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Income Differentials & Rate of Time Preference: A Developing Country Perspective

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Abstract

Estimating time preferences in developing countries like India, is essential for designing public policies that influence savings and investment decisions. However, limited data availability and various economic constraints restrict the estimation process and its analysis. Following Lawrance (1991) framework, this paper adopts Euler equation approach to estimate individual time preferences and assess its relation with one's income level, in the context of India. Using a national level household survey, the CMIE CPHS dataset spanning 2014-2019, the average RTP for the Indian population is estimated to be 0.0689. It means that on average, individuals in India are willing to forgo 6.89% of future consumption to have the same amount of consumption today. Furthermore, the results show that wealthier individuals are marginally more patient than poorer ones, exhibiting decreasing marginal impatience. These findings have significant policy implications for shaping redistributive, welfare, and growth policies in India.

Keywords: rate of time preference, euler equation, household survey data, India
JEL: E21, C61, D91

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1 Introduction

Time preferences play a pivotal role in shaping crucial aspects of individual lives, affecting a wide set of their decisions, ranging from savings and borrowing to education and health choices. Estimation of time preferences can thus be instrumental in framing policies which directly affect individual decisions. While time preferences are fundamentally shaped by psychological factors that reflect how one values one's future vis-à-vis one's present (Hoel et al. (2016)), socio-economic factors such as income, education and caste are also stated to affect time preferences and thus individual behaviour (Lawrance (1991)). Theory and empirical evidence from developed nations have consistently indicated a negative relationship between income and time preferences, highlighting the phenomenon of decreasing marginal impatience (DMI) (Laibson et al. (2007); Trostel and Taylor (2001); Lawrance (1991); Chakrabarty (2023)). For instance, DMI is reported by De Lipsis (2021) using a sample of European countries , Bradford et al. (2017) in USA, Kossova et al. (2013) in Russia, among many others. These studies based in developed nations show that people with higher income are willing to delay gratification for greater future rewards. However, literature also shows that time preferences, and hence this relationship could vary across regions (Wang et al. (2016)), economic well-beings (Dohmen et al. (2015)), culture (Rieger et al. (2021)), past consumption behaviour (Das (2003)) *etc.* Yet, this relationship is relatively less explored in the context of developing countries. This paper contributes to the literature by empirically identifying how income, as a socio-economic factor, may affect time preferences in a developing country, specifically India.

Existing studies have highlighted the economic implications of the relationship between income and time preferences. In economies characterised by varying levels of time preferences, more patient individuals, preferring future consumption over present consumption, are likely to begin investing at lower interest rates compared to less patient individuals, who prioritise immediate consumption. Laibson et al. (2007) and Lawrance (1991) document that higher-income individuals tend to exhibit greater patience. Thus, when investments in an economy depend on time preferences, and time preferences correlate with income levels, estimating the relationship between income and time preferences becomes crucial. In addition to determining investments & interest rates, this relationship also aids in designing policies. As indicated by Frederick et al. (2002), if the costs associated with long-term projects are high, they are less likely to be undertaken in societies with predominantly less patient individuals. This relationship holds significant implications for developing countries that require substantial long-term public investments, but face data scarcity challenges that complicate the estimation of time preferences.

There are three common methods for empirically assessing time preferences. The first involves lab experiments where individuals choose between lesser immediate and more delayed rewards (Falk et al. (2018)). Although this method provides precise control, it may lack external validity and could be affected by the nature of the lab environment and the Hawthorne effect [1]. Despite these limitations, it has been widely used in the literature, ranging from various small samples (Fuchs (1980)) to large cross-country analyses (Dohmen et al. (2015)). The second method assumes perfect selfishness for individuals and measures the preference assigned to their future as the probability of their survival in the future Freeman et al. (2018). Although easy to assess, the method relies on inaccurate behavioral assumption of complete selfishness. The final method evaluates time preferences by analysing individual consumption choices over time, and deriving the preferences by matching household decisions with a baseline utility function (Lawrance (1991); Trostel and Taylor (2001); Sun (2023)). Although criticised for its restrictive functional form (Laibson et al. (2007)), this approach is valued for its reliance on real world data (Frederick et al. (2002)). However, this approach is often limited to developed countries as it requires large panel data on consumption expenditures and income, which is typically unavailable in developing nations. A further constraint on the applicability of this method in developing countries arises from the assumption that households act optimally, a premise that may not hold in developing regions facing poverty, limited access to credit and insufficient insurance (Jalan and Ravallion (2002); Rand (2007); Ludvigson and Paxson (2001); Escanciano et al. (2015)). This study aims to measure time preferences in developing countries while addressing these limitations of the Euler equation approach.

This paper takes the case of India to formalise the methodology for measuring time preferences in a developing country case. It adopts the rate of time preference (RTP) framework to mathematically

[1] The Hawthorne effect refers to the phenomenon where participants alter their decisions because they are aware they are being observed in a study, often choosing what they believe to be socially acceptable or expected responses instead of their true preferences. This effect can distort the measurement of individual time preferences in lab environments and result in biased data. Research underscores the need to consider this effect to improve the reliability of experimental outcomes in economics (Levitt and List (2011), Frederick et al. (2002)).

represent time preferences. A few studies have previously estimated RTP in Indian context. Ogaki and Atkeson (1997) derive RTP value for rural India using the ICRISAT dataset. Due to the limited sample of 104 households for 5 time periods of the ICRISAT dataset, they had to adopt a parsimonious econometric model where the RTP was interpreted as the mean change in consumption growth rates after changing income. This limits interpretability of the results. Therefore, even if the results are true at village level for short time periods, these results may not be generalised for the entire economy. Other studies on RTP measurement for India focus on specific health policy contexts, like Dang (2023), or examine the entire economy assuming perfect selfishness, as demonstrated in the work by Murty et al. (2020). Other works to derive RTP in India relies on choice-based experiments such as Dohmen et al. (2015), and Wang et al. (2016).

This paper is based on the rate of time preferences (RTP) framework formalised by Uzawa (1969) and combines it with the Lawrance (1991) framework, suitably adjusted to account for economic constraints in potential consumption optimisation in India. As RTP reflects psychological attitude that shapes intertemporal choices, which are influenced by socio-economic conditions (Frederick (2003)), this paper follows Lawrance (1991) in assuming that RTP can be modeled as a linear function of various observable pre-sample socio-economic characteristics. This paper uses the Consumer Pyramids Household Survey (CPHS) data from India, a national level household survey, conducted by the Centre for Monitoring Indian Economy (CMIE). CPHS is a longitudinal dataset that provides information on various socio-economic aspects of households in India, based on surveys conducted every 4 months. A log-linearised Euler equation is adopted to derive the relationship between income and RTP in this context. The approach requires information on income, intertemporal choices, credit constraints, demographics, and various socio-economic characteristics at the household level. CMIE CPHS data is used to obtain that information. Additionally, RBI data repositories are used to collect information on interest rates, price indices and tax rates.

The referred Lawrance (1991) framework requires a split of sample. Accordingly, the financial year $2014-15$ is selected as the pre-sample period and financial years of $2015-2020$ form the sample period. The household specific socio-economic conditions of pre-sample period are used to analyse the effects on household RTP measure. Thus, the estimated RTP measures with pre-sample data are time invariant for the sample period. This time invariance conforms to existing empirical evidence that eliminates endogeneity arising from reverse causality while estimation (Bartoš et al. (2021); Sutter et al. (2020)). The information on other variables of the Euler equation is taken from the sample period. After determination of all variables in the Euler's equation, pooled OLS is used to estimate the RTP in this context. The results confirm a negative relationship between RTP and income levels for the Indian economy, reinforcing the concept of DMI. This implies that richer individuals have lower urgencies for immediate gratification. As income increases, individuals often feel financially more secure, reducing the pressure to make hasty decisions for short-term gains. This is critical for developing countries like India, where domestic savings are key to financing investments in infrastructure, education, and health.

The rest of the paper is structured as follows: Section 2 briefly describes the background and literature in this domain. Section 3 describes the mathematical model referred for log-linearised Euler equation estimation and explains the methodology adopted to derive the results. Section 4 provides details on the data set, chosen variables, and the pre-processing required to perform the analysis. Section 5 explains the derived results in two parts. Section 5.1 presents the key findings and robustness checks are reported in Section 5.2. Section 6 provides the concluding remarks.

2 Background

Several studies have measured time preferences through cross-country analyses, typically employing choice-based experiments (Wang et al. (2016); Dohmen et al. (2015); Falk et al. (2018)). Due to the lack of household level consumption data across various countries worldwide, consumption analyses are generally limited to individual countries, predominantly developed ones. An exception is the work of De Lipsis (2021), which estimates RTP for 11 developed nations using data from the Global Consumption and Income Project, and the Euler equation approach. This approach is more amenable for individuals in developed countries as they optimise intertemporal utility based on social security nets (Lawrance (1991); Trostel and Taylor (2001); Laibson et al. (2007); De Lipsis (2021)). However, the situation is more complex for developing countries. Agents in these countries face strict credit and affordability constraints, limiting their choices and complicating the consideration of these factors when applying the Euler equation. Consequently, RTP measurements in developing countries using consumption data from secondary sources is relatively sparse (Sun (2023); Ogaki and Atkeson (1997)).

The presence of market imperfections and affordability constraints in emerging economies cast doubts on the accuracy of macroeconomic estimates. Therefore, checking the value of the estimates after controlling for each imperfection becomes important. Many papers highlight the role of cultural and socio-economic disparities while deriving RTP measures (Falk et al. (2018)). This recognition dates back to Fisher (1930), who proposed that limited resources, lack of foresight, and reduced self-control often lead to impatience among low-income individuals. Likewise, Becker and Mulligan (1997) highlight that time preferences are critically dependent on wealth levels and vary widely across nations. During a psychological assessment by Shechter et al. (2011), it was found that students' efforts to learn long-term versus short-term scores varied across nations. This assessment controlled for the interest in the topic and IQ levels of students. Other cross-country experiments report that cultural and geographical differences, along with economic variables like income, interest rate, and inflation significantly affect RTP (Wang et al. (2016); Dohmen et al. (2015)). On similar grounds, a very recent work by Chakrabarty (2023) explains how the instinct to "catch up with the joneses" leads people belonging to a more unequal society to act more impatiently compared to a fairly equal society. These evidences strongly advocate for a separate analysis on time preferences for different nations.

Various alternatives for measuring RTP exists in the literature. Most research works rely on choice-based experiments that are performed in controlled lab environment (Wang et al. (2016); Dohmen et al. (2015); Falk et al. (2018)). By systematically varying the reward amounts and the delay periods, researchers infer the discount rates which reflect how individuals devalue future rewards in favor of immediate ones. For instance, Wang et al. (2016) conducts surveys in 53 countries to estimate discount rates and establish their relation with various individual characteristics such as age, socio-economic background, health choices, educational achievements, household demographics and income. This approach allows for precise control through experimental conditions and the ability to isolate the effect of time preferences from other confounding factors. However, this method has several drawbacks. One major limitation is the potential lack of external validity, as the controlled environment of the lab may not accurately capture real-world decision-making processes. Additionally, participants' behaviour in a lab may be influenced by factors such as the artificiality of the task or the presence of the experimenter, through the Hawthorne effect. Furthermore, the stakes in lab experiments are often different from those in real-life decisions, which can affect the generalisability of the findings (Frederick et al. (2002)). In spite of these drawbacks, this method has been employed in numerous studies. Beginning with Fuchs (1980) for evaluation of time preferences in a limited sample, the method experimented with different types of question formulation (Cohen et al. (2020); Frederick et al. (2002)) and has recently delved into analysis with large cross country representative samples (Dohmen et al. (2015)).

The Green book method or Ramsey rule is another approach for calculating the RTP. It assumes that people are completely selfish and the value they place on the future equals the probability of their survival in future. Therefore, at the aggregate level, this approach uses the death rates in the economy to measure RTP (Freeman et al. (2018)). It is widely used for macroeconomic analysis and policy decisions by the governments worldwide (Murty et al. (2020); Gollier (2012)). While this method is straightforward and avoids sampling biases, the methodology relies on inaccurate assumptions like complete selfishness and the use of average death rates as a proxy for individual survival. Such assumptions have been criticised by many behavioural studies that favour affirmative action and bequest preferences (Stark and Nicinska (2015)).

Some papers adopt the lifecycle hypothesis to perform simulations using the balance sheet data of households like their credit card debts, liquidity constrained assets, bank investments or cashless consumption expenditure *etc* (Laibson et al. (2007)). This framework (heavily relying on the quality of the balance sheet data) provides accurate results for the developed world, where formal sector constitutes a very large share of the economy. The imperfect and the informal nature of markets in developing countries leads to the existence of incomplete balance sheets for most households. Moreover, developing countries also lack the financial instruments necessary to accumulate wealth and the borrowing information needed for RTP calculation.

The log-linearised form of Euler's equation presents a suitable alternative for calculating RTP, as it assumes a baseline utility function to derive the equation and the match them with the actual choices of the household. However, Carroll (2001) argues that such linear equations poorly approximate the original non-linear form. Extending the argument, Attanasio and Low (2004) show that poor approximations are true only in the short run and the accuracy improves with longer time horizons, implying the applicability of this method. Also, this method is often considered a more reliable approach since it relies on real-world data (Laibson et al. (2007), Frederick et al. (2002)). The nationwide secondary datasets required in its computation effectively correct for idiosyncrasies and sampling biases. Furthermore, the adopted data is not susceptible to the informal and primitive structure of the financial markets (Lawrance (1991)). Two approaches exist to estimate RTP using Euler's method. The residual-based approach, adopted by Sun (2023), starts with observing the values of all components of the Euler equation except RTP. Afterwards, it identifies RTP as the residual term in regression performed with the observed variables. This approach is straightforward but doesn't explicitly consider the influence of psychological factors. Moreover, it leaves the scope for the influence of factors other than the components of Euler equation as well, which are unrecognisable. In contrast, Lawrance (1991) employs a particular functional form for RTP which allows for the independent computation of RTP, isolated from other unaccounted variables. We believe that this approach offers a detailed insight into time preferences relative to other estimation techniques discussed earlier. Therefore, it is chosen as the preferred method for this analysis.

3 Model

The basic structure of the consumer optimisation problem is derived from Lawrance (1991) where individuals maximise the expected value of their time-separable intertemporal utility. Here, the RTP is assumed to be time invariant because once framed, subsequent modifications in psychological factors require longer to alter (Costa Jr and McCrae (1997)). The utility function is maximised subject to the budget constraint in equation 1.

$$\text{Max. } V_{it} = E_t \left[\sum_{\tau=t}^{N} (1+\delta_i)^{t-\tau} * \frac{FS_{i,\tau}^{1-\beta} (C_{i,\tau}/FS_{i,\tau})^{1-(1/\gamma)}}{1-(1/\gamma)} \right] \tag{1}$$

$$\text{subject to } A_{i,\tau+1} = (1 + r_{i,\tau+1}) * (A_{i,\tau} + Y_{i,\tau} - C_{i,\tau})$$

Here, $\tau \in [t, ..., N]$ represents time period and satisfies the terminal condition where $A_{iN} \geq 0$. E_t represents mathematical expectations, and δ_i is the time-invariant RTP measure. $FS_{i,\tau}$ denotes the family size of individual i. $Y_{i,\tau}$ and $C_{i\tau}$ represent the income and consumption expenditure of the individual i and his/her respective wealth levels $(A_{i,\tau})$ at time τ. $r_{i,\tau+1}$ signifies the expected real interest rate faced by individual i in the next period. Since consumption expenditures in secondary datasets are measured at the household level, individual utility is derived from per capita consumption (C_t/FS_t), not its aggregate value. The term $FS_i^{1-\beta}$ enters the utility function to express the utility derived from economies of scale $(\beta \geq 0)$ and γ represents the elasticity of substitution between present and future consumption. The first-order condition for the maximisation exercise in equation 1 gives the following Euler equation.

$$E_t \left[\left(\frac{1 + r_{i,t+1}}{1+\delta_i} \right) \left(\frac{C_{i,t+1}/FS_{i,t+1}}{C_{i,t}/FS_{i,t}} \right)^{-\frac{1}{\gamma}} \left(\frac{FS_{i,t+1}}{FS_{i,t}} \right)^{-\beta} \right] = 1 \tag{2}$$

Assuming rational expectations and flexible prices, individual i follows Euler equation, but with a random forecast error $(\epsilon_{i,t+1})$. This error arises due to the future uncertainty, which is assumed to be uncorrelated with the current state, possessing a mean value of 0. These errors signal a deflection from rational choices made by individuals. After incorporating the forecast error, the empirical estimation for the non-linear Euler equation is carried out with performing log-linearisation. However, prior to transitioning from theoretical analysis to empirical evaluation, it is essential to consider measurement errors as well. To address them in the model, following relationship is assumed between reported consumption and actual consumption: $C_{i,t}^{*} = C_{i,t} exp(v_{i,t})$. Here, $v_{i,t}$ refers to the random measurement error of the household i. After their incorporation, the log-linear Euler equation takes the following form.

$$ln\left(\frac{C_{i,t+1}}{C_{i,t}}\right) = \gamma ln(1+\delta_i) + \gamma ln(1+r_{i,t+1}) + (1-\beta\gamma) ln\left(\frac{FS_{i,t+1}}{FS_{i,t}}\right) -\gamma\left(\epsilon_{i,t+1} - 1/2\epsilon^2_{i,t+1}\right) - v_{i,t+1} + v_{i,t} \tag{3}$$

The observed variables in equation 3 must be utilised to calculate the individual level RTP. The RTP represents psychological elements that are also influenced by various socio-economic experiences. These experiences shape consumption attitudes by forming habits (Carroll et al. (2000)), changing future perspectives (Caplin and Leahy (2001)), and creating awareness about evolving preferences (Ariely and Wertenbroch (2002)). However, this evolution of time preferences occur over longer periods (Frederick et al. (2002)). Since our sample period is only 5 years, we can assume the dependence of RTP on time invariant socio-economic factors, specifically $ln(1+\delta_i) = \bar{\delta} + \sum_{k=1}^{K} \rho'_k X_{k,i}$. This facilitates the empirical observation of all variables belonging to equation 3. The final estimation equation takes following form.

$$ln\left(\frac{C_{i,t+1}}{C_{i,t}}\right) = \alpha + \sum_{k=1}^{K} \rho_k X_{k,i} + \gamma ln(1+r_{i,t+1}) + \theta ln\left(\frac{FS_{i,t+1}}{FS_{i,t}}\right) + e_{i,t+1} \tag{4}$$

Here, $\alpha = \gamma\left(1/2\sigma^2_\epsilon - \bar{\delta}\right)$ is the intercept and γ is the percentage increase in per capita consumption growth rate as the expected interest rate increases by one percentage point. $\rho_k = \gamma\rho'_k$ registers the effect of historical socio-economic experience on the percentage change in the growth rate of per capita consumption. Similarly, $\theta = 1 - \beta\gamma$ explains the economies of scale by measuring the impact of percentage change in family size on percentage change in growth rate of consumption per capita. Finally, $e_{i,t+1} = \gamma\left(-1/2\sigma^2_\epsilon + 1/2\epsilon^2_{i,t+1} - \epsilon_{i,t+1}\right) - v_{i,t+1} + v_i, t$ is the combined error term. Once these parameters are obtained through the regression results, they are used to retrieve the value of RTP[2] from equation 5. Here, RTP is derived to be a function of socio-economic factors, their respective

[2]Please refer to the Appendix of Lawrance (1991) for detailed derivation

parameters, intercept of the regression equation, γ and the standard errors.

$$ln(1+\delta_i) = -\gamma^{-1}\left(\alpha + \sum_{k=1}^{K}\rho_k X_{k,i}\right) + 1/2\sigma_\epsilon^2 \tag{5}$$

Our paper follows the log-linearised Euler equation approach by employing the methodology developed by Lawrance (1991) and subsequently used by Trostel and Taylor (2001). Drawing from the CMIE CPHS data spanning 2015 to 2020, this paper investigates the relation between initial levels of socio-economic factors, specifically income, on RTP.

The log-linearised Euler equation 4 includes $r_{i,t+1}$ as a proxy for the expected value of real interest rate faced by an individual i in period, $t+1$. The expected value is considered as the intertemporal choices do not depend on actual returns, but on the expected value of future returns, as perceived in the present. Available data can only capture the actual value, and not the expected values. Hence, a two-stage least squares (2SLS) technique is adopted to first derive the expected rate of return for individuals by regressing the actual interest rate ($R_{i,t+1}$) on its one year lag while controlling for other variables belonging to the equation 4. This expected value accounts for the future family growth rates and economic constraints, indicating that individuals plan on the basis of their expectations of future conditions. These forward-looking expectations are influenced by socio-economic factors, which are also controlled while predicting the expected interest rates.

In the second stage, the derived value of expected interest rate is used to estimate equation 4. Here, the logarithm of the intertemporal consumption growth rate is regressed on several factors: socio-economic variables relevant to the rate of time preference (RTP), the logarithm of the growth rate of family size to adjust household consumption to per capita terms, and the expected interest rates derived from the first stage of the analysis. The *log of expected future interest rate* is influenced by expectations that differ across various socio-economic groups. Therefore, the expected interest rate derived in the first stage introduces an additional channel for the RTP to affect intertemporal decisions. This mechanism allows past experiences to shape an individual's psychology and expectations for the future.The resulting functional form of the Euler equation studied in this paper (equation 4) is crucially dependent on the assumption that economic constraints are non-binding. This assumption hardly holds true in the case of developing countries due to frequent shocks, poverty, absence of social security, and capital market imperfections. This study detects these constraints within the CMIE CPHS dataset, explores methods to mitigate the bias and either removes or adjusts the Euler equation to account for them.

Developing economies experience frequent economic shocks that may constrain household budgets over time. To isolate the effect of socio-economic factors on intertemporal choices, we need to consider such shocks in the Euler equation. Accordingly, this paper follows Lawrance (1991) by taking time dummies as representative variables for aggregate shocks. In addition to aggregate shocks, capital market imperfections also impact household budget constraints and hence must be taken into account. Assessing credit constraints typically involves analysing credit card debt, loan denials, and the reasons behind them (Laibson et al. (2007)). The CMIE CPHS lacks such detailed information. To address the limitation, this paper constructs a "borrowing dummy" variable. Individuals who reported any borrowing during the sample period are assumed to be non-credit constrained, while those who did not borrow are categorised as credit constrained. Given that approximately 25% of the households in our dataset were credit constrained, we opted to create a dummy variable to account for this factor, rather than excluding these households from the analysis. It is important to highlight that households which did not borrow are deemed to be credit-constrained in this dummy variable. We recognise that this assumption has its drawbacks as it might inaccurately categorise individuals who did not need credit during the sample period. Nevertheless, due to data constraints, this approach offers the most suitable proxy for assessing credit access. Another key factor constraining economic choices in developing countries is poverty. It creates a cycle in which immediate survival needs take precedence over long-term goals. Because many people lack basic necessities and social security in emerging economies, their choices don't reflect their true desires, causing them to deviate from the behaviour predicted by Euler equation. Approximately 11% of the households in our data had an average yearly per capita income below the poverty line at least once in the sample period [3]. We drop these households to generate consistent estimates.

[3] see Appendix B.3 for the criteria used to identify the poor

4 Dataset and Pre-processing

The CMIE has been conducting national household surveys covering demographics, consumption, income, ownership, and aspirations of households residing in rural and urban areas in India. The sample and questionnaire underwent several changes in 2015. Specifically, the method for capturing monthly expenditure on certain food items was altered in April 2015, and 8.4% non-responsive households were substituted with new ones. Such alterations prevent a direct comparison of the data between 2014 and subsequent years. However, we leverage these variations for our study as it allows us to select a base year and correspondingly, the socio-economic variables. We take the financial year $2014-15$ as the pre-sample year [4], and data for subsequent years is used to evaluate intertemporal consumption dynamics. Due to the likelihood of distortions in income and consumption demand, data after the onset of the COVID-19 pandemic is excluded from the analysis. However, the study incorporates data during demonetisation [5] and GST [6] as these may be considered sudden shocks to consumption decisions, with implications for RTP measures (Wadhwa (2019)). Thus, the selected period of our study spans FY$2015-16$ through FY$2019-20$, with FY$2014-15$ as the pre-sample period. With data collected in three waves every year, 18 waves are taken for each household in the data.

To check for outliers, 0.8% household heads who were younger than 18 years or older than 90 years were excluded from the sample to retain $1,12,982$ households. For one of the checks performed in Section 5, we eliminate poor households from consideration to arrive at a sample of $1,00,031$ households. However, the robustness checks performed in Section 5.2 take the original sample of $1,12,982$ households into account. The survey reports monthly data on income and consumption expenditure, requiring a recall period that can extend upto four months. As the quality of data for such long recall periods has often been questioned (Jha and Basole (2023); Patnaik et al. (2023)), this study selects the observation with the shortest recall period as a representative for each wave.

[4] The pre-sample period refers to the period from which the value of socio-economic variables are derived. For more information refer to Lawrance (1991)

[5] During 2016 demonetisation, the Indian government invalidated the INR500 and INR$1,000$ currency notes in an effort to tackle black money, corruption, and counterfeit currency (Chanda and Cook (2022)).

[6] The Goods and Services Tax (GST) implemented in India in 2017 consolidated various indirect taxes into one unified tax system, aiming to streamline the tax framework and enhance compliance (Bhalla et al. (2023)).

The first step of our analysis controls for socio-economic variables such as, age, education, caste, and pre-sample income to estimate the relation between interest rate and consumption growth rates. While the chosen socio-economic variables (education, income, caste, and age) captures RTP, representing individual characteristics, the elements of consumption expenditure and family size in equation 5 relate to the entire household. Consequently, the socio-economic variables attributed to the family are taken to be the features of the representative agent of the household, who makes decisions and provides for the well-being of the entire family. CMIE CPHS asks respondents to designate the head of the household and state how each family member is related to the reported head. However, Bairoliya et al. (2021) argued that such responses are often unable to identify the true head of the household, especially in a joint family setup. Rather than basing the response on decision making abilities or financial contributions, numerous Indian households appoint the eldest family member as the head, solely out of respect. Such specifications introduce bias in the results. Consequently, the criteria for identifying the household head was modified, assigning the title to the family member who earned the highest income in a given year[7]. The financial head identifiers differed from the reported heads in about 30% households. To mitigate the bias arising from this unmatched discrepancy, two cases were examined. In the first instance, unmatched cases could be removed from the sample to carry out further analysis. The second case considered the financial head as the true head of the family.

4.1 Consumption

CMIE CPHS collects data on consumption expenditure profile of the *entire* household for 136 goods. This paper follows Luengo-Prado (2006) to consider a set of 31 non-durable expenditure heads. This includes food & beverages, toiletries, clothing & apparel, medicines, cleaning supplies, fuel, office supplies, exhaustible consumer goods such as personal care products, snacks, *etc.*. All these expenditure heads were separately added to derive the monthly non-durable consumption expenditure. Its value in real terms was obtained by adjusting the nominal values with the respective state-wise rural-urban Consumer Price Index (CPI) as explained in Appendix B.2. The month having

[7]see Appendix B.1 for further details

the shortest recall period for each wave in sampling period was used to determine the wave-level real consumption expenditure for non-durable goods and this was used for further analysis.

4.2 Interest Rates

Information about the interest rate faced by the individual/household is not provided in the CMIE CPHS dataset. Therefore, an indirect approach has been used in this paper to derive the real interest rate ($\hat{r}_{j,t+1}$) faced by the head of the household. To this end, information on Treasury 365, a long-term national interest rate (r_{t+1}) is sourced from the RBI website 6. The total interest income obtained from savings is taxed at a rate of $\mu_{j,t+1}$. Therefore, the net interest rate is adjusted accordingly. Here, $\mu_{j,t+1}$, the tax rate refers to the percentage tax paid out of total income. After adjusting the national rates with individual-specific tax rates and area-specific inflation rates (CPI_t/CPI_{t+1}), the future real interest rates for the individuals are derived using the following expression (Lawrance (1991)).

$$\hat{r}_{j,t+1} = i_{t+1}\left(1 - \mu_{j,t+1}\right)\frac{CPI_t}{CPI_{t+1}} - 1$$

While the CMIE CPHS data lacks individual tax rate information, we can estimate these rates based on the surveyed income levels and government tax schemes. Although these estimates may be less accurate due to tax evasion and India's substantial informal economy, this method remains the best option in the absence of a valid alternative to find individual interest rates. The state-wise rural-urban CPI values are used to determine the inflation in Appendix B.2, and the government tax slabs for each financial year are derived from the Finance Bills provided in the annual budgets. Table C1 in the Appendix C provides an overview of the tax regimes in effect during the sampling period.

4.3 Family Size

This paper calculates the *adult equivalent family size* by assigning weights according to the age and gender of each member in a household. This specification enables an accurate assessment of each individual's food and utility needs, by providing one with respective weights. A calorie-based weighing metric is adopted from Claro et al. (2010) and is provided in Table C2 of Appendix C. The metric was specifically developed for Brazil, an emerging economy like India. The weights of all members of the household are derived from this metric and added for each wave to finally obtain the measure of adult equivalent family size. The month with the shortest recall period is taken as the wave representative.

4.4 The Socio-economic Variables

As the household head is assumed to be the key decision-maker in a family, the features of household head are taken as the representative of the entire household. Thus, education, caste, age, and initial income of the household head have been used in the first stage of estimation (Lawrance (1991); Trostel and Taylor (2001)). The pre-sample income is derived by averaging the real income per wave of the household head during the pre-sample period. Nominal income of the head for each wave is deflated using the state-wise rural-urban CPI values[8] from the RBI data repository to yield the real income of the household head for each wave in the pre-sample period. Following Jha and Lahoti (2022), this paper categorises the maximum education of the household head into four levels: illiterate/primary school, secondary (grades $6 - 10$), high school (grade 12), and graduate or above. According to Indian culture, caste is classified into groups: unreserved or intermediate castes (GEN), scheduled castes (SC) or scheduled tribes (ST), and other backward classes (OBC). The last reported age of the household head in the pre-sample period represents the age variable.

5 Results

5.1 Key Empirical Results

Table 1 presents the descriptive statistics for the variables used in this paper. Consumption growth rate of non-durable goods, adult equivalent and family size ratio are presented in the first two rows. Considerable variation exists in the consumption growth rates. The second and third panels of

[8] see Appendix B.2 for further details

Table 1 presents tax-inflation adjusted real interest rates socio-economic characteristics of financial head of the household and reported head of the household respectively. This variation between the financial head and the reported head results in a higher average age of the household head, along with a decrease in the percentage of households with college education and a reduction of average income in the sample. This section presents results separately for the financial head and reported head, while considering differential constraints faced by the households.

Table 1 Descriptive Statistics

Variables	**Mean**	**Standard Deviation**	**Min.**	**Max.**
Consumption Ratio $(C(t+1)/C(t))$	1.07	0.528	0	295.98
Family Size Ratio $(FS(t+1)/FS(t))$	1.099	0.233	0.049	18.21
Financial Head:				
Real Interest Rate (R_{t+1})	0.066	0.007	0.037	0.094
Age	43.586	12.504	18	90
% of Lower Caste Households (SC/ST & OBC)	62.9	48.3	0	1
% whose Education $\geq$ College Education	20	39.9	0	1
Income	88.849	74.853	0	1698.755
Reported Head:				
Real Interest Rate (R_{t+1})	0.066	0.007	0.038	0.094
Age	49.754	12.339	18	90
% of Lower Caste Households (SC/ST & OBC)	62.9	48.3	0	1
% whose Education $\geq$ College Education	17	37.5	0	1
Income	74.108	75.379	0	1698.755
Other Income Specifications:				
Weighted Assets	0.008	0.007	0	0.091
Total Household Income	135.976	115.881	0	2330.700

The mean & standard deviations reported in table are for the complete sample of households (including poor). The % of households specified for describing education and caste are with reference to the whole sample. Financial heads are household representatives who earn maximum in the pre-sample year, whereas the reported heads are titled by household members during the survey. Weighted assets proxies for wealth levels by weighing the ownership of physical assets according to Bairoliya et al. (2021) and adding them.

Pooled-OLS regression is used to estimate the log-linearised Euler equation (Equation 4) [9]. We apply Pooled-OLS due to the presence of time-invariant socio-economic variables which are essential in RTP calculations. Alternative methods such as fixed effects and random effects do not consider these time-invariant factors.

[9] The consistency of the obtained Pooled-OLS linear regression results is verified in non-linear setting as well using Particle Swarm Optimisation, a machine learning algorithm. The adopted methodology and consistency of results are presented in Appendix A

Table 2 presents the regression results where financial heads are considered to be the representative decision maker of the household. The first column of Table 2 reports the baseline results calculated without any binding constraint. The baseline results in column 1 of Table 2 present a seemingly counter-intuitive finding: a negative and statistically significant coefficient for the interest rate. This implies that under *ceteris paribus* conditions, higher interest rates may lead to reduced consumption growth. This negative coefficient could arise if the income effect [10] dominates the substitution effect [11]. This would occur when a rise in future income due to higher interest rates motivate consumers to save less and consume more today. However, such behaviour typically requires a very large discounting for future income (high RTP) (Varian (2014)). Alternatively, this negative coefficient could also arise in reference to Frederick et al. (2002). The paper suggests that people have a tendency to keep smaller gains in income for the same period's consumption only. Only when a large income gain comes, they substitute consumption over periods as a substantial increase in interest rates generate significant future returns, enabling people to shift consumption to the present and justify the negative coefficient of interest rate. However, the maximum observed interest rate change between two periods is only 0.5%, which is unlikely to justify the negative coefficient. Given these findings, preferences are unlikely to defend a negative and statistically significant interest rate under normal circumstances. In order to address this inconsistency, three alternative factors regarding economic constraints can be explored. Aggregate economic shocks and other economy wide effects can create situations that incentivise increased present consumption regardless of high interest rates. Secondly, credit-constrained households may start gaining access to credit after interest rate hikes, prompting them to borrow against future consumption. Lastly, determination of preferences of poor consumers from household consumption choices is not possible as they don't have the purchasing power to optimise and make choices. Therefore, in order to derive accurate estimates of time preferences, controlling for such economic constraints becomes necessary.

[10]When interest rates rise, savers' future income also increases. Anticipating this higher future income, people can afford to spend relatively more in the present without significantly impacting their future finances. This increase in present consumption is attributed to the income effect and may lead to a negative coefficient in column 1 of Table 2.

[11]When interest rates rise, the relative price of consuming any commodity in future falls. Therefore, people may opt to save more in present and consume in the future when the cost is lower. This is due to the substitution effect, and it negates the possibility of a negative coefficient in column 1 of Table 2. Since substitution effect and income effect operates in the opposite direction, one effect may dominate the other according to the household preferences

Table 2 Estimated Euler Equation Results using Financial Head as the Household Representative

Specifications	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$
Interest Rate	-2.30153^{***} (0.16740)	30.68366^{***} (4.65373)	31.13632^{***} (4.71959)	29.55639^{***} (4.89925)
Family Size	0.33413^{***} (0.00294)	0.35229^{***} (0.00231)	0.35213^{***} (0.00231)	0.35151^{***} (0.00249)
$5 \leq$ Edu ≤ 10	-0.00005 (0.00078)	0.00024 (0.00077)	0.00036 (0.00077)	0.00047 (0.00082)
$10 <$ Edu ≤ 12	-0.00122 (0.00107)	0.00055 (0.00110)	0.00096 (0.00111)	0.00106 (0.00115)
$12 <$ Edu	-0.00113 (0.00105)	0.00978^{***} (0.00189)	0.01066^{***} (0.00193)	0.01127^{***} (0.00201)
Caste (OBC)	-0.00148^{**} (0.00077)	-0.00052 (0.00076)	-0.00093 (0.00076)	-0.00094 (0.00081)
Caste (SC/ST)	0.00045^{***} (0.000847)	0.00138^{*} (0.00084)	0.00125 (0.00084)	0.00151^{*} (0.00089)
Age	$-6.97e^{-06}$ (0.00002)	0.00002 (.00003)	0.00003 (0..00003)	0.00003 (0.00003)
Income	-0.00004^{***} $(5.37e^{-06})$	0.00007^{***} (0.00002)	0.00007^{***} (0.00001)	0.00008^{***} (0.00002)
Time Dummies	No	Yes	Yes	Yes
Non-Credit Constrained Households	No	No	Yes	Yes
Non-Poor Households	No	No	No	Yes
#Observations	1, 12, 982	1, 12, 982	1, 12, 982	1, 00, 031
R^2	0.0191	0.0419	0.0420	0.0410

Log-linearised Euler equation estimation results for FY2015-16 to FY2019-20 are shown in the table. $log(C(t+1)/C(t))$ is the outcome variable. Caste, education, income and age are taken from the pre-sample period ($FY2014-15$) for the financial head, who earned the maximum in that period. The values for intercept, wave dummies and borrowing dummy are not presented in the table. Time indicators are jointly significant at the 1% level and are included in all economic constraint analyses (column 2 to column 4).

To incorporate the effect of aggregate shocks and other economy wide changes, the paper introduces time dummies into the baseline model (Table 2 column 2). Notably, all time dummies became statistically significant. It confirms the importance of temporal effects beyond the variables included in the Euler equation. Furthermore, after the introduction of time dummies, the coefficient estimate for interest rate variable reverses the sign to become positive and significant at the 1% level. This implies that economy wide factors created conditions that incentivised present-biased consumption, which is a preference for immediate consumption over future benefits. Even after controlling for credit constraints in the third column and further restricting the sample to exclude the poorest households in column 4, a similar positive and significant relationship was obtained between interest rates and intertemporal consumption growth. Thus, the use of time dummies is crucial for obtaining the results.

Larger families generally have higher needs (Lawrance (1991)). Accordingly, the respective non-durable consumption growth rates rise with family size. The evidence corroborates this theory with a positively significant coefficient of family size obtained for all cases in Table 2. Since the estimated coefficient of interest rate, $\gamma \approx 30$ in Table 2, the coefficient of family size, $1 - \beta\gamma \approx 0.35$ in column $2 - 4$, the value of $\beta \approx 0.022$ in Table 2. This shows economies of scale effect in Indian population as well, where a 1% increase in family size reduces the per capita non-durable expenditure approximately by 1.5%.

Higher education represents a long-term investment due to the opportunity cost associated with not working. Thus, individuals with higher education are expected to exhibit similar behaviour by planning for longer periods in their consumption choices as well (Weisbrod (1962)). This is evidenced by the positive and significant coefficient of having at least a college degree in Table 2. However, the estimated results do not show a significant difference in consumption patterns between illiterates, secondary school graduates, and high school graduates. The positively significant coefficients of SC/ST category households when financial heads are taken as the household representative depict positive social mobility in this section of the society as compared to the unreserved and intermediate castes. On the other hand, age is found to be statistically insignificant in influencing consumption growth rates. This result is consistent with Bairoliya et al. (2021) who found that life cycle consumption and savings patterns do not change with age for the Indian economy, using the CMIE CPHS dataset. Finally, the pre-sample income is found to be positively and significantly related to the consumption growth rates. It shows that *ceteris paribus*, the growth rate of consumption is higher for the rich compared to the poor sections of the society.

As a final step in Table 3, RTP estimates are derived for households on the basis of their income class. Comprehending this relationship is important to incentivise households and improve effectiveness of government policies related to investment in the form of money, health, and education. To derive this relationship with income, households were divided into 10 income quantiles and the RTP value of households belonging to each quantile was averaged to produce the RTP for each quantile in Table 3. It was found that as the income quantile rises, the corresponding RTP value falls marginally. That is, *ceteris paribus*, rich households act more patiently compared to the poor. These results favour the literature on diminishing marginal impatience (DMI)[12].

The effect of incorporating economic constraints is also evident from the RTP values presented in Table 3. The RTP values rise in all income classes as credit dummy is added to the regression. This rise in RTP signifies a greater level of impatience among people when the effect of imperfect credit markets is separately taken into account. Thus, we can infer that all classes of households act more patiently, against their preference, when credit markets are imperfect. A similar behavior is seen when only the non-poor sample is considered. The income classes from which the sub-sample of poor households is removed register greater impatience levels. Whereas, the other income classes don't register any change. These observations indicate that people act more patiently in presence of economic constraints, following a behavior against their will. Therefore, inclusion of economic constraints holds crucial importance in deriving the true estimates of RTP.

[12]Both theoretical and empirical studies endorse DMI. Koopmans (1972), Barro (1995), and Becker and Mulligan (2003) provided theoretical justifications for why DMI is logical and intuitive. Consequently, Das (2003) developed a method to incorporate DMI for devising analytical solutions. Concurrently, various empirical approaches, such as experiments by Wang et al. (2016), Dohmen et al. (2015) and many others, Euler equation estimation by Lawrance (1991), Trostel and Taylor (2001) *etc.* and simulations by Laibson et al. (2007) among others were established, all supporting DMI.

Table 3 Quantile-wise RTP Values when using Financial Head as the Household Representative

Average Real Pre-Sample Income Quantile	Rate of Time Preference			
	Baseline	With Time Dummies	With Credit Dummy	Non-Poor Only
10	0.07485 (0.00045)	0.06993 (0.00012)	0.06996 (0.00013)	0.06999 (0.00011)
20	0.07449 (0.00045)	0.06992 (0.00007)	0.06996 (0.00008)	0.06998 (0.00008)
30	0.07428 (0.00044)	0.06990 (0.00008)	0.06994 (0.00008)	0.06992 (0.00009)
40	0.07409 (0.00045)	0.06988 (0.00009)	0.06991 (0.00009)	0.06991 (0.00009)
50	0.07391 (0.00046)	0.06986 (0.00009)	0.06989 (0.00009)	0.06989 (0.00009)
60	0.07366 (0.00045)	0.06982 (0.00011)	0.06986 (0.00011)	0.06986 (0.00011)
70	0.07332 (0.00046)	0.06978 (0.00012)	0.06981 (0.00013)	0.06981 (0.00013)
80	0.07269 (0.00050)	0.06968 (0.00015)	0.06971 (0.00016)	0.06971 (0.00016)
90	0.07163 (0.00058)	0.06952 (0.00017)	0.06953 (0.00018)	0.06953 (0.00018)
100	0.06909 (0.00204)	0.06917 (0.00028)	0.06918 (0.00029)	0.06918 (0.00029)

Estimated value of household specific RTP for FY2015-16 to FY 2019-20, derived from the 2SLS technique were classified on the basis of various income quantiles. Households were divided in 10 income quantiles. The first column of baseline results simply takes equation 4, without any economic constraint. The second column introduces wave (time) dummies to account for economy wide shocks. In addition to time dummies, the third column introduces credit dummy. The last column takes all three economic constraints - time dummies, credit dummy, and poverty removal into account. The values in the first row of each cell represents the mean RTP values for the respective income quantile. The term in brackets reflect its standard deviation.

Table 4 considers the reported head of household as the decision-maker, rather than the financial head, and uses his or her socio-economic characteristics for analysis. The results obtained show similar effects and significance compared to those in Table 2, demonstrating robustness of our findings. The only notable difference is the higher magnitude of the interest rate parameter, γ, and its standard error in row 1 of Table 4. Despite this, the significance of γ remains identical to that in Table 2. These results are used to derive the RTP values presented in Table 5. Like before, a consistent but marginally negative relationship between RTP and income quantiles is observed, confirming DMI.

Despite each economic constraint hypothesised to have an effect on the consumption growth rate, a similar magnitude of coefficients is observed while incorporation of all the constraints in Table 2 and Table 4. It shows the robustness of this methodology in the derivation of RTP. It also shows that consumption growth rates are significantly influenced by various economic constraints. Following Lawrance (1991), the predicted interest rate obtained from equation 4 gives the expected interest rates for each household in the next period. This expected value derived from parameters obtained in Table 2 ranges from $(0.032, 0.098)$ with a mean of 0.061 when financial head is taken as the household representative. When reported heads are considered as household representatives, the parameters obtained in Table 4 gives an expected value that ranges from $(0.051, 0.075)$ with a mean of 0.063 . These are used in estimation of the second stage regression equation where the log of consumption ratio is regressed over the log of interest rate, log of family size ratio, and other socio-economic characteristics. The regression coefficients and their standard errors are used in equation 5 to derive the RTP for each household. Irrespective of the type of head adopted to represent a household, 0.069 is the derived mean RTP value for the sample, that is 6.9%. This estimate is aligned with value of 5.6% found by Ogaki and Atkeson (1997), but differs significantly from 0.023 reported in the findings of Murty et al. (2020). The primary distinction between the two papers lies in their methodology. Similar to our approach, Ogaki and Atkeson (1997) use household choices to determine the RTP value. In contrast, Murty et al. (2020) employ the Ramsey rule and derive RTP from societal death rates.

Table 4 Estimated Euler Equation Results using Reported Head as the Household Representative

Specifications	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$
Interest Rate	-2.2632^{***} (0.16848)	42.09945^{***} (6.20105)	45.40985^{***} (6.57078)	41.93548^{***} (6.21121)
Family Size	0.33405^{***} (0.00296)	0.35175^{***} (0.00230)	0.35219^{***} (0.00231)	0.35178^{***} (0.00251)
$5 \leq$ Edu ≤ 10	-0.00007 (0.00076)	-0.00064 (0.00075)	-0.00049 (0.00075)	-0.00034 (0.00080)
$10 <$ Edu ≤ 12	-0.00188 (0.00127)	-0.00023 (0.00128)	0.00097 (0.00133)	0.00091 (0.00137)
$12 <$ Edu	-0.00229^{**} (0.00115)	0.01343^{***} (0.00252)	0.01607^{***} (0.00282)	0.01628^{***} (0.00292)
Caste (OBC)	-0.00138^{*} (0.00077)	0.00030 (0.00078)	-0.00046 (0.00076)	-0.00041 (0.00081)
Caste (SC/ST)	0.00104 (0.00082)	0.00192^{***} (0.00085)	0.00155^{*} (0.00084)	0.00185^{**} (0.00090)
Age	-0.00010^{***} (0.00003)	-0.00002 (0.00002)	-0.00001 (0.00003)	0.00002 (0.00003)
Income	-0.00004^{***} ($4.90e^{-06}$)	0.00009^{***} (0.00001)	0.00011^{***} (0.00002)	0.00009^{***} (0.00002)
Time Dummies	No	Yes	Yes	Yes
Non-Credit Constrained Households	No	No	Yes	Yes
Non-Poor Households	No	No	No	Yes
#Observations	$1,12,982$	$1,12,982$	$1,12,982$	$1,00,031$
R^2	0.0190	0.0417	0.0417	0.0406

Log-linearised Euler equation estimation results for FY2015-16 to FY2019-20 are shown in the table. $log(C(t+1)/C(t))$ is the outcome variable. Caste, education, income and age are taken from the pre-sample period ($FY2014-15$) for the reported head, who was given the head's position during survey. The values for intercept, wave dummies and borrowing dummy are not presented in the table. Time indicators are jointly significant at the 1% level and are included in all economic constraint analyses (column 2 to column 4).

Table 5 Quantile-wise RTP Values when using Reported Head as the Household Representative

Average Real Pre-Sample Income Quantile	Rate of Time Preference			
	Baseline	With Time Dummies	With Credit Dummy	Non-Poor Only
10	0.07392 (0.00064)	0.07014 (0.00002)	0.07039 (0.00003)	0.07041 (0.00003)
20	0.07422 (0.00074)	0.07010 (0.00003)	0.07036 (0.00003)	0.07036 (0.00004)
30	0.07429 (0.00079)	0.07005 (0.00002)	0.07031 (0.00003)	0.07033 (0.00003)
40	0.07426 (0.00077)	0.07003 (0.00002)	0.07028 (0.00003)	0.07028 (0.00003)
50	0.07413 (0.00073)	0.07001 (0.00002)	0.07025 (0.00003)	0.07025 (0.00003)
60	0.07399 (0.00071)	0.06997 (0.00002)	0.07022 (0.00003)	0.07022 (0.00003)
70	0.07375 (0.00068)	0.06994 (0.00002)	0.07019 (0.00003)	0.07019 (0.00003)
80	0.07324 (0.00068)	0.06989 (0.00003)	0.07013 (0.00004)	0.07013 (0.00004)
90	0.07227 (0.00072)	0.06976 (0.00005)	0.06999 (0.00006)	0.06999 (0.00006)
100	0.07008 (0.00182)	0.06943 (0.00026)	0.06964 (0.00028)	0.06964 (0.00028)

Estimated value of household specific RTP for FY2015-16 to FY 2019-20, derived from the 2SLS technique were classified on the basis of various income quantiles. Households were divided in 10 income quantiles. The first column of baseline results simply takes equation 4, without any economic constraint. The second column introduces wave (time) dummies to account for economy wide shocks. In addition to time dummies, the third column introduces credit dummy. The last column takes all three economic constraints - time dummies, credit dummy, and poverty removal into account. The values in the first row of each cell represents the mean RTP values for the respective income quantile. The term in brackets reflect its standard deviation.

5.2 Robustness Checks

To determine the robustness of the obtained RTP estimates, this section considers different specifications of the primary variable of interest i.e. the pre-sample income. Table 6 presents the log-linearised Euler equation estimation results for different specifications and Figure 1 shows the corresponding RTP values derived for the different income quantiles.

First, we adopt the concept of weighted assets as used in Bairoliya et al. (2021) as a proxy for prosperity levels. Here, information on the household ownership of 13 physical assets such as television, washing machine, cars, AC *etc.* is considered. The weight of each asset is based on the proportion of households owning it in the sample (Bairoliya et al. (2021)). This weighting addresses the issue of significant value differences between assets. In essence, assets with wider ownership are considered less valuable compared to those owned by a smaller proportion of the sample. Similar to the previous specification, the estimated results in the second column of Table 6 indicate that the significance of the coefficients obtained remains robust even after changing the metric of pre-sample income to weighted assets. Second, pre-sample income can be seen as a reflection of the prosperity level of the household. Since all members can contribute to the prosperity of a family, the first robustness check in column 1 of Table 6 replaces pre-sample income of financial head with the pre-sample total income of the household, i.e. income from wages, rents, businesses *etc.* The coefficients and their significance are similar to the case where income of financial head was taken.

In the next series of robustness checks, we relax the assumption that the financial head makes decisions on behalf of the family. Therefore, the title of head reported during the survey is taken as the true head, which may include seniors as well. Instead of financial head's socio-economic characteristics, the age, caste and education of the reported head is now used to perform the robustness checks in this case. Similar to the specification with financial head as a representative, the weighted assets of family in the pre-sample period, and total income of the household during this period are taken into consideration.

The second panel of Table 6 displays the results of the log-linearised Euler equation estimation. Similar to our primary results, the coefficients of all alternate measures of income are found to be positive and significant at 1%. All other parameters, with the exception of age when reported head is

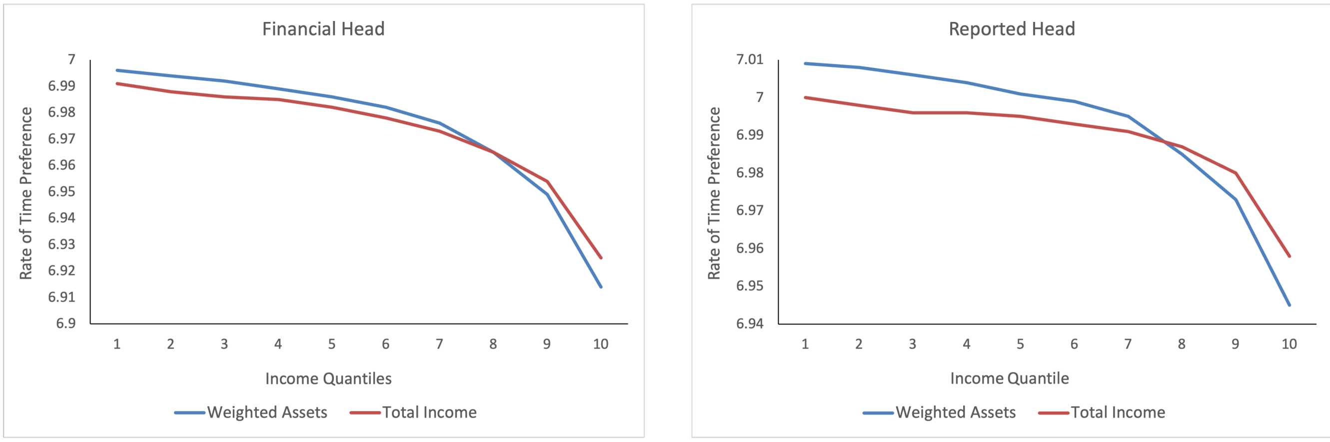
Table 6 Estimated Euler Equation with Different Income Specifications

Specifications	Financial Head		Reported Head	
	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$	$log(C_{t+1}/C_t)$
Interest Rate	30.00407*** (4.32852)	29.57746*** (4.46294)	40.51732*** (5.75859)	39.70671*** (5.81690)
Family Size	0.35196*** (0.00228)	0.35231*** (0.00231)	0.35137*** (0.00228)	0.35179*** (0.00231)
$5 \leq$ Edu ≤ 10	−0.00030 (0.00078)	0.00052 (0.00078)	−0.00012 (0.00076)	0.00002 (0.00075)
$10 \leq$ Edu ≤ 12	−0.00051 (0.00112)	0.00120 (0.00113)	−0.00115 (0.00129)	0.00138 (0.00133)
$12 \leq$ Edu	0.00758*** (0.00187)	0.01047*** (0.00194)	0.01123*** (0.00241)	0.01543*** (0.00264)
Caste (OBC)	0.00043 (0.00079)	−0.00049 (0.00077)	0.00013 (0.00083)	0.00024 (0.00079)
Caste (SC/ST)	0.00256*** (0.00088)	0.00151* (0.00089)	0.00305*** (0.00090)	0.00156* (0.00086)
Age	−0.00003 (0.00003)	0.00002 (0.00003)	−0.00020*** (0.00003)	−0.00017*** (0.00003)
Weighted Assets	0.80925*** (0.14558)	–	0.85279*** (0.14726)	–
Total Income	–	0.00003*** ($9.95e^{-06}$)	–	0.00003*** ($9.33e^{-06}$)
#Observations	1, 12, 982	1, 12, 982	1, 12, 982	1, 12, 982
R^2	0.0419	0.0419	0.0417	0.0418

Robustness checks for Log-linearised Euler equation estimation results after incorporation of only wave (time) dummies, and no other economic constraints for FY2015-16 to FY2019-20. Socio-economic characteristics for two different specifications of head of the household, financial head and reported head, are reported. For each type of head, robustness across two types of pre-sample income (weighted assets, and total income) are checked. The case with financial and reported head's income is already presented in column 2 of Table 2 and 4. The financial head earns maximum in the pre-sample period, and the reported head is identified as head by the respondents. Weighted assets index measures the amount of physical assets owned by the household. Total income of the household sums all types of income for all members of the household, including wages, business profits, transfers, interest rates, and pensions. The intercept and wave dummies are not presented in the table, but are significant at 1% level.

taken as the head of the household, are comparable in both magnitude and significance. Given that decision-making is in the hands of the predominantly non-working retired population, a negatively significant coefficient for age aligns with the life-cycle hypothesis. As individuals age, they perceive having less time to live and therefore tend to consume more in the present. Therefore, the obtained coefficient values are expected when the reported heads have the decision-making power.

Figure 1 Derived RTP Values for Robustness Checks



The relationship of income classes with the estimated value of RTP on the basis of various combinations of household head (financial head in left panel and reported head in right) & income specifications (weighted assets in blue line graphs and total income in red). The RTP values are derived from the respective Euler equation estimates of Table 6.

The parametric values obtained in Table 6 are used to derive the RTP values to check the relationship with income. Figure 1 plots the RTP values associated with the robustness checks. The figure shows that as income rises, RTP value falls in all the specifications, favouring DMI. Moreover, the values are similar to the initial results here as well, demonstrating the robustness of our key findings.

6 Conclusion & Future Work

This study utilises the CMIE CPHS data, a national-level household survey, to estimate RTP for the Indian economy. As a developing economy, India faces unique economic constraints, cultural dynamics, and socio-economic factors that differ significantly from those in developed countries, where household budgets are generally less constrained. Consequently, RTP indicators from developed nations cannot be directly applied to the economies like India. This paper adapts the traditional RTP measurement method, devised by Lawrance (1991) for developed economies, by incorporating the economic challenges faced by Indian households into the analysis. We find that the inclusion of time dummies is sufficient to determine robust RTP values in this context as the key results remain robust to the inclusion of economic constraints. However, we also find that inclusion of developing country specific constraints like imperfect credit markets and poverty increases the RTP values. It means that people act more patiently in presence of economic constraints, following a behavior against their will. Therefore, irrespective of the robust trends, incorporation of country specific economic constraints is important in obtaining the true RTP values in the economy.

The results also indicate that under *ceteris paribus* conditions, the RTP values decrease marginally with increasing income, which confirms DMI i.e. the rich are marginally more patient than the poor. The obtained value of 6.986% as the average RTP is lower compared to the results drawn from choice-based experiments such as Wang et al. (2016) and Dang (2023), and higher compared to the estimates drawn by Ramsey rule in Murty et al. (2020). However, the value lies closer to the results obtained from secondary data analyses. Ogaki and Atkeson (1997) calculated the RTP for rural India to be 5.6%, employing the Euler equation approach, similar to our study. We also validate our results by estimating the parameters of non-linear Euler equation 2 using particle swarm optimisation (PSO). This machine learning based validation technique, derived from Dong et al. (2005) reconfirms our key findings.

Since the rich are found to exhibit more patience in the Indian context, they are more likely to save and invest a greater proportion of their income, leading to a faster accumulation of wealth. In contrast, the poor, being less patient, may prioritise immediate consumption over saving, exacerbating wealth inequality over time. Governments could implement targeted savings programs or incentives, such as matched savings plans (e.g., Individual Development Accounts) to encourage long-term saving among the poor. Financial education programs that focus on the benefits of delayed consumption and long-term financial planning could also help bridge the gap (Laibson (1997)). Social security schemes could help alleviate the immediate consumption needs of the poor, reducing the adverse effects of impatience (Piketty and Saez (2003)). Less patient individuals may be more inclined to borrow money at high interest rates, increasing their financial vulnerability. Promoting access to low-interest credit for the poor could help them smooth consumption over time, reducing their need for high-cost borrowing (Bertrand and Morse (2011)). Given that the poor are less patient and may struggle with long-term financial planning, policy interventions that use behavioral nudges can be effective. For example, automatically enrolling individuals in retirement savings plans could significantly improve participation rates among the less patient population (Thaler and Benartzi (2004)).

Given that the key results are based on certain simplifying assumptions, future work may consider other forms of interest rates besides t-365 to check the relation between income and time preferences. Also, identifying a different borrowing dummy to check for the effect of credit constraints may be worth exploring. Lastly, the use of a more generalised utility function to estimate the RTP values is left as an extension for the future.

Dataset Description

- Tax Slab Data
  - Direct Taxes for 2015-16 from **Finance Bill, 2015**

    Date of access: 2 June 2024
  - Direct Taxes for 2016-17 from **Finance Bill, 2016**

    Date of access: 2 June 2024
  - Direct Taxes for 2017-18 from **Finance Bill, 2017**

    Date of access: 2 June 2024
  - Direct Taxes for 2018-19 from **Finance Bill, 2018**

    Date of access: 2 June 2024
  - Direct Taxes for 2019-20 from **Finance Bill, 2019**

    Date of access: 2 June 2024
- Consumption & Socio-Economic Variables Data
  - **CMIE CPHS Data**

    Date of access: 2 June 2024
- Monthly CPI Data - State-wise Rural Urban
  - **RBI Data Repository for CPI**

    Date of access: 2 June 2024
- Interest Rates Data
  - **RBI Data Repository for Interest Rates**

    Date of access: 2 June 2024

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Appendix

A Appendix 1

Validation with Particle Swarm Optimisation

In order to provide robustness to our linearised estimation, we adopt particle-swarm optimisation (PSO). It is a machine learning technique used to find the optimal parameteric values of a predefined non-linear regression equation (Dong et al. (2005)). The algorithm takes a set of points in the parametric space and calls them particles. Each particle represents a possible combination of parameters. These particles explore a space formed by pre-defined parameter ranges. Each particle remembers its own best solution found so far (personal best or pbest) and is aware of the best solution discovered by the entire group (global best or gbest). Through iterations, the particles adapt their movements based on these two influences. They are drawn towards both their own pbest and the swarm's gbest, while also incorporating an element of chance to investigate new regions of the parameter space. This iterative process of seeking better solutions ultimately guides the swarm towards converging on the parameter set that minimises the difference between the predicted and actual values in the non-linear regression equation.

In the current scenario, the non-linearised Euler equation 2 is optimised to obtain the parameters. Similar to the case of log-linearised regression, all variables belonging to equation 2 are observable, except RTP (δ_i). Thus, the assumption of a linear dependence of RTP on socio-economic factors is maintained to finally produce the following non-linear estimation equation.

$$\left(\frac{1+\hat{r}_{i,t+1}}{1+\bar{\delta}+\sum_{k=1}^{K}\rho'_k X_{k,i}}\right)\left(\frac{C_{i,t+1}}{C_{i,t}}\right)^{-\frac{1}{\gamma}}\left(\frac{FS_{i,t+1}}{FS_{i,t}}\right)^{1-\beta\gamma}\left(\sum_{t=1}^{T} e_t \text{ wave}_t\right)^{\eta}=1$$

The expected interest rate $\hat{r}_{i,t+1}$ is derived from the first step of the 2SLS regression, and time dummies were introduced in a non-linear fashion to produce the same log-linearised Euler equation, along with time dummies. A parameter space was constructed for each of the parameters: $\gamma, \beta, \eta, \bar{\delta}, \rho_k'$s and e_ts. To obtain the value of RTP, $\bar{\delta}$ and $\rho_k' s$ are the coefficients of interest. Interestingly, with random parameter initialisation, the optimisation yielded values close to the log-linearised estimates after 100 iterations. Moreover, when initialised with the linear regression estimates, the values remained unchanged, confirming the validity of the log-linear regression estimates. It establishes the validity of the simplified and interpretable log-linearised regression results obtained in the results section.

B Appendix 2

This section describes the construction of various variables that are finally employed in the analysis.

B.1 Defining & Comparing Specifications for the Head of the Household

The identification of financial head in the CMIE CPHS dataset follows an elaborate process. At first, the mean of monthly wage income of each household member is computed for the pre-sample period. The member earning maximum income should be the financial head. However, this is not the case because CMIE CPHS considers business income separately, and not under member income. Therefore, a member is called the financial head only if the average income of that member is greater than the average business income of the household. If not, then the reported head (who is nominated as the head during the survey) is kept as the financial head of the household as well. However, the hold on decision-making power is a separate issue. Financial heads are supposed to have the final say/veto in household decisions because of their earnings. On the other hand, reported heads of the household could have the final say in household decisions based on their experience and respect. Therefore, a separate analysis is carried out for reported heads as household representatives in Section 5.

Table A1 Difference between Financial Head & Reported Head

Features	Financial Head	Reported Head
Earnings	Max average income (FY 2014-15)	Might not earn
Survey Response	Not titled during survey	Titled by respondents during survey
Decision Maker	Because of earning	Because of title

B.2 CPI Adjustments

The income and non-durable consumption expenditure are deflated with monthly General CPI values with base year $2011-12$. These CPI values are obtained from the RBI data repository and are collected separately for each state-region type combination every month. There are two types of region in every state, rural and urban. The calculations for real income, real consumption expenditure, and inflation are carried out using the following formulas:

$$\text{Real Income}_t = \frac{\text{Income}_t}{\text{General CPI}_t}$$

$$\text{Real Consumption}_t = \frac{\text{Consumption}_t}{\text{General CPI}_t}$$

The income and consumption data for each wave are derived by considering the CPI, income and expenses in the representative month of that wave.

B.3 Identification of the Poor

Similar to the CPI values, the state-wise rural-urban poverty lines were last released by the government of India in $2011-12$. Since both CPI and poverty lines have the same base period, the poverty lines were updated every month according to the following formula:

$$\text{Poverty Line}_t = \frac{\text{Poverty Line}_{t-1} * \text{CPI}_t}{\text{CPI}_{t-1}}$$

Once the real poverty lines with the base year of 2011-12 were established, the next step was to calculate the average yearly per capita income for all households. This was done by dividing the real income figures (obtained in the previous section) by the adult equivalent family sizes for each wave, and then taking the yearly average. A household is considered poor in a year if its average per capita income is at or below the corresponding poverty line. If the household is found poor in at least one of the years considered in this study (FY $2014-15$ to FY $2019-20$), it was considered poor and therefore removed while treating the economic constraint related to poverty.

C Appendix 3

Table C1 Tax Slabs for Finding Real Interest Rates

Year	Annual Income	Adults (≤ 60)	Seniors ($60 \geq age \geq 80$)	Super Seniors (≥ 80)
FY $2015-16$, FY $2016-17$	0 to $2.5L$	0	0	0
	$2.5L$ to $3L$	$0.1(x-2.5L)$	0	0
	$3L$ to $5L$	$0.1(x-2.5L)$	$0.1(x-3L)$	0
	$5L$ to $10L$	$25,000+0.2(x-5L)$	$20,000+0.2(x-5L)$	$0.2(x-5L)$
	$\geq 10L$	$1.25L+0.3(x-10L)$	$1.2L+0.3(x-10L)$	$1L+0.3(x-10L)$
FY $2017-18$, FY $2018-19$, FY $2019-20$	0 to $2.5L$	0	0	0
	$2.5L$ to $3L$	$0.1(x-2.5L)$	0	0
	$3L$ to $5L$	$0.1(x-2.5L)$	$0.1(x-3L)$	0
	$5L$ to $10L$	$25,000+0.2(x-5L)$	$20,000+0.2(x-5L)$	$0.2(x-5L)$
	$\geq 10L$	$1.25L+0.3(x-10L)$	$1.2L+0.3(x-10L)$	$1L+0.3(x-10L)$

Tax slabs released for different age-income combinations in Central Government's Annual Budget. Here, x represents the annual income of the individual (calculated by taking the average of the financial head's wave income and multiplying it by 12) and L refers to the money measuring denomination 'lakh'.
Source: Finance Bills, India Budget 6

Table C2 Adult Equivalence Scale for Different Age-Gender Groups

Age (years)	**Gender**	**Weight**	**Age (years)**	**Gender**	**Weight**
0 - 1	Any	0.29	11 - 14	Female	0.86
1 - 3	Any	0.51	15 - 18	Female	0.86
4 - 6	Any	0.71	19 - 24	Female	0.98
7 - 10	Any	0.78	25 - 50	Female	1
			50 - 999	Female	0.75
11 - 14	Male	0.98	11 - 14	Undisclosed	0.90
15 - 18	Male	1.18	15 - 18	Undisclosed	1
19 - 24	Male	1.14	19 - 24	Undisclosed	1
25 - 50	Male	1.14	25 - 50	Undisclosed	1
50 - 999	Male	0.90	50 - 999	Undisclosed	0.75

Calorie based weight metric across different age-gender groups used for finding adult equivalent family size.
Source: Calro *et. al.* (2010)