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

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Abstract

The canonical prediction of life-cycle models, that individuals smooth consumption over their lifetime, has mostly been tested in 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 little growth in nondurable consumption expenditures after adjusting for family size. Surprisingly, this flat adjusted profile coexists with substantial income growth and a sharp rise in the savings/surplus rate over the life cycle. We show that lumpy non-housing durable accumulation is an important use of this life-cycle surplus, helping reconcile high savings rates with flat measured adult-equivalent nondurable consumption. Quantitatively, non-housing durable stock growth accounts for about one-third of accumulated life-cycle surplus by age 45, and an augmented expenditure profile that adds imputed non-housing durable investment flows to nondurables raises adult-equivalent life-cycle growth from 8.4% to 27.9%.

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

JEL Classification: E21, J10, O11.

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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 nondurable consumption in India to be hump-shaped, roughly comparable to the U.S., though the

[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), and Dotsey et al. (2025).

hump is slightly 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, 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 when we look at the income profile: 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.). This late and sustained income growth, combined with flat adjusted nondurable expenditures, implies a sharp rise in the household surplus rate, defined as income net of nondurable expenditures as a share of income, from about 13% to more than 40% between ages 30 and 55.

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 for 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.

The evidence has three parts. First, using comprehensive information on major and minor durable purchases, we construct a measure of non-housing durable stock and show that it rises steeply—about 120%—over the life cycle. We then discipline the magnitude of this durable channel on surplus with a stock-accounting exercise. Under our benchmark calibration, non-housing durable stock growth accounts for about 33.2% of accumulated life-cycle surplus by age 45. Thus, observed non-housing durables are an economically meaningful early-life component of the surplus allocation, but they do not exhaust the life-cycle savings hump. The remaining surplus is consistent with other assets that CPHS does not fully value over the life cycle, including real estate, business assets, financial assets, gold, and precautionary buffers. Second, we show empirically that stated purchase intentions are associated with higher savings rates, and event-time profiles show higher savings rates near non-housing durable purchase episodes and lower rates afterward; very few households borrow from banks to finance these goods. Third, we document heterogeneity consistent with credit access: urban and nuclear households display faster growth in family-size-adjusted nondurables and earlier non-housing durable accumulation than rural and extended households. We relegate housing and real estate to a separate discussion. They are quantitatively central to Indian household portfolios but follow a different empirical pattern from movable non-housing durable goods.

The interaction of later income growth and credit frictions thus reallocates the life-cycle surplus, realized late, toward non-housing durables and other asset accumulation rather than solely toward higher per-adult-equivalent nondurable spending. Measured nondurables remain flat, but this does not imply that broader expenditures or durable-related consumption services are flat: once imputed non-housing durable investment flows are added to nondurables, the adult-equivalent profile becomes substantially steeper: adult-equivalent growth rises from 8.4% to 27.9%. We interpret this as evidence that the nondurable-only profile understates broader life-cycle resource use. 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 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 limited access to credit markets can interact with lumpy non-housing durable purchases and broader asset accumulation to help explain a flat measured nondurable 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,

[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).

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 seasonal shocks and multigenerational family structures remain valid concerns, the emergence of a large middle class (or at the very least, a large section of the population emerging out of poverty), fertility rates that are currently below replacement, and high aggregate savings rates, provide additional rationale for our research.[3]

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, housing 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. 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.[4] 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.

CPHS comprises 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.[5] 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

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

[4] 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.

[5] 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.

like reported intentions to purchase major assets, such as houses, and non-housing durables, such as 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.[6] 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.[7] Table 1 provides some summary statistics that we discuss further below, after explaining the U.S. PSID data.

How comparable are the CPHS survey estimates to other measures of consumption expenditures and incomes? Detailed independent survey data on household income are scarce, so we focus on consumption expenditures.[8] Our main external benchmark are the Household Consumption Expenditure surveys carried out by the National Sample Survey Office (NSSO).[9] Appendix Section A harmonizes nondurable categories across CPHS and NSSO, applies the relevant survey weights, and compares both levels and category shares in Table A.1. The broad aggregates are close: annual nondurable expenditures are Rs. 86,944 in CPHS and Rs. 85,285 in NSSO, while family-size adjusted nondurable expenditures are Rs. 38,278 and Rs. 36,020, respectively. Some differences remain, especially for health and education, consistent with NSSO's more detailed consumption modules and differences in recall periods and category definitions. As an additional aggregate check, the separate 2014–15 NSSO survey of durable goods and services also asks about total household consumption expenditures (GOI (2016)). Monthly household consumption expenditures from the 2014 CPHS surveys were INR 7,951 for India as a whole, INR 6,802 for rural households, and INR 10,270 for urban households, corresponding to 97%, 102%, and 91% of the government survey counterparts. Finally, the per-capita real consumption expenditure annual growth in CPHS was 6.7%, close to the national-accounts per-capita private consumption expenditure growth of 6.2%.[10]

[6] 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.

[7] 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.

[8] We return to income measurement error in Section 4.3, where we benchmark CPHS wage earnings against PLFS and compare surplus-implied wealth profiles with AIDIS wealth profiles.

[9] The Indian government withheld the release of the 2017–18 round of the consumption expenditure survey due to concerns that estimated expenditures were lower than in the 2011–12 survey. Researchers have also relied on the Rural Economic & Demographic Survey (REDS), a rural panel of about 9,000 households last conducted in 2006, and the India Human Development Survey (IHDS), conducted in 2004–05 and 2011–12 with a panel component.

[10] This is reassuring given concerns raised by Somanchi (2021). Gupta et al. (2021) and Roy and Van Der Weide (2025) also address related concerns.

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, beginning 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.

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 share is 23%. Non-mortgage housing-related expenditure shares, which include rent, utilities, and communications, are somewhat lower in CPHS than in PSID. Transportation and health care, unsurprisingly, account for much larger shares in the U.S. Appendix Section B provides a detailed discussion about each expenditure category for both countries.

With respect to demographics, the average age of the household head is similar across the two samples, though slightly lower in CPHS than in PSID after applying survey weights. Given that India is a younger population, the relatively high age of the CPHS household head still 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. Throughout the paper, the OECD scale refers to the modified OECD equivalence scale, which assigns a weight of 1 to the household head, 0.5 to each additional adult, and 0.3 to each child aged 16 or under. Lastly, the family-size and OECD adult-equivalent scales differences between the two countries are as expected.

4 Life-Cycle Patterns

In this 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.

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

Table 1: Comparison of PSID and CPHS datasets

	CPHS		PSID	
	Mean	Fraction	Mean	Fraction
Age of household head	49.51		52.54	
Annual income	10,244.39		81,261.21	
Annual expenditures	6,020.87		37,446.39	
Food	3,108.74	0.55	7,859.90	0.23
Non-mortgage housing	1,175.84	0.19	7,578.91	0.25
Transport	161.78	0.03	9,044.32	0.22
Health	150.28	0.02	3,579.37	0.10
Education	216.78	0.03	1,264.37	0.02
Clothing	671.93	0.11	1,318.92	0.03
Recreation	27.68	0.00	2,759.07	0.06
Family size	4.17		2.01	
OECD scale	2.37		1.40	
Adjusted expenditures	2,650.82		26,815.99	
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. Adjusted expenditures are annual expenditures divided by the OECD adult equivalent scale.

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:

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

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.

4.2 Consumption

Figure 1 compares the estimated 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 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 do so by adjusting total household expenditures using OECD equivalents. One way to think about the role of demographic adjustment is through a simple accounting decomposition. Let j index the age of the household head, let C_j denote household-level nondurable expenditure at age j, let n_j denote the adult-equivalent scale, and let $c_j = C_j/n_j$ denote adult-equivalent nondurable expenditure. Then

$$\log C_j = \log n_j + \log c_j. \tag{2}$$

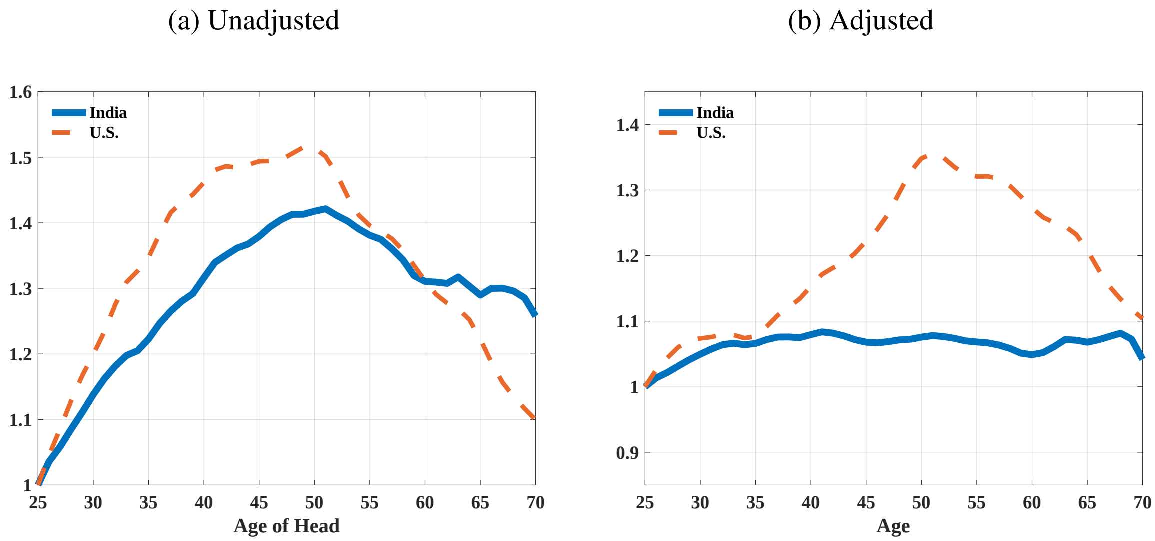
[12]Refer to column 1 of Appendix Tables H.1 and H.2 for time and birth cohort effects for Indian and U.S. households, respectively.

[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 H.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.

Thus, the gap between the unadjusted and adjusted profiles is a demographic accounting object: it reflects how the adult-equivalent scale n_j changes with household size and composition over the life cycle.

After adjusting for demographics, U.S. household consumption grows by more than 30% (Figure 1, panel (b)). 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%. For Indian households, roughly 80% of the unadjusted growth is absorbed by changes in household size and composition whereas it is only 29% for US households.[14] These results, as well as the subsequent ones in this sub-section, are summarized in Table 2.

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



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 show 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

[14] $(42.09 - 8.32)/42.09 \simeq 0.80$

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 nondurable 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 aged 16 or under, 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.

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).[15]

These structural differences have direct implications for the adult-equivalence scale used in converting household consumption to adult-equivalent consumption. In our benchmark specification, we use the OECD adult equivalence scale which assigns a weight of 1 to household head, 0.3 to each child aged 16 or under, and 0.5 to each adult over the age of 16. Panel (c) of Figure 2 plots the size of the adult equivalent using this 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 the presence of multigenerational families keeps household size elevated.

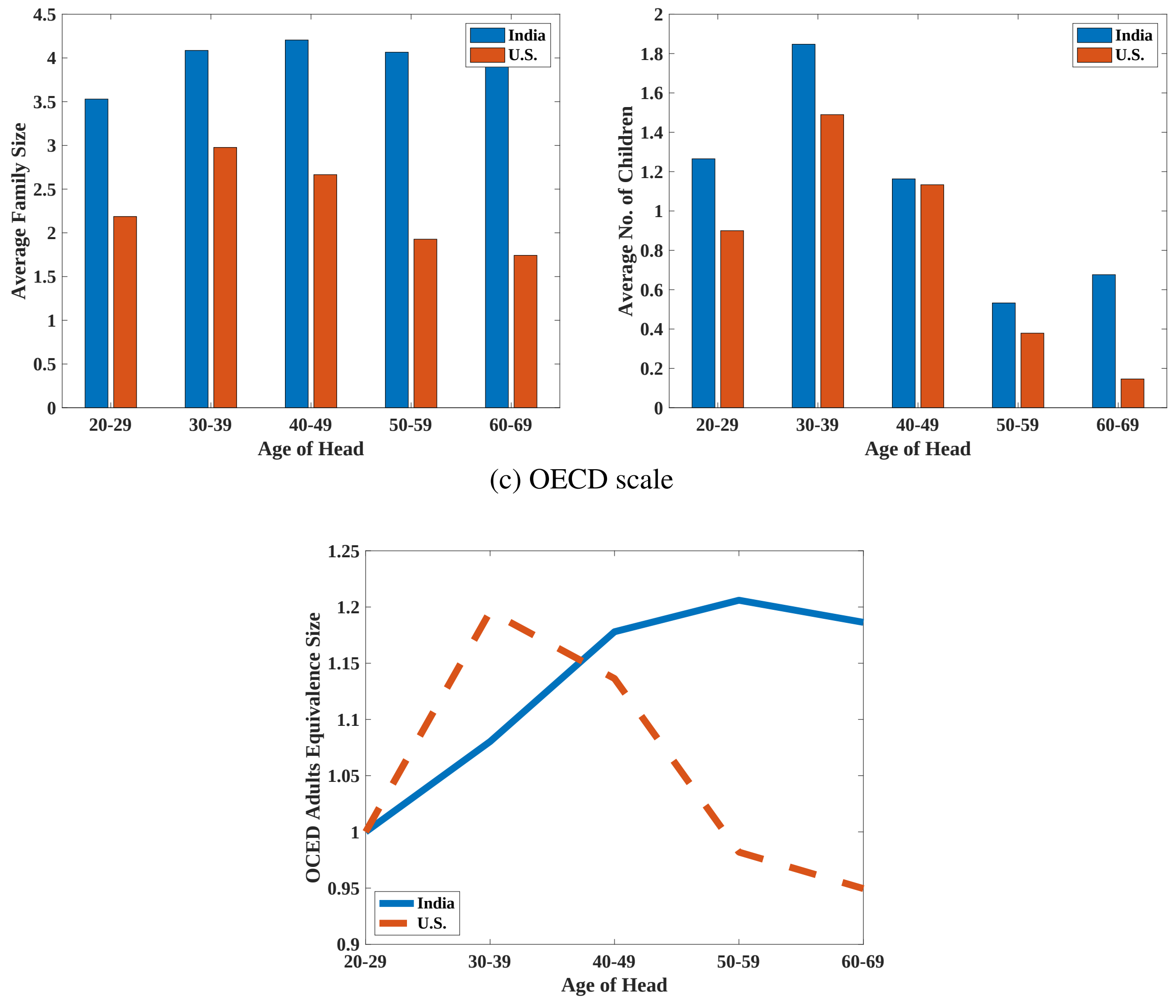
Because the family-size adjustment is quantitatively central to this result, Section 6.2 revisits the equivalence-scale assumption directly. We re-estimate the adjusted Indian nondurable profile over a grid of child and additional-adult weights and compare each profile to the adjusted U.S. nondurable profile. The flatness of the Indian adjusted profile is not a knife-edge implication of the modified OECD scale: across the grid, the Indian profiles remain substantially flatter than the U.S. profile. We also verify that this pattern is not specific to CPHS. Appendix Figure A.1 overlays estimated life-cycle profiles for nondurable expenditures from CPHS and NSSO, using harmonized categories, the same adult-equivalent adjustment, and the same methodology outlined in Section 4.1. In both datasets, unadjusted nondurable expenditures rise over the life cycle, while the family-size-adjusted profiles remain much flatter. Thus, the main consumption fact is also visible in NSSO, a survey designed specifically to measure household consumption expenditures.

[15] 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 H.3 and H.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.

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 aged 16 or under, 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 are substantial differences in the pattern of consumption growth between the two family types. Nuclear families exhibit a markedly steeper life-cycle 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 multigenerational 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 fact that, in extended families headed by someone around age 45, older parents may no longer be earners, whereas in households headed by someone age 60 or older, both the head and cohabiting adult children may still be earning.[16]

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, the profile is initially flat and then declines at later ages.

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.[17] 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.[18] 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.

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 is likely to differ considerably. 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,

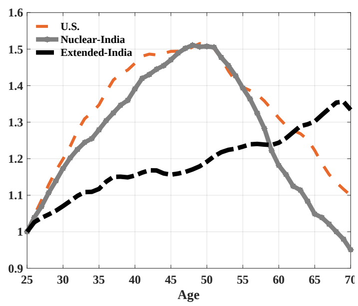
[16] In Section 6.1 we discuss the issue of head of household further.

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

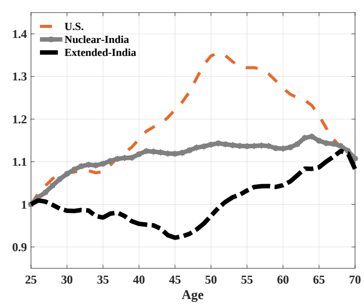
[18] Appendix Figure H.4 provides estimates of both adjusted and unadjusted life-cycle consumption by education status of the head.

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

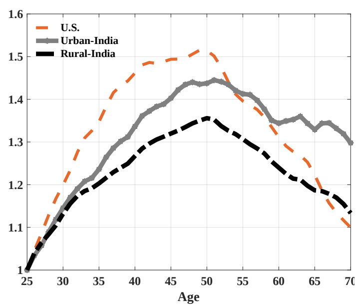
(a) Family Type - Unadjusted



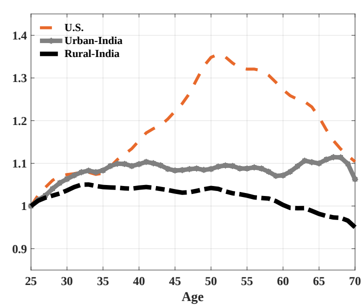
(b) Family Type - Adjusted



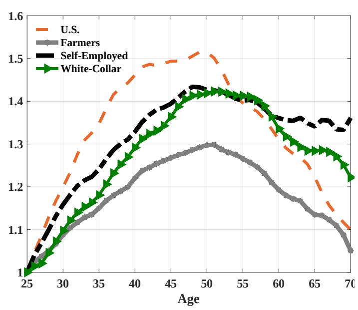
(c) Region - Unadjusted



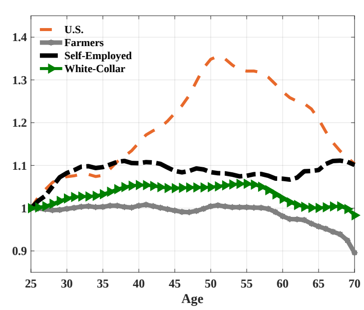
(d) Region - Adjusted



(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 aged 16 or under, and 0.5 to each adult over the age of 16.

Appendix Figure H.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. Growth in food and transportation expenditures in urban India is similar to that of the U.S. The education and health panels should be interpreted more cautiously because the profiles are normalized to age 25; in the U.S., age-25 education and health expenditures are small and these categories become important later in the life cycle. Housing expenditures (net of mortgage payments) grow substantially more for Indian households. Appendix Figure H.3 further confirms that the stark differences in consumption spending between Indian and U.S. households are not driven by differences in education and health spending alone. Appendix Figure D.1 demonstrates that the flat, adjusted life-cycle consumption profile for India persists even after excluding food expenditures. The fact that food, which *a priori* represents a primary source of potential smoothness, cannot account for this flatness is particularly illuminating within the context of structural transformation. While utility functions featuring a subsistence constraint are common in models of structural change, food is clearly not driving consumption smoothness here, despite the vast per capita income differences between the U.S. and India.

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 two 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%.[19] This makes it unlikely that younger households are extensively borrowing against future income growth to smooth consumption. A second possibility is the polar opposite: Indian households may be severely borrowing constrained and consume their income each period, while their adult-equivalent income exhibits little life-cycle growth. 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.

4.3 Income

We use the same methods as described in Section 4.1 to estimate age-income profiles for both countries.[20] Figure 4 shows that growth in total household income in India is comparable to that

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

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

of the U.S.[21] While U.S. households experience a roughly 100% growth in income (as compared to age 25), Indian counterparts experience about 106% growth. These are life-cycle growth rates from the estimated age profiles, not annual growth rates. We normalize predicted income to age 25 and report $100 \times (\widehat{y}_{\text{peak}}/\widehat{y}_{25} - 1)$, where $\widehat{y}_{\text{peak}}$ is the maximum predicted income over the ages shown.[22] 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.[23] 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.[24] Interestingly, we find that income growth exceeds the U.S. profile for urban households, nuclear families, and self-employed households: 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 H.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

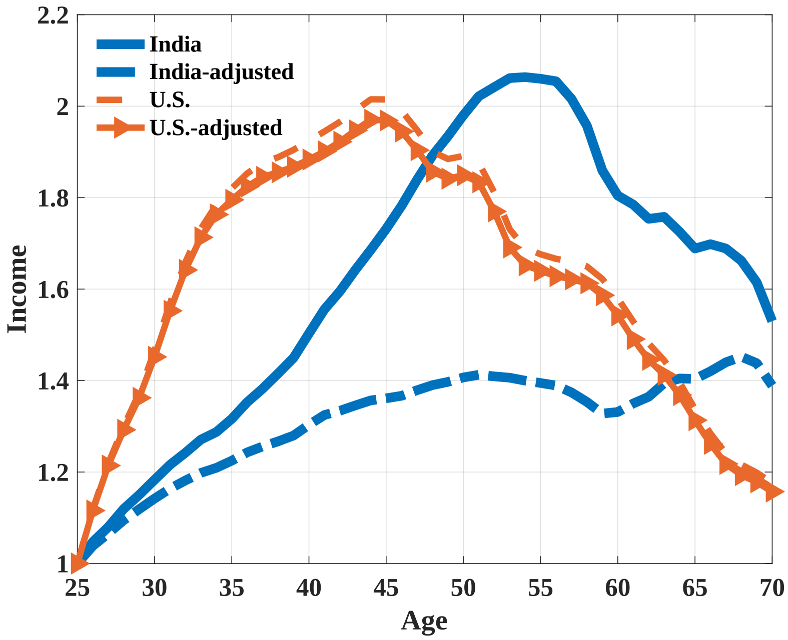
[21] Refer to column 2 of Appendix Tables H.1 and H.2 for time and birth cohort effects for Indian and U.S. households, respectively.

[22] Given that income measurement error may be an important concern, Appendix Section E provides two validation checks. First, we benchmark CPHS wage earnings against PLFS, the cleanest externally comparable income component, and find similar wage levels and life-cycle profiles among positive-wage households. Second, we use the estimated CPHS surplus-rate and income profiles to construct surplus-implied total-wealth profiles; these profiles are broadly comparable to AIDIS total net wealth under plausible real-return assumptions.

[23] 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.

[24] Appendix Figure H.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.

household is in their mid-fifties. This may reflect the fact that at that age, the second generation 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.[25] 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.

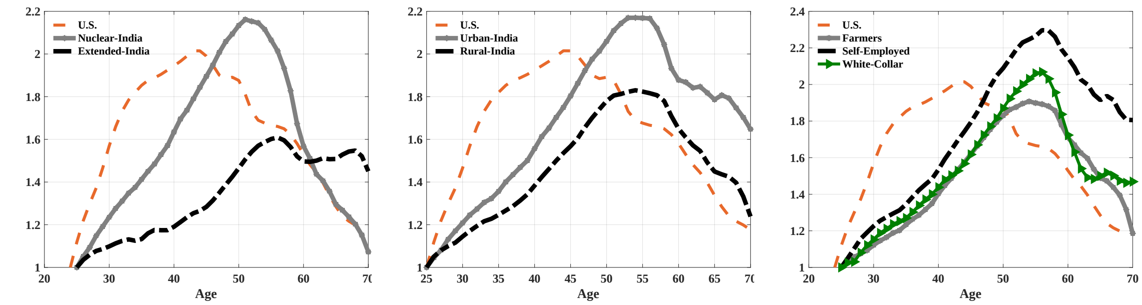
4.4 Savings rate

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.

[25]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.

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

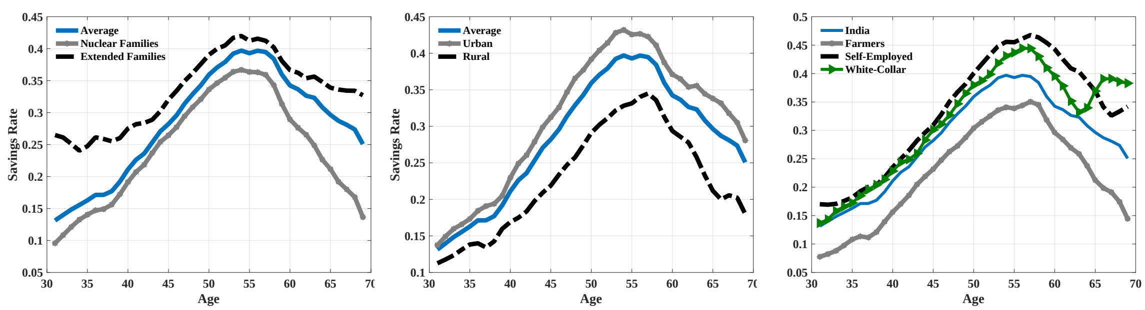
(a) Family Type (b) Region (c) Occupation



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.

Figure 6 displays patterns in the evolution of savings/surplus rate.[26] For India as a whole, we find a substantial increase in the savings rate — increasing from 13% to roughly 40% over the life cycle.[27] 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

[26]Since the differences between India and the U.S. with respect to consumption and income have been discussed at length, we restrict our attention to India for this and the remaining sections of the paper.

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

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.

There are two interesting things to note along the occupation margin.[28] 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.

The magnitude of this surplus raises an accounting question: how much of the life-cycle surplus can plausibly be linked to observed durable accumulation, and how much remains for other uses such as financial assets, real estate, business assets, gold, or precautionary saving? Section 5.3 addresses this question directly. We report both a stock-accounting exercise, which maps the non-housing durable stock path into accumulated life-cycle surplus, and an augmented expenditure profile, which adds imputed non-housing durable investment flows to nondurable expenditures.

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).[29] We use the model to highlight potential mechanisms and derive simple predictions that we take to the data. We intentionally abstract from housing and real estate in this framework. Housing is quantitatively important in Indian household portfolios, but institutionally different from movable, non-housing durables: homeownership is already high among young household heads, housing is often tied to intergenerational living arrangements and family transfers, appreciates in value compared to durable goods, and CPHS does not provide comparable life-cycle housing values. We return to a discussion on housing further below.

5.1 Environment

Each household chooses nondurable consumption c_t, non-housing durable investment i_t, and next–period financial assets a_{t+1}. The non-housing 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:

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

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

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

[29] Yang (2009) also considers a framework with durables, but focuses on explaining home purchases and renovations.

The budget constraint and laws of motion are:

$$a_{t+1} = (1+r)\Big[a_t + y_t - c_t - i_t - \kappa\,\mathbf{1}\{i_t > 0\}\Big], \tag{3}$$

$$d_{t+1} = (1-\delta)\,d_t + i_t, \qquad i_t \geq 0, \qquad \delta \in (0,1), \tag{4}$$

$$a_{t+1} \geq \underline{a}, \qquad \text{(borrowing constraint)}. \tag{5}$$

where y_t is exogenous labor income, i_t is non-housing 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 (3) (marginal utility of wealth) and $\gamma_t \geq 0$ the multiplier on (5).

5.2 Optimality conditions and mechanisms

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

$$\lambda_t \;\geq\; \beta(1+r)\,\lambda_{t+1}, \tag{6}$$

$$a_{t+1} \;\geq\; \underline{a}, \tag{7}$$

$$\big(\lambda_t - \beta(1+r)\lambda_{t+1}\big)\,\big(a_{t+1} - \underline{a}\big) = 0. \tag{8}$$

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:

$$u_c\Big(\tilde{c}_t, s(d_t, n_t)\Big) \;=\; \beta(1+r)\,u_c\Big(\tilde{c}_{t+1}, s(d_{t+1}, n_{t+1})\Big) \;+\; \gamma_t. \tag{9}$$

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.

Non-housing 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:

$$\text{(adjust, } i_t > 0) \qquad u_s\big(\tilde{c}_t, s(d_t, n_t)\big)\,s_d(d_t, n_t) \;=\; \lambda_t \cdot UC, \tag{10}$$

$$\text{(no adjust, } i_t = 0) \qquad u_s\big(\tilde{c}_t, s(d_t, n_t)\big)\,s_d(d_t, n_t) \;\leq\; \lambda_t \cdot UC. \tag{11}$$

In summary, the above equations imply, conditional on adjusting, the marginal utility benefit of one more unit of non-housing 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)[30].

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 non-housing durable-specific borrowing), which limits intertemporal smoothing and pushes households to self–finance lumpy non-housing durables. When expected income growth is back-loaded, $\gamma_t > 0$ in (9) 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 (10)-(11) may lead households to accumulate buffers until wealth crosses a purchase threshold, then convert liquid savings into d_t in lumps. Because many non-housing durables provide services with strong within-household scale economies, 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.[31]

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 non-housing durables (vehicles, appliances, livestock, and productive household equipment). 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. Below, we empirically

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

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

show that this flatness is specific to the nondurable-only measure: when we augment nondurable expenditures with imputed non-housing durable investment flows, the adult-equivalent life-cycle profile becomes substantially steeper.

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.

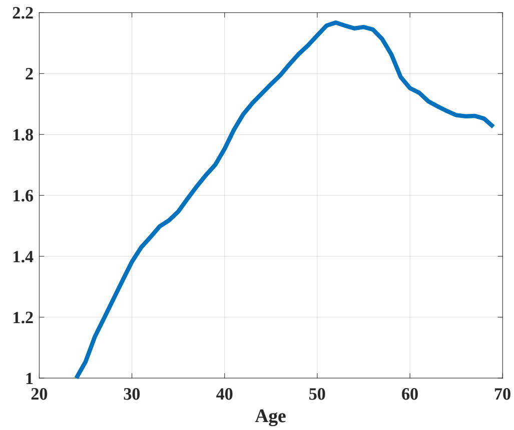
Empirical evidence: We show four empirical facts to support this. (i) Non-housing durables accumulate late in life, near the income and savings-rate peak, and account for an economically meaningful share of accumulated surplus; (ii) stated non-housing durable purchase intentions are associated with higher savings rates; (iii) event-time profiles show higher savings rates around non-housing durable purchase events and lower rates afterward; and (iv) very few households use bank credit to finance these purchases, consistent with self-financing. We then discuss housing and real estate as an important contrast.

1. Late-life accumulation of non-housing durables. Figure 7 provides the estimated age profile (using the same methodology as described in section 4.1 above) of our measure of non-housing durable stocks of Indian households.[32] The figure shows 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 (including housing) 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 non-housing durables.

Quantifying the role of non-housing durables. We next ask how much of the accumulated life-cycle surplus can be accounted for, in an accounting sense, by observed non-housing durable accumulation. Starting from the budget constraint (3) and non-housing durable law of motion (4), we set the fixed adjustment cost to zero and derive an accounting identity that maps the observed non-housing durable stock path into implied non-housing durable investment and depreciation. Appendix Section G provides the derivation and empirical inputs. In the benchmark, which uses initial net financial assets including gold/bullion/ornaments from *All India Debt and Investment Survey* (AIDIS, GOI (2014)), $r = 5\%$, and $\delta = 15\%$, non-housing durable stock growth accounts for 33.2% of accumulated surplus by age 45, 13.9% by age 50, and 7.0% by age 55 (Table 3). This exercise should not be interpreted as a causal decomposition of the savings-rate hump or

[32] Refer to appendix F for the construction of non-housing durable goods measure.

Figure 7: Accumulation of Non-Housing Durable
Over the Life Cycle of Household Head



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

as a complete allocation of household surplus. It excludes real estate, business assets, and other nonfinancial assets because CPHS does not provide comparable life-cycle monetary values for these categories. Across the four robustness exercises varying r and δ, the age-45 contribution ranges from 24.7% to 50.3%. Thus, observed non-housing durable accumulation is quantitatively important in the first half of the working life, even though it does not mechanically exhaust all uses of accumulated surplus, especially at later ages.

Table 3: Non-Housing Durable Stock Growth as a Share of Accumulated Life-Cycle Surplus

				Non-Housing Durable Stock Share* (%)		
Scenario	a_0	r	δ	Age 45	Age 50	Age 55
Benchmark	**17,112**	**0.05**	**0.15**	**33.16**	**13.86**	**6.96**
Low real return	17,112	0.03	0.15	31.58	14.47	7.70
High real return	17,112	0.07	0.15	36.84	13.63	6.38
Low depreciation	17,112	0.05	0.13	24.74	11.74	6.18
High depreciation	17,112	0.05	0.17	50.28	16.92	7.96

Notes: *The numerator is $d_t - d_0$, where d_k is the CPHS non-housing durable stock profile valued using NSSO prices. The denominator is the right-hand side of Appendix equation (16). Initial net financial assets including gold/bullion/ornaments, a_0, are estimated from AIDIS households whose head is age 25–27 and are in Indian Rupees (INR).

Additionally, we construct a nondurable-plus-durable-investment profile in the spirit of Fernández-Villaverde and Krueger (2007). Specifically, we add imputed non-housing durable investment flows, i_t, to nondurable expenditures, c_t, and also construct the corresponding adult-equivalent profile, $(c_t+i_t)/n_t$ (refer to Appendix Section G.2 for details). This augmented expenditure profile is considerably steeper than the nondurable-only profile. In the benchmark, peak adult-equivalent growth rises from 8.4% for nondurables alone to 27.9% once non-housing durable investment flows are included; the analogous unadjusted growth rises from 42.1% to 65.7% (Table 4). This exercise should not be interpreted as a full rental-equivalent service-flow calculation, but it shows that the flat nondurable profile masks substantial life-cycle growth in broader expenditure flows associated with durable acquisition.

Table 4: Durable Investment and Life-Cycle Expenditure Growth

Profile	Nondurable growth	Augmented growth	Durable contribution
Unadjusted	42.1%	65.7%	35.8%
Adult-equivalent	8.4%	27.9%	70.1%

Notes: Growth is measured from age 25 to the peak of the corresponding estimated profile. Augmented expenditure equals nondurable expenditure plus imputed non-housing durable investment flows. The durable contribution is the share of augmented peak growth accounted for by the additional growth from durable investment flows, relative to the nondurable-only profile. For example, for adjusted adult-equivalent consumption this is $(27.9 - 8.4)/27.9 \approx 0.70$.

2. Non-housing durable purchase intentions and household savings rates. A distinctive feature of the CPHS is a battery of questions that elicit households' intentions to purchase specific assets and durable goods over the next 120 days. We use these stated intentions to document whether households in imminent-purchase states exhibit higher savings rates, as predicted by the mechanism.

Two concerns naturally arise: the informational content of stated intentions and their endogenous relationship with savings. We address the first by showing that stated *intentions* significantly predict *realized* purchases within the survey, indicating nontrivial information content.[33] On the second, we interpret these estimates descriptively rather than causally: purchase intentions may reflect household saving propensities, income shocks, or the timing of other resources, so the coefficients should be read as associations between imminent purchase states and savings rates. 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:

$$s_{it} = \sum_{j=1}^{J} \beta^j z_{it}^j + \alpha X_{it} + \gamma_c + \delta_t + \epsilon_{it} \tag{12}$$

where s_{it} is the savings rate of household i at time t (wave), z_{it}^j is reported intentions to purchase asset or 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 5 provides OLS estimates of the association between reported intentions to purchase major assets and non-housing durables, including houses, cars, two-wheelers, tractors, and cattle, and the 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

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

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 pure life-cycle and income effects on savings rates, we add controls for the age of the household head (column 3) and measures of household ownership of non-housing durable goods and the education status of the head (column 4). Overall, reported purchase intentions are strongly and significantly associated with household savings rates. In column (4), reported intentions to purchase a house are associated with a 3.67 percentage point (p.p.) higher savings rate. The corresponding coefficients for non-housing durables are also positive: car purchase intentions are associated with a 2.75 p.p. higher savings rate, two-wheeler intentions with a 1.18 p.p. higher savings rate, and tractor and cattle intentions with 1.93 and 1.30 p.p. higher savings rates, respectively. The housing coefficient should be interpreted cautiously. In the Indian setting, where homeownership is already high even among young household heads, a reported house purchase may reflect land acquisition, additions, renovations, incremental construction, household partition, an upgrade, or a secondary property. These events can be large in value, but they are not necessarily the start of a new savings episode in the same way as a car, two-wheeler, or tractor purchase.

Appendix Tables H.6-H.12 provide these estimates separately for urban and rural areas, extended and nuclear families, farmers, self-employed, and white-collar worker households, respectively. Car purchase intentions are significantly associated with savings rates 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 associations for urban households, they are associated with rural savings rates that are 7.52 and 3.82 p.p. higher, respectively. The patterns are similar for farmers. Taken together, these exercises support the interpretation that desired purchases of high-value assets are an important motive for savings, while the coefficients themselves remain descriptive associations.

Appendix Table H.13 provides analogous associations for reported intentions to purchase other smaller non-housing durables like television sets, washing machines, coolers, power inverters, computers, and refrigerators. We find that intentions to purchase all of these, with the exception of power inverters, are positively and statistically significantly associated with 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 buying episode, documenting the timing of household savings around realized non-housing durable purchases. In particular, we estimate the following relationship:

$$s_{it} = \sum_{\ell \neq 0} \beta_\ell \mathbf{1}\{\, t - t_i^{(j)} = \ell \,\} + \alpha X_{it} + \gamma_c + \delta_t + \varepsilon_{it}, \tag{13}$$

where ℓ indexes event time in survey waves, $\ell = 0$ is the omitted purchase period, $t_i^{(j)}$ is the purchase date of non-housing 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. The event-study coefficients are therefore interpreted relative to the purchase wave. As with the intention regressions, this is a descriptive timing exercise rather than a causal design, since households may time purchases around income shocks, transfers, or other resource availability.

Figure 8 plots the estimated event-study coefficients $\hat{\beta}_\ell$ for major non-housing durable purchases such as cars, two-wheelers, tractors, and cattle. The coefficient at $\ell = 0$ is normalized to

Table 5: OLS Estimates of Intentions to Purchase Housing and Non-Housing Durables on Savings Rate in India

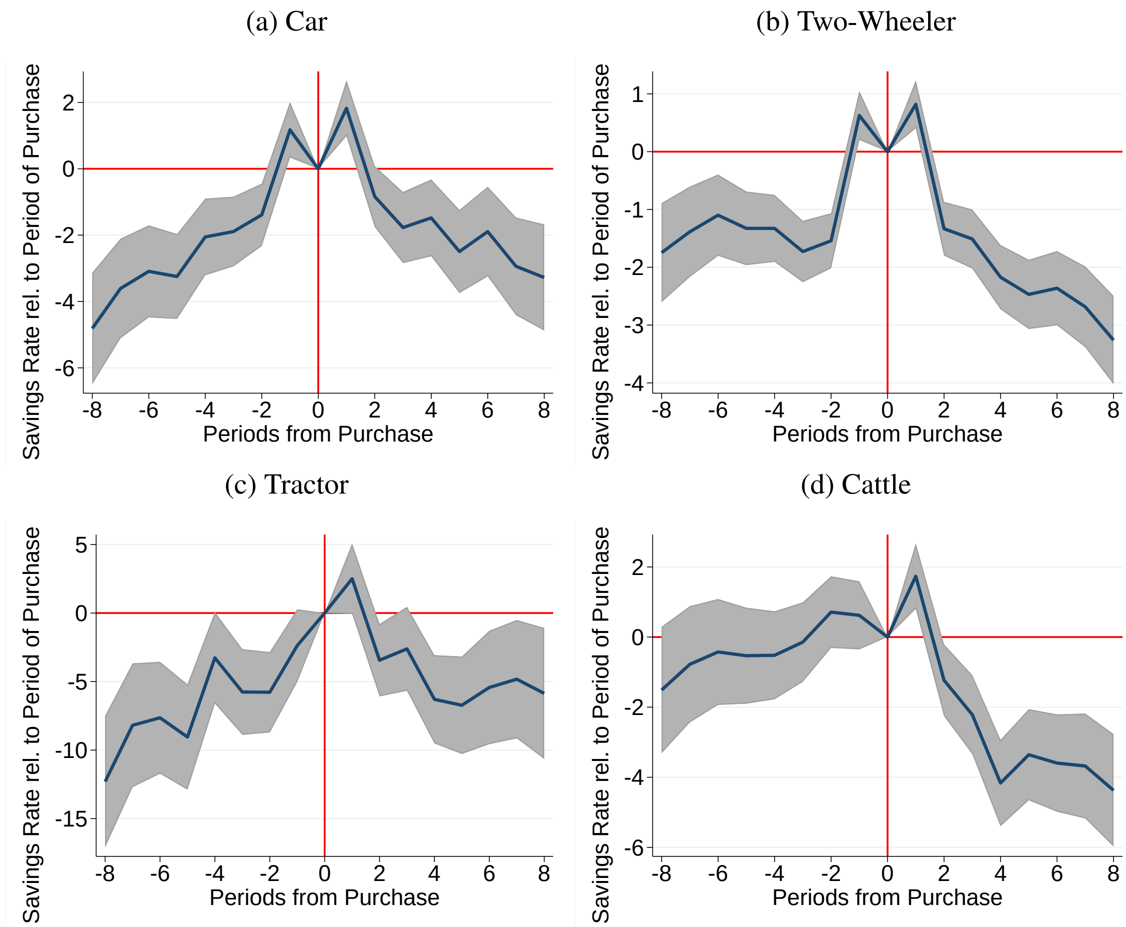
	(1)	(2)	(3)	(4)
Intend to Buy House=1	0.0964***	0.0881***	0.0876***	0.0367***
	(25.73)	(24.00)	(24.01)	(10.51)
Intend to Buy Car=1	0.122***	0.103***	0.101***	0.0275***
	(44.65)	(38.68)	(37.87)	(10.80)
Intend to Buy 2-Wheeler=1	0.0109***	0.00540*	0.00477*	0.0118***
	(4.86)	(2.45)	(2.17)	(5.63)
Intend 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 $\times$ Age of Head			0.00270***	0.00277***
			(79.52)	(85.23)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000199***	-0.0000203***
			(-87.72)	(-93.36)
Non-Housing 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 12. 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 non-housing durable goods measure is detailed in Appendix Section F
t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

zero, so the figure reports percentage-point differences in the savings rate relative to the purchase wave. The shaded regions correspond to 95% confidence intervals. For most durables, savings rates are lower several waves before the purchase, rise toward the purchase window, and are lower again several waves after the purchase. Appendix Tables H.14 and H.15 report the corresponding coefficients, standard errors, and formal tests; these tests reject the null that the relevant event-time coefficients are jointly zero for cars, two-wheelers, and tractors. Appendix Figure H.8 and Appendix Table H.16 show that the main timing pattern is also visible when the event-study regressions include household fixed effects.

The evidence is strongest for cars, two-wheelers, and tractors, while the cattle profile is less precisely aligned in event time. 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 purchases may occur near the beginning or end of the household's observed panel.

Figure 8: Event-Study Coefficients for Savings Rates Around Durable Purchases



Notes: The graph reports event-study coefficients for the household savings rate, in percentage points, relative to event time 0, the omitted purchase period. The shaded regions correspond to 95% confidence intervals. Controls include dummies for calendar time, birth cohort, and a third-order age polynomial. Standard errors are clustered at the household level.

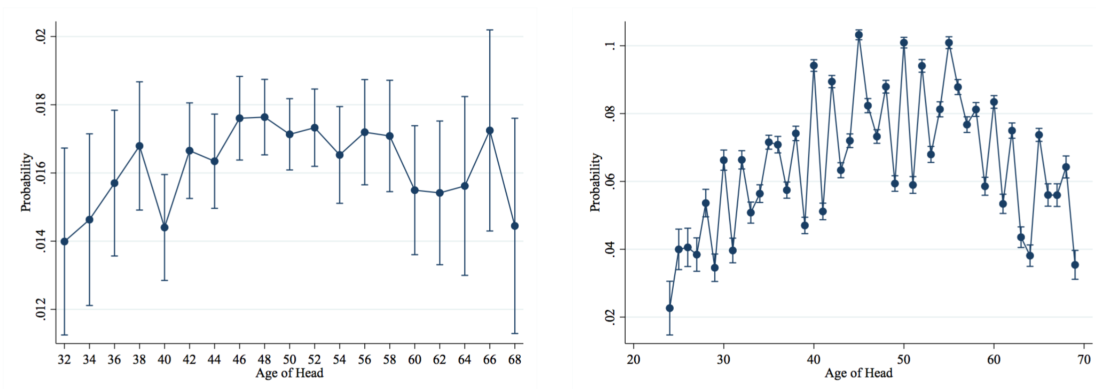
4. Self-financing of non-housing durables. While we do not observe direct measures of households' access to formal credit, we do observe whether they report borrowing from a financial institution for specific purchases or making installment payments on such purchases (including purchases made earlier). We find supporting evidence that the vast majority of Indian households self-finance both major and minor non-housing durable purchases. Panel (a) of Figure 9 shows the probability of borrowing to finance non-housing consumer durables (e.g., refrigerators, air conditioners, televisions). We find that a very small share of households borrow to finance the purchase of non-housing consumer durables (about 1.4–1.8%), and this profile is roughly flat over the life cycle. Panel (b) considers a related survey item: the share of households making installment payments toward a non-housing 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.

In summary, these results indicate that the vast majority of Indian households self-finance both major and minor non-housing durable purchases, consistent with limited use of formal finance for non-housing durable purchases.

Figure 9: Borrowing for Non-Housing Durable Purchases

(a) Probability of Borrowing

(b) Probability of Making an Installment Payment



Notes: Probability of borrowing for non-housing consumer durables reflects the fraction of households who have reported any outstanding borrowing to finance non-housing 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 non-housing durables.

Housing and real estate. Real estate is central to household portfolios in India, but it is empirically distinct from the durable mechanism above. Data collected from AIDIS surveys show that real estate accounts for 77% of urban assets and 91% of rural assets (GOI (2021)), while CPHS indicates that 96% of rural and 98% of urban household heads age 25 already own a house. This high initial ownership makes housing less informative about midlife accumulation through new self-financed purchases. The appendix evidence reinforces this distinction. Appendix Figure H.9, which uses the same event-time normalization as Figure 8, shows no comparable near-purchase buildup for house purchases: savings rates are below the purchase-period level in the waves immediately before purchase and fall sharply afterward. Appendix Figure H.10 shows that formal borrowing and installment payments for house purchases are also limited. We therefore treat housing as a separate residual asset channel, likely reflecting inheritance, inter-vivos transfers, household partition, incremental construction, or asset reallocation, rather than the same self-financed purchase pattern we document for non-housing durables.

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

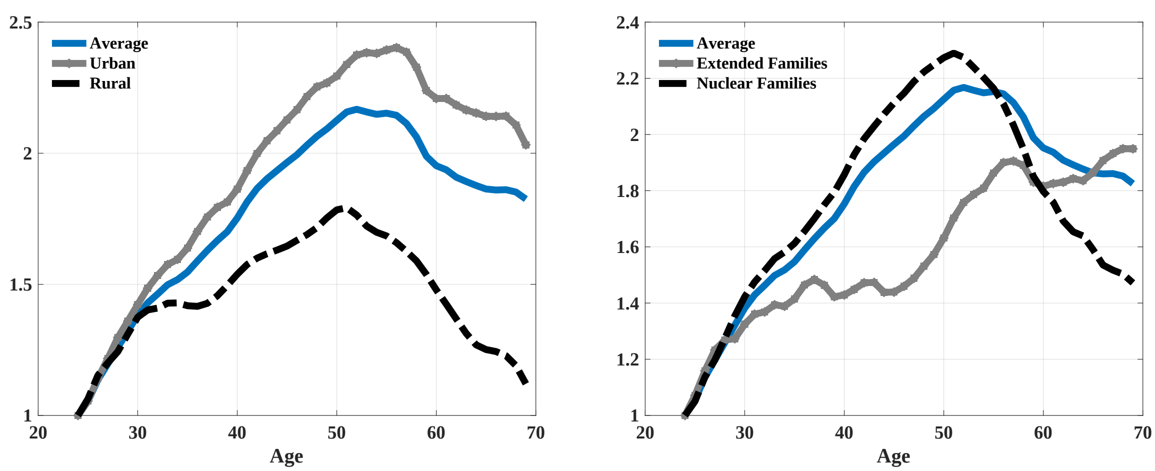
Rationale. Relaxing credit (unsecured or durable-specific) lowers the shadow value of liquidity, narrows the inaction band for durables, and brings purchases forward. Earlier purchases and looser constraints allow more midlife growth in adult-equivalent nondurables relative to otherwise similar households 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).[34]

Reinforcing this, Panels (a)–(b) of Figure 10 show that the non-housing 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 non-housing durable acquisition.

Figure 10: Accumulation of Non-Housing Durables Over the Life Cycle of Household Head By Region and Family Type

(a) By Region (b) By Family



Notes: Household non-housing durable stock relative to age 25 (household head) is reported. It is constructed using information on the possession of major and minor non-housing durable goods like car, two-wheeler, television, tractor, refrigerator, electric generator, washing machine and so on.

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

[34] Appendix Figure H.11 shows that borrowings for non-housing consumer durables are indeed higher in urban areas than rural areas.

equivalents, and the treatment of home production for consumption. We also check the robustness of life-cycle growth patterns to alternative estimation strategies. Appendix Section D reports additional consumption-profile checks using non-food expenditures, group-based pseudo-panels, income-quartile pseudo-panels, and within-household local slopes.

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.[35] 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 multigenerational 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 6: 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 6 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 H.12 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

[35] 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.

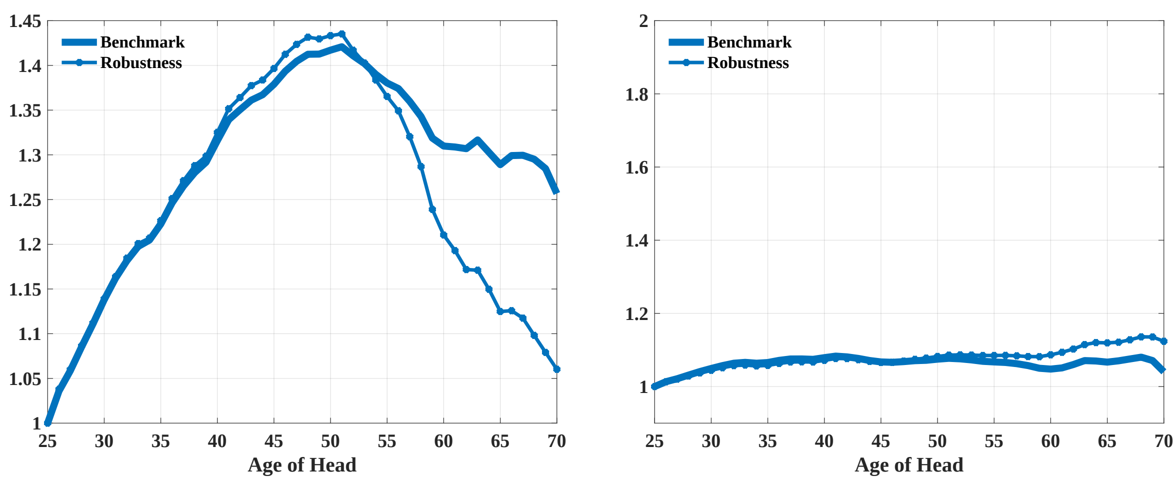
earners.[36] For easier comparison, we also include the benchmark consumption profiles (i.e., using reported household head). Unadjusted consumption still peaks around age 50 with a roughly 43% growth relative to age 25, comparable to what we estimated earlier. However, the decline in consumption after age 50 is much more pronounced compared to the benchmark. This indicates 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 H.13. Finally, Appendix Figure H.14 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.[37]

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

(a) Unadjusted

(b) Adjusted



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 aged 16 or under, and 0.5 to each adult over the age of 16.

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

[37]A different concern might be regarding the definition of a household in CPHS. The survey uses the definition of a shared kitchen for a household. In our examination of the data on only 0.026% of household-wave observations had a non-family member residing in the household.

6.2 Consumption scales

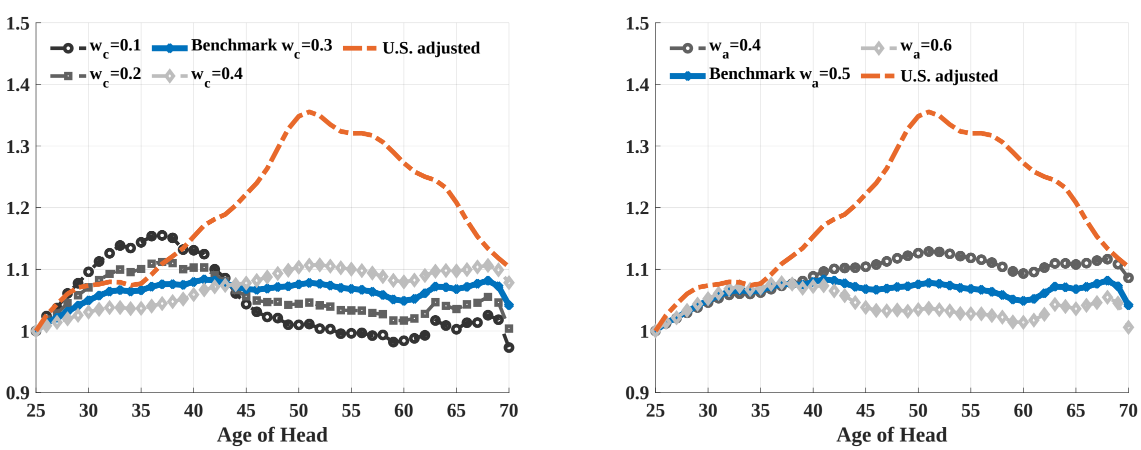
Adjusting total household consumption by an equivalence scale allows us to capture the effects of changing demographics on life-cycle consumption patterns. In the benchmark analysis, we use a modified OECD scale that assigns a value of 1 to the household head, 0.5 to each additional adult, and 0.3 to each child. Since the adjustment is especially important in India, we test whether the headline flatness result depends on these particular weights. For each household, we define

$$n_i(w_a, w_c) = 1 + w_a \times \text{additional adults}_i + w_c \times \text{children}_i,$$

and recompute adjusted nondurable expenditures over the grid $w_a \in \{0.4, 0.5, 0.6\}$ and $w_c \in \{0.1, 0.2, 0.3, 0.4\}$. The benchmark modified OECD profile corresponds to $w_a = 0.5$ and $w_c = 0.3$. Lower values allow for stronger economies of scale or lower child costs, while the high end of the grid allows children and additional adults to receive more weight than in our benchmark.

Figure 12: Equivalence-Scale Sensitivity: Adjusted Life-Cycle Nondurable Consumption

(a) Varying child weights, $w_a = 0.5$ (b) Varying adult weights, $w_c = 0.3$



Notes: The figure reports adult-equivalent nondurable expenditure profiles for Indian households estimated under alternative equivalence-scale weights, alongside the adjusted U.S. nondurable profile. Each profile is normalized to age 25. The equivalence scale is $1 + w_a\times$ additional adults $+ w_c\times$ children. The benchmark Indian and U.S. profiles, shown in blue and orange respectively, use $w_a = 0.5$ and $w_c = 0.3$.

Figure 12 reports two slices through the grid. Panel (a) fixes the additional-adult weight at the benchmark value and varies the child weight; Panel (b) fixes the child weight at the benchmark value and varies the additional-adult weight. The main lesson is that the qualitative result is robust. Across the full twelve-profile grid, the age-25-to-peak growth in adjusted nondurable expenditures remains modest, ranging from about 8 to 16 percent. The benchmark Indian profile peaks at about 8 percent growth, and even the specifications that generate the largest increase remain far below both the unadjusted Indian profile (about 42 percent growth) and the adjusted U.S. profile (about 30 percent growth). Thus, changing the adult and child weights can move the exact magnitude of the adjusted Indian profile, but it does not turn the Indian profile into the sustained mid-life hump observed in the U.S.

As an additional check, we also use the household equivalence scale proposed by NRC (1995) and later used by Nie (2020): $n_i = (n_{Ai} + 0.7n_{Ki})^{0.7}$, where n_{Ai} is the total number of adults and n_{Ki} is the total number of children. This formulation distinguishes between household-composition effects and economies of scale.[38] This alternative scale yields slightly higher adjusted consumption growth over the life cycle: 12.3 percent, compared with 8.3 percent in the benchmark. The profile remains far flatter than the U.S. adjusted profile, reinforcing that the central result is not driven by the specific modified OECD weights.

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 7 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 H.15 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.

[38] For a couple with two children, the value is 2.35 under the NRC scale and 2.1 under our modified OECD scale. In India, within-family resource allocation tends to be highly skewed in favor of males, which neither scale addresses. For more on intra-household inequality in resource allocation, see Browning et al. (2013); Calvi et al. (2023).

Table 7: 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.

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 7 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 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.

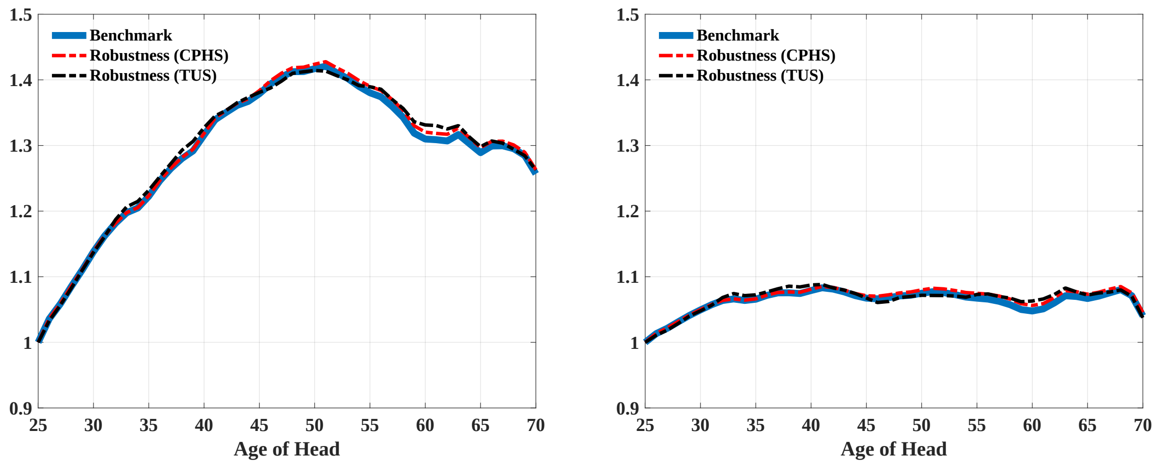
In sum, across both data sources the augmented consumption measure does not materially change our core life-cycle facts (a flat equivalence-scale–adjusted profile with a late, muted peak); see Figure 13 and Appendix Figure H.15.

6.4 Alternate specification

Next, we test the robustness of our life-cycle 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

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 aged 16 or under, and 0.5 to each adult over the age of 16.

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 life-cycle 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 life-cycle 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 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. life-cycle consumption. In panels (a) and (b) of Figure 14, the dashed black lines indicate that average life-cycle 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%.

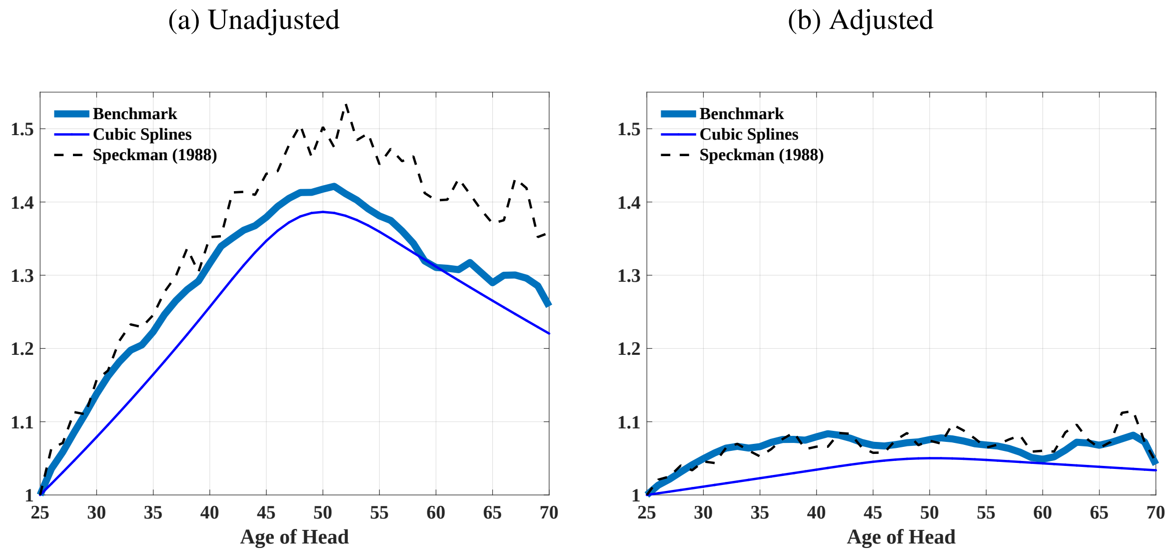
6.4.3 Longer CPHS Panel

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 H.16). 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.

7 Discussion and Concluding Remarks

Using a recently introduced, nationally representative panel of Indian households, we document life-cycle profiles of nondurable consumption, income, and savings/surplus rates in India and compare them with analogous profiles for U.S. households. The comparison reveals a sharp contrast. Before demographic adjustment, nondurable expenditures in India grow substantially over the life cycle and look broadly similar to the U.S. profile. After adjusting for family size and composition, however, the Indian profile becomes nearly flat, while the U.S. profile continues to display sizable midlife growth. This flat adult-equivalent nondurable profile is especially striking because Indian household income rises strongly and peaks later than in the U.S. Consistent with

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 aged 16 or under, and 0.5 to each adult over the age of 16.

this divergence, the Indian savings/surplus rate—defined as household income net of nondurable expenditures as a share of income—rises from about 13% to more than 40% between ages 35 and 55. Thus, Indian households do not smooth nondurable expenditures in the standard perfect-markets life-cycle sense. The main life-cycle finding is robust to a wide range of measurement and specification checks, suggesting that the flat adjusted nondurable profile is not an artifact of household-head assignment, food-heavy expenditure weights, equivalence-scale choice, pseudo-panel aggregation, or the relatively short baseline panel.

We provide evidence for one mechanism that helps reconcile flat adult-equivalent nondurable expenditures with high measured surplus: borrowing constraints combined with lumpy, largely self-financed accumulation of non-housing durables. Guided by a life-cycle model with borrowing constraints, durable services, and lumpy adjustment costs, we show that a physical asset stock constructed from major and minor non-housing durables rises steeply over the life cycle, with roughly 120% growth at its peak, and that its timing closely tracks the peak in the savings/surplus rate. Our benchmark stock-accounting indicates that non-housing durable stock growth accounts for 33.2% of accumulated life-cycle surplus by age 45, 13.9% by age 50, and 7.0% by age 55. These estimates indicate that observed non-housing durables are an economically meaningful component of surplus allocation, especially earlier in the working life. Consistent with the non-housing durable channel, reported purchase intentions are associated with higher savings rates, event-time profiles show savings rates rising around major non-housing durable purchases and falling afterward, and very few households report using formal credit to finance these purchases. Finally, we show that an augmented expenditure profile that adds imputed non-housing durable investment flows to nondurables raises adult-equivalent life-cycle growth from 8.4% to 27.9%, narrowing much of the U.S.–India gap in this augmented expenditure-flow measure.

Our interpretation of the residual savings/surplus rate remains necessarily broad. The evidence identifies non-housing durable accumulation as one visible and quantitatively meaningful component of surplus allocation, not as a complete portfolio decomposition or a causal accounting of all saving motives. As discussed above, land and housing are two other important physical assets that require their own separate analysis (and data). Some of the remaining surplus may reflect dowry-related saving, which is consistent with the coexistence of smooth adult-equivalent nondurable expenditures and saving for large purchases. However, we cannot separately identify dowry saving from precautionary saving, real estate accumulation, business investment, or other household objectives without additional variation, such as the gender composition of children or marriage-market shocks.[39] Distinguishing among these motives is an important direction for future work.

Finally, our findings have important macroeconomic and welfare implications. If households must self-finance lumpy durable purchases because formal credit markets are thin, young households may lower measured nondurables while postponing access to durable services—transport, refrigeration, appliances, communications, and productive household equipment—that directly affect welfare and household productivity. This delay is a welfare margin that is not visible in nondurable expenditure profiles alone. At the macro level, widespread self-financing of durables may raise demand for liquid and safe assets and shape household portfolios toward short-maturity saving instruments, such as fixed deposits, rather than longer-horizon financial claims. Deeper durable-backed credit could bring durable services earlier in the life cycle and change the composition of household saving, although a calibrated welfare or general-equilibrium analysis is beyond the scope of this paper. Quantifying those welfare gains and portfolio-level macroeconomic effects is a natural agenda for future research.

[39]Anukriti et al. (2022) uses an identification strategy such as the gender of the first child to examine savings behavior in rural households.

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Online Appendix

A CPHS–NSSO Consumption Validation

We provide a comparison of the CPHS consumption data against NSSO consumption data here. NSSO is the natural external benchmark because it is India's official household consumption survey and contains detailed expenditure modules. CPHS is valuable for our purposes because it is high-frequency and includes income, demographics, and asset information in a panel structure; NSSO is useful as a cross-sectional validation of whether the consumption aggregates and life-cycle patterns in CPHS are plausible.

We harmonize the nondurable expenditure categories across the two datasets, apply the relevant household survey weights, and construct the same modified-OECD adult-equivalent scale in both sources. Table A.1 compares levels and category shares. The table uses NSSO 2011–12, while the estimated profile comparison below uses repeated NSSO consumer-expenditure rounds from 2000 through 2012. We do not add the 2022–23 HCES to the Age-Period-Cohort (APC) profile because doing so would create a long gap in survey years and would fall outside the 2014–2019 CPHS baseline period. The broad aggregates are very similar: annual nondurable expenditures are Rs. 86,944 in CPHS and Rs. 85,285 in NSSO, while adjusted nondurable expenditures are Rs. 38,278 and Rs. 36,020, respectively. The weighted CPHS food share is also close to the NSSO benchmark, 55% compared with 52%. Remaining differences are concentrated in categories such as health and education, where NSSO's more detailed modules and differences in recall periods are likely to matter.

We next compare the estimated life-cycle profiles implied by the two datasets. For both CPHS and NSSO, we construct comparable nondurable expenditure measures, apply the same modified-OECD adult-equivalent scale, and estimate the profiles using the same methodology outlined in Section 4.1. The NSSO profile is estimated using repeated NSSO consumer-expenditure rounds from 2000 through 2012. Figure A.1 shows that the central pattern is visible in both datasets. In both CPHS and NSSO, unadjusted nondurable expenditures rise over the life cycle. Once the same adult-equivalent adjustment is applied, however, the profiles are much flatter. This validation is reassuring for the paper's main interpretation: the near-flat adult-equivalent nondurable profile is not a peculiarity of CPHS category weights or survey design, but is also visible in NSSO consumption data.

B Harmonizing CPHS and PSID Expenditure Categories

B.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.

Table A.1: Comparison of CPHS and NSSO datasets

	CPHS		NSSO	
	Mean	Fraction	Mean	Fraction
Age of household head	49.51		46.23	
Annual expenditures	86,943.55		85,284.84	
Food	44,890.84	0.55	40,640.22	0.52
Non-mortgage housing	16,979.92	0.19	17,370.08	0.20
Transport	2,336.30	0.03	5,201.65	0.05
Health	2,170.45	0.02	5,924.95	0.07
Education	3,130.36	0.03	4,729.02	0.04
Clothing	9,702.50	0.11	6,614.21	0.08
Recreation	399.61	0.00	1,236.60	0.01
Family size	4.17		4.56	
OECD scale	2.37		2.46	
Adjusted expenditures	38,278.26		36,020.35	
Observations	974442	974442	97961	97961

Notes: Expenditure data are annual real rupee values. The NSSO column uses the 2011–12 consumption survey. Non-mortgage housing includes rent, power, and communication fees in CPHS and the harmonized housing category in NSSO. Adjusted expenditures are annual expenditures divided by the OECD adult equivalent scale. Fractions are weighted averages of household-level category shares.

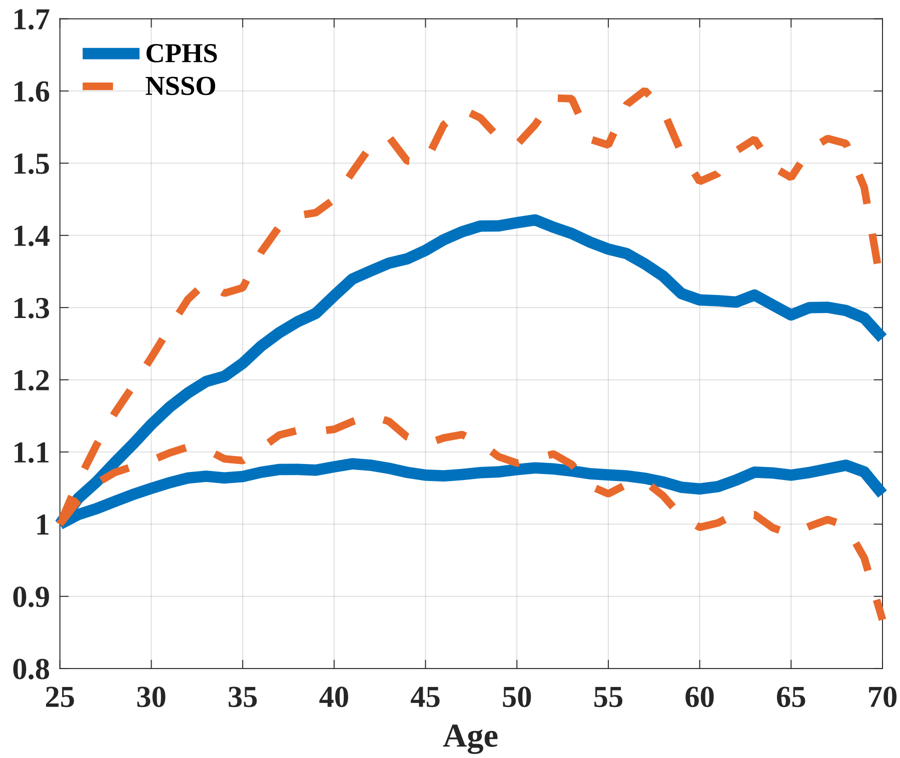
In the PSID, we use the total family food expenditure variable, which includes expenditures for food at home, delivered food, and food eaten away from home. We do not have any measures of intoxicants reported separately in PSID. Even though households report annual expenditures on food starting in 1999,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

B.2 Housing

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

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

Figure A.1: Estimated CPHS and NSSO Life-Cycle Nondurable Consumption Profiles



Notes: The figure reports estimated nondurable expenditure profiles by age of the household head, normalized to age 25, for CPHS and NSSO. The NSSO profile uses repeated NSSO consumer-expenditure rounds from 2000 through 2012. Expenditure categories are harmonized across datasets. Adjusted profiles divide nondurable expenditures by the same modified-OECD adult-equivalent scale in both datasets. Profiles are estimated using the same methodology outlined in Section 4.1.

B.3 Clothing

Expenditures in CPHS in this category include clothing, footwear, and cosmetics. Clothing and footwear include household expenditures on garments, jackets, woolens, clothing accessories, and footwear; cosmetics include household expenditures on cosmetics and toiletries, including dental care products and bathing soap.

Clothing expenditures reported by PSID households include expenditures 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.

B.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”, and “Toll Charges and Airfare”. Note that expenditures related to vehicle purchases are reported separately and not included in our measure.

Transportation-related expenditures in PSID include expenditures for vehicle loans, leases, down payments, insurance, other vehicle expenditures, repairs and maintenance, gasoline, parking and carpooling, bus and train fares, taxicabs, and other transportation. We net out vehicle down-payment and lease-related expenditures from this measure to obtain a measure that is more comparable to CPHS.

B.5 Health

CPHS data report health expenditures on medicines, doctor's fees, X-ray tests, hospitalization fees, health-insurance premiums, and related items.

Health expenditures in PSID include total family health-care expenditures, including spending on hospitals and nursing homes, doctors, prescription drugs, and insurance.

B.6 Education

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

Education expenditures in PSID include all schooling-related expenditures.

B.7 Recreation

Recreation expenditures in CPHS include expenditures on electronic storage devices, entertainment, and games/toys. Electronic storage devices include pen drives, hard disks, memory cards, CDs, DVDs, cassettes, records, and other media. Entertainment includes movie tickets, theatre tickets for drama, music concerts or general entertainment programs, tickets and subscriptions to entertainment clubs such as discotheques, tickets to tournament matches or other sports events, and tickets to zoos, museums, art galleries, planetariums, circuses, theme parks, etc. Games/toys include indoor or outdoor toys, sports equipment, and other materials for children and/or adults.

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

B.8 Others

In CPHS data, the other category includes household expenditures on domestic help/laundry, vehicle repairs, 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 PSID expenditures on home repairs and maintenance, furnishings, and household equipment in this category, including household textiles, furniture, floor coverings, major appliances, small appliances, and miscellaneous housewares.

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.

D Additional Consumption Robustness Checks

This section reports additional checks that address whether the flat adult-equivalent nondurable profile is driven by the composition of the consumption basket, by mixing households with different family structures, or by the pseudo-panel construction.

D.1 Non-food nondurable profiles

Because food is a large share of nondurable expenditure in India, we re-estimate the life-cycle profiles after excluding food expenditures. Figure D.1 shows that unadjusted non-food nondurable expenditure growth in India is much closer to the U.S. profile than total nondurable expenditure growth. After the adult-equivalent adjustment, however, the Indian non-food profile remains substantially flatter than the U.S. profile. Thus, the flat adjusted profile is not mechanically driven by the high food share alone.

D.2 Group-based pseudo-panels

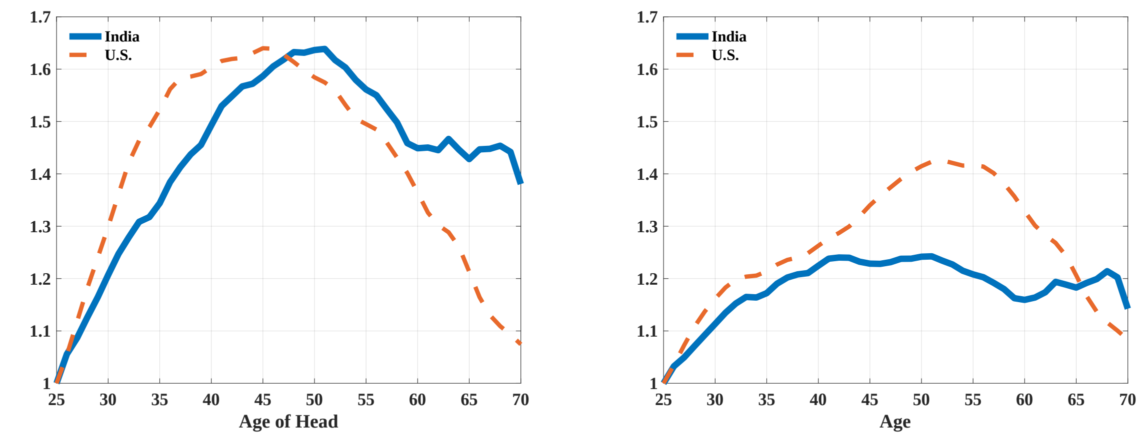
To address concerns that the aggregate pseudo-panel could mix younger nuclear households with older extended households, we repeat the baseline exercise within four groups defined by urbanicity and family type: rural nuclear, rural extended, urban nuclear, and urban extended households. Figure D.2 reports the results. Unadjusted nondurable expenditures rise within most groups, but the adult-equivalent profiles remain much flatter in every case. The urban groups display somewhat more adjusted growth than the rural groups, but none approaches the U.S. adjusted profile.

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

Figure D.1: Life-Cycle Non-Food Nondurable Consumption Profiles

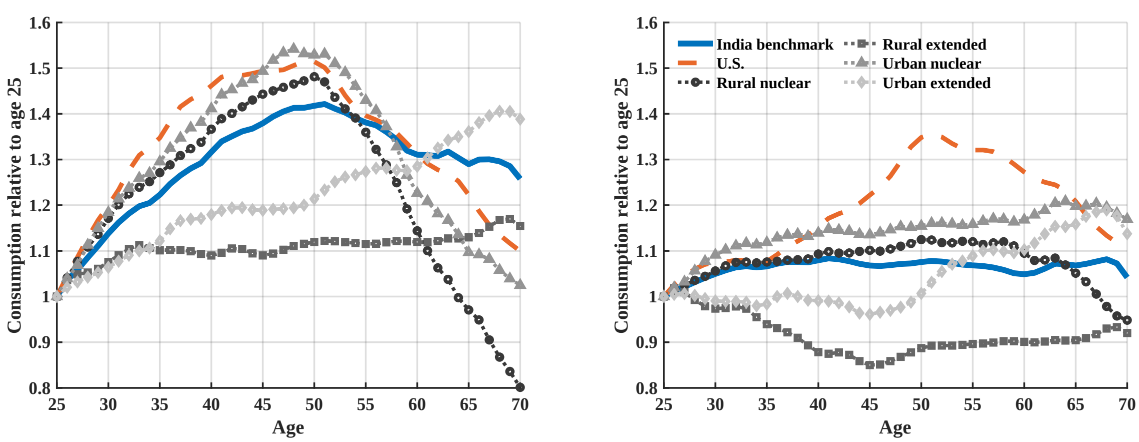
(a) Unadjusted (b) Adjusted



Notes: The figure reports non-food nondurable expenditure profiles by age of the household head, normalized to age 25, for both the U.S. and India. Adjusted profiles divide non-food nondurable expenditures by the modified-OECD adult-equivalent scale.

Figure D.2: Group-Based Pseudo-Panel Consumption Profiles

(a) Unadjusted (b) Adjusted



Notes: The figure reports nondurable expenditure profiles by age of household head, normalized to age 25. The India benchmark profile is shown in blue, the U.S. profile in orange, and the four India group-specific profiles in gray. Group profiles are estimated using the same APC/pseudo-panel method as the baseline, separately for rural nuclear, rural extended, urban nuclear, and urban extended households. Adjusted profiles divide nondurable expenditures by the modified-OECD adult-equivalent scale.

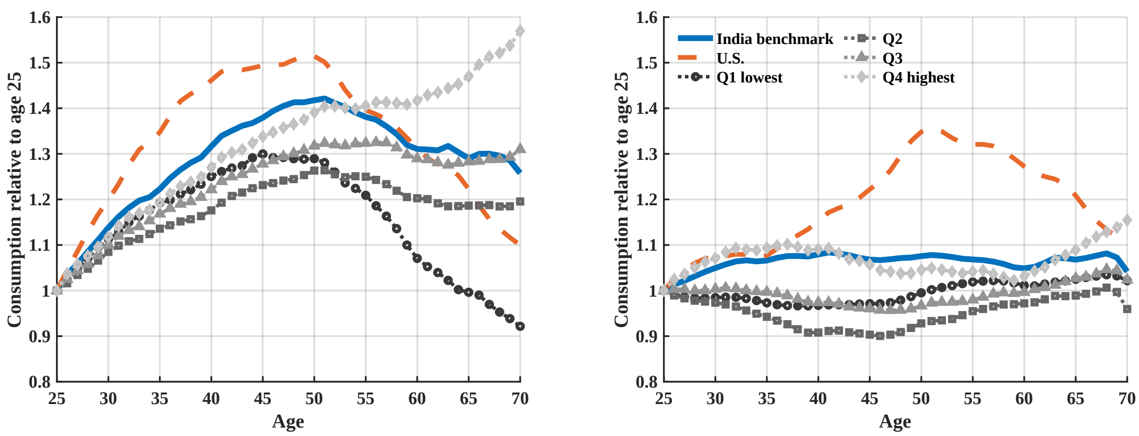
D.3 Income-quartile pseudo-panels

We also estimate the consumption profiles separately by income quartile. To avoid mechanically conflating income rank with life-cycle income growth, households are assigned to income quartiles separately within each age of the household head, using total real household income and CPHS survey weights. Figure D.3 shows that the top income quartile has the strongest unadjusted growth and somewhat more adjusted growth than the lower quartiles. Even so, the adjusted top-quartile profile remains well below the U.S. adjusted profile.

Figure D.3: Income-Quartile Pseudo-Panel Consumption Profiles

(a) Unadjusted

(b) Adjusted



Notes: The figure reports nondurable expenditure profiles by age of household head, normalized to age 25. The India benchmark profile is shown in blue, the U.S. profile in orange, and the four India income-quartile profiles in gray. Income quartiles are constructed separately within each age of the household head using total real household income and CPHS survey weights. Adjusted profiles divide nondurable expenditures by the modified-OECD adult-equivalent scale.

D.4 Panel-based local slopes

As an internal validation of the pseudo-panel evidence, we use the household-wave CPHS panel to compute within-household forward log changes in adult-equivalent nondurable expenditures over one-year and two-year horizons. Since CPHS households are interviewed every four months, the one-year difference is a three-wave change and the two-year difference is a six-wave change, annualized. We multiply these annualized log changes by 100 before estimating the age-bin means, so the reported coefficients are in annualized log percentage points. We remove wave-by-year fixed effects from these growth rates to absorb common macro and seasonal shocks, then estimate the mean residualized growth rate by five-year age bin of the household head. Standard errors are clustered at the household level and the regressions use CPHS household weights.

Table D.1 reports the results. The estimated local slopes are small across ages in both the all-available panel and the strict balanced-panel sample, consistent with the near-flat adult-equivalent nondurable profile in the cohort-based analysis.

Table D.1: Panel-Based Local Slopes for Adult-Equivalent Nondurable Expenditures

Age of head	All available panel		Strict balanced panel	
	1-year	2-year	1-year	2-year
25–29	0.27	0.06	0.11	-0.71
30–34	0.10	-0.24	-0.35	-0.65
35–39	-0.16	-0.20	-0.14	0.11
40–44	-0.59	-0.45	-0.43	-0.26
45–49	-0.22	0.03	-0.22	-0.08
50–54	0.53	0.53	0.51	0.54
55–59	-0.08	0.04	0.21	0.09
60–64	0.22	0.31	-0.00	0.28
65–70	0.64	-0.03	0.91	-0.17
Households	182,291	150,628	22,622	22,622
Differences	1,492,979	1,093,551	316,708	248,842

Notes: The table reports annualized within-household changes in log adult-equivalent nondurable expenditures, reported as log percentage points, after removing wave-by-year fixed effects. Thus, an entry of 0.64 corresponds to 0.64 annualized log percentage points, or approximately 0.64 percent per year in log terms. Age is measured at the start of the difference. Adult-equivalent nondurable expenditures use the same modified-OECD scale and nondurable expenditure definition as the baseline analysis. The all-available panel uses every household with the relevant forward difference. The strict balanced panel keeps households observed in every wave of the 2014–2019 sample. Regressions use CPHS household weights; standard errors are clustered at the household level.

E Validation of CPHS Income

This appendix provides two checks on income measurement in CPHS. First, we compare the component of income that can be most cleanly benchmarked externally—wage earnings—against the Periodic Labour Force Survey (PLFS), India's official nationally representative labor-force survey. Second, we use the estimated CPHS surplus-rate and income profiles to back out implied wealth accumulation and compare the resulting profile with AIDIS total net household wealth. These exercises are useful because the main savings-rate object in the paper is a residual, income net of nondurable expenditures as a share of income. If CPHS income were systematically overstated at older ages, the estimated life-cycle surplus profile could be mechanically inflated.

We focus on household wage earnings rather than total income because wages are the cleanest comparable income component across the two surveys. In CPHS, wage earnings include household income from wages, overtime, and bonuses. In PLFS, wage earnings include regular salaried/wage earnings and casual wage earnings, summed across all household members. Casual daily wages reported for the last seven days are converted to monthly units. Both datasets are deflated using the same state-sector-month CPI series and annualized. We use CPHS household weights and PLFS first-visit cross-sectional weights, so the all-India comparison is not driven by CPHS's urban oversample or by the urban rotating panel in PLFS.

Our preferred validation restricts each dataset to households with positive wage earnings. This compares the amount of wage income reported by households that report wage receipt in each survey and avoids conflating income measurement with differences in the extensive margin of wage work across survey designs. PLFS asks earnings questions through a labor-market activity module and records earnings conditional on current or usual work status, while CPHS collects household income by source. Consistent with this difference, the unconditional share of households with positive wage earnings is much lower in PLFS than in CPHS; the positive-wage comparison is therefore the cleaner validation of reported wage amounts.

Figure E.1 reports the validation. Panel (a) compares the life-cycle profile of household wage earnings among positive-wage households. Panel (b) compares average wage earnings by within-survey wage decile for the same positive-wage sample. The two surveys line up closely. The weighted mean annual wage income among positive-wage households is Rs. 137,916 in CPHS and Rs. 128,625 in PLFS. Thus, conditional on wage receipt, CPHS does not report implausibly high wage amounts relative to an independent official labor-market survey.

This exercise does not imply that every component of income is measured identically across the two surveys. In particular, PLFS self-employment earnings are closer to gross earnings over the last 30 days, whereas CPHS business income is closer to business profit. For this reason, we use wage earnings as the main external validation. The close agreement for the most directly comparable component makes it unlikely that the paper's residual savings pattern is driven by a gross overstatement of CPHS wage income. Measurement problems in non-wage income would have to be strongly age-patterned and large enough to overturn both this wage validation and the wealth-profile comparison below.

We next ask whether the residual surplus implied by CPHS income and nondurable expenditures generates plausible wealth accumulation when compared with an independent wealth survey. Let j index the age of the household head, let s_j denote the estimated CPHS surplus rate at age j, and let Y_j denote the estimated CPHS household income profile. The implied annual surplus flow is $s_j Y_j$. We then construct an implied total-wealth profile recursively as

$$W_{j+1}^{CPHS}(r) = (1+r)W_j^{CPHS}(r) + s_j Y_j,$$

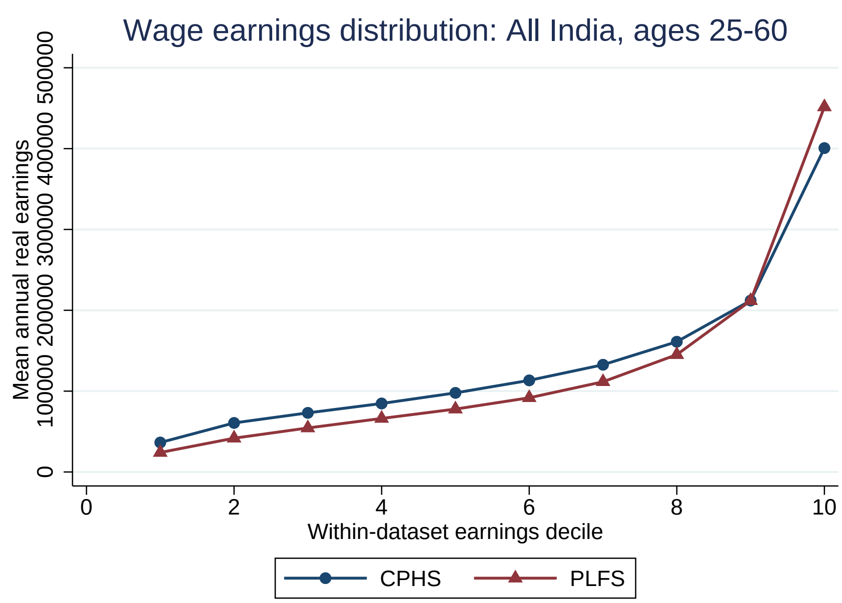
where $W_{25}^{CPHS}(r)$ is initialized using AIDIS total net household wealth for household heads age 25. AIDIS total wealth includes financial assets, gold/bullion/ornaments, real estate, and physical assets net of debt. Because this object combines heterogeneous assets—housing, real estate, financial assets, gold, and non-housing durables—with different returns, depreciation rates, liquidity, and valuation error, this exercise should be interpreted as an approximate plausibility check rather than a portfolio decomposition. We therefore report three real-return scenarios, $r \in \{1.5\%, 2\%, 3\%\}$, rather than a single preferred return.

Figure E.2 compares the resulting CPHS-implied wealth profiles with AIDIS total net wealth. The implied profiles are of the same broad order of magnitude as AIDIS. Under the 2% return scenario, CPHS-implied wealth is Rs. 0.37 million at ages 25–29 compared with Rs. 0.42 million in AIDIS, Rs. 1.02 million at ages 45–49 compared with Rs. 1.39 million in AIDIS, and Rs. 1.92 million at ages 55–59 compared with Rs. 1.98 million in AIDIS. The implied profiles overshoot AIDIS wealth at older ages, especially under the higher-return scenario. This is not surprising because the simple accumulation equation does not model inter vivos transfers, bequests, late-life dissaving, health shocks, mortality selection, or asset-specific depreciation. Nevertheless, the comparison shows that the CPHS surplus profile implies wealth accumulation that is broadly plausible relative to independent AIDIS wealth data.

Figure E.1: Validation of CPHS Wage Earnings Against PLFS

(a) Life-cycle profile, households with positive wage earnings

(b) Distribution by wage decile, households with positive wage earnings

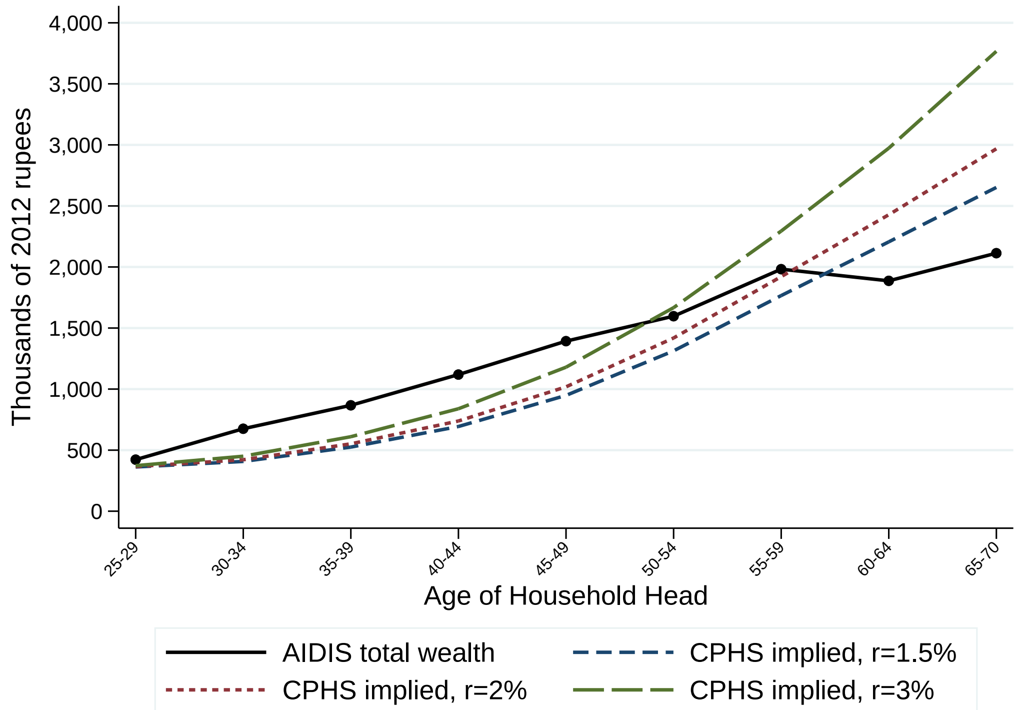


Notes: The figure compares CPHS and PLFS household wage earnings. CPHS wage earnings include household income from wages, overtime, and bonuses. PLFS wage earnings include regular salaried/wage earnings and casual wage earnings summed across household members. Both datasets are deflated using the same state-sector-month CPI series and annualized. The sample is restricted to households with positive annual wage earnings in the relevant dataset.

F Non-Housing Durable Goods

CPHS does not report expenditures on non-housing durables but provides a detailed inventory of major and minor durable goods owned by the households. We impute the price of these goods

Figure E.2: CPHS Surplus-Implied Wealth and AIDIS Wealth



Notes: The CPHS-implied wealth profiles are constructed by multiplying the estimated CPHS surplus-rate profile by the estimated CPHS income profile to obtain annual surplus levels, then accumulating those surplus flows starting from AIDIS total net wealth at age 25. AIDIS total wealth includes financial assets, gold/bullion/ornaments, real estate, and physical assets net of debt. Because total wealth combines heterogeneous assets with different returns and depreciation rates, we report three real-return scenarios: 1.5%, 2%, and 3%. All series are in real 2012 rupees and plotted in thousands.

and use the information on non-housing durable goods ownership in the survey to construct total value of the non-housing durable stock. 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 non-housing durable goods by calculating a weighted (and unweighted) average price of a certain category by state and region (rural/urban sector). The non-housing 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 non-housing durable goods in each category to generate total household non-housing durable stock.

Table F.1 provides the prices and share of households owning each type of physical assets by region —urban and rural.

Table F.1: Price and Distribution of Non-Housing 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 non-housing durable goods are in 2014 rupees, from the 72nd round of NSSO dataset (July 2014 - June 2015) (GOI (2016)). 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 non-housing durable asset stock in CPHS.

G Quantifying the Role of Non-Housing Durable Goods

This appendix describes the accounting exercise used in Section 5 to quantify the role of non-housing durables in accumulated life-cycle surplus.

G.1 Accumulated Surplus and Non-Housing Durable Stock Growth

We start from the budget constraint and non-housing durable law of motion in equations (3)–(4). For this accounting exercise, we set the fixed adjustment cost to zero, $\kappa = 0$. The non-housing durable law implies

$$i_t = d_{t+1} - (1-\delta)d_t. \tag{14}$$

Substituting this expression into the budget constraint and forward-substituting from age 25, which we denote by period 0, gives

$$a_t = (1+r)^t a_0 + \sum_{k=0}^{t-1}(1+r)^{t-k}(y_k - c_k) - \sum_{k=0}^{t-1}(1+r)^{t-k}\left[d_{k+1} - (1-\delta)d_k\right]. \tag{15}$$

Using the non-housing durable stock path to rewrite the last term, subtracting a_0, and adding $d_t - d_0$ to both sides yields

$$\begin{aligned} a_t - a_0 + d_t - d_0 = {} & \left[(1+r)^t - 1\right]a_0 + \sum_{k=0}^{t-1}(1+r)^{t-k}(y_k - c_k) \\ & + \left[(1+r)^t(1-\delta) - 1\right]d_0 - rd_t - \sum_{k=1}^{t-1}(1+r)^{t-k}(r+\delta)d_k. \end{aligned} \tag{16}$$

The left-hand side is the increase in the modeled household asset position, namely financial assets plus non-housing durable stock. In a complete household balance sheet, changes in land, housing, real estate, business assets, and other nonfinancial assets would also appear on the left-hand side. We do not include those assets because CPHS does not report monetary values for them over the life cycle, so the exercise should be interpreted as a non-housing durable-specific accounting calculation.

The statistic reported in the main text is

$$\text{Non-housing durable contribution at age } t = \frac{d_t - d_0}{RHS_t}, \tag{17}$$

where RHS_t is the right-hand side of equation (16). The numerator is the observed rise in the non-housing durable stock. The denominator is the accumulated life-cycle surplus implied by the income, nondurable expenditure, initial asset, and non-housing durable stock profiles.

The non-housing durable stock profile d_k as shown in Figure 7 is constructed from CPHS non-housing durable ownership, valued using NSSO prices. The value at age 25 is $d_0 = 43{,}460$ in real 2012 rupees. The corresponding stock levels are $d_{45} = 85{,}406$, $d_{50} = 93{,}432$, and $d_{55} = 95{,}696$. As an external validation of the level of the non-housing durable stock, Badarinza et al. (2017) report a mean non-housing durable-goods stock of Rs. 58,660 from AIDIS (GOI (2014)). Our estimated average imputed CPHS non-housing durable stock for ages 25–70, weighting ages by their CPHS age distribution and converting to real 2012 rupees, is Rs. 68,857. Thus, the CPHS-imputed non-housing durable stock is close to an independent AIDIS benchmark once both are expressed in the same real rupee units.

We use the estimated CPHS household income profile for y_k and the estimated CPHS surplus-rate profile for $(y_k - c_k)/y_k$. Since the surplus-rate profile starts at age 31, we set the surplus rate equal to zero for ages 25–30. Initial assets, a_0, are measured using AIDIS households whose head is age 25–27. We construct a_0 as net financial assets including gold/bullion/ornaments: shares, other financial assets, loans receivable, and gold/bullion/ornaments, net of outstanding cash and kind debt. The weighted mean is $a_0 = 17{,}112$ in real 2012 rupees.

The benchmark uses $r = 0.05$ and $\delta = 0.15$. The real interest rate is close to the average real lending-rate benchmark for India.[40] The depreciation rate is consistent with standard values for household non-housing durables: the Bureau of Economic Analysis reports annual depreciation rates of 15 percent for several non-housing consumer-durable categories, including kitchen and other household appliances (U.S. Department of Commerce, Bureau of Economic Analysis, 2003), and Monacelli (2009) notes that vehicle depreciation is around 15 percent annually. We also vary one parameter at a time, using $r \in \{0.03, 0.07\}$ and $\delta \in \{0.13, 0.17\}$, the results are shown in Table 3.

G.2 Augmented Expenditure Profiles

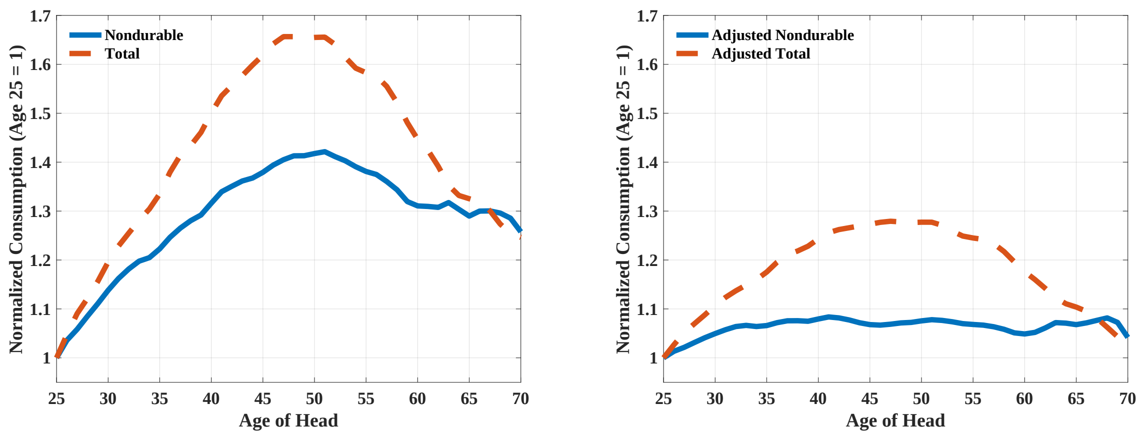
As a complementary exercise, we construct an augmented expenditure profile that adds imputed non-housing durable investment flows to nondurable expenditures. Specifically, we compute $c_t + i_t$ and its adult-equivalent counterpart, $(c_t + i_t)/n_t$, where i_t is the flow of newly acquired non-housing durables in CPHS valued using NSSO prices. This investment-flow measure is the natural counterpart to the surplus-rate calculation, because $y_t - c_t$ is a resource flow and durable purchases are one destination for that flow. It should not be interpreted as a full rental-equivalent durable service-flow measure, which would require stronger assumptions about depreciation, utilization, and within-household nonrivalry.

Figure G.1 shows that adding these non-housing durable investment flows makes the life-cycle expenditure profile substantially steeper. Peak adult-equivalent growth rises from 8.4 percent for nondurables alone to 27.9 percent for augmented expenditures. Thus, the flat nondurable profile does not imply that broader expenditures associated with durable acquisition are flat over the life cycle.

[40] The real interest rate is 2000-2020 average taken from World Development Indicators (data.worldbank.org).

Figure G.1: Nondurable and Augmented Life-Cycle Expenditure Profiles

(a) Unadjusted (b) Adjusted



Notes: Augmented expenditure equals nondurable expenditure plus imputed non-housing durable investment flows. Durable flows are constructed from newly acquired non-housing durables in CPHS valued using NSSO prices. Adjusted profiles divide expenditures by the modified-OECD adult-equivalent scale. Profiles are normalized to age 25.

H Additional Figures and Tables

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

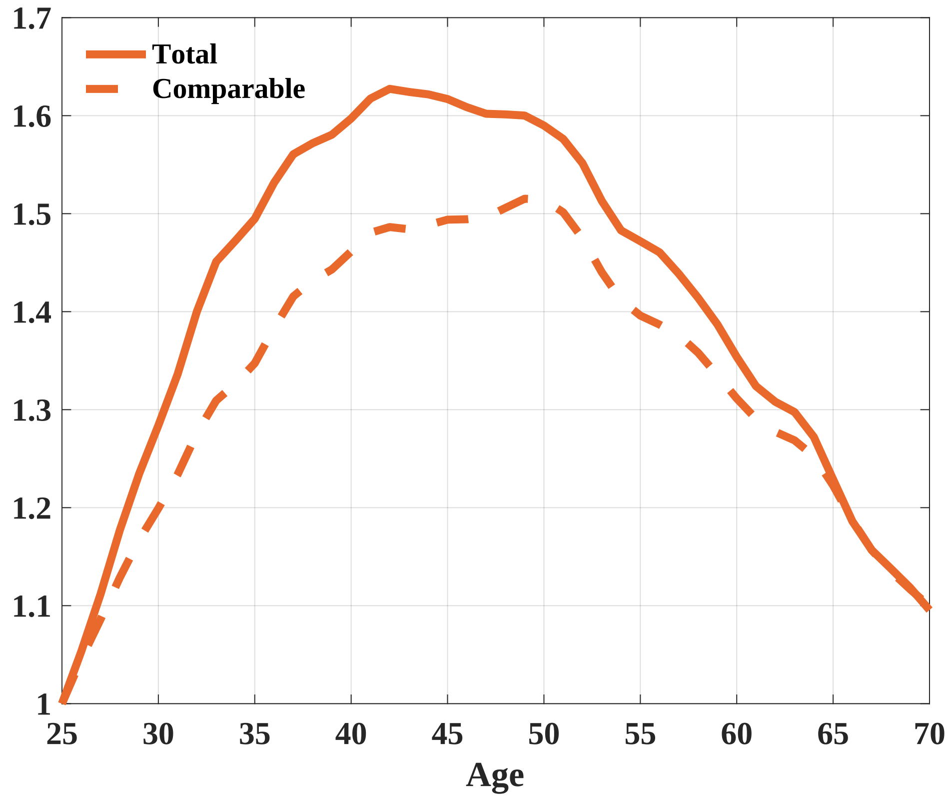
	(1) Ln(Consumption)	(2) Ln(Income)
Linear time trend	-0.0002	0.0086
Time Dummy = 3	-0.0710*	0.0051
Time Dummy = 4	-0.1280**	-0.0813
Time Dummy = 5	-0.1757**	-0.0630
Time Dummy = 6	-0.2103**	-0.0654
Time Dummy = 7	-0.2257*	-0.0632
Time Dummy = 8	-0.1314	-0.0162
Birth Cohort Dummy = 2	-0.0155	0.0037
Birth 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 H.3: Household Composition by Age of Household Head

Age Group	Spouse	Children 0-5	Children 6-10	Children 11-16	Parents	Grand children	Others	Number
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.

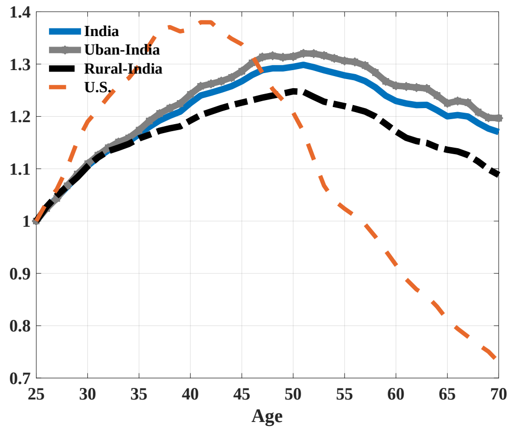
Figure H.1: Unadjusted Life-Cycle Consumption in the U.S.
by Age of Household Head



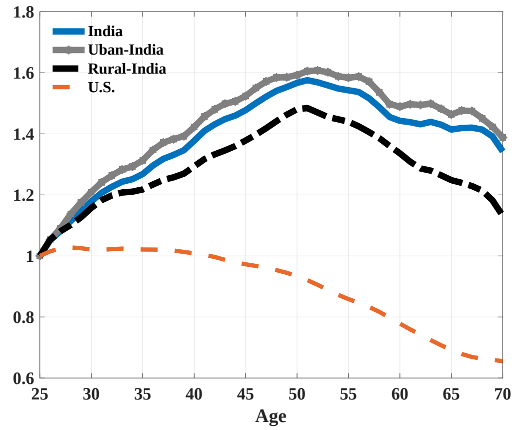
Notes: Total household consumption relative to age 25 (household head) is reported. Data for the U.S. comes from the PSID. Comparable categories include total expenditures on 1) food 2) transportation 3) education 4) childcare 5) health care 6) clothing 7) household repairs and furnishing 8) trips and 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 H.2: Unadjusted Life-Cycle Consumption
by Age of Household Head and Expenditure Categories

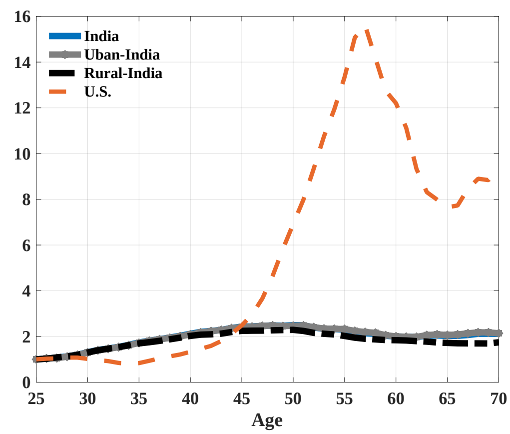
(a) Food



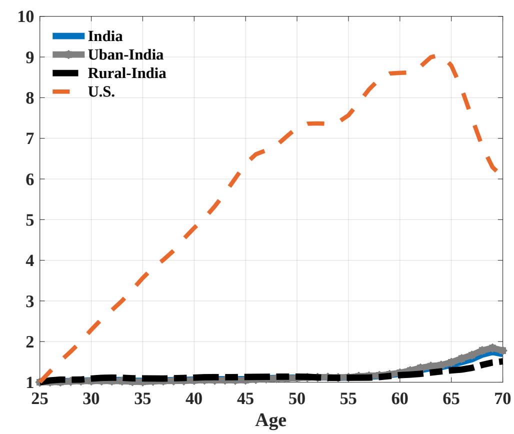
(b) Non-Mortgage Housing



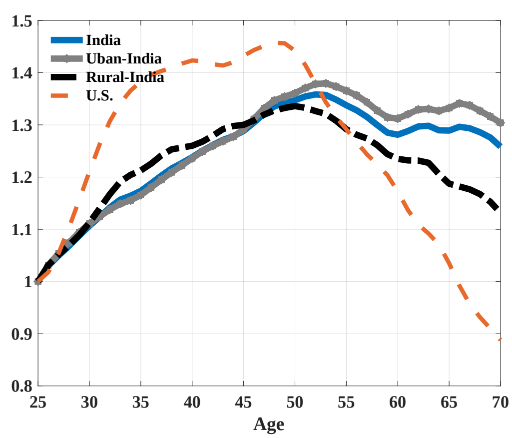
(c) Education



(d) Health



(e) Transportation



Notes: Each profile is normalized to age 25 of the household head.

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

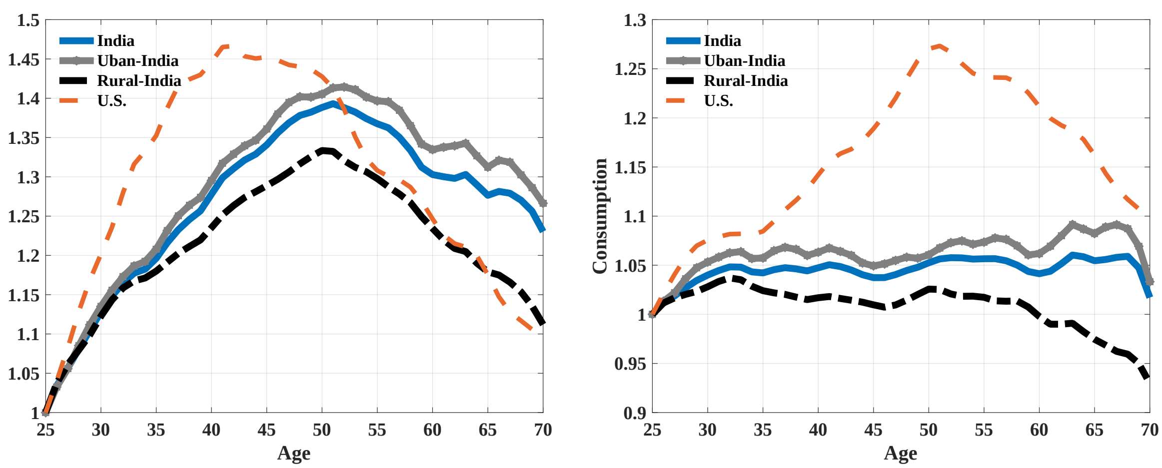
Age Group	Children 0-5	Children 6-10	Children 11-16	Parents	Grand children	Others
20-29	1.29	1.35	1.22	1.25	1.48	1.68
30-39	1.18	1.48	1.47	1.20	1.55	1.62
40-49	1.18	1.31	1.51	1.14	1.51	1.27
50-59	1.23	1.34	1.34	1.07	1.70	1.16
60-69	1.21	1.37	1.40	1.04	1.89	1.14
70-79	1.18	1.33	1.39	1.05	1.99	1.14
80-89	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 H.3: Life-Cycle Consumption Less Education and Health by Age of Household Head

(a) Unadjusted

(b) Adjusted

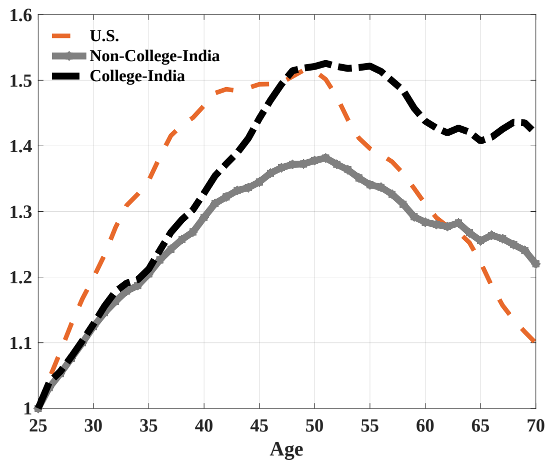


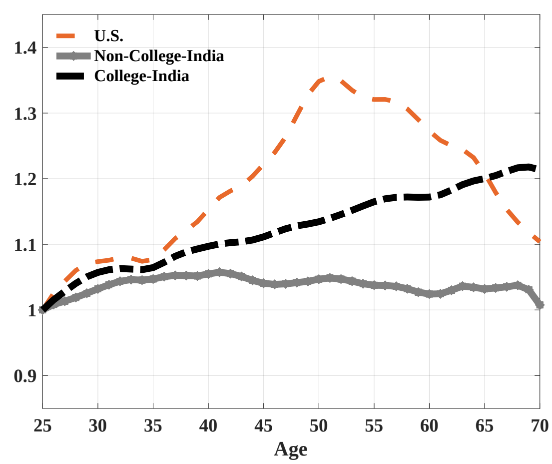
Notes: Consumption relative to age 25 (household head) is reported for both U.S. and India. Data for the U.S. comes from the PSID. Expenditure categories include total expenditures on 1) food 2) transportation 3) childcare 4) clothing 5) household repairs and furnishing 6) trips and recreational activities 7) housing related to 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 child aged 16 or under and 0.5 to each adult over the age of 16.

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

(a) Unadjusted

(b) Adjusted

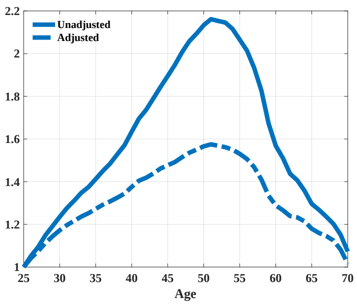




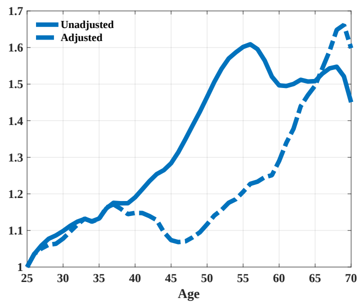
Notes: Household consumption relative to age 25 (household head) is reported for both U.S. and India. Data for the U.S. comes from the PSID. Adjusted refers to total household consumption divided by family size using a modified OECD scale which assigns a weight of 1 to household head, 0.3 to each child aged 16 or under 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 related to 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 H.5: Life-Cycle Income
by Age of Household Head, Family Type, Region and Occupation

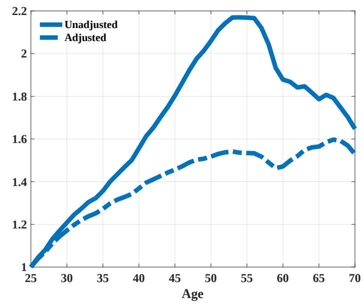
(a) Nuclear Families



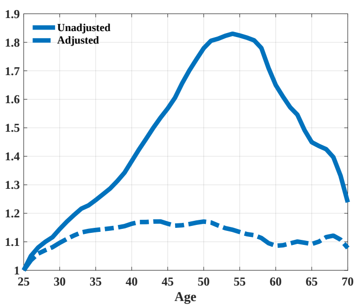
(b) Extended Families



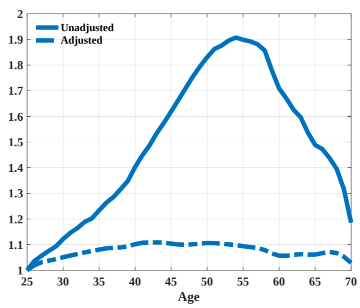
(c) Urban India



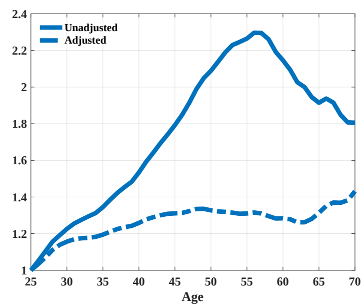
(d) Rural India



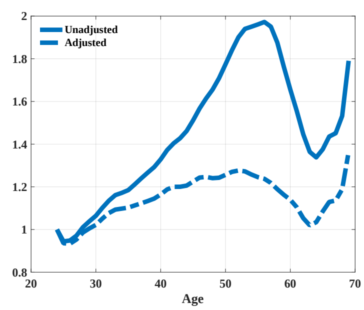
(e) Farmers



(f) Self Employed

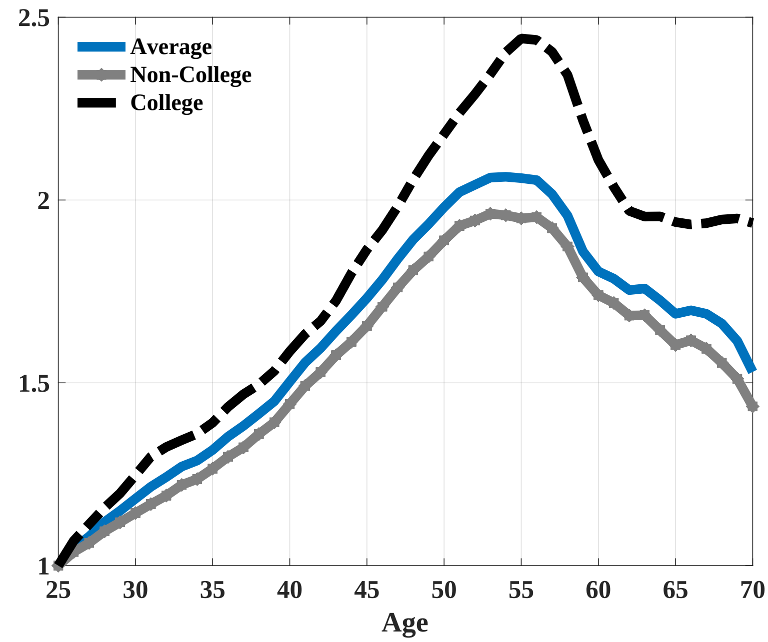


(g) White-Collared Workers



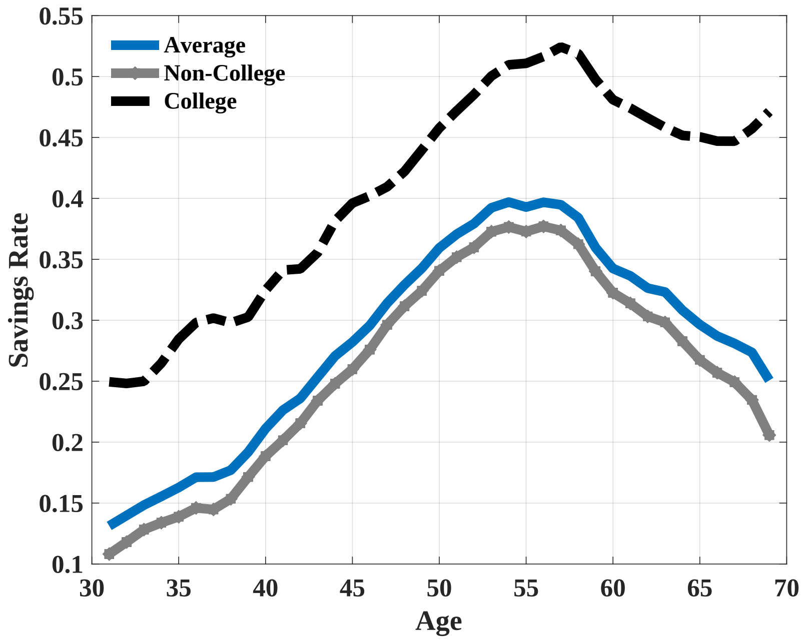
Notes: Adjusted income reports estimates of total household income divided by number of earning members. Total household income relative to age 25 (household head) is reported for each region and family size type. Family income for India includes income from all sources including private/public transfers,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

Figure H.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 H.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 H.5: Probit Estimates of Intentions to Purchase House and 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 H.6: OLS Estimates of Intentions to Purchase House and 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 Buy 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 × Age of Head			0.00258***	0.00272***
			(64.38)	(71.69)
Age of Head × Age of Head × Age of Head			-0.0000192***	-0.0000201***
			(-71.67)	(-79.02)
Non-Housing 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 H.7: OLS Estimates of Intentions to Purchase House and 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 Buy 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 × Age of Head			0.00296***	0.00290***
			(47.47)	(47.25)
Age of Head × Age of Head × Age of Head			-0.0000214***	-0.0000210***
			(-51.24)	(-50.93)
Non-Housing 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 H.8: OLS Estimates of Intentions to Purchase House and 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 Buy 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)
Non-Housing 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 H.9: OLS Estimates of Intentions to Purchase House and 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 Buy 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)
Non-Housing 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 H.10: OLS Estimates of Intentions to Purchase House and 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 Buy 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)
Intend 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 $\times$ Age of Head			0.00295***	0.00290***
			(52.58)	(51.93)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000218***	-0.0000213***
			(-57.25)	(-56.50)
Non-Housing 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 H.11: OLS Estimates of Intentions to Purchase House and 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 Buy 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 $\times$ Age of Head			0.00365***	0.00361***
			(50.06)	(51.85)
Age of Head $\times$ Age of Head $\times$ Age of Head			-0.0000258***	-0.0000253***
			(-52.41)	(-53.67)
Non-Housing 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 H.12: OLS Estimates of Intentions to Purchase House and 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 Buy 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)
Non-Housing 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 H.13: OLS Estimates of Intentions to Purchase Other Non-Housing 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)
Non-Housing 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 H.14: Event-Study Coefficients for Savings Rates Around Durable and Housing Purchases

Event time	House	Car	Two-wheeler	Tractor	Cattle
-8	1.22 (0.74)	-4.81 (0.86)	-1.75 (0.44)	-12.30 (2.44)	-1.51 (0.92)
-7	1.47 (0.64)	-3.61 (0.77)	-1.39 (0.40)	-8.19 (2.30)	-0.78 (0.85)
-6	1.41 (0.57)	-3.09 (0.71)	-1.10 (0.36)	-7.64 (2.08)	-0.42 (0.77)
-5	-0.52 (0.52)	-3.25 (0.65)	-1.33 (0.32)	-9.05 (1.96)	-0.53 (0.70)
-4	-1.73 (0.47)	-2.05 (0.59)	-1.33 (0.30)	-3.27 (1.70)	-0.52 (0.64)
-3	-3.64 (0.46)	-1.89 (0.54)	-1.73 (0.27)	-5.76 (1.59)	-0.14 (0.58)
-2	-4.50 (0.41)	-1.39 (0.48)	-1.54 (0.24)	-5.78 (1.50)	0.71 (0.52)
-1	-2.38 (0.37)	1.17 (0.43)	0.63 (0.22)	-2.38 (1.35)	0.62 (0.50)
0	0.00 (omitted)	0.00 (omitted)	0.00 (omitted)	0.00 (omitted)	0.00 (omitted)
1	-3.00 (0.34)	1.82 (0.43)	0.82 (0.21)	2.51 (1.31)	1.74 (0.48)
2	-5.24 (0.39)	-0.84 (0.47)	-1.33 (0.24)	-3.44 (1.34)	-1.23 (0.52)
3	-6.28 (0.42)	-1.77 (0.55)	-1.51 (0.26)	-2.61 (1.56)	-2.21 (0.58)
4	-8.11 (0.46)	-1.48 (0.59)	-2.17 (0.28)	-6.30 (1.64)	-4.16 (0.63)
5	-8.67 (0.48)	-2.49 (0.64)	-2.47 (0.31)	-6.73 (1.81)	-3.36 (0.66)
6	-8.59 (0.51)	-1.89 (0.69)	-2.36 (0.33)	-5.43 (2.11)	-3.59 (0.71)
7	-9.61 (0.55)	-2.94 (0.75)	-2.68 (0.36)	-4.83 (2.20)	-3.68 (0.76)
8	-10.01 (0.60)	-3.28 (0.82)	-3.26 (0.39)	-5.86 (2.44)	-4.37 (0.82)

Notes: Each cell reports the event-time coefficient, in percentage points, with the clustered standard error in parentheses. Event time 0 is the omitted purchase period and is normalized to zero. Controls include calendar-wave fixed effects, birth-cohort fixed effects, and a third-order polynomial in age of the household head. Standard errors are clustered at the household level.

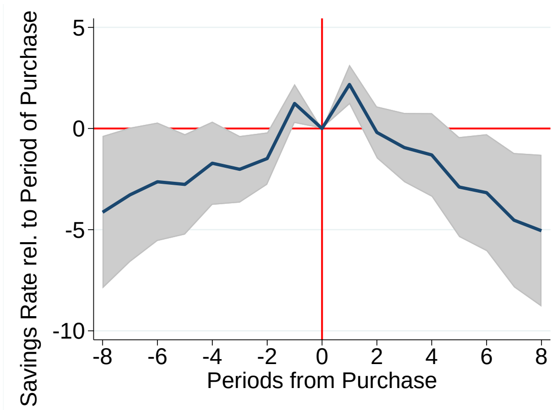
Table H.15: Event-Study Tests for Savings Rates Around Durable and Housing Purchases

Asset	All pre-purchase coefficients	Near-purchase buildup	Post vs. pre average
House	0.000	0.000	0.000
Car	0.000	0.000	0.306
Two-Wheeler	0.000	0.000	0.347
Tractor	0.000	0.000	0.006
Cattle	0.265	0.224	0.034

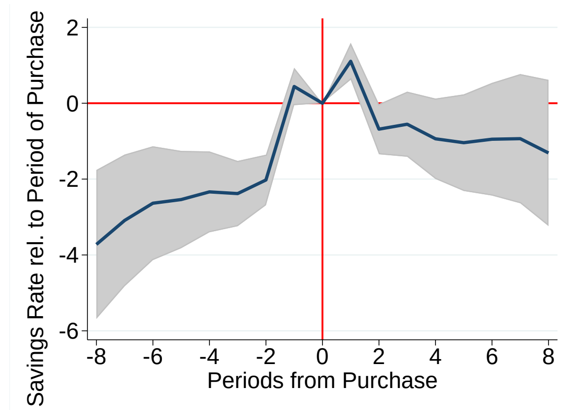
Notes: Entries are p-values. The all-pre-purchase test jointly tests equality to zero for event-time coefficients -8 through -1. The near-purchase buildup test jointly tests equality to zero for event-time coefficients -3 through -1. The post-vs.-pre test compares the average coefficient at event times 1 through 3 with the average coefficient at event times -3 through -1.

Figure H.8: Household Fixed-Effect Event-Study Coefficients for Savings Rates Around Asset Purchases

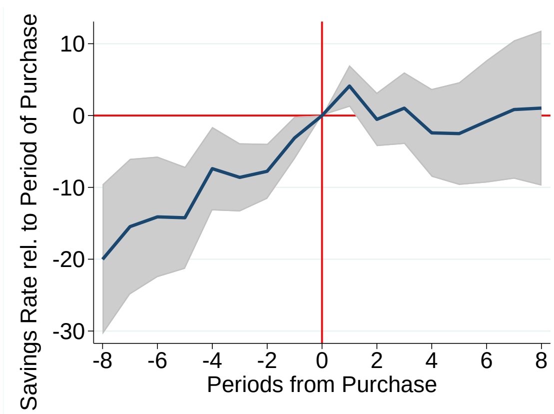
(a) Car



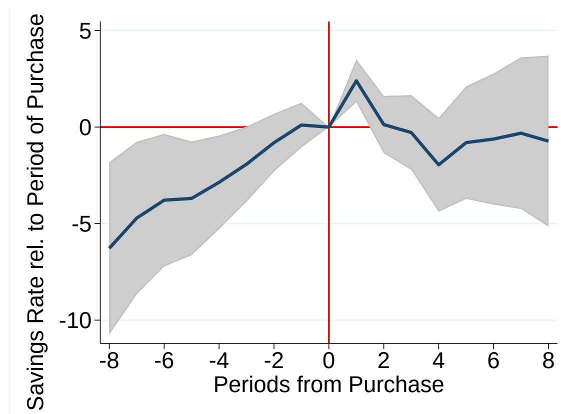
(b) Two-Wheeler



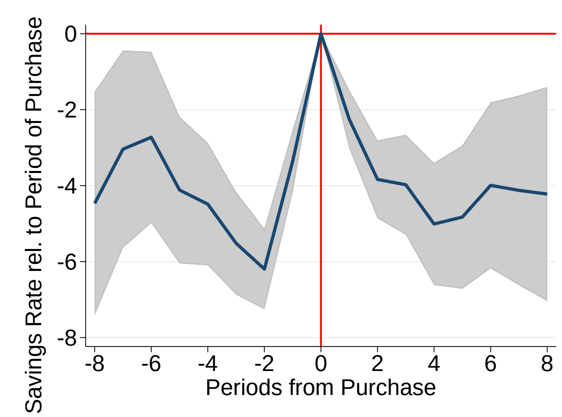
(c) Tractor



(d) Cattle



(e) House



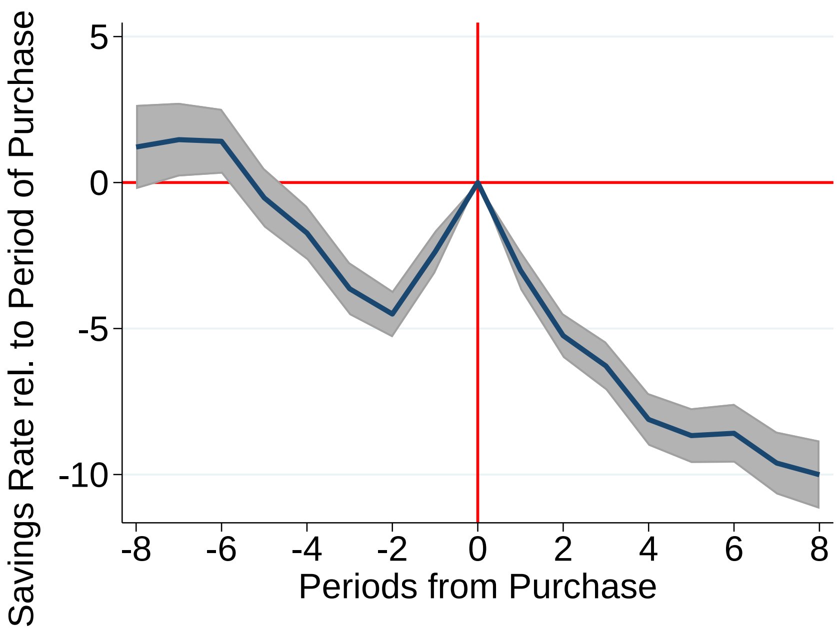
Notes: The figure plots household fixed-effect event-study coefficients for the household savings rate, in percentage points, relative to event time 0, the omitted purchase period. The shaded regions correspond to 95% confidence intervals. Controls include household fixed effects, calendar-wave fixed effects, and a third-order age polynomial. Standard errors are clustered at the household level.

Table H.16: Household Fixed-Effect Event-Study Tests

Asset	All pre-purchase coefficients	Near-purchase buildup	Post vs. pre average
House	< 0.001	< 0.001	0.030
Car	< 0.001	< 0.001	0.260
Two-wheeler	< 0.001	< 0.001	0.012
Tractor	< 0.001	< 0.001	0.004
Cattle	0.073	0.059	0.164

Notes: Entries are p-values from household fixed-effect event-study regressions. The all-pre-purchase test jointly tests whether event-time coefficients -8 through -1 are zero. The near-purchase buildup test jointly tests whether event-time coefficients -3 through -1 are zero. The post-vs.-pre test compares the average coefficient at event times 1 through 3 with the average coefficient at event times -3 through -1. All regressions include household fixed effects, calendar-wave fixed effects, and a third-order age polynomial. Standard errors are clustered at the household level.

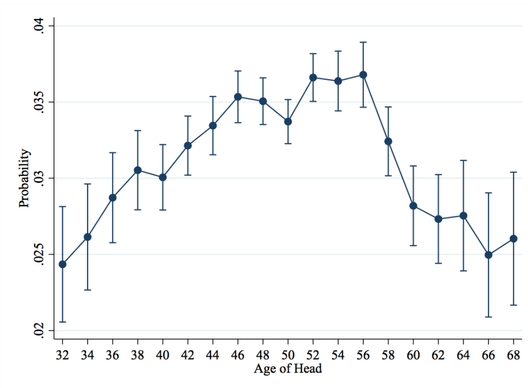
Figure H.9: Event-Study Coefficients for Savings Rates Around House Purchases



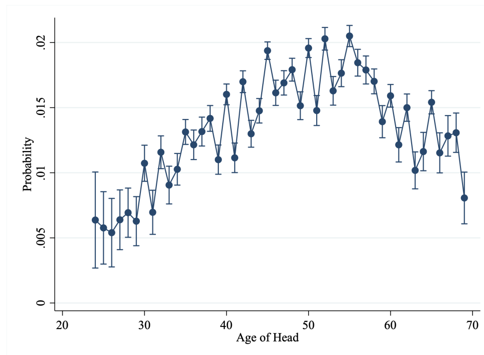
Notes: The graph reports event-study coefficients for the household savings rate, in percentage points, relative to event time 0, the omitted purchase period. The shaded region corresponds to the 95% confidence interval. Controls include dummies for calendar time, birth cohort, and a third-order age polynomial. Standard errors are clustered at the household level.

Figure H.10: 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 H.11: Borrowing for Non-Housing Consumer Durables By Regions

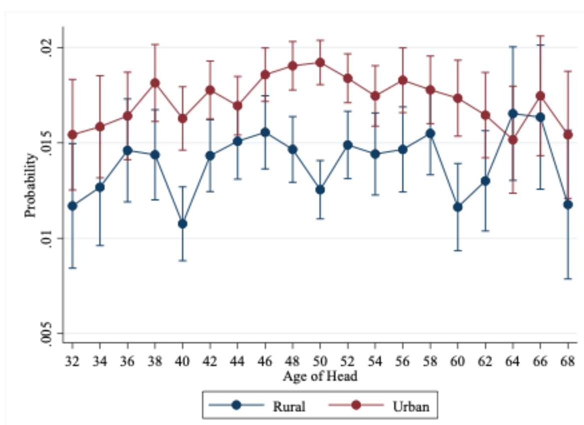
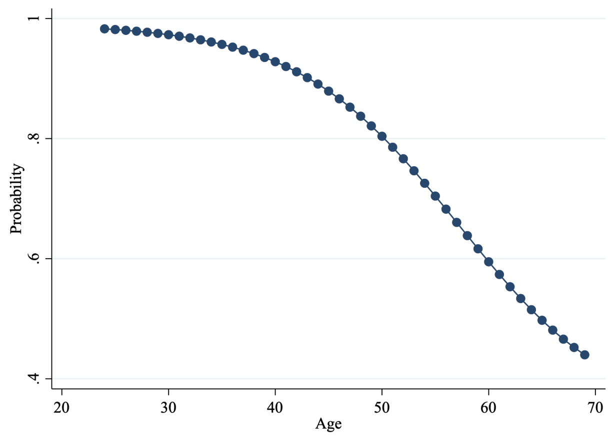
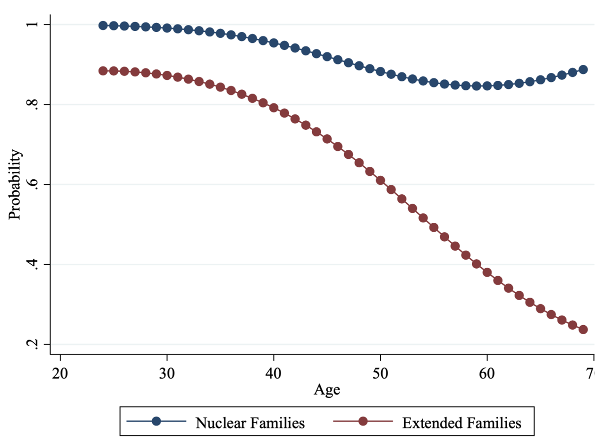


Figure H.12: Households With Heads as Primary Earning Members
by Age of Head

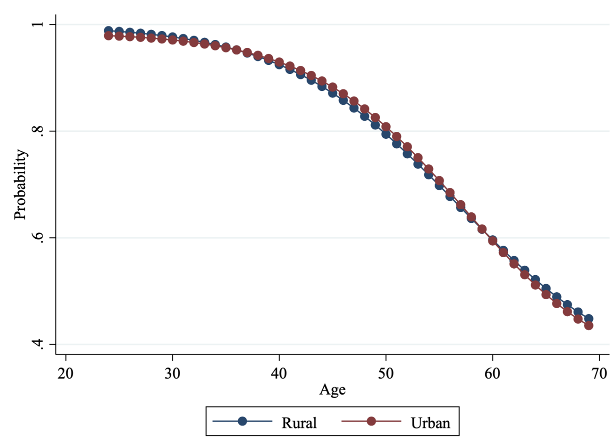
(a) All



(b) By Family Type



(c) By Region Type



(d) By Occupation

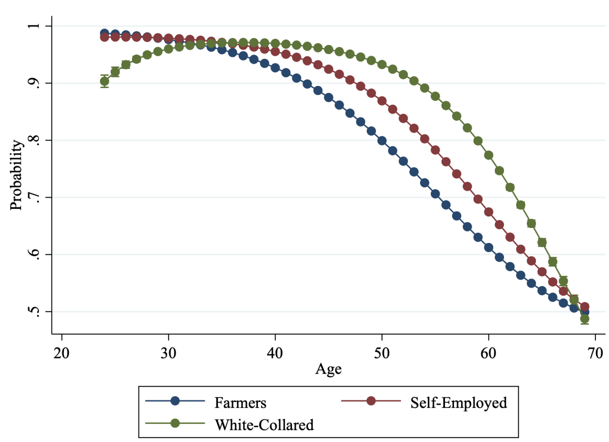
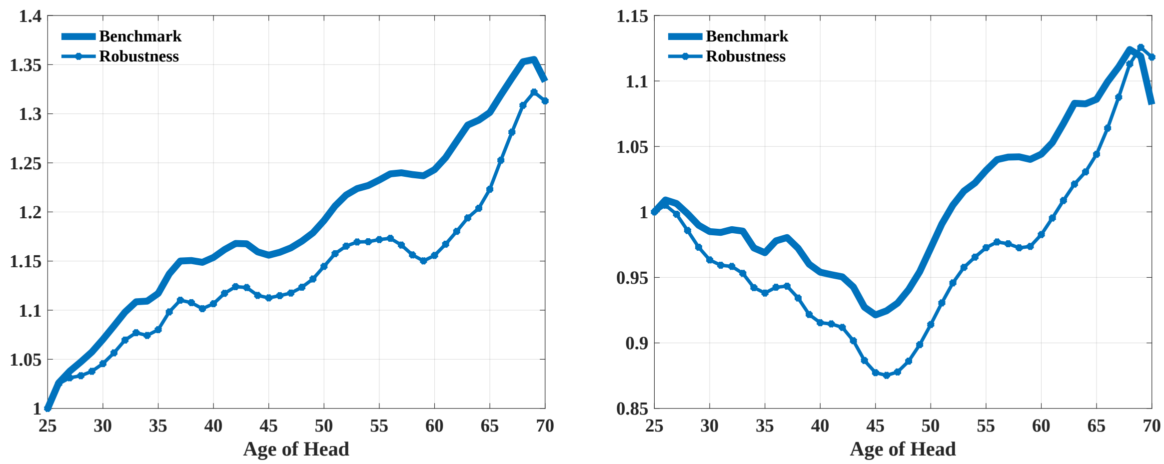


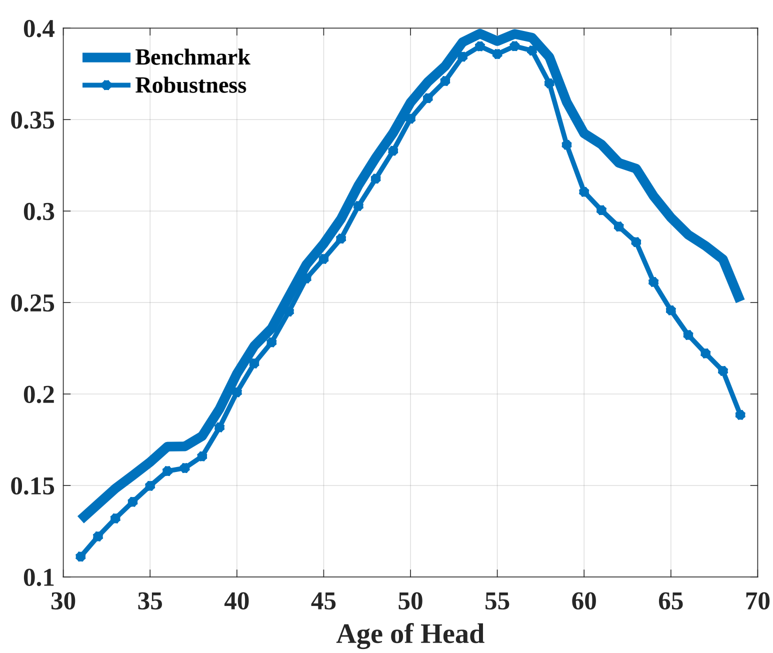
Figure H.13: Head Robustness: Life-Cycle Consumption
by Age of Household Head for Extended Families

(a) Unadjusted (b) Adjusted



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

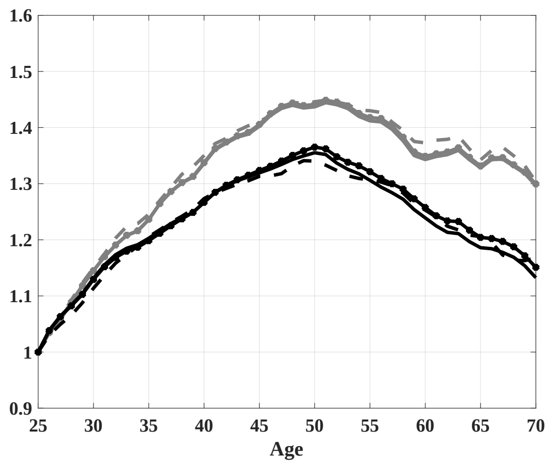
Figure H.14: Head Robustness: Life-Cycle Savings Rate
by Age of Household Head



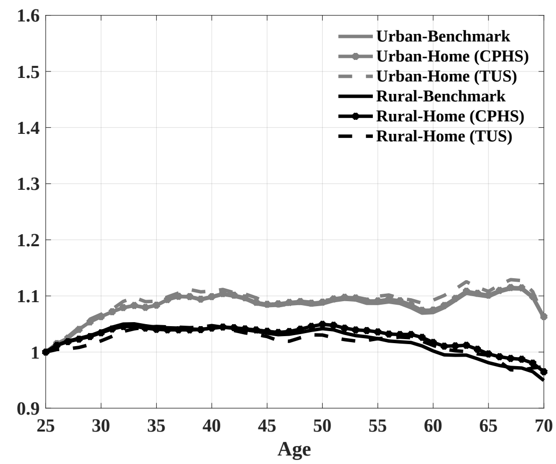
Notes: Savings rate is computed as income net of total nondurable consumption as a fraction of total income. This robustness exercise drops all households where head is not the primary earning member.

Figure H.15: Home Production Robustness: Life-Cycle Consumption by Age of Household Head

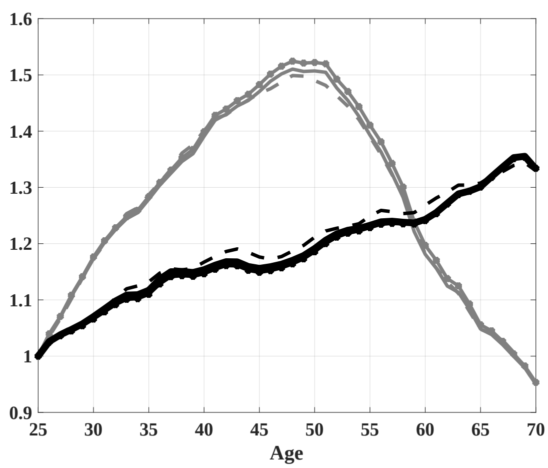
(a) Unadjusted-Region



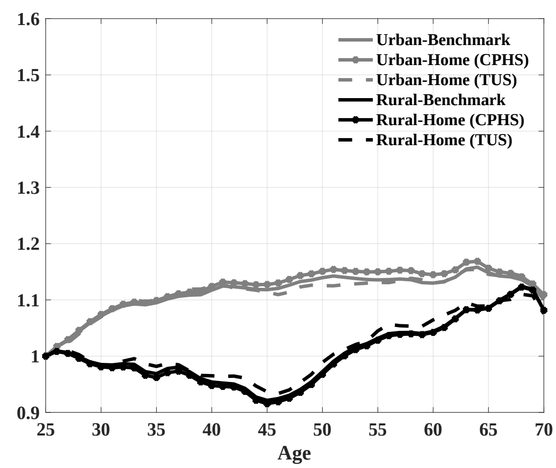
(b) Adjusted-Region



(c) Unadjusted-Family Type



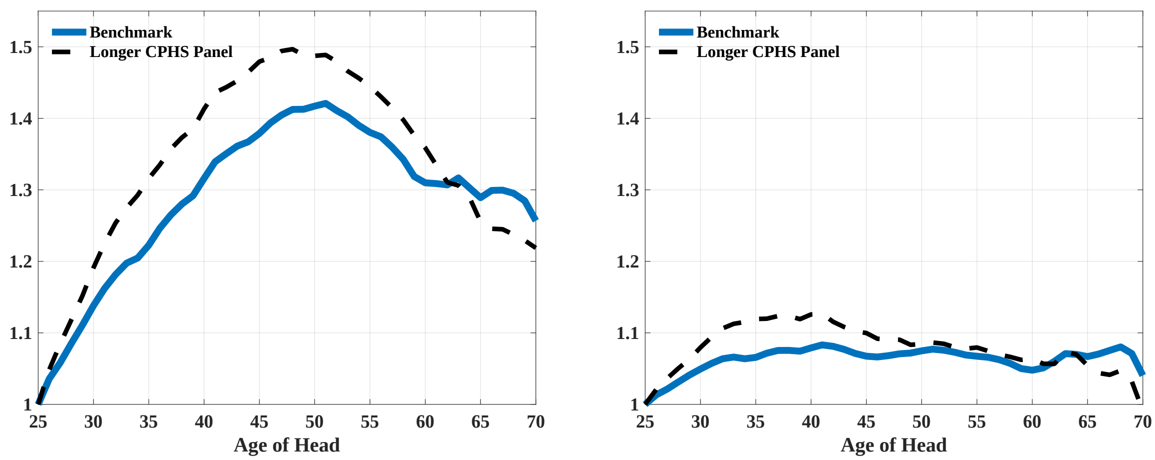
(d) Adjusted-Family Type



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

Figure H.16: 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 aged 16 or under, 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).

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