302***	0.00272***
		(120.84)	(47.13)	(44.33)
Birth Cohort		-0.0306***	0.000580	0.00218**
		(-277.06)	(0.75)	(2.94)
Age of Head			-0.110***	-0.115***
			(-66.46)	(-72.09)
Age of Head × Age of Head			0.00270***	0.00277***
			(79.52)	(85.23)
Age of Head × Age of Head × Age of Head			-0.0000199***	-0.0000203***
			(-87.72)	(-93.36)
Durable Goods				0.00242***
				(226.57)
Education				0.00828***
				(231.04)
Constant	0.291***	0.397***	1.557***	1.522***
	(1307.92)	(582.88)	(54.65)	(55.79)
Observations	2073080	2073080	2073080	2073080

Notes: The table estimates equation 11. Each observation is a household-wave. Intention to buy takes a value of 1 if the respondent plans to purchase the product over the next 120 days. Construction of durable goods measure is detailed in Appendix Section B
t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix Table D.13 provides the effect of reported intentions to purchase other smaller durables like television sets, washing machines, coolers, power inverters, computers, and refrigerators on the savings rate. We find that intentions to purchase all of these, with the exception of power inverters, have positive and statistically significant effects on the savings rate.

3. Savings around durable purchases. Since we observe households making durable goods purchases, we can also look at how the savings rate changes around the durable buying episode, to understand the role of durables in determining overall savings behavior of Indian households. In particular, we estimate the following relationship:

$$s_{it} = \sum_{\ell \neq -1} \beta_\ell \, \mathbf{1}\{\, t - t_i^{(j)} = \ell \,\} + \alpha X_{it} + \gamma_c + \delta_t + \varepsilon_{it}, \tag{12}$$

where ℓ indexes event time (monthly leads/lags), $\ell = -1$ is the omitted category, $t_i^{(j)}$ is the purchase date of durable j, and γ_c and δ_t denote cohort and period fixed effects. Finally, X_{it} is a vector of controls and ϵ_{it} is an independent, mean zero, random error. A time period here is a wave.

Figure 8 shows savings rates around the period of major durable purchases such as cars, two-wheelers, tractors, and cattle for Indian households. In all these cases, we find an increase in savings up to the period of actual purchase and a decline soon after the purchase. The decline in savings immediately following the purchase is apparent for most durables but quite stark for cattle (savings rate declines by roughly 6 p.p. following a cattle purchase). Note that even though we observe households in our survey for multiple years, we can only reliably estimate these event-time relationships for a limited number of waves surrounding these purchases, as these could be happening toward the beginning or end of the time horizon over which we observe the households.

4. Self-financing of durables. While we do not observe direct measures of households' access to formal credit, we do observe whether they report borrowing from a financial institution for specific purchases or making installment payments on such purchases (including purchases made earlier).

Panels (a) of Figure 9 shows the probability of borrowing to finance consumer durables (e.g., refrigerators, air conditioners, televisions). We find that a very small share of households borrow to finance the purchase of consumer durables (about 1.4–1.8%), and this profile is roughly flat over the life cycle. Panels (b) considers a related survey item: the share of households making installment payments toward a durable purchase. Here the shares are somewhat higher and exhibit a hump; nevertheless, on average, only about 4–6% of households report making such payments.[34] In summary, these results indicate that the vast majority of Indian households self-finance both major and minor durable purchases, indicating lack of access to financial markets for financing the purchase of durables.

Implication 3: Credit access shifts timing and raises midlife growth of adjusted nondurables.

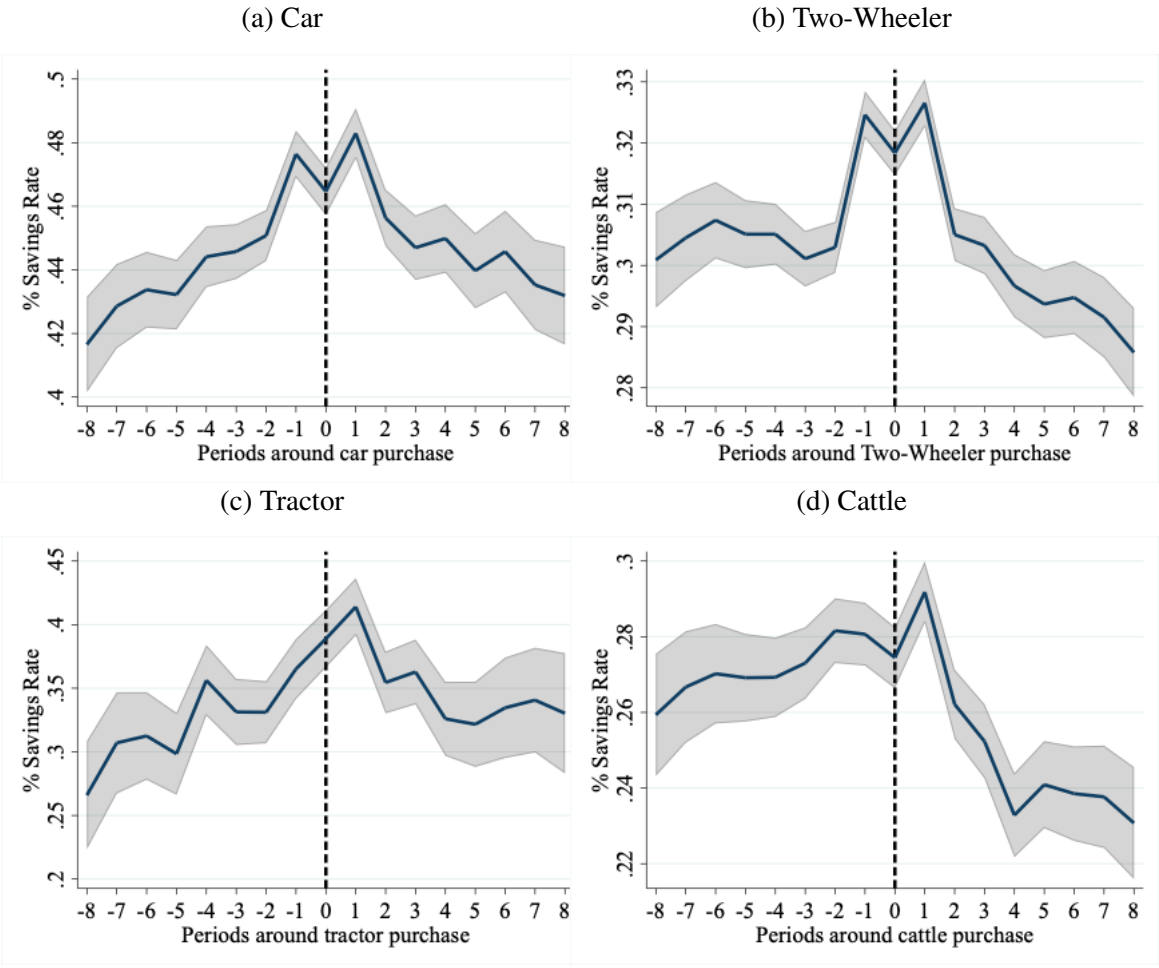
Rationale. Relaxing credit (unsecured or durable-specific) lowers the shadow value of liquidity, narrows the inaction band for durables, and brings purchases forward. Earlier purchases and looser constraints allow more midlife growth in adult-equivalent nondurables relative to otherwise similar households facing tighter credit.

Empirical support. Consistent with this mechanism, our estimated adult-equivalent consumption profiles show markedly higher growth where credit is plausibly looser. Panels (d)–(e) of Figure 3 indicate that urban households and nuclear families experience faster growth in family-size–adjusted consumption—about 10.5% for urban households and 15.8% for nuclear families—relative to their rural and extended-family counterparts (roughly 5% and 8.3%, respectively).[35]

[34] Refer to appendix figures D.8 for *savings around durables*, and 9 for *self-financing of durables* in the context of a house purchase.

[35] Appendix Figure D.10 shows that borrowings for consumer durables are indeed higher in urban areas than rural areas.

Figure 8: Savings Rate and Durable Purchase Event



Notes: The graph reports household savings rate around the time of a durable purchase. Controls include dummies for calendar time, birth cohort, and a third order age polynomial.

Reinforcing this, Panels (a)–(b) of Figure 10 show that the durable stock grows substantially faster earlier in the life cycle for urban and nuclear households than for rural and extended households, consistent with earlier relaxation of borrowing constraints and the corresponding shift toward lumpy durable acquisition.

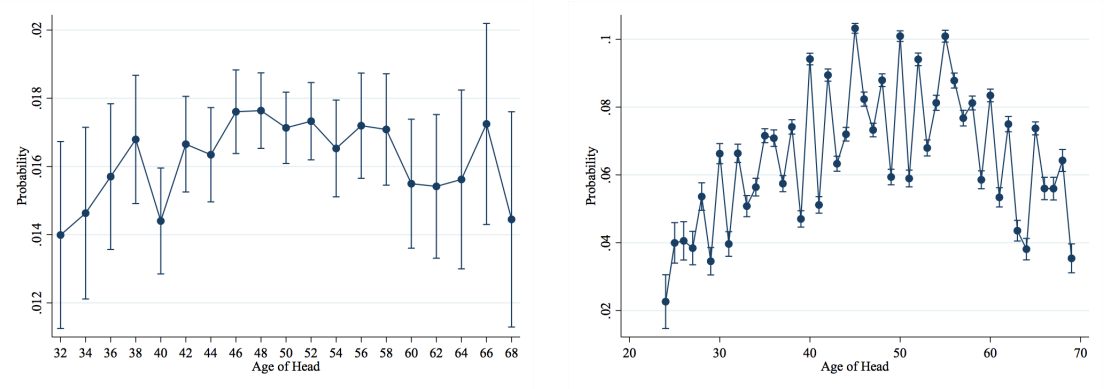
6 Robustness

So far, our analysis has focused on the aggregate and some large subgroups that characterize households in India. We now revisit some of our empirical life-cycle results after factoring in definition and measurement issues that are likely to be pertinent not just for India but developing countries in general. We consider alternative definitions of the head of household, adult equivalents, and the treatment of home production for consumption. We also check the robustness of

Figure 9: Borrowing Durable Purchases

(a) Probability of Borrowing

(b) Probability of Making an Installment Payment

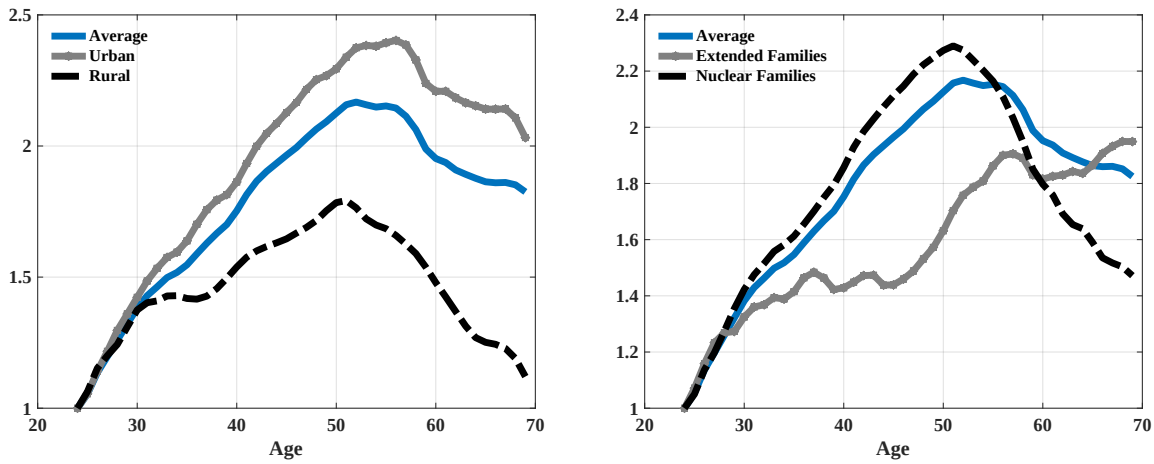


Notes: Probability of borrowing for consumer durables reflects the fraction of households who have reported any outstanding borrowing to finance consumer-durable purchases which include refrigerators, air conditioners, pump-sets, television, mobile phones, computers, music systems, musical instruments, sports gear, cooking range, furnishings, etc. Installment payments refer to "equal monthly installments" (EMI) for durables.

Figure 10: Accumulation of Physical Assets Over the Life Cycle of Household Head By Region and Family Type

(a) By Region

(b) By Family



Notes: Household physical asset stock relative to age 31 (household head) is reported. It is constructed using information on the possession of major and minor durable goods like car, two-wheeler, television, cattle, tractor, refrigerator, electric generator, washing machine and so on.

life-cycle growth patterns to alternative estimation strategies.

6.1 Household head

We use the self-reported status to ascertain the household head in the survey data. Since the focus of the paper is to understand the patterns in the evolution of consumption, income, and savings over the life cycle, it is important that the reported head of the household is an actual head and not a "figurative head." In other words, measurement errors in determining the head of the household could be problematic for our analysis of consumption and income growth over the life cycle of the household, which is proxied by the age of the head. Household heads in censuses and surveys are usually individuals who are primary earners, and/or primary decision makers.[36] It is unclear if this is the case in the context of developing countries with different cultural norms and living arrangements. This can be particularly problematic in multi-generational households, which comprise roughly 30% of our sample. In such a setting, it is conceivable that households may be reporting the head based on seniority in terms of age and not household decision making.

Table 4: Share of Households With Heads as Primary Earning Members

	Avg.	Urban	Rural	Extended	Nuclear	Farmer	Self-Emp.	White-Collar
Share	0.78	0.76	0.78	0.47	0.92	0.81	0.85	0.90

To deal with this issue, we repeat our analysis after reclassifying the head on the basis of earnings status. Specifically, we use the earnings information for each household member to determine the highest earner and designate this person as the financial head. Table 4 provides some insights on the overlap between the reported head and the financial head as constructed above. For India as a whole, the financial head is also the reported head for a majority (78%) of households. However, there are some interesting differences worth noting. Predictably, in the case of extended families, only half of the reported heads are also the primary earners. It is also interesting to note that living in a rural vs. urban area does not predict divergence between the two definitions. Households where the reported head has a white collar job are most likely to have the same person as the financial head. Appendix Figure D.11 goes further and traces the likelihood of the financial head being the same as the reported head by age, for different regions, family types, and occupations. The figures clearly show the "seniority" factor – older households are more likely to have reported a "figurative head" than a financial head. This is particularly true in extended families where only 20% of the reported household heads are also the financial heads at age 70. The analogous statistic is 70% for nuclear families.

Figure 11 shows both the household (i.e., unadjusted) and the adult equivalent (adjusted) life-cycle consumption profiles when we only consider households where the heads are also the primary earners.[37] For easier comparison, we also include the benchmark consumption profiles (i.e., using reported household head). Unadjusted consumption still peaks around age 50 with a roughly 43% growth relative to age 25, comparable to what we estimated earlier. However, the decline in consumption after age 50 is much more pronounced compared to the benchmark. This indicates

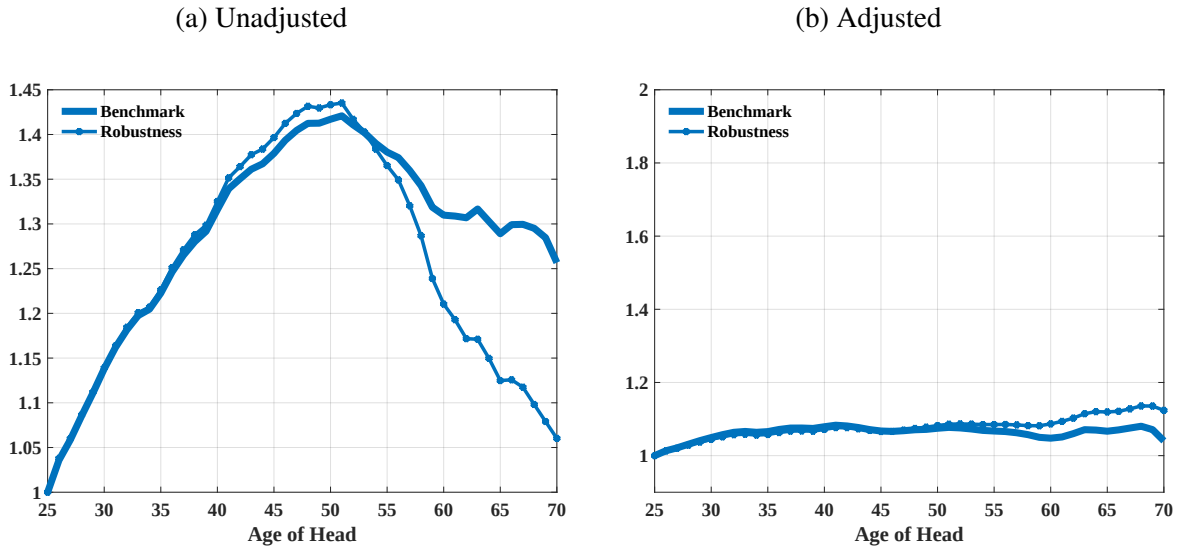
[36] Refer to Smith (1992) for an interesting history of family and households and Budlender (2003) for a discussion on identifying a household head in data collection.

[37] We drop all household-wave observations from our sample where the reported head and financial heads are not the same.

that while potential measurement errors in determining the household head may not have any effect on our measurement of consumption growth over the life cycle of Indian households, it could result in underestimating the decline in household consumption at later ages. Indeed, the decline now closely resembles that of nuclear families (Figure 3a). Adjusted consumption patterns remain mostly unaffected.

We also revisited the consumption profile of extended families. Recall that the consumption per equivalent adult bottoms at around age 50. It turns out that even when we restrict the sample to only those extended families where the head of household is also the primary earner, this pattern does not change. In other words, the U-shape is not due to a mislabeling of the household head. The profile is displayed in Appendix Figure D.12. Finally, Appendix Figure D.13 reports the savings rate of households after dropping heads who are not financial heads. We find the same hump-shape pattern even though the levels are somewhat lower.

Figure 11: Head Robustness: Life-Cycle Consumption
by Age of Household Head



Notes: This robustness exercise drops all households where the head is not the primary earning member. Household consumption relative to age 25 (household head) is reported for Indian households. Adjusted refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16.

6.2 Consumption scales

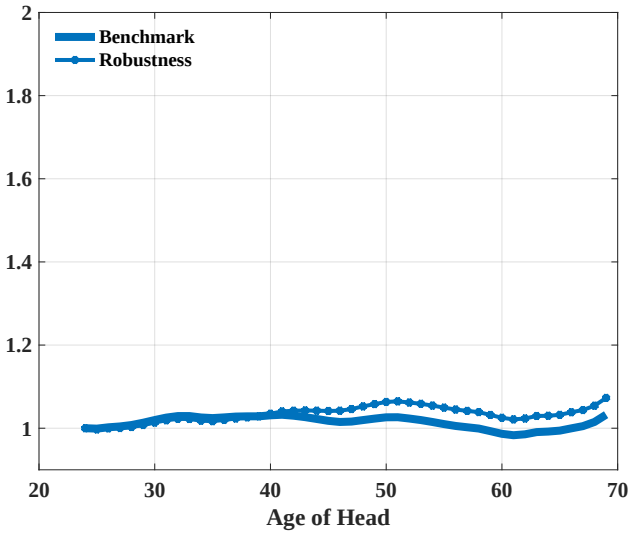
Adjusting total household consumption by an equivalence scale allows us to capture the effects of changing demographics on life-cycle consumption patterns. In our benchmark analysis, we have used the OECD scale that assigns a value of 1 to the household head, 0.5 to each additional adult, and a value of 0.3 for each child. In order to test the sensitivity of our result to a specific form of scaling, we use an alternate household equivalence scale proposed first by NRC (1995), and later

used by Nie (2020) among others. This scale is given as:

$$n_i = (n_{Ai} + 0.7 * n_{Ki})^{0.7}$$

where n_{Ai} is the total number of adults in household i including the head and n_{Ki} is the total number of children. This formulation allows the equivalence scale to distinguish between household composition effects (the different consumption requirements of adults relative to children) and economies of scale.[38] Figure 12 provides adjusted consumption expenditures using both the benchmark OECD and the NRC (1995) scale. We find that the latter results in slightly higher growth in adjusted consumption over the life cycle than the OECD scale. Specifically, adjusted consumption now grows by 12.3% (8.3% in benchmark) over the life cycle and reaches its peak at age 68 (41 in benchmark). Intuitively, because the NRC (1995) scale assigns a larger weight to children (0.7 per child, versus 0.3 in our modified OECD scale) and embeds stronger economies of scale via the 0.7 exponent, it lowers adult-equivalents most at younger, child-dense ages—mechanically raising measured growth in adult-equivalent consumption and shifting the profile's peak later. The general pattern of relatively smooth consumption remains largely unchanged.

Figure 12: Scale Robustness: Adjusted Life-Cycle Consumption by Age of Household Head



Notes: Adjusted household consumption relative to age 25 (household head) is reported for Indian households. This figure compares consumption when using the OECD equivalent scale (Benchmark) to that proposed by NRC (1995): $n_i = (n_A + 0.7 * n_K)^{0.7}$.

[38]For a couple with two children, the value is 2.35 while it is 2.1 for OECD. In India, within family resource allocation tends to be highly skewed in favor of males, which neither scale addresses. For more on the intra-household inequality in resource allocation, see Browning et al. (2013). Calvi et al. (2023) argue that the OECD parameters over-correct for economies of scale and lead to significantly lower consumption based poverty rates in Bangladesh.

6.3 Home production

We next explore the possibility of home production crowding out some expenditures on nondurable consumption. Two forms are especially relevant: (i) agricultural production for self-consumption, more common in rural areas; and (ii) household chores with market substitutes (e.g., hiring domestic help, a common practice among urban Indian middle-class households). Because these activities substitute for market purchases, expenditure-based measures can understate actual consumption and its growth over the life cycle (Dotsey et al., 2014). Although valuing total home production is difficult, we use two datasets to construct the best available measures of the first type (agricultural self-consumption). As the second type is largely unobserved in both U.S. and Indian surveys, we focus on imputing the value of agricultural home production.

6.3.1 Estimates from CPHS

First, the CPHS survey data used in this analysis provided imputed values based on self-reports, allowing us to measure the first type of home production. Households are asked about the "total quantity of agricultural or commercial goods produced that were self consumed by the household in the last month." The value of home production is then derived by multiplying the quantity of the agricultural goods produced by the household by the price of the crop in the local market. For self-employed households, goods taken from their own "kirana" (grocery) stores or restaurants or those earned in kind through the barter system are also included in this estimate. The first panel in Table 5 provides some summary statistics of the annual estimated value of home production in USD PPP. It is interesting to note that these estimates are quite small compared to expenditures on annual nondurable consumption and somewhat larger in rural areas than in urban areas as expected.

We add these imputed values of home production to our nondurable consumption expenditure measure and re-run the benchmark analysis to estimate life-cycle profiles of consumption. Figure 13 reports both adjusted and unadjusted consumption profiles. We find that there are no significant effects of home production on the growth of consumption over the life cycle – both when adjusted and unadjusted for demographics. Appendix Figure D.14 shows these profiles by region and family type. As expected, the small differences are due to rural areas and extended families as urban profiles remain completely unchanged.

6.3.2 Estimates from Time Use Survey (2019)

Next, instead of using the CPHS's own values of home production, we use estimates from the Government of India's 2019 Time Use Survey (TUS), using only the household schedule rather than the time-diary microdata. Specifically, we proxy the value of home production with two variables captured in the survey: the imputed value of usual monthly consumption from home-grown stock and the imputed value of usual monthly consumption from wages in kind, free collection, gifts, etc. For each TUS household we construct the monthly home-production value as a sum of these two components. The second panel of Table 5 compares these estimates of home production obtained from TUS (2019) to that of the CPHS sample. These estimates are noticeably larger from their CPHS counterparts.

We then compute averages by the age of the household head, region (urban vs. rural), and family type (nuclear vs. extended). These averages are merged to the CPHS survey data and added

Table 5: Home Production Estimates

	Home Production		Nondurable Expenditures	
(in USD PPP)	Mean	Std. Dev.	Mean	Std. Dev.
CPHS				
Average	158.69	648.07	6354.75	786053.52
Urban	36.78	345.88	8597.05	1381065.04
Rural	217.11	743.90	5280.32	3894.99
Time Use Survey (2019)				
Average	625.41	1120.59	7048.61	5651.81
Urban	312.14	958.51	9716.19	7262.49
Rural	828.46	1170.17	5320.02	3296.26

Notes: Home production here refers to the imputed value of agricultural and commercial goods produced for self-consumption.

to nondurable consumption to form an augmented consumption measure that includes implicit in-kind consumption from home production. We then re-estimate the same age profiles using our APC framework on these augmented CPHS outcomes. Figure 13 shows that just like with the CPHS data, there are no significant effects of home production on the growth of consumption over the life cycle – both when adjusted and unadjusted for demographics.

In sum, across both data sources the augmented consumption measure does not materially change our core life-cycle facts (a flat equivalence-scale–adjusted profile with a late, muted peak); see Figure 13 and Appendix Figure D.14.

6.4 Alternate specification

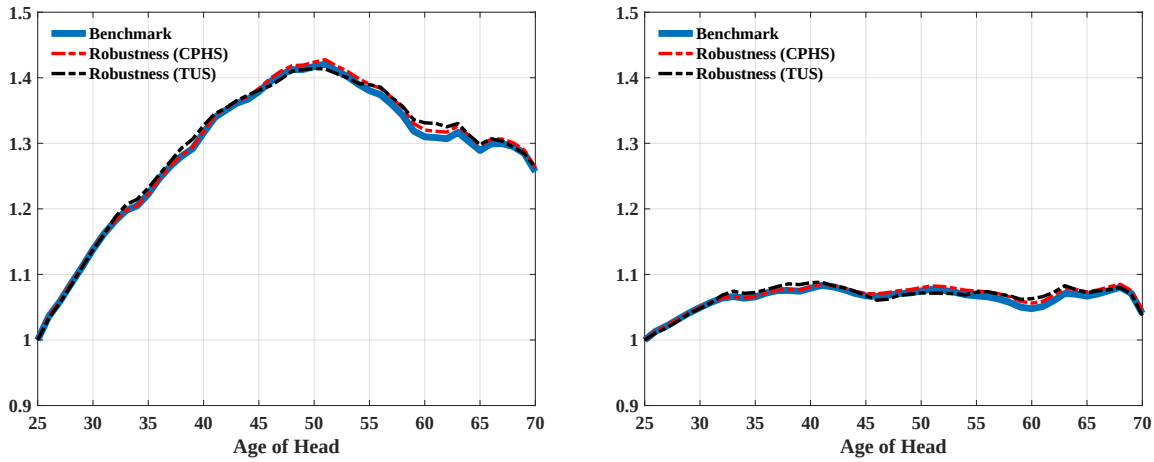
Next, we test the robustness of our lifecycle consumption growth patterns to alternative estimators. Specifically, we first replace the baseline kernel smoother for the nonparametric age profile with a flexible cubic spline (series) estimator and vary the number and placement of knots. Next, we implement the partially linear two–step estimator from Speckman (1988), which residualizes the outcome and parametric controls on age via kernel regression before an OLS step. Across both exercises, the key message is unchanged: there is strong lifecycle growth in aggregate household consumption, while the family-size–adjusted consumption profile is relatively flat. We discuss each in detail below.

6.4.1 Alternative smoother for the age profile.

Our baseline recovers the nonparametric age profile $g(a)$ via a kernel smoother in a partial–linear specification that assigns aggregate linear drift to calendar time and removes level and trend from the period indicators. To verify that the lifecycle pattern is not an artifact of the particular smoother or its tuning, we re–estimate the model replacing the kernel with a flexible cubic–spline (series) approximation to $g(a)$ and vary the number of interior knots over a wide grid. Identification of period and cohort components is kept identical to the baseline, and we evaluate

Figure 13: Home Production Robustness: Life-Cycle Consumption
by Age of Household Head

(a) Unadjusted (b) Adjusted



Notes: This robustness exercise adds estimates of home production to household consumption expenditures using CPHS or TUS (2019) survey data. Household consumption relative to age 25 (household head) is reported for Indian households. Adjusted refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16.

the profile at the sample–mean period and the base cohort. Across spline specifications (from relatively tight to relatively flexible) the implied age profiles are substantively unchanged. In panels (a) and (b) of Figure 14, the blue lines indicate that average life–cycle growth in household consumption is roughly 38.5% (vs. 42% in the baseline), while family–size–adjusted consumption growth is about 5.0% (vs. 8.3%). Overall, this exercise indicates that our findings are driven by the data rather than by the specific smoothing device used to recover $g(a)$.

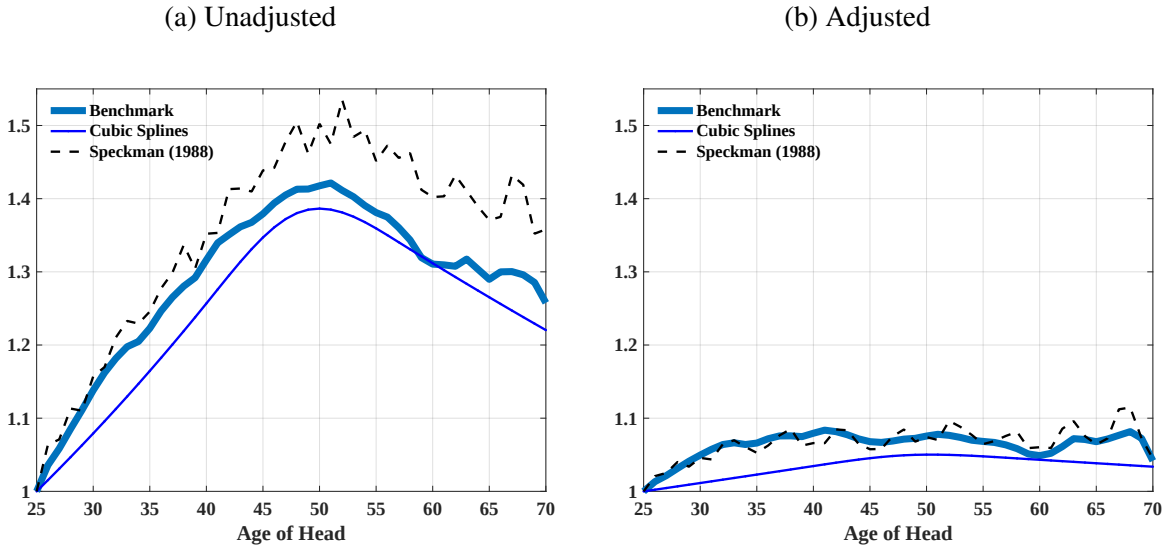
6.4.2 Speckman (1988) two–step partially linear estimator.

As a further check, we re–estimate the age–period–cohort specification using the partially linear two–step estimator of Speckman (1988). The procedure first nonparametrically smooths the conditional means $E[\ln C \mid a]$ and $E[X \mid a]$ over age a (with X denoting the parametric controls), and then runs OLS of the residualized outcome $\ln C - \widehat{E[\ln C \mid a]}$ on the residualized covariates $X - \widehat{E[X \mid a]}$ to obtain $\hat{\beta}$. The age profile is then recovered as $\hat{g}(a) = \widehat{E[\ln C \mid a]} - \widehat{E[X \mid a]}\hat{\beta}$. We implement the smoother with a standard Epanechnikov (Nadaraya–Watson) kernel and consider several bandwidths. Throughout, we retain the baseline APC identification and evaluate $\hat{g}(a)$ at the sample–mean period $\bar{t}$ and the base cohort. Our implementation follows Fernández-Villaverde and Krueger (2007), who apply Speckman's estimator to U.S. lifecycle consumption. In panels (a) and (b) of Figure 14, the dashed black lines indicate that average lifecycle growth in aggregate household consumption is steeper than in the baseline (about 53.5% versus 42%) while the family–size–adjusted profile is similar, at roughly 9.6% versus 8.3%.

6.4.3 Longer CPHS Panel

As a final robustness check, we re–estimate the APC specification on an extended CPHS sample that includes waves after 2019 (until 2022). The key result is unchanged: aggregate (unadjusted) household consumption exhibits pronounced life-cycle growth, whereas the family–size–adjusted profile remains comparatively flat. Quantitatively, the extended window yields a slightly more pronounced aggregate consumption growth profile (refer to Appendix Figure D.15). We treat this as corroborative rather than as our main estimate for two reasons. First, the 2020–2022 period is dominated by pandemic–related shocks (lockdown, mobility restrictions, and post-lockdown rebounds) that can amplify common period movements and composition effects (e.g., selective non-response, migration, and changes in household formation). In our identification these shocks enter the period block through linear drift plus detrended deviations, but the extra volatile years can still tilt the fitted drift and raise the apparent slope of the aggregate age curve without reflecting structural life-cycle behavior. Second, measurement conditions and spending deflators were unusually turbulent in 2020–2022, which complicates level comparisons even after our normalizations. For these reasons we retain 2014–2019 as the primary sample and report the extended results as a robustness exercise here, interpreting the stronger aggregate life-cycle growth as consistent with pandemic-era period effects rather than a revision to the underlying age profile.

Figure 14: Estimator Robustness: Life-Cycle Consumption by Age of Household Head



Notes: Household consumption relative to age 25 (household head) is reported across all specifications. Adjusted refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16.

7 Discussion and Concluding Remarks

Using a recently introduced, nationally representative panel of Indian households, we investigate the patterns in life-cycle consumption, income, and savings rate. We compare these life-cycle profiles to that of U.S. households to further understand how consumption and savings behavior in a developing country differs from the experiences of a developed country like the U.S. Our study reveals intriguing similarities and contrasts between the two countries.

In the first part of the analysis, we find that the growth in total nondurable consumption expenditures in India, especially urban areas, is very similar to that of the U.S. households ($\approx 50\%$). However, stark contrasts are revealed when comparing family-size-adjusted expenditure profiles. While U.S. households still experience 30% growth in expenditures, all the growth in nondurable consumption disappears for Indian households. This presents a puzzle, given that Indian households experience a significant growth in income. To investigate this further, we estimate the age profile of the savings rate for Indian households and find that it exhibits a prominent hump where household income net of nondurable expenditures grows from 13 to more than 40% between ages 35 and 55. The finding that nondurable consumption, after adjusting for family size, stays relatively flat while the savings rate continues to grow, implies that households in India do not smooth consumption in the traditional life-cycle-perfect-markets sense.

In the second part of the paper, we explain how nondurable consumption remains relatively flat despite high savings rates by using insights from a life-cycle model with borrowing constraints, augmented to include durables and lumpy adjustment costs. Consistent with the predictions of the model, we show that a physical asset stock constructed using all major and minor durable goods owned by households rises steeply (roughly 120% growth) over the life cycle. Moreover, the timing of the peak of the profile matches the peak timing of the savings rate. Second, we show that reported intentions to purchase physical assets predict higher savings rates. Further, the household savings rate increases prior to a major durable purchase and declines subsequently. Finally, urban and nuclear households - groups more likely to have easier credit access - show faster growth in nondurables and earlier durable accumulation.

We conduct a host of robustness tests to check the sensitivity of our key finding of flat adjusted nondurable consumption profile. A major threat to the life-cycle analysis is the variability in the definition of the household head: whether the reported "head" refers to the primary earner or to a symbolic figure later in the household's life cycle. In order to test this, we relabel the household head as the member with the highest income in the family and redo our analysis. We find that the growth in consumption is fairly robust to this alternate definition of head. Life-cycle profiles are also robust to the inclusion of home production measures of goods, different equivalence scales, and econometric specifications.

Readers might be concerned that, unlike the literature that has emerged from the U.S. and other countries, ours relies on a panel that has a much shorter time frame of six years. In our robustness section, we show that a longer time period covering the Covid period, yields largely similar profiles. While a longer panel would have been ideal, the growth of the Indian economy during this period has also been rapid. Real per capita consumption expenditures both in the survey data and national accounts statistics average 6-6.5% growth annually. In other words, cumulative growth in expenditures during this period was easily equivalent to what one might see in the U.S. over more than a decade. Furthermore, even for the U.S. there is some recent evidence suggesting that life-cycle analysis using long panels may generate artificial humps that hide systematic time

variation (Aksoy et al., 2025). Similarly, Chamon and Prasad (2010) find evolving patterns for China.

A related criticism with respect to a short panel is that younger households might be consuming more in anticipation of higher income growth compared to older households. This can naturally cause the consumption profile to appear smoother than the underlying data. This is a genuine concern, especially in a fast-growing economy. However, India has now been growing rapidly for more than two decades. Thus, even those household heads who are in their forties and fifties would have formed similar expectations at the start of their earnings cycle. Moreover, urban households, where these effects might be stronger, actually show steeper growth.

Although we see a widening gap between household income and consumption, and we show that saving for consumer durables is a significant reason, we cannot precisely apportion how much of the resulting saving takes the form of financial versus non-financial assets such as gold jewelry. This brings us to a topic that we have been silent about so far – the role of dowry (bride price) in the motivation for savings. In part, this is because it is difficult to disentangle the dowry motive from other reasons, such as precautionary savings. Certainly, our twin findings that consumption per equivalent adult remains smooth, while saving for large durable purchases, are consistent with a dowry motive. Beyond that, separating a dowry motive from other drivers is difficult. This is well-known in the development literature, where usually one has to use identification strategies such as the gender of the first child to extricate differences in savings and childhood investments.[39] The aggregate implications of the dowry motive for consumption and savings in India are an area ripe for future research.

[39] Anukriti et al. (2022) use this strategy to examine savings behavior in rural households.

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Online Appendix

A Expenditure Categories

A.1 Food

In CPHS, we sum up expenditures on three broad items — food, intoxicants and restaurant meals. Food items include cereals & pulses, edible oils, spices, vegetables & fruits, meat, fish & eggs, milk & milk products, ready-to-eat food, spices, bread, snacks, noodles & pasta, flakes, muesli & oats, confectionery & ice-creams, health supplements, tea, coffee, sweeteners, and beverages, juices & bottled water. Intoxicants include liquor and tobacco products. Restaurant meals include food and non-alcoholic beverages consumed in restaurants or snack joints.

In the PSID, we use the total family food expenditure variable which includes expenditures for food at home, delivered, and eaten away from home. We do not have any measures of intoxicants reported separately in PSID. Even though households report annual expenditures on food starting 1999, we restrict our analysis to years between 2005 and 2019 as some of the other expenditure items like clothing, trips etc (present in CHPS) only became available in PSID starting 2005.

A.2 Housing

Non-mortgage housing expenditures in CHPS include expenditures on rent and bills, power and communication. Rents and bills include household expenditures on house rent, water charges, society charges, and any other taxes. Power expenditures are a sum total of the household expenditures on cooking fuel, petrol, diesel and electricity. Finally, communication expenditures include household expenditures on landline telephone bill and mobile phone charges.

PSID reports several categories of housing expenditures like mortgage and loan payments, rent, property tax, insurance, and utilities including gas, electricity, water and other items. Since, mortgage payments are not included in CHPS, we restrict the expenditures to those other than mortgage-related. Specifically, we exclude mortgage and loan payments, property tax and insurance from total housing expenditures.

A.3 Clothing

Expenditures in CHPS in this category include clothing, footwear and cosmetics. While former includes household expenditure on clothing (such as garments, jackets, woolens, etc), clothing accessories and footwear, latter includes household expenditure on cosmetics and toiletries including dental care products and bathing soap.

Clothing expenditures in PSID reported by households include expenditures incurred on on clothing and apparel, including footwear, outerwear, and products such as watches or jewelry. As far as we know, PSID does not report any expenditures separately on cosmetics.

A.4 Transportation

In CPHS, transport expenditures relate to various modes of transport and other charges. including "Daily Bus/Train/Ferry Fare", "Auto-rickshaw/Taxi Fare", "Outstation Bus/Train Fare", "Parking Fees", "Toll Charges and Airfare". Note that expenditures related to vehicle purchase are reported separately and not included in our measure.

Transportation related expenditures in PSID include expenditures for vehicle loan, lease, and down payments, insurance, other vehicle expenditures, repairs and maintenance, gasoline, parking and car pool, bus fares and train fares, taxicabs and other transportation. We net out vehicle down payment and lease related expenditures from this measure to get a more comparable measure to CHPS.

A.5 Health

CPHS data report health expenditures related to expense on medicines, doctor's fees, X-Ray tests, hospitalization fees, premium for health insurance, etc.

Health expenditures in PSID include total family health care expenditures including spending on hospital and nursing home, doctor, prescription drugs and insurance.

A.6 Education

In CPHS, this is the sum total of household expenditure on education. It includes expenses on stationery, school/college fees, private tuition fees, additional professional education, overseas education, hobby classes and other items of education.

Education expenditures in PSID include all schooling related expenditures.

A.7 Recreation

Recreation expenditures in CPHS include expenditure on electronic storage devices, entertainment and games/toys. Electronic storage devices include pen drives, hard disks, memory cards, CDs, DVDs, cassettes, records and other mediums. Entertainment includes movie tickets, theatre tickets for drama, music concerts or general entertainment programs, tickets and subscriptions to entertainment clubs such as discotheque, tickets to sports events like tournament matches or other sports events, tickets to the zoo, tickets to museums, art galleries, planetariums, circus, theme parks, etc. Games/toys includes all kinds of indoor or outdoor toys or sports equipments or materials for children and/or adults.

Recreation category in PSID inlcude expenditures on trips and vacations, including transportation, accommodations, and recreational expenses on trips as well as on other recreation and entertainment activities, including tickets to movies, sporting events, and performing arts and hobbies including exercise, bicycles, trailers, camping, photography, and reading materials.

A.8 Others

In CPHS data, the other category include household expenditure on domestic help/laundry, repair of vehicles, remittances sent, social obligations, religious obligations, etc. It includes all

household expenses that were excluded from the above categories.

To keep the definitions close, we include expenditures on home repairs and maintenance as well as furnishing in PSID in this category as well as expenditure on household furnishings and equipment, including household textiles, furniture, floor coverings, major appliances, small appliances and miscellaneous housewares.

B Durable Goods and Physical Assets

CPHS does not report expenditures on durables but provides a detailed inventory of major and minor durable goods owned by the households. We impute the price of these goods and use the information on durable goods ownership in the survey to construct total expenditures on durables. The price data we use come from the 72nd round of the National Sample Survey Organization (NSSO), which is a large-scale cross-sectional household survey on durable and service consumption that was conducted by the Indian government during 2014-15. We obtain the price of durable goods by calculating a weighted (and unweighted) average price of a certain category by state and region (rural/urban sector). The durable goods categories include cars, tractors, washing machines, fridges, coolers, televisions, two-wheelers, generators, laptops, and air-conditioner units (AC's). The prices are then merged with the CPHS data by category-state-region and multiplied by the number of units of durable goods in each category to generate total household durable expenditures.

Table B.1 provides the prices and share of households owning each type of physical assets by region —urban and rural. Note that we exclude housing and livestock from our measure of the value of the stock of physical assets owned by households. This is due the fact that NSSO dataset used in imputing prices does not provide expenditures on either.

C Occupational Classification

The "People of India" files provide information on the occupation of each household member including the head. Appendix Table C.1 below shows the various occupations of the head and its distribution in our sample for overall and for both urban and rural areas. Given these classifications, three broad groups emerge for the working-age head — those working on farm or related activities, those working on their own business and those working in professional white-collared jobs. Given this we re-code occupations for the analysis conducted in this paper into the following three groups. First we define farmer as those working as *Agricultural Labourer*, *Organised Farmer*, *Small Farmer* or *Wage Labourer*. We classify self-employed as those reported as *Qualified Self Employed Professionals*, *Self Employed Entrepreneur*, *Self employed professional*, *Small Trader/Hawker/ Businessman without Fixed Premises* or *Businessman*. Finally we combine categories such as *White collar worker*, *White Collar Clerical Employees*, *Legislator/Social Worker/ Activists*, *Manager* and *White-Collar Professional Employees and Other Employees* into a single white-collar category. Since reported occupation of the head can change over multiple observed waves leading to retirement, we classify household head's occupation based on the one reported at the time of first interview.

Table B.1: Price and Distribution of Durable Goods by Sector

	Price				Share (%)	
	Rural		Urban		Rural	Urban
	Mean	s.d.	Mean	s.d		
Two-wheelers	48045.77	10565.78	51714.02	9163.42	52.1	70.5
Cars	330098.92	143932.66	456889.21	150094.70	3.5	12.7
Tractors	205178.77	168800.84	126272.99	90364.00	4.3	0.4
Cooler	5438.09	1660.02	7969.82	7496.36	32.5	50.0
Fridge	13156.90	2493.34	14549.15	2996.25	37.8	72.7
AC units	29264.96	18935.65	30190.64	5633.47	2.5	13.7
Generator	13329.04	5984.94	18062.56	9292.29	10.3	25.5
Television	12190.13	5729.27	18020.45	6336.04	87.1	97.8
Washing machine	11809.07	3013.60	13518.15	3382.45	12.8	37.3
Laptop	22510.20	7311.12	27582.81	7469.56	2.3	14.3
Observations	309		326			

Prices of durable goods are in 2014 rupees, from the 72th round of NSSO dataset (July 2014 - June 2015). The price of tractors is only available for rural households, while the price of AC units (air conditioners) is only available for urban households. We use the available prices to impute for the value of the asset stock in CPHS.

Table C.1: Occupation of Household Head

	All	Urban	Rural
Agricultural Labourer	4.14	0.74	11.24
Businessman	8.77	11.66	2.74
Home Maker	6.76	7.36	5.51
Home-based Worker	0.64	0.77	0.37
Industrial Workers	3.96	4.97	1.86
Legislator/Social Worker/ Activists	0.06	0.06	0.05
Manager	0.32	0.45	0.06
Non-Industrial Technical Employee	1.52	1.87	0.79
Organised Farmer	4.13	1.04	10.59
Qualified Self Employed Professionals	0.46	0.63	0.10
Retired/Aged	10.30	12.07	6.61
Self Employed Entrepreneur	9.28	11.42	4.82
Self employed professional	0.75	0.94	0.33
Small Farmer	9.32	1.50	25.66
Small Trader/Hawker/ Businessman without Fixed Premises	3.93	4.88	1.93
Student	0.01	0.01	0.01
Support Staff	7.16	8.89	3.55
Unoccupied	0.46	0.49	0.39
Wage Labourer	19.66	19.34	20.35
White Collar Clerical Employees	3.69	4.76	1.46
White collar worker	1.24	1.65	0.39
White-Collar Professional Employees and Other Employees	3.44	4.52	1.19
Total	100.00	100.00	100.00

D Additional Figures and Tables

Table D.1: OLS Estimates of Birth Cohort and Time Effects on Consumption, Income, and Savings Rate of Indian Households

	(1) Ln(Consumption)	(2) Ln(Income)	(3) Savings
Linear time trend	0.0112***	0.0156***	0.0015***
Time Dummy = 3	-0.0686***	-0.0744***	-0.0016
Time Dummy = 4	-0.0926***	-0.1156***	-0.0251
Time Dummy = 5	-0.1421***	-0.1686***	-0.0307
Time Dummy = 6	-0.1073***	-0.2247***	-0.1203***
Time Dummy = 7	-0.1180***	-0.2593***	-0.1396***
Time Dummy = 8	-0.2069***	-0.3217***	-0.1355***
Time Dummy = 9	-0.2927***	-0.3728***	-0.1144**
Time Dummy = 10	-0.3279***	-0.3519***	-0.0627
Time Dummy = 11	-0.3129***	-0.3244***	-0.0645
Time Dummy = 12	-0.2746***	-0.3230***	-0.1121*
Time Dummy = 13	-0.3117***	-0.3021***	-0.0614
Time Dummy = 14	-0.3243***	-0.2968***	-0.0642
Time Dummy = 15	-0.3419***	-0.3035**	-0.0766
Time Dummy = 16	-0.3547***	-0.3144**	-0.0653
Time Dummy = 17	-0.4121***	-0.3643***	-0.0489
Birth Cohort Dummy = 2	-0.0056	-0.0282**	-0.0303***
Birth Cohort Dummy = 3	-0.0136	-0.0677***	-0.0513***
Birth Cohort Dummy = 4	-0.0454***	-0.1106***	-0.0562***
Birth Cohort Dummy = 5	-0.0593***	-0.1330***	-0.0556***
Birth Cohort Dummy = 6	-0.0512**	-0.1288***	-0.0527**
Birth Cohort Dummy = 7	-0.0334	-0.1010***	-0.0350
Birth Cohort Dummy = 8	-0.0270	-0.0700*	-0.0098
Birth Cohort Dummy = 9	-0.0228	-0.0360	0.0275
Birth Cohort Dummy = 10	-0.0155	0.0203	
Observations	779	779	663

Table D.2: OLS Estimates of Birth Cohort and Time Effects on Consumption and Income of U.S. Households

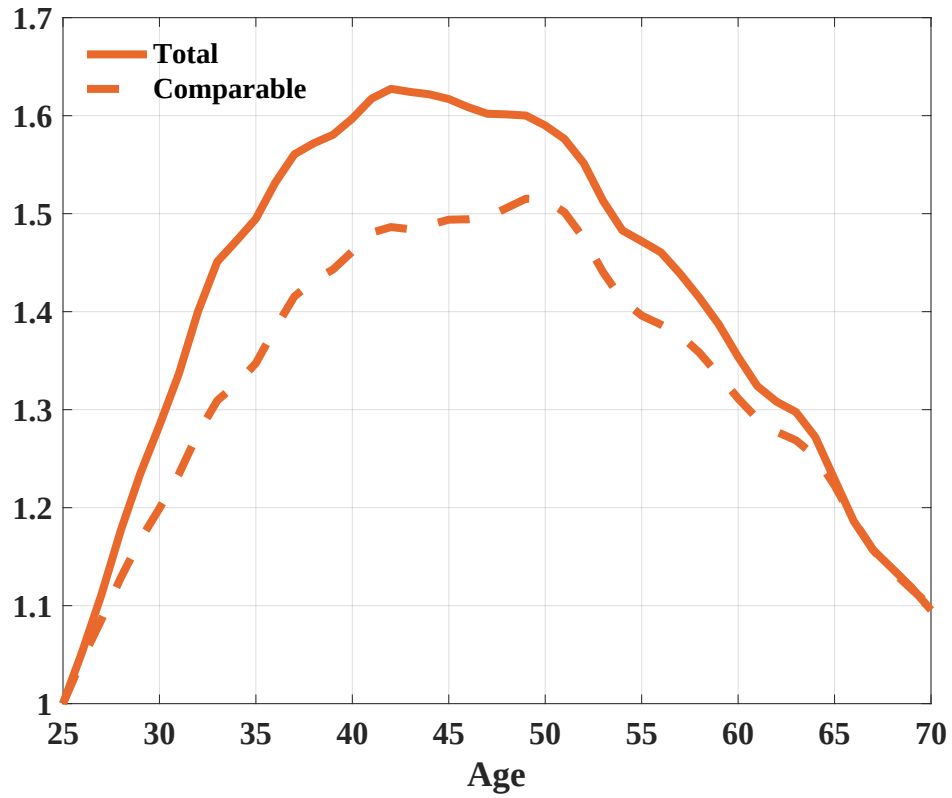
	(1) Ln(Consumption)	(2) Ln(Income)
Linear time trend	-0.0002	0.0086
Time Dummy = 3	-0.0710*	0.0051
Time Dummy = 4	-0.1280**	-0.0813
Time Dummy = 5	-0.1757**	-0.0630
Time Dummy = 6	-0.2103**	-0.0654
Time Dummy = 7	-0.2257*	-0.0632
Time Dummy = 8	-0.1314	-0.0162
Birth Cohort Dummy = 2	-0.0155	0.0037
Birth Cohort Dummy = 3	0.0802*	0.0451
Birth Cohort Dummy = 4	0.0480	0.0504
Birth Cohort Dummy = 5	0.0978	0.1283
Birth Cohort Dummy = 6	0.0091	0.0326
Birth Cohort Dummy = 7	-0.0592	-0.1090
Birth Cohort Dummy = 8	-0.0554	-0.1730
Birth Cohort Dummy = 9	-0.0102	-0.1544
Birth Cohort Dummy = 10	-0.0132	-0.1623
Birth Cohort Dummy = 11	-0.0109	-0.1468
Birth Cohort Dummy = 12	-0.0556	-0.2477
Birth Cohort Dummy = 13	-0.0775	-0.3040
Birth Cohort Dummy = 14	-0.0370	-0.2626
Observations	505	505

Table D.3: Household Composition by Age of Household Head

Age Group	Spouse	Children			Parents	Grand children	Others	Number
		0-5	6-10	11-16				
20-29	0.87	0.54	0.38	0.05	0.17	0.00	0.12	3.53
30-39	0.92	0.23	0.63	0.44	0.11	0.00	0.05	4.09
40-49	0.89	0.05	0.21	0.55	0.07	0.03	0.08	4.20
50-59	0.83	0.10	0.13	0.18	0.03	0.18	0.26	4.07
60-69	0.75	0.13	0.21	0.16	0.01	0.37	0.45	4.04
70-79	0.69	0.10	0.21	0.22	0.00	0.47	0.52	4.11
80-89	0.59	0.06	0.15	0.22	0.00	0.51	0.56	4.11
Total	0.84	0.12	0.26	0.33	0.06	0.15	0.21	4.10
Observations	2,356,598							

Notes: Columns 2-8 report the fraction of households reporting the presence of respective members. Others in the extended family refer to presence of siblings, their families or other relatives living in the same household. Family size refers to the total number of members in the household.

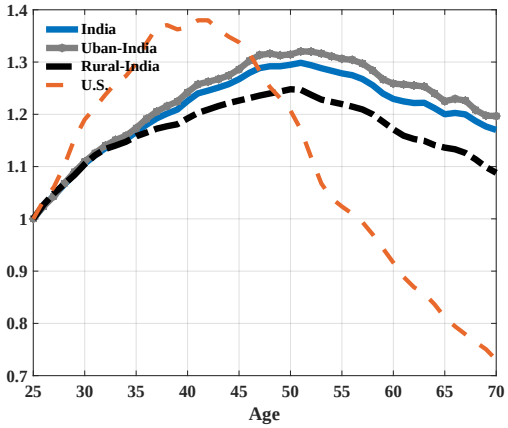
Figure D.1: Unadjusted Life-Cycle Consumption in the U.S.
by Age of Household Head



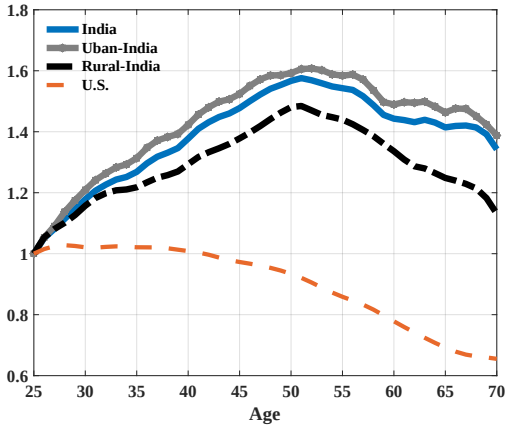
Notes: Total household consumption relative to age 25 (household head) is reported. Data for the U.S. comes from the PSID. Comparable categories include total expenditures on 1) food 2) transportation 3) education 4) childcare 5) health care 6) clothing 7) household repairs and furnishing 8) trips and recreational activities 9) housing related to rent, utility, telephone and internet. Total consumption includes, in addition to comparable categories, mortgage, property taxes and home owner's insurance.

Figure D.2: Unadjusted Life-Cycle Consumption
by Age of Household Head and Expenditure Categories

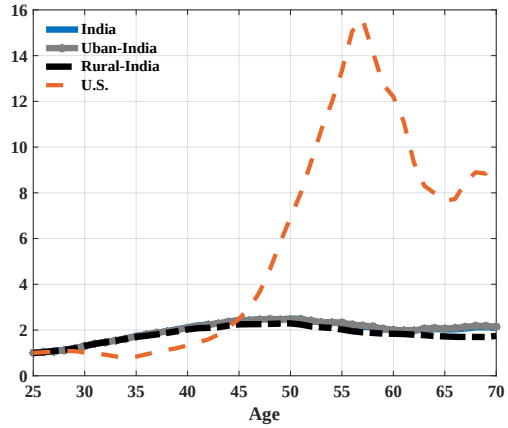
(a) Food



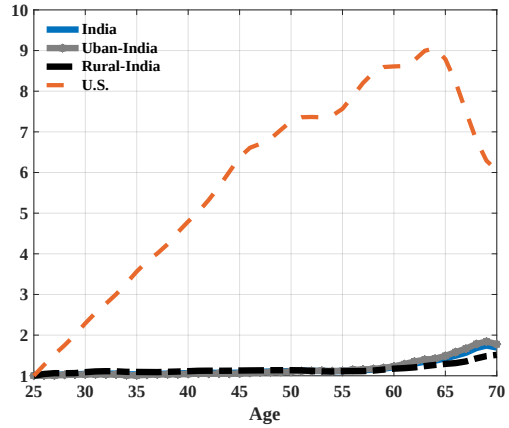
(b) Non-Mortgage Housing



(c) Education



(d) Health



(e) Transportation

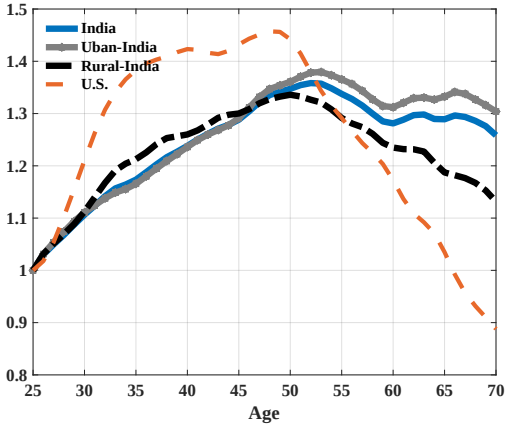


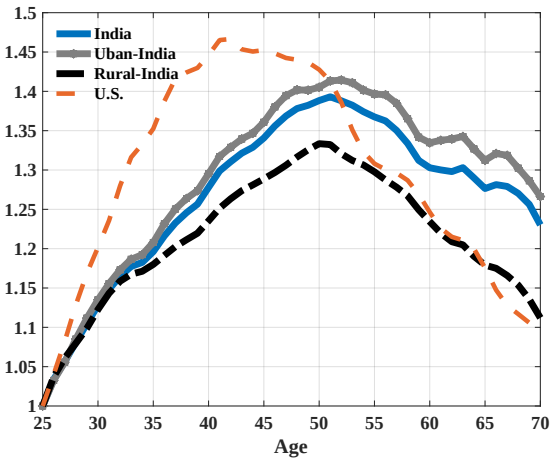
Table D.4: Average household size by age of household head

Age Group	Children			Parents	Grand children	Others
	0-5	6-10	11-16			
20-29	1.29	1.35	1.22	1.25	1.48	1.68
30-39	1.18	1.48	1.47	1.20	1.55	1.62
40-49	1.18	1.31	1.51	1.14	1.51	1.27
50-59	1.23	1.34	1.34	1.07	1.70	1.16
60-69	1.21	1.37	1.40	1.04	1.89	1.14
70-79	1.18	1.33	1.39	1.05	1.99	1.14
80-89	1.16	1.32	1.35	1.04	2.02	1.14
Total	1.21	1.39	1.46	1.16	1.83	1.19
Observations	1,472,085					

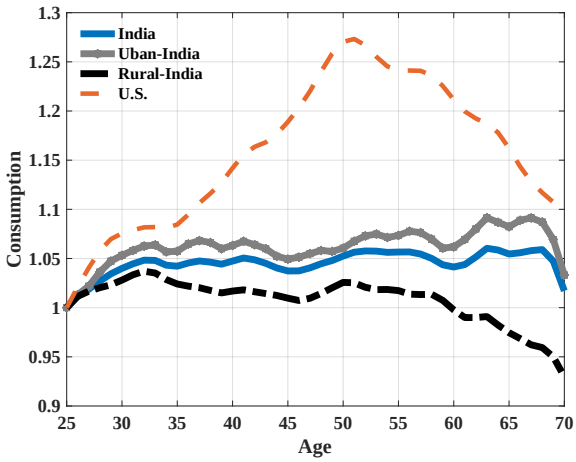
Notes: Columns 2-7 report the average number of each type of member present in the household, conditional on having them. Others in the extended family refer to presence of siblings, their families or other relatives living in the same household.

Figure D.3: Life-Cycle Consumption Less Education and Health by Age of Household Head

(a) Unadjusted



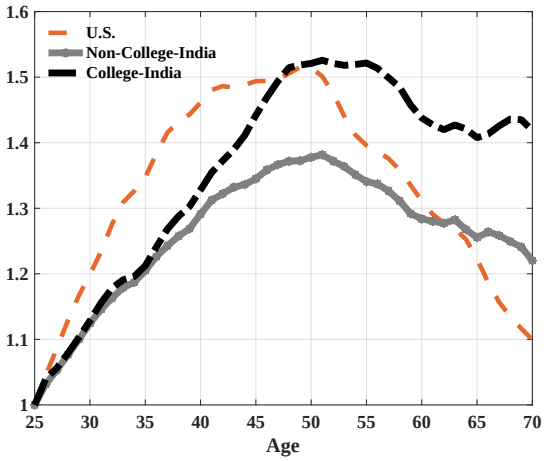
(b) Adjusted



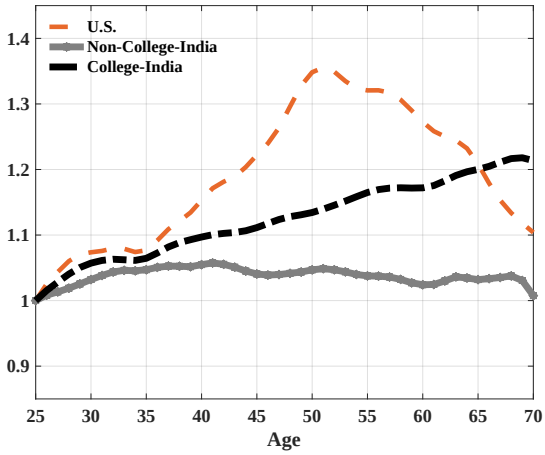
Notes: Consumption relative to age 25 (household head) is reported for both U.S. and India. Data for the U.S. comes from the PSID. Expenditure categories include total expenditures on 1) food 2) transportation 3) childcare 4) clothing 5) household repairs and furnishing 6) trips and recreational activities 7) housing to related rent, utility, telephone and internet. Total household consumption in panel (b) is adjusted for family size by using a modified OECD scale which assigns a weight of 1 to household head, 0.3 to each children under/of the age of 16 and 0.5 to each adult over the age of 16.

Figure D.4: Life-Cycle Consumption
by Age and Education Status of Household Head

(a) Unadjusted



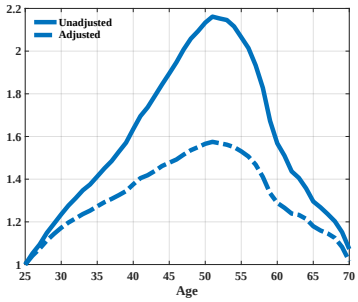
(b) Adjusted



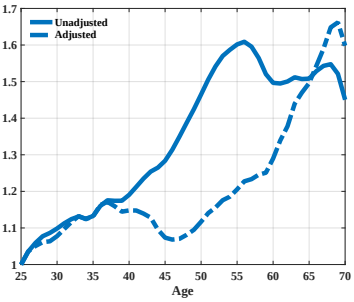
Notes: Household consumption relative to age 25 (household head) is reported for both U.S. and India. Data for the U.S. comes from the PSID. Adjusted refers to total household consumption divided by family size using a modified OECD scale which assigns a weight of 1 to household head, 0.3 to each children under/of the age of 16 and 0.5 to each adult over the age of 16. Expenditure categories include total expenditures on 1) food 2) transportation 3) education 4) childcare 5) health care 6) clothing 7) household repairs and furnishing 8) trips and recreational activities 9) housing to related rent, utility, telephone and internet. College refers to those with graduate or post-graduate degrees (including doctorate and MPhil degrees). Non-college includes those without any formal education.

Figure D.5: Life-Cycle Income
by Age of Household Head, Family Type, Region and Occupation

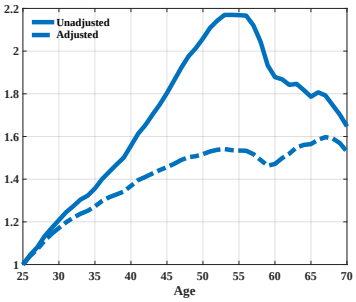
(a) Nuclear Families



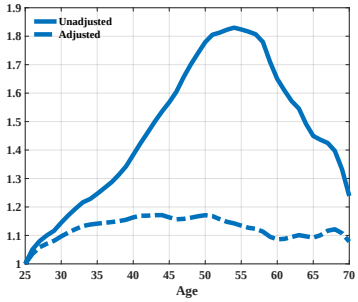
(b) Extended Families



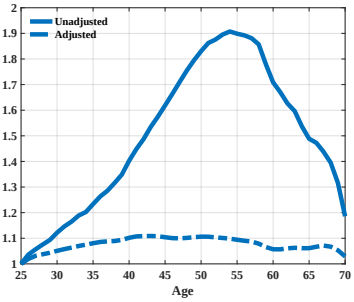
(c) Urban India



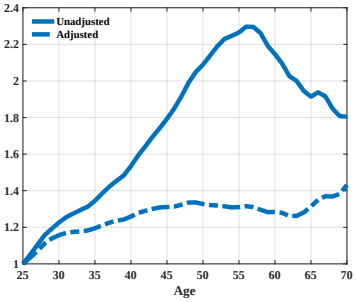
(d) Rural India



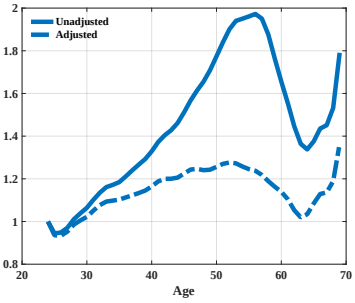
(e) Farmers



(f) Self Employed

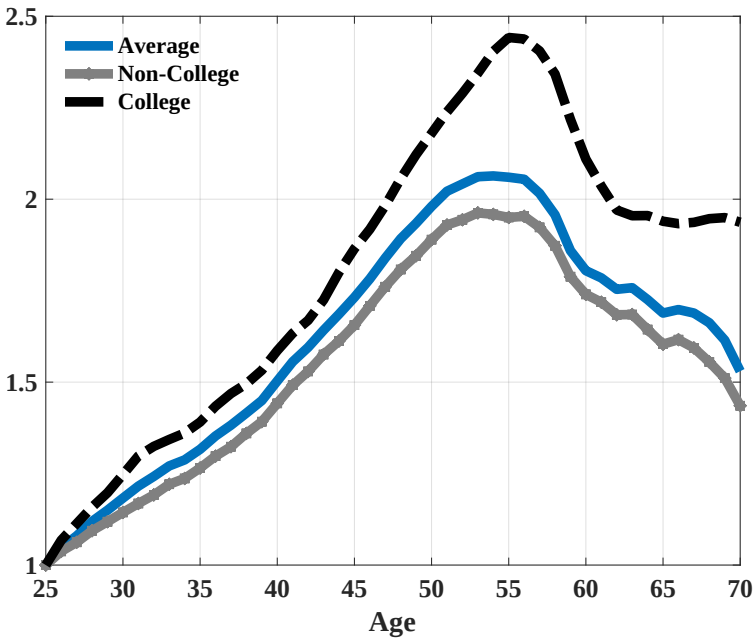


(g) White-Collared Workers



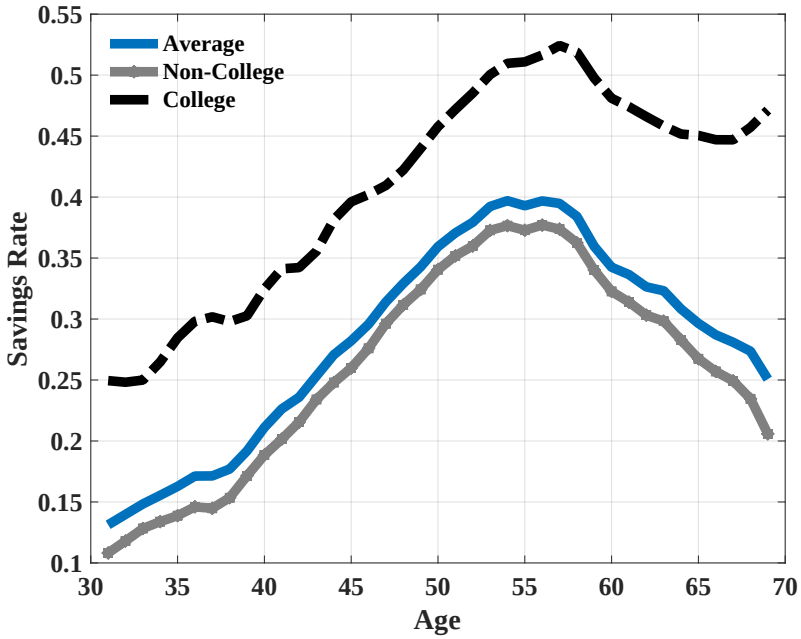
Notes: Adjusted income reports estimates of total household income divided by number of earning members. Total household income relative to age 25 (household head) is reported for each region and family size type. Family income for India includes income from all sources including private/public transfers, profits, lotteries, wages, overtime, bonus, interest payments, dividends and insurance payments.

Figure D.6: Life-Cycle Income
by Age and Education Status of Household Head



Notes: Total household income relative to age 25 (household head) is reported. Family income for India includes income from all sources including private/public transfers, profits, lotteries, wages, overtime, bonus, interest payments, dividends and insurance payments. College refers to those with graduate or post-graduate degrees (including doctorate and MPhil degrees). Non-college includes those without any formal education.

Figure D.7: Life-Cycle Savings Rate
by Age and Education Status of Household Head



Notes: Savings rate is computed as total household income net of total nondurable consumption as a fraction of total household income. College refers to those with graduate or post-graduate degrees (including doctorate and MPhil degrees). Non-college includes those without any formal education.

Table D.5: Probit Estimates of Intentions to Purchase Durables on Actual Purchases in Future

	(1) Bought House	(2) Bought Car	(3) Bought tractor	(4) Bought Cattle
Intend to Buy House in Previous Wave	0.693***			
	(25.02)			
Intend to Buy House 2 Waves Back	0.248***			
	(6.37)			
Intend to Buy Car in Previous Wave		0.535***		
		(19.12)		
Intend to Buy Car 2 Waves Back		0.464***		
		(15.23)		
Intend to Buy Tractor in Previous Wave			0.727***	
			(8.54)	
Intend to Buy Tractor 2 Waves Back			0.455***	
			(4.07)	
Intend to Buy Cattle in Previous Wave				0.657***
				(23.12)
Intend to Buy Cattle 2 Waves Back				0.348***
				(9.41)
Constant	-2.357***	-2.693***	-3.245***	-2.571***
	(-797.14)	(-626.04)	(-360.56)	(-689.99)
Observations	1705700	1705700	1705700	1705700

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.6: OLS Estimates of Intentions to Purchase Durables on Savings Rate in Urban India

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0922***	0.0837***	0.0837***	0.0314***
	(22.53)	(20.90)	(21.03)	(8.33)
Intend to By Car=1	0.120***	0.0997***	0.0972***	0.0318***
	(40.76)	(34.44)	(33.79)	(11.66)
Intend to Buy 2-Wheeler=1	0.0115***	0.00387	0.00273	0.00892***
	(4.27)	(1.47)	(1.04)	(3.59)
Intend to Buy Tractor=1	-0.0147	-0.0146	-0.0165*	-0.0268***
	(-1.76)	(-1.80)	(-2.04)	(-3.50)
Intend to Buy Cattle=1	-0.0255***	-0.0322***	-0.0317***	-0.00806
	(-5.27)	(-6.81)	(-6.73)	(-1.81)
Time Dummy		0.00557***	0.00323***	0.00307***
		(107.57)	(42.85)	(42.83)
Birth Cohort		-0.0313***	0.00103	0.00317***
		(-239.00)	(1.14)	(3.69)
Age of Head			-0.104***	-0.112***
			(-52.89)	(-60.05)
Age of Head $\times$ Age of Head			0.00258***	0.00272***
			(64.38)	(71.69)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000192***	-0.0000201***
			(-71.67)	(-79.02)
Durable Goods				0.00231***
				(192.81)
Education				0.00883***
				(215.03)
Constant	0.312***	0.419***	1.453***	1.461***
	(1187.24)	(522.79)	(43.18)	(45.79)
Observations	1413340	1413340	1413340	1413340

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.7: OLS Estimates of Intentions to Purchase Durables on Savings Rate in Rural India

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0769***	0.0674***	0.0658***	0.0491***
	(8.89)	(7.93)	(7.78)	(5.89)
Intend to By Car=1	0.0836***	0.0721***	0.0690***	-0.00204
	(12.91)	(11.31)	(10.87)	(-0.33)
Intend to Buy 2-Wheeler=1	0.0147***	0.0101*	0.0104**	0.0187***
	(3.66)	(2.54)	(2.64)	(4.83)
Intend to Buy Tractor=1	0.111***	0.100***	0.0983***	0.0752***
	(13.23)	(12.19)	(11.99)	(9.32)
Intend to Buy Cattle=1	0.0527***	0.0419***	0.0420***	0.0382***
	(11.84)	(9.56)	(9.63)	(8.89)
Time Dummy		0.00553***	0.00349***	0.00267***
		(68.66)	(29.41)	(22.70)
Birth Cohort		-0.0283***	-0.00109	-0.00000711
		(-140.30)	(-0.76)	(-0.00)
Age of Head			-0.126***	-0.123***
			(-41.29)	(-41.04)
Age of Head $\times$ Age of Head			0.00296***	0.00290***
			(47.47)	(47.25)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000214***	-0.0000210***
			(-51.24)	(-50.93)
Durable Goods				0.00255***
				(110.80)
Education				0.00491***
				(60.63)
Constant	0.245***	0.338***	1.817***	1.713***
	(601.03)	(267.13)	(34.70)	(33.21)
Observations	659740	659740	659740	659740

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.8: OLS Estimates of Intentions to Purchase Durables on Savings Rate in Nuclear Families

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.101***	0.0908***	0.0898***	0.0406***
	(22.75)	(20.69)	(20.59)	(9.73)
Intend to By Car=1	0.123***	0.103***	0.0996***	0.0224***
	(37.74)	(32.31)	(31.30)	(7.35)
Intend to Buy 2-Wheeler=1	0.00947***	0.000137	-0.00185	0.00584*
	(3.55)	(0.05)	(-0.71)	(2.34)
Intend to Buy Tractor=1	0.0411***	0.0355***	0.0330***	0.0234***
	(5.87)	(5.14)	(4.81)	(3.57)
Intend to Buy Cattle=1	0.00741	-0.00589	-0.00569	0.0150***
	(1.96)	(-1.58)	(-1.53)	(4.24)
Time Dummy		0.00629***	0.00427***	0.00382***
		(118.62)	(55.21)	(51.47)
Birth Cohort		-0.0278***	-0.000611	0.00146
		(-189.93)	(-0.65)	(1.64)
Age of Head			-0.112***	-0.109***
			(-53.34)	(-54.57)
Age of Head $\times$ Age of Head			0.00279***	0.00270***
			(64.07)	(64.92)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000212***	-0.0000204***
			(-71.46)	(-71.92)
Durable Goods				0.00233***
				(177.05)
Education				0.00898***
				(209.05)
Constant	0.258***	0.354***	1.537***	1.405***
	(963.38)	(379.33)	(43.52)	(41.61)
Observations	1435786	1435786	1435786	1435786

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.9: OLS Estimates of Intentions to Purchase Durables on Savings Rate in Extended Families

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0879***	0.0850***	0.0862***	0.0314***
	(13.24)	(12.89)	(13.14)	(5.01)
Intend to By Car=1	0.123***	0.112***	0.109***	0.0456***
	(25.66)	(23.41)	(23.05)	(10.04)
Intend to Buy 2-Wheeler=1	0.0210***	0.0174***	0.0169***	0.0230***
	(5.26)	(4.38)	(4.26)	(6.09)
Intend to Buy Tractor=1	0.0187	0.0176	0.0165	0.0118
	(1.83)	(1.73)	(1.63)	(1.22)
Intend to Buy Cattle=1	0.000218	-0.00507	-0.00548	0.0122*
	(0.04)	(-0.85)	(-0.92)	(2.14)
Time Dummy		0.00242***	0.000787***	0.000761***
		(31.66)	(7.04)	(7.11)
Birth Cohort		-0.0178***	0.00228	0.00256*
		(-87.92)	(1.68)	(1.98)
Age of Head			-0.0812***	-0.0678***
			(-25.87)	(-22.62)
Age of Head $\times$ Age of Head			0.00203***	0.00180***
			(32.47)	(30.16)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000151***	-0.0000139***
			(-37.21)	(-35.83)
Durable Goods				0.00237***
				(131.29)
Education				0.00821***
				(127.00)
Constant	0.364***	0.413***	1.231***	0.877***
	(952.56)	(394.31)	(22.61)	(16.87)
Observations	637294	637294	637294	637294

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.10: OLS Estimates of Intentions to Purchase Durables on Savings Rate in Farming Households

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0755***	0.0723***	0.0711***	0.0626***
	(10.70)	(10.50)	(10.39)	(9.21)
Intend to By Car=1	0.0610***	0.0441***	0.0414***	-0.0144*
	(9.99)	(7.41)	(6.99)	(-2.45)
Intend to Buy 2-Wheeler=1	0.0250***	0.0130***	0.0127***	0.0173***
	(7.40)	(3.94)	(3.85)	(5.30)
Intend to Buy Tractor=1	0.0930***	0.0775***	0.0742***	0.0533***
	(11.18)	(9.55)	(9.19)	(6.66)
Intent to Buy Cattle=1	0.0543***	0.0337***	0.0340***	0.0269***
	(12.63)	(8.02)	(8.13)	(6.50)
Time Dummy		0.00749***	0.00508***	0.00460***
		(106.09)	(49.12)	(44.43)
Birth Cohort		-0.0333***	-0.000385	0.000106
		(-180.80)	(-0.31)	(0.09)
Age of Head			-0.122***	-0.120***
			(-44.83)	(-44.31)
Age of Head × Age of Head			0.00295***	0.00290***
			(52.58)	(51.93)
Age of Head × Age of Head × Age of Head			-0.0000218***	-0.0000213***
			(-57.25)	(-56.50)
Durable Goods				0.00251***
				(105.92)
Education				0.00122***
				(15.07)
Constant	0.225***	0.333***	1.657***	1.599***
	(624.97)	(284.45)	(35.84)	(34.87)
Observations	802561	802561	802561	802561

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.11: OLS Estimates of Intentions to Purchase Durables on Savings Rate in Self-Employed Households

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0818***	0.0716***	0.0707***	0.0201**
	(11.22)	(10.05)	(9.97)	(2.96)
Intend to By Car=1	0.100***	0.0838***	0.0823***	0.0294***
	(20.33)	(17.35)	(17.12)	(6.38)
Intend to Buy 2-Wheeler=1	0.0170***	0.0123**	0.0117*	0.0117**
	(3.65)	(2.71)	(2.57)	(2.69)
Intend to Buy Tractor=1	0.0272*	0.0324*	0.0310*	0.0117
	(2.04)	(2.48)	(2.38)	(0.94)
Intend to Buy Cattle=1	-0.0163*	-0.0194**	-0.0168*	-0.000970
	(-2.18)	(-2.66)	(-2.31)	(-0.14)
Time Dummy		0.00435***	0.00204***	0.00300***
		(49.56)	(15.86)	(24.27)
Birth Cohort		-0.0341***	0.000505	0.00222
		(-142.25)	(0.33)	(1.50)
Age of Head			-0.160***	-0.161***
			(-45.18)	(-47.54)
Age of Head × Age of Head			0.00365***	0.00361***
			(50.06)	(51.85)
Age of Head × Age of Head × Age of Head			-0.0000258***	-0.0000253***
			(-52.41)	(-53.67)
Durable Goods				0.00268***
				(135.66)
Education				0.00636***
				(84.21)
Constant	0.303***	0.444***	2.410***	2.336***
	(674.50)	(297.39)	(40.26)	(40.83)
Observations	459168	459168	459168	459168

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.12: OLS Estimates of Intentions to Purchase Durables on Savings Rate in White Collar Worker Households

	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0542***	0.0526***	0.0521***	0.0164*
	(6.64)	(6.53)	(6.50)	(2.10)
Intend to By Car=1	0.0450***	0.0430***	0.0417***	0.0257***
	(8.74)	(8.44)	(8.22)	(5.22)
Intend to Buy 2-Wheeler=1	-0.00272	-0.00191	-0.00233	-0.00789
	(-0.40)	(-0.29)	(-0.35)	(-1.23)
Intend to Buy Tractor=1	-0.0156	-0.0187	-0.0189	-0.0124
	(-0.87)	(-1.05)	(-1.07)	(-0.72)
Intend to Buy Cattle=1	-0.0554***	-0.0472***	-0.0457***	-0.0191
	(-4.66)	(-4.01)	(-3.90)	(-1.68)
Time Dummy		0.000205	-0.00110***	-0.000905***
		(1.75)	(-6.32)	(-5.33)
Birth Cohort		-0.0260***	0.00142	0.00211
		(-73.10)	(0.68)	(1.04)
Age of Head			-0.172***	-0.165***
			(-31.99)	(-31.61)
Age of Head $\times$ Age of Head			0.00392***	0.00376***
			(35.02)	(34.54)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000281***	-0.0000268***
			(-36.71)	(-36.06)
Durable Goods				0.000856***
				(45.03)
Education				0.00795***
				(83.10)
Constant	0.470***	0.603***	2.811***	2.556***
	(788.41)	(282.16)	(31.57)	(29.52)
Observations	207518	207518	207518	207518

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.13: OLS Estimates of Intentions to Purchase Other Durables on Savings Rate in India

	(1)	(2)	(3)	(4)
Intend to Buy Television=1	0.0550***	0.0446***	0.0443***	0.0230***
	(22.23)	(18.36)	(18.37)	(9.93)
Intend to Buy Refrigerator=1	0.00286	-0.00338	-0.00387	0.0103***
	(1.36)	(-1.64)	(-1.89)	(5.26)
Intend to Buy Cooler=1	0.0226***	0.0136***	0.0137***	0.0148***
	(9.21)	(5.66)	(5.72)	(6.45)
Intend to Buy Inverter=1	0.00553*	0.000193	-0.00129	-0.00723**
	(2.14)	(0.08)	(-0.51)	(-2.99)
Intend to Buy Washing Machine=1	0.0254***	0.0159***	0.0153***	0.0221***
	(14.15)	(9.01)	(8.70)	(13.15)
Intend to Buy Computer=1	0.0846***	0.0700***	0.0683***	0.0108***
	(34.11)	(28.74)	(28.23)	(4.65)
Time Dummy		0.00520***	0.00292***	0.00265***
		(117.63)	(45.53)	(43.02)
Birth Cohort		-0.0307***	0.000563	0.00211**
		(-277.48)	(0.73)	(2.86)
Age of Head			-0.111***	-0.115***
			(-66.61)	(-72.15)
Age of Head $\times$ Age of Head			0.00270***	0.00277***
			(79.68)	(85.29)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000200***	-0.0000203***
			(-87.88)	(-93.42)
Durable Goods				0.00243***
				(227.29)
Education				0.00829***
				(231.27)
Constant	0.290***	0.398***	1.562***	1.524***
	(1293.05)	(583.78)	(54.81)	(55.88)
Observations	2073080	2073080	2073080	2073080

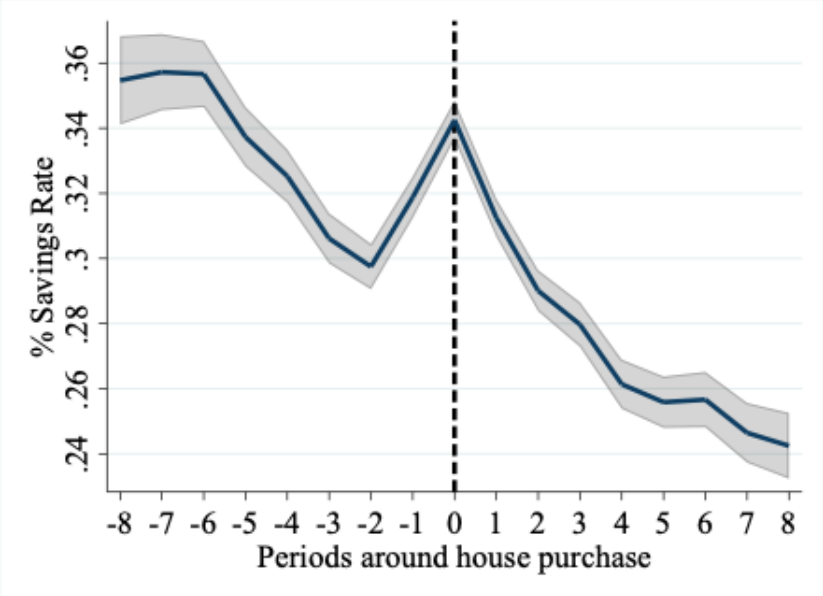
t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.14: Average Age of Purchasing
Consumer Durables

	Avg.	Urban	Rural	Nuclear	Extended	Farmers	Self-Employed	White-Collar
House	48.9	48.9	48.8	47.1	53.9	48.2	47.4	47.7
Car	51.3	51.4	51.0	49.5	54.9	51.2	49.7	49.2
2-Wheeler	49.1	49.1	49.0	47.1	54.2	48.6	47.8	47.8
Cattle	48.8	49.0	48.8	46.6	54.1	48.5	46.9	47.3
Tractor	49.9	47.9	50.0	47.1	55.3	49.7	48.4	46.0

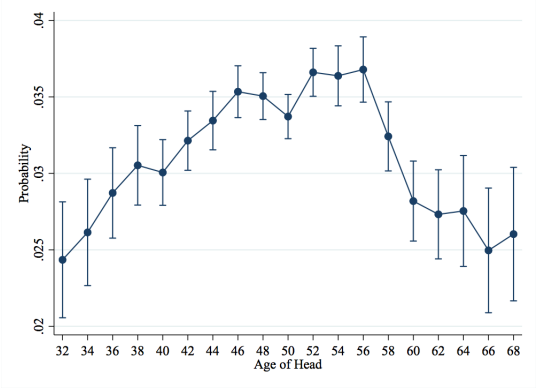
Figure D.8: Savings Rate and House Purchase Event



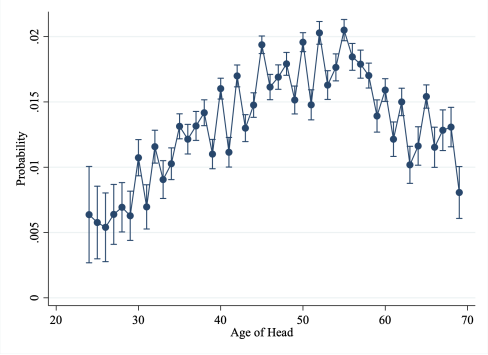
Notes: The graph reports household savings rate around the time of a house purchase. Controls include dummies for calendar time, birth cohort, and a third order age polynomial.

Figure D.9: Borrowing for House

(a) Probability of Borrowing



(b) Probability of Making an Installment Payment



Notes: Probability of borrowing for house reflects the fraction of households who have reported any outstanding borrowing to finance house purchases. Installment payments refer to "equal monthly installments" (EMI) for house.

Figure D.10: Borrowing for Consumer Durables By Regions

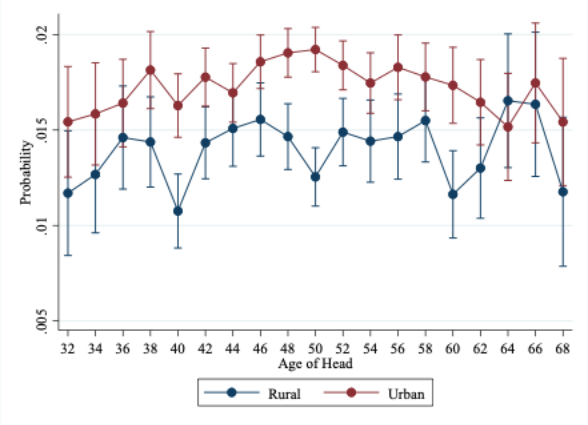
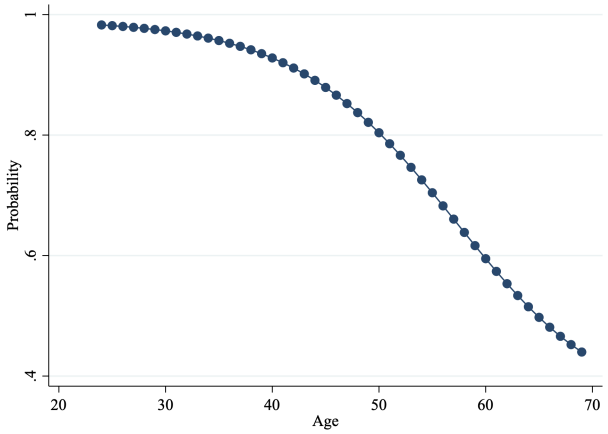
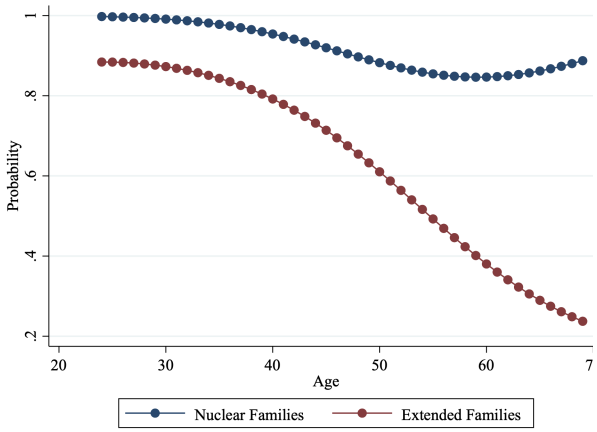


Figure D.11: Households With Heads as Primary Earning Members by Age of Head

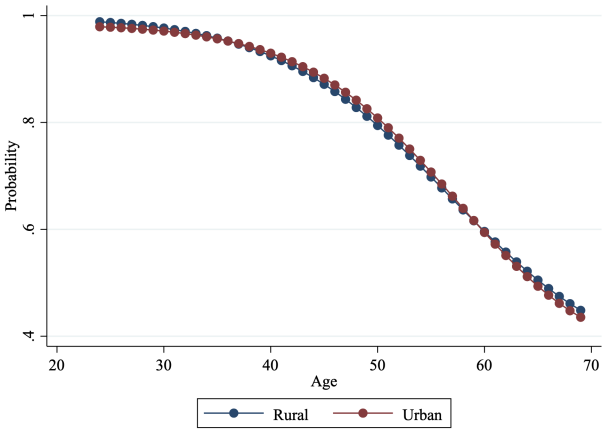
(a) All



(b) By Family Type



(c) By Region Type



(d) By Occupation

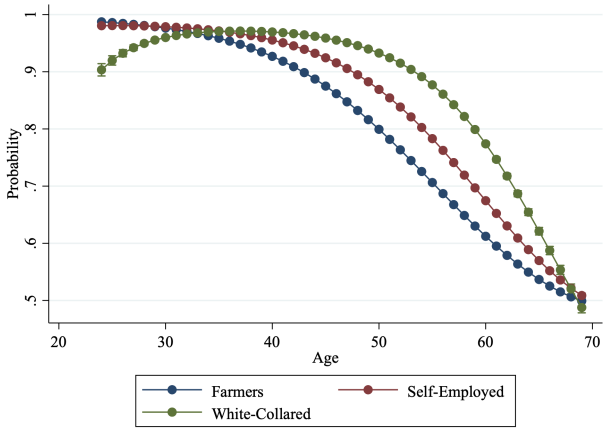
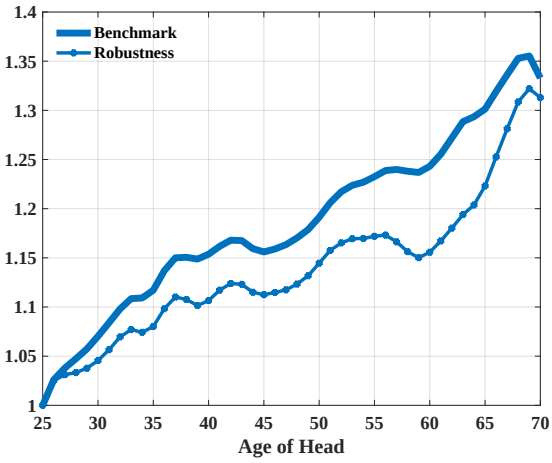
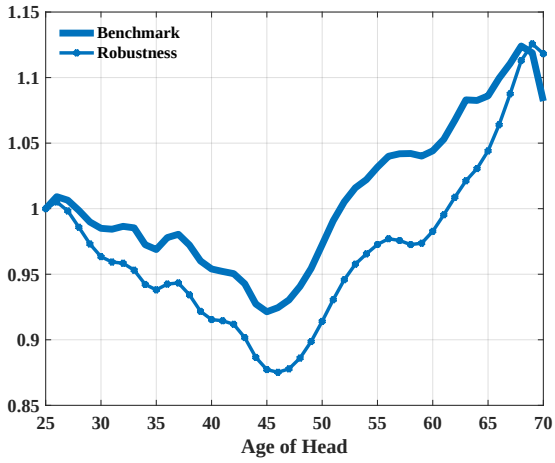


Figure D.12: Head Robustness: Life-Cycle Consumption
by Age of Household Head for Extended Families

(a) Unadjusted

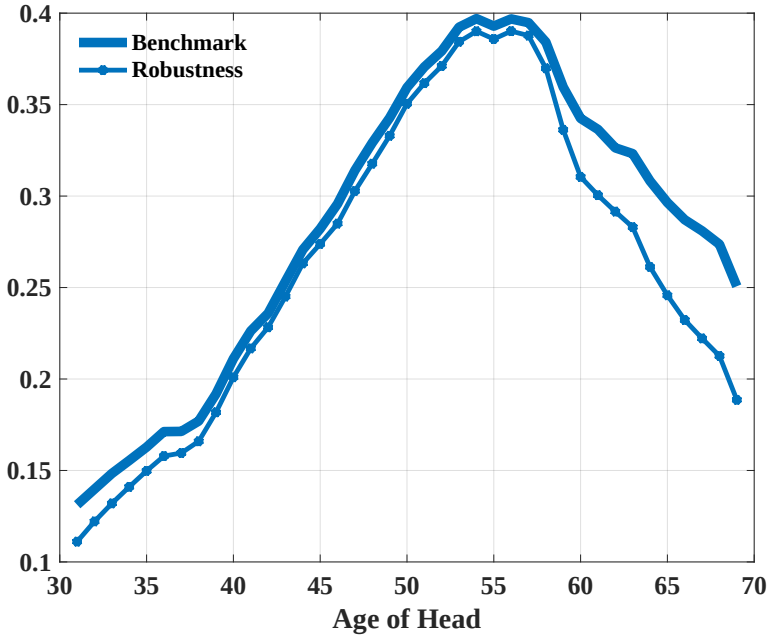


(b) Adjusted



Notes: This robustness exercise drops all extended family households where the head is not the primary earning member.

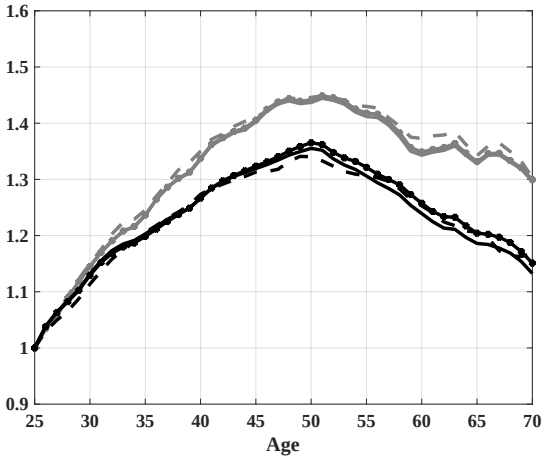
Figure D.13: Head Robustness: Life-Cycle Savings Rate
by Age of Household Head



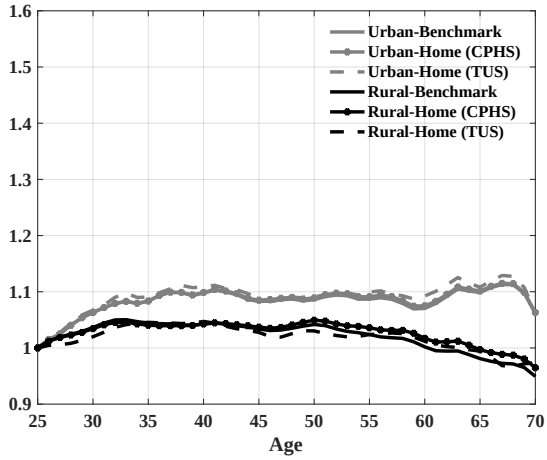
Notes: Savings rate is computed as income net of total nondurable consumption as a fraction of total income. This robustness exercise drops all households where head is not the primary earning member.

Figure D.14: Home Production Robustness: Life-Cycle Consumption by Age of Household Head

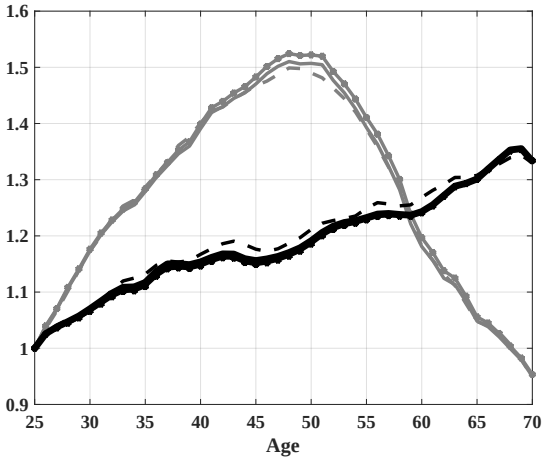
(a) Unadjusted-Region



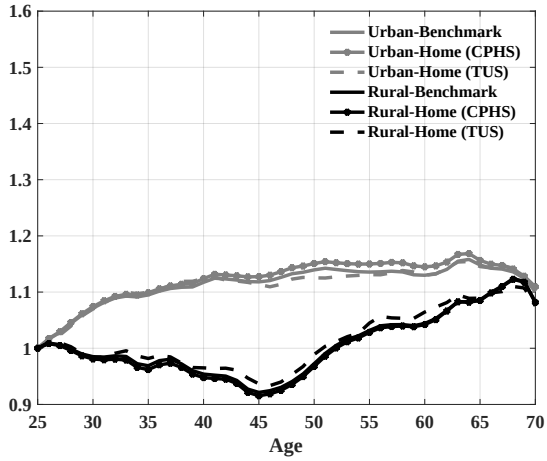
(b) Adjusted-Region



(c) Unadjusted-Family Type



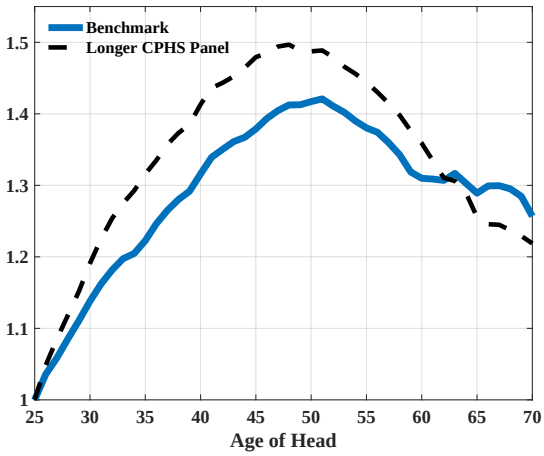
(d) Adjusted-Family Type



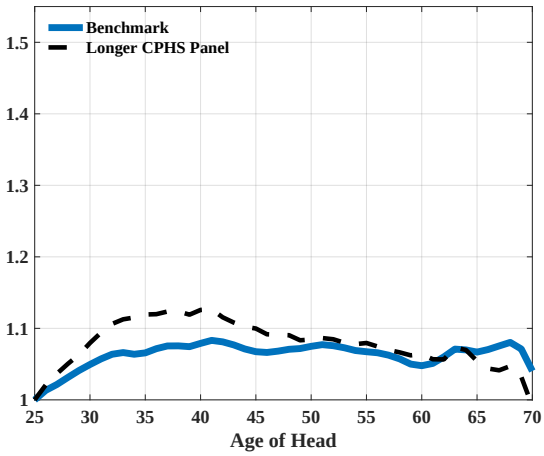
Notes: This robustness exercise adds estimates of home production to household consumption expenditures.

Figure D.15: Longer CPHS Panel Robustness : Life-Cycle Consumption by Age of Household Head

(a) Unadjusted



(b) Adjusted



Notes: Household consumption relative to age 25 (household head) is reported for both benchmark estimates and robustness exercise. Extended CPHS data in the robustness exercise cover years from 2014-2022. Adjusted refers to total household consumption divided by family size using a modified OECD scale that assigns a weight of 1 to household head, 0.3 to each child under/of the age of 16, and 0.5 to each adult over the age of 16. Expenditure categories include total expenditures on: 1) food, 2) transportation, 3) education, 4) childcare, 5) healthcare, 6) clothing ,7) household repairs and furnishing, 8) trips and recreational activities, 9) housing (rent, utility, telephone and internet).