DO EXPENDITURES ON SOCIAL OBLIGATIONS PUSH INDIAN HOUSEHOLDS TOWARD DEBT CYCLING? EVIDENCE FROM A CORRELATED RANDOM EFFECTS ANALYSIS

by Riya Vishwakarma

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CONTENTS

Abstract

The practice of debt cycling is incurring new debt to pay back existing debt obligations which has emerged as a pervasive and structurally embedded feature of Indian household finance, yet the role of culturally mandated social obligation expenditure in initiating and perpetuating this debt cycle remains scarcely understood. While existing literature documents the scale of ceremonial and social expenditure among Indian households and its association with indebtedness, the empirical evidence of causality using rigorous panel data econometrics is less. Using the longitudinal data from the Centre for Monitoring Indian Economy's Consumer Pyramids Household Survey (CPHS) spanning 2020 to 2024, covering more than 1,80,000 households, we examine the effect of social obligation expenditure on the probability of debt cycling by estimating a Correlated Random Effects Probit model with the Mundlak device, which controls for the time-invariant unobserved household heterogeneity while retaining the full sample and all the time-invariant regressors. The study finds that social obligation expenditure significantly and robustly increases the probability of household debt cycling, with the effect operating primarily through a delayed repayment stress mechanism. Thus, expenditure on social obligations create large and unavoidable liquidity shocks that are structurally incompatible with fixed loan repayment schedules, particularly for households with volatile incomes, triggering new borrowing to service existing debt in the following period. This calls for community level interventions to reduce the arms race in social obligation spending and broader income stabilisation schemes targeting the high income-volatility that the study identifies as the dominant proximate driver of household debt cycling in India.

Keywords: social obligation expenditure; debt cycling; household indebtedness; income volatility; Correlated Random Effects Probit; CPHS; panel data; India

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1. Introduction

In India, household indebtedness is tied to and shaped by forces that are simultaneously economic and cultural. These forces are daughters' marriages, death ceremonies, religious functions and rituals which compel households to incur large socially mandated expenditures (Rao, 2001). Across all occupational categories, the fundamental driver of cycle of debt dependence and debt cycling is social obligation (Khan, 2023). At first, as the households are unable to meet their need from their savings or income, they borrow to meet these obligations, then borrow again to repay the previous loans and ultimately enter a cycle of debt cycling which is structurally different from the productive or investment driven borrowing which sometimes encourage end to this. Also, sometimes this debt dependence persists through generations.

Allocation of expenditures toward social consumption is done to sustain dignity, reciprocity, and community memberships. These expenditures are important for survival within socially embedded economies like India (Banerjee & Duflo, 2007). These expenditures signal status, honour, and social legitimacy. Not participating in these socially mandated actions may result in social exclusion, loss of reputation, weakening of kinship ties, and erosion of access to informal support networks (Kane et al., 2023; Woldehanna et al., 2022). Debt and borrowing are socially embedded. Debt is shaped by caste, class, gender, locality, and power hierarchies (Guerin, 2014). The availability of credit is spread unevenly across country and states. In this overlapping formal and informal credit environment, households move back and forth through multiple lending and repayment schedules. This leads to significant debt cycling incidents.

The social networks also act as a mediator in accessing formal credit. Stronger social networks characterised by participation in community activities significantly increases the probability and share of formal borrowing (Chugh, 2025). In the country, there has been long-run historical record of reversal of formal credit accessibility. Successive All India Debt and Investment Survey

(AIDIS) rounds reveal that post-independence era saw considerable success in weaning rural households away from moneylenders, with falling incidence of rural indebtedness, but after the financial sector reforms in 1991, this trend reversed (Rajakumar et. al., 2019). Accessibility of credit is different across caste groups. Lower caste households exhibit higher incidence of indebtedness but face greater barriers to formal credit (Ram & Neha, 2025). The gap between social obligation and financial capacity is widest for those who are most excluded from institutional credit.

Through the behavioural lens, the sociological pressures, cognitive biases, and social obligations are the factors driving the borrower to borrow beyond repayment capacity (Schicks, 2013). Such obligatory spendings constitute the largest regularly scheduled expenditure category, larger than spending on health or education (Rao, 2001; Purcell, 2021). The economic consequences of such expenditures extend well beyond the event itself (Sumastuti, 2024). Yet the specific mechanisms through which recurring social expenditure leads to debt cycling or borrowing for repayment is understudied. The phenomenon of debt cycling has undergone little rigorous econometric treatment in the academic literature.

This study was motivated from a convergence of factors. First, a substantial body of evidence is directed not toward productive investment but toward consumption smoothing and social expenditure (Sangwan et. al., 2020). Second, there is a gendered dimension to this indebtedness, which is that women disproportionately bear the responsibility of managing household debt, and their borrowings including borrowings through Self-Help Groups (SHGs) and microfinance institutions are used to meet the same social obligations that male income is expected, but often fails to cover (Kane et al., 2023). Third, with increasing number of microcredit providers, households are now accessing credit much more easily than was earlier possible, thus enabling debt cycling at scale (Puliyakot and Pradhan, 2024). Fourth, such expenditures may persist even during periods of income instability, unemployment, or repayment burden (Rutherford, 2001; Ruthven, 2002).

Against this backdrop, the present study makes contributions by proving a rigorous econometric treatment of the relationship between socially obligatory expenditure and debt cycling. Specifically, the study tests whether higher expenditures on social obligations increase the probability that households borrow to repay existing debts and by how much. For this, the study employs the Correlated Random Effects (CRE) framework on the longitudinal datasets from Centre for Monitoring Indian Economy (CMIE), namely, Consumer Pyramids Household Survey (CPHS). This framework controls for the unobserved heterogeneity. In this, the distinction between within-household variation in social spending and between-household variation is mapped clearly on the CRE decomposition.

The remainder of this paper is organised as follows. Section 2 covers literature review. Section 3 deals with data and its description. Section 4 contains the methodology. Section 5 shows the descriptive analysis. Section 6 covers results, followed by conclusions and policy implications in Section 7.

2. Literature Review

The earliest works explaining socially compelled expenditure points out that in stratified societies, spending serves communicative purposes (Veblen, 1899). According to theory of Leisure Class, individuals engage in "conspicuous consumption", that is, use resources to signal wealth and social standing, and "pecuniary emulation" which is the engine driving this behaviour. Individuals perpetually benchmark themselves against those above them in the social hierarchy, generating an upward pressure on spending that is structurally independent of absolute income levels. Even as the income falls, and even as the household incur debt to maintain appearances, the spending tends to be sticky. The theory of social custom further formalises this mechanism, exhibiting how community enforced norms create equilibria deviation from optimal household financial condition which has reputational costs large enough to override individual financial rationality (Akerlof, 1980).

Borrowing for repayment is self-reinforcing. A high-cost debt leads to debt service obligations, which itself generates further debt service, creating a complete cycle which acts as a trap. Evidence for this phenomenon is that the poor households in Bangladesh, India, and South Africa manage multiple borrowings which are recycled to manage repayment and expenditure obligations (Collins et. al., 2009). Loan purpose has been identified as a strong predictor of over indebtedness. The related concept of over indebtedness has four dimensions, namely, the economic, implying the total debt burden relative to income; the subsistence, implying the inability to basic needs while servicing debt; the temporal, implying persistence over medium to long term; and the psychological, implying the subjective distress associated with indebtedness (Leandro & Botelho, 2022; Hu et al., 2021). The anthropological and sociological literature on Indian households has long documented the social compulsion to spend on life-cycle ceremonies regardless of economic circumstance (Khan, 2023; Kaushik, 2018; Banerjee & Duflo, 2007; di Falco & Bulte, 2011).

Traditionally, economic theories of credit viewed borrowing as a mechanism for productive investment and intertemporal consumption smoothing. The life-cycle hypothesis (Modigliani & Ando, 1963) and the permanent income hypothesis (Friedman, 1957) explain household borrowing as a strategy for consumption smoothing over time, with household borrowing during periods of low income in expectation of higher future earnings. Further, the buffer-stock saving model demonstrates that households facing volatile income maintain precautionary savings and borrow when those buffers are exhausted (Sumastuti, 2024). But income smoothing and consumption smoothing are distinct strategies with different risk implications and that poor households facing income risk without adequate insurance mechanisms are particularly vulnerable to debt accumulation (Morduch, 1995; Agyepong et al., 2024).

The expenditure on social obligations is not always wasteful as it also generates private economic and social returns (Rao, 2001). In rural India, this spending is positively associated with tangible benefits such as lower food prices, higher social status, a greater frequency of meal invitations from community members. This is exactly like an investment, but in social capital. Also, participating in such spending and activities shows sociability and willingness to establish communal relationships. This social capital ensures labour market access, information transmission, and risk insurance (Hu et al., 2021; Woldehanna et al., 2022). Households that perceive themselves as socially disadvantaged may engage in increased borrowing to finance visible consumption and ceremonial expenditure (Chichaibelu & Waibel, 2018).

The above argument is supported by the social capital theory, which identifies social networks as resources that facilitate economic action, including access to credit (Bourdieu, 1986; Coleman, 1988; Putman, 2000; di Falco & Bulte, 2011). The foundational work on the strength of weak ties tells a similar story that bonding networks (strong ties) and building networks (weak ties) brings benefits related to societal functions and activities (Granovetter, 1973). Critically, heterogeneity analysis reveals that the social network effect on formal borrowing is concentrated among rural and lower caste households, precisely the groups most structurally excluded from formal credit (Chugh, 2025).

The international studies are consistent with the findings among Indian households. In Indonesia, social networks facilitate the identification of borrowing sources and improve loan approval rates (Okten & Osili, 2004). Similarly, in Uganda, stable friendships and mutual trust are positively associated with formal institutional credit access (Heikkila et. al., 2016). Dutch households' behaviour is consistent with the 'keeping up with the Joneses' mechanism, and the households that perceive their income as below the network average more likely to carry debt (Georgarakos et. al., 2014). Households in Tanzania, demonstrate positive association between household income and social capital measured at the village level, with the richest households in the most socially rich villages enjoying incomes approximately four times higher than the poorest households in the least socially rich villages (Narayan & Pritchett, 1999). The facts above lead to the conclusion that social capital has dual nature. On one hand, strong networks facilitate credit access and provide informal insurance, on the other hand, they impose the social obligation expenditures that drive debt cycling (Woldehanna et al., 2022; di Falco & Bulte, 2011; Hu et al., 2021).

The mechanism of debt cycling may hide over indebtedness before it manifests as visible arrears, making it a leading rather than a lagging indicator of financial distress. The existing approaches to defining over indebtedness, which focus predominantly on default, arrears, or debt-to-income ratios systematically fail to capture the full extent of debt distress among poor borrowers. Early literature classifies a household that meets its repayment obligations by withdrawing children from school, skipping meals, or selling assets is not over indebted; yet from a customer protection standpoint, it is deeply so (Schicks, 2013; Kamath et. al., 2008).

Direct field-based evidence has shown the presence both taste-based and statistical discrimination in formal loan access against the lower caste (Karthick & Madheswaran, 2018; Kumar & Venkatachalam, 2019; Prakash, 2015). Dalit borrowers are funnelled disproportionately towards non-productive loan purposes such as medical expenses and household consumption rather than productive investment (Ram & Neha, 2025). This pattern is consistent with the broader credit market segmentation that reinforces rather than eliminating existing inequalities. In rural South India also, credit access is mediated simultaneously by caste, class, and location (Guerin et. al., 2013).

The literature establishes that the socially obligatory expenditures are a pervasive and economically significant feature of Indian households which is enforced by community norms independently of financial capacity and debt cycling is a documented phenomenon among Indian households. However, gaps still remain. While the structural patterns of Indian household indebtedness are deeply studied descriptively and role of social obligation expenditure is established quantitatively, there is no panel econometric study that formally models the causal relationship between obligatory expenditure and debt cycling at the household level. The present study addresses these gaps by providing panel econometric treatment of the relationship between social obligation expenditure and debt cycling, using the Correlated Random Effects Probit framework (Mundlak device) to differentiate between within-household causal effects and between-household selection effects (Bates et al., 2024; Wei & Zhang, 2022; Papke & Wooldridge, 2022). It incorporates income volatility, occupation, asset ownership, education, and household type to do an integrated analysis.

3. Data Description

The Consumer Pyramids Household Survey (CPHS), conducted by the Centre for Monitoring Indian Economy (CMIE) is one of the largest and most comprehensive longitudinal household surveys in India, covering a nationally representative sample of households across all states and union territories for both urban and rural areas. The survey is conducted either every month (monthly) or every four month (three waves per year). The different datasets, namely, Aspirational India, Consumption Pyramids, and Income Pyramids are used to form a national panel representing income groups, occupational categories, household types, and geographic regions. The survey employs a stratified random sampling design. The country is divided into homogeneous strata based on geographic and socioeconomic characteristics, and households are selected using systematic random sampling within each stratum. The panel being used spans survey waves 19 through 33, corresponding to the years from 2020 to 2024, accounting for 15 waves and 5 years.

The dependent variable is a self-reported binary indicator and tells whether a household has reported at least one borrowing episode in the wave has the stated purpose of repaying existing debts or meeting existing loan obligations. While self-reported measures of loan purpose are subject to recall bias and social desirability effects, the CPHS collects this information at four-monthly intervals which substantially reduces the recall error compared to annual surveys and the short reference period encourages accurate recollection of recent financial transactions.

The primary explanatory variables of interest are the natural logarithm of total monthly household expenditure on social obligations and the one period lag of it, capturing the social obligation expenditure in the previous wave. The social obligation expenditure covers spending on weddings, engagement ceremonies, birth and naming ceremonies, community feasts, gifts to community members, and other social ceremonies and events. The logarithmic transformation compresses the right-skewed distribution of raw social expenditure and yields a semi-elasticity interpretation. The lagged variable tests whether social obligation spending in one period predicts debt cycling in the subsequent period, that is, the delayed repayment mechanism. The use of lagged variable strengthens the causality link as the contemporaneous variable might show reverse causality between the social spending and borrowing for repayment.

The other explanatory variables are the natural log of income and the coefficient of variation of household income, defined as the standard deviation of household income across all observed waves divided by the mean income across the waves. The log of income captures the level effect of the income on debt cycling and coefficient of variation of income capture the volatility in income or unpredictability. The household experiencing large fluctuations are likely to face difficulty in planning debt service obligations. The control variables are also included to account for observed household characteristics that may confound the relationship between social obligation expenditure and debt cycling, which are monthly expenditure on food, health, EMI for house and durables; number of houses owned; the household type on the basis of lifecycle stage; level of education; and type of occupation.

Table 1. Summary statistics of all variables

Variable	Definition	Expected relationship	Observations	Mean	Standard deviation
Dependent Variable					

Debt cycling (borr_for_repay) (0,1)	Binary variable = 1 if household borrowed in the survey wave for the purpose of repaying existing debt obligations, and 0 otherwise	- (Outcome variable)	16,22,779	0.062	0.241
Key Independent Variables: Social Obligation Expenditure					
Log social expenditure (ln_social)	Natural log of household expenditure on social obligations	+ (Rao, 2001; Khan, 2023)	16,23,268	2.366	2.485
Lagged log social expenditure (L1_ln_social)	One-period lag of ln_social; social obligation spending in the preceding four-month survey wave. Tests the delayed repayment stress mechanism.	+ (Khan, 2023; Schicks, 2013)	11,74,598	2.385	2.435
Income and Income Volatility					
Log household income (ln_inc)	Natural log of total household income aggregated across all sources.	- (Morduch, 1995)	1,623,268	9.898	0.793
Lagged log income (L1_ln_inc)	One-period lag of ln_inc; household income in the preceding four-month survey wave.	-	11,74,598	9.899	0.705
Income coefficient of variation (income_cv)	Standard deviation of household income across all observed waves divided by mean income across those waves. Captures income unpredictability and volatility.	+ (Collins et al., 2009; Morduch, 1995)	16,13,884	0.351	0.203
Consumption Expenditure Controls					
Log food expenditure (ln_food)	Natural log of household expenditure on food items. Acts as a proxy for consumption pressure and financial distress under debt burden.	+ (Banerjee & Duflo, 2007)	16,23,268	8.662	0.377

Log health expenditure (ln_health)	Natural log of household expenditure on health including out-of-pocket medical costs, medicines, and hospitalisation.	Ambiguous	16,23,268	5.480	1.305
Debt Service Obligations and Asset Wealth					
Monthly housing EMI (m_exp_emi_for_house)	Monthly instalment paid toward housing loans. Captures structured formal debt service and financial discipline	- (Lusardi & Mitchell, 2014)	16,23,268	129.4 56	1,088.066
Monthly durables EMI (m_exp_emi_for_durables)	Monthly instalment paid toward consumer durable loans (appliances, electronics, furniture). Captures formal consumer credit repayment discipline.	-	16,23,268	41.11 9	355.298
Houses owned (houses_owned)	Count of residential properties owned by the household. Proxy for asset wealth and availability of collateral or liquidity buffer.	- (Ghosh et al., 2000)	16,23,268	1.018	0.186
Household Type (Categorical)					
Young/Nuclear household (base)	Household headed by a young adult with a nuclear family structure; no elderly members or multiple adult generations. Serves as the omitted reference category.	Base category	—	—	—
Prime-age household	If household head is in prime working age and household includes working-age members.	+ (Collins et al., 2009)	1,623,268	—	—
Mixed household	If household includes members of multiple generations.	+	1,623,268	—	—
Senior-inclusive household	If household includes elderly members aged 60 or above.	Ambiguous	1,623,268	—	—
Education Level (Categorical)					

Illiterate/Primary (base)	Household head has no formal schooling or has completed primary level only. Serves as the omitted reference category for financial literacy comparisons	Base category	—	—	—
Middle education	If household head has completed secondary schooling up to matriculation level.	- (Lusardi & Mitchell, 2014)	1,623,268	—	—
Higher education	If household head has completed graduation or higher. Captures strong financial literacy and more stable income.	- (Lusardi & Mitchell, 2014; Agarwal et al., 2009)	1,623,268	—	—
Occupation (Categorical)					
Casual labour/Unemployed (base)	Household head is engaged in daily-wage casual labour or is currently unemployed. Represents the most income-insecure group and serves as the omitted reference category	Base category	—	—	—
Self-employed	If household head is self-employed in business, trade, or services. Captures income irregularity and absence of formal employment protections.	+ (Khan, 2023)	1,623,268	—	—
Salaried	If household head is in regular salaried employment. Captures income regularity, formal sector access, and debt management capacity.	- (Morduch, 1995)	1,623,268	—	—
Farmer	If household head is a cultivator or agricultural worker. Captures seasonal income cycles, weather risk, and high social obligation	+ (Collins et al., 2009; Rao, 2001)	1,623,268	—	—

	expenditure in agricultural communities.				
Retired/Other	If household head is retired or in other non-working status. Captures post-employment income stability through pension and accumulated savings.	- (Morduch, 1995)	1,623,268	—	—

Note: Observations and summary statistics for continuous variables are drawn from the CMIE Consumer Pyramids Household Survey (CPHS), waves 19–33 (2020–2024). (+) indicates a positive expected effect on borr_for_repay; (−) indicates a negative expected effect. (+) indicates a negative expected effect. (—) in the Expected relationship column denotes the outcome variable or base category. Source: CMIE CPHS.

4. Descriptive Analysis

The overall prevalence of debt cycling in the selected sample dataset stands at a 6.18 percent of the total household observations in the panel. While this aggregate figure may appear modest, it indicates a pronounced and structurally worrying upward trajectory across the fifteen waves of the Consumer Pyramids Household Survey (CPHS) for the time period January 2020 to December 2024.

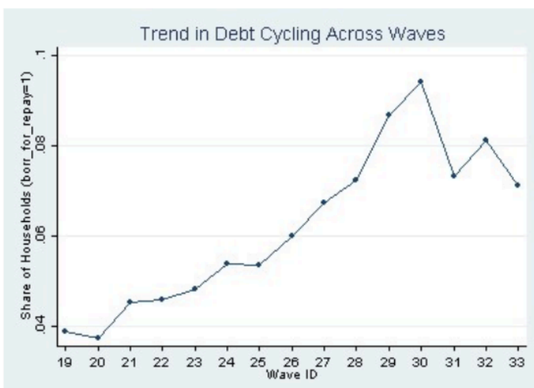

Figure 1: Note: Y-axis shows share of households with borr_for_repay = 1 in each wave. Source: CMIE CPHS.

In the first phase of figure 1, that is, waves 19 and 20 (January to August, 2020), the rate is at its lowest at around 3.87 and 3.74 percent respectively, which coincides with the COVID-19 lockdown restrictions that suspended social gatherings, ceremonies and credit market activity simultaneously. In the second phase, that is, waves 21 to 28 (September 2020 to April 2023), the rate increased at a steadily and monotonically from 4.54 to 7.24 percent as social activity resumed and post-pandemic borrowing pressure accumulated. In the third phase, that is, waves 29 to 30 (May to December, 2023), the recycling rate accelerates sharply to its peak of 9.43 percent which is more than double of the rate in wave 19. Lastly, in the fourth phase, that is, wave 31 to 33 (January to December, 2024), the rate moderates slightly to around 7.13 and 8.14 percent. This post peak moderation is not the returning of the rate at the pre-pandemic levels suggesting a structural deterioration in household debt conditions rather than a transitory cyclical shock (Sumastuti, 2024).

The trend of debt cycling among household groups can be better understood through the transition matrix between consecutive waves which uses the panel structure of the dataset.

Table 2: Transition matrix for debt cycling

Status at t-1\t	Non-cycler (t)	Cycler (t)	Total
Non-cycler (t-1)	98.52% (10,79,935)	1.48% (16,239)	10,96,174
Cycler (t-1)	25.82% (20,067)	74.18% (57,638)	77,705
Total	93.71% (11,00,002)	6.29% (73,877)	11,73,879

Note: Matchet consecutive wave observations. Source: CMIE CPHS

Rolling over debt is overwhelmingly chronic rather than episodic. Among all the household that recycled in previous period (t-1) 74.18 percent continue to recycle in the next period also. Conversely, only 1.48 percent of non-recycling households fall into recycling in any given wave. This asymmetry in the recycling rate, that is, a near zero entry and near three in four persistence rate is consistent with the debt trap characterisation, where once a household enters the recycling state, structural forces such as accumulated interest, reduced repayment capacity, and ongoing social obligations make the exit extremely difficult. The households which are the chronic cyclers constitute the most financially vulnerable segment of the population and are primary concern motivating this study.

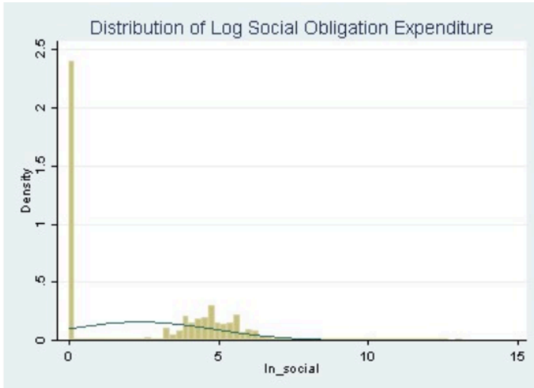

Figure 2: Note: ln_social = log(m_exp_social_obligations + 1). Normal density overlay in blue. Source: CMIE CPHS.

There is a large number of observations at zero, that is, more than half of all household-wave observations report no social obligation spending in a given wave. This finding is consistent with the lumpy and episodic nature of the social obligation argued in the counterfactual framework because ceremonies do not occur in every wave for every household. Among the households that do incur social spending, the distribution is heavily right-skewed. The log of social expenditure is concentrated in the range of 3 to 7 with a long tail extending till 13. This skewness validates the log transformation of the variable and indicates that a minority of households' bear vary large social obligation burden.

Table 3: Difference in social spending among households

Variables	Non-cyclers	Cyclers	Difference	t-statistic
Log of social expenditure (mean)	2.318	3.099	0.781***	-96.76
Share of social expenditure out of total expenditure	0.60%	0.73%	0.13pp	-
Median social share (%)	0.00%	0.49%	0.49pp	-

Note: *** $p < 0.001$. Social share = m_exp_social_obligations / tot_exp × 100. Source: CMIE CPHS

The household doing debt cycling spend substantially more on social obligations. The mean of log of social obligation expenditure for cycler households is 3.099 compared to 2.318 for non-cycler households. The difference in the mean is 0.781 percentage points which is equivalent to approximately 2,18 times the social spending in levels. The t-test confirms that the difference in statistically significant. This finding is further reinforced by the expenditure share analysis. Among the non-cycler households, the median social share is zero while among cyclers it is 0.49 percent, thus, social spending is more consistently present and proportionally larger for households in the debt cycling state.

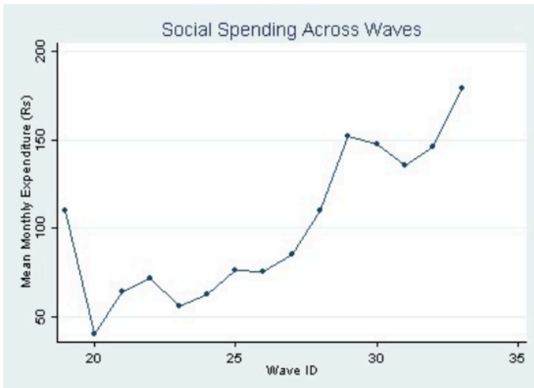

Figure 3: Note: Mean monthly household social obligation expenditure (Rs) by CPHS wave. Source: CMIE CPHS.

The trend and tracks of the mean social obligation across the survey period is shown in the figure 3. This also changes in different phases. Firstly, wave 19 records elevated mean of approximately 110. This is followed by a sharp collapse in spending to approximately 35 in wave 20 which shows the effect of the COVID-19 lockdown. Then in the next phase the spending recovers slowly and unevenly during the time period of waves 21 to 25 with expenditure hovering between 55 and 85. From wave 26 onward, the spending increases sharply reaching approximately 150 by wave 30. This trend then continues to reach its all-time high of approximately 175 at wave 33. This trend follows the post-pandemic surge with a catch-up effect where deferred weddings, religious events, and community ceremonies were compressed in the shorter window generating unusually large contemporaneous spending burdens.

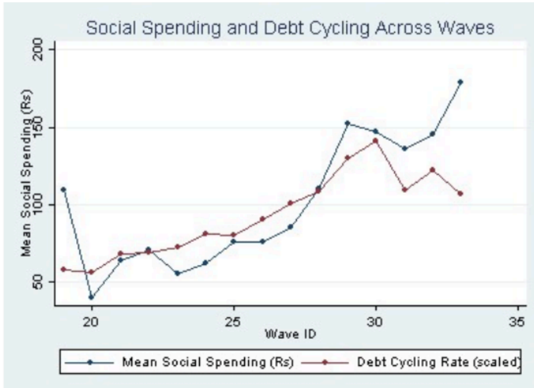

Figure 3: Note: Blue line = mean social spending (Rs, left axis). Red line = debt cycling rate × 1,500 (scaled for comparability). Source: CMIE CPHS.

The figure 3 captures the combination of the trend series of debt-recycling and social obligation expenditure. Here, the two series exhibit strong co-movement. During the COVID-19 collapse in wave 20 both the series fall simultaneously and sharply. This finding is like a natural experiment in which the social obligation expenditure was forcefully suspended which was followed by an immediate reduction in the debt cycling (Sumastuti, 2024). This further provides descriptive evidence of a causal link. After the collapse period, during wave 21 to 26, debt cycling practice recovered faster than social expenditure which is consistent with the lagged transmission. The households continued to service debt incurred from pre-pandemic social obligations even before new social obligation expenditure resumed. This mechanism will be capture by model 1 (with lagged variables). Further, during the time period of waves 26 to 30, both the series escalate, thus reflecting a contemporaneous transmission as post-pandemic ceremony catch-up created immediate liquidity shock. This mechanism is captured by the model 2 (with contemporaneous or level variables). After wave 30, the social obligation expenditure shows continued rise but debt cycling partially moderates. This may reflect household adaptation but the structural risk clearly persists.

In conclusion, the rate of debt cycling has more than doubled from wave 19 to wave 30 and has not returned to the pre-pandemic levels indicating a structural deterioration rather than a cyclical fluctuation in Indian household financial situation. The 74.18% period to period persistence rate and the prevalence of household debt cycling across five or more waves confirms that it leads to trap for a meaningful share of Indian households. Ultimately, the co-movement of social spending and debt cycling across waves including the COVID-19 natural experiment provides compelling pre-regression evidence of a causal link.

5. Methodology

5.1 Econometric Model

This paper employs the Correlated Random Effects (CRE) Probit model, based on the Mundlak (1978) device and non-linear models by Chamberlain (1982, 1984) and Wooldridge (2010, 2019). The Mundlak device here augments the random effects probit model by including the within group means of all time-varying explanatory variables as additional regressors. The CRE probit approach has been extended to handle nonlinear fractional and binary response models with unbalanced panels and endogenous regressors (Bates et al., 2024), and has been applied to panel probit settings with time-varying individual effects to recover asymptotically unbiased average marginal effects (Wei & Zhang, 2022). This combines the consistency of the fixed effects estimation and the flexibility of the random effects estimation, thus retaining all observation and time-invariant variables, and yields population average marginal effects in a straightforward manner. This method involves three basic steps. First, latent variable representation of the binary outcome.

$$y^*_{it} = x_{it}\beta + \alpha_i + \varepsilon_{it}$$

where, x_{it} is a vector of observed time-varying regressors, β is the vector of structural parameters of interest, α_i is the unobserved household-specific effect, and ε_{it} is an idiosyncratic error term that is independent of x_{it} and α_i and follows a standard normal distribution. The binary outcome is:

$$y_{it} = 1 \text{ if } y^*_{it} > 0, 0 \text{ otherwise}$$

The vector β captures the within-household causal effect of changes in social obligation expenditure on the latent propensity to recycle debt, conditional on the household-specific effect. Second, modelling the correlation between household-specific effect and observed regressors by projecting α_i linearly onto the household-specific time means of the time-varying regressors:

$$\alpha_i = \bar{x}_i\lambda + u_i, u_i \sim N(0, \sigma_u^2)$$

where, $x_i = (1/T_i)\ \Sigma\ x_{it}$ is the vector of household-specific time means of the time-varying regressors, λ is a vector of parameters capturing the correlation between the individual effect and the regressors, and u_i is a household-specific residual that, by construction of the linear projection, is mean-independent of $\bar{x}_i$. the Mundlak projection thus decomposes the individual effect into a component that is explained by the time-average behaviour of the household and a genuinely random residual that is uncorrelated with all regressors. Third, substituting the Mundlak projection into the latent equation yields the estimable CRE Probit specification:

$$y^*_{it} = x_{it}\beta + \bar{x}_i\lambda + u_i + \varepsilon_{it}$$

The conditional probability of observing $y_{it} = 1$ is:

$$P(y_{it} = 1 \mid x_{it}, \bar{x}_i) = \Phi(x_{it}\beta + \lambda)$$

This is obtained after integrating over the distribution of u_i. This is precisely a random effects probit model with the household-specific means included as additional regressors alongside the time-varying regressors. Estimation proceeds by maximum likelihood, with the likelihood function integrated over the distribution of u_i using multivariate Gauss-Hermite quadrature to evaluate the likelihood contribution of each household. The standard errors are clustered at the household level to account for the within-household serial correlation in the idiosyncratic error ε_i.

The estimator obtained is the estimator of the coefficients on the time-varying regressors and it is numerically equivalent to the fixed effects estimator, capturing the within-household causal effect of the changes in social obligation expenditure on the probability of debt cycling. The coefficients on the time-varying variables are identified from the between-household variation in these characteristics, given that the correlation between time-varying regressors and the individual effect has been absorbed by the Mundlak terms.

The estimation methodology presents an internal Hausman test (Papke & Wooldridge, 2022). The null hypothesis H_0: $\lambda = 0$ tests whether the group means (Mundlak terms) are jointly significant. Rejection of this null implies that the individual-specific effects are correlated with the time-varying regressors, confirming that the standard Random Effects assumption is violated and that the CRE correction is necessary. This test is computed from a Wald test on the joint significance of all Mundlak terms in the estimated model and represents an internal, model-based alternative to the external Hausman test (Papke & Wooldridge, 2022).

The parameter $\rho = \sigma^2_u / (\sigma^2_u + 1)$ measures the proportion of total variance in the latent dependent variable attributable to the unobserved household-specific effect u_i rather than idiosyncratic error. The value of sigma u is the estimated standard deviation of the household level unobserved heterogeneity distribution. High values of ρ (approaching unity) indicate that household-level heterogeneity is the dominant source of variation in debt cycling behaviour, confirming that the panel structure of the data is essential for consistent estimation.

The parameters estimated by the CRE probit model cannot be interpreted directly as marginal effects on the probability of debt cycling. To interpret the findings correctly, we compute Average Partial Effects (APEs), which is the average change in the probability of debt cycling associated with a unit change in a regressor, averaged across the full distribution of households (Bates et al., 2024; Wei & Zhang, 2022). The APE for the kth continuous regressor is defined as:

$$APE_k = (1/N)\ \Sigma_i\ \varphi(x_{it}\hat{\beta} + \bar{x}_i\hat{\lambda}) \cdot \hat{\beta}_k$$

where, $\varphi(\cdot)$ is the standard normal probability density function, $\hat{\beta}$ and $\hat{\lambda}$ are the maximum likelihood estimates, and the average is taken over all N household-wave observations in the sample. Also, the overall significance of the model is understood through the Wald chi^2 test which tests the joint null hypothesis that all slope coefficients in the model are zero, obtained in regression output.

5.2 Pre-regression Diagnostic Tests

To justify the use of the econometric model we ran a few diagnostic tests, which are, namely, Breusch-Pagan LM test, Mundlak joint test, and Strict exogeneity test. As the datasets contains large number of observations, so to make it computationally easier these tests were conducted using linear panel model (LPM) equivalent specifications. This approach is true to the standard practice in applied microeconomics (Wooldridge, 2010).

Table 4: Diagnostics test summary

Test	Null	Statistic	p-value
Breusch-Pagan LM	Variance of u = 0	$X^2(1) = 27{,}00{,}000$	< 0.001
Mundlak joint significane	Group means jointly = 0	$X^2(4) = 5180.63$	< 0.001

Strict exogeneity	Leads jointly insignificant	F(21,84.814) = 20.41	< 0.001

Notes: Breusch-Pagan LM test estimated via random effects GLS. Mundlak test is a joint Wald test on group mean in the CRE augmented RE specification. Strict exogeneity done via fixed effects and augmented with one period leads on ln_social and ln_inc. Robust standard errors clustered at the hh_id. Source: CMIE CPHS

The Breusch-Pagan test here rules out pooled probit because the null hypothesis of zero individual specific variance with an intra-class correlation of value 0.55 (rho). This indicates that over half of the total variation in the outcome is attributable to household specific effects. The random effects assumption of zero correlation between regressors and unobserved household effects is tested through the Mundlak augmented specification. This is further through the joint significance of group means. This test also rejects the null hypothesis, implying that Mundlak terms are significant. The standard RE probit is therefore inconsistent and CRE Mundlak specification is needed. The use of specifically CRE transformation and not the standard fixed effects model in the analysis is due to the fact that our dataset contains many dummy variables, one of which is the dependent variable. The application of fixed effects is eliminated as it resulted in the truncation of the dataset approximately by 80 percent, hence the application of CRE with Mundlak device. Finally, to test the reverse causality between the key regressors and the dependent variable, a strict exogeneity test is implemented by augmenting the fixed effects specification with one period leads of log social expenditure and log income. Here, the leads are jointly significant confirming that contemporaneous variables are endogenous. Therefore, the estimation of two different models, one with lagged independent variables and one with contemporaneous variables.

6. Results

In this section we provide the results from the regression using the Correlated Random Effects Probit with Mundlak Device. There are two models being used for the analysis. The first model uses the lagged variables and the second variable uses the contemporaneous variables as the key independent variables. The model examines the relationship between social obligation expenditure and probability of debt cycling, controlling for the relevant household characteristics such as level of income, education, occupation, and household type.

The model itself includes diagnostic test which shows how this methodology is relevant for our study. In the outputs, the Mundlak device tests and acts as a correction for the standard random effects assumption failure. The group means are all highly statistically significant meaning the regressors are correlated with unobserved heterogeneity and random effects assumption fails, so CRE transformation is relevant. The panel model is justified rather than a pooled cross-section probit because it accounts for individual effects as rho value in models is very high. It also confirms the random effect structure and highlights why controlling for the correlation between u_i and regressors via Mundlak device is important. Moreover, the large values of σ_u tells that there is substantial unobserved between household variation in the output. The overall significance of model is shown by the large chi^2 statistics. The models use robust standard errors clustered at the household level which accounts for the fact that the observations within the same households across waves are not independent. The wave fixed effects in the models are highly significant confirming the need for a method which controls for both unobserved individual effect (through CRE with Mundlak device) and common time effects (through wave fixed effects).

Model 1: Correlated Random-Effects Probit Regression Results (Lagged Independent Variables)

Variable	Coefficient	Robust SE	AME (dy/dx)
L1.ln_social (Lagged)	0.0345***	0.0019	0.0015
L1.ln_inc (Lagged)	-0.0025	0.0099	-0.0001
ln_food	0.3960***	0.0226	0.0170
ln_health	0.0042	0.0045	0.0002
income_cv	1.0608***	0.0349	0.0456
m_exp_emi_for_house	-0.00005***	0.00000	-0.000002
m_exp_emi_for_durables	-0.00003***	0.00001	-0.000001
houses_owned	-0.1713***	0.0300	-0.0074
mean_ln_social	0.2793***	0.0056	—
mean_ln_inc	1.0023***	0.0238	—
mean_ln_food	-1.1751***	0.0401	—
mean_ln_health	-0.1985***	0.0099	—

Household Type (Ref: Young-inclusive)			
Prime-age	0.3704***	0.0232	—
Mixed	0.3217***	0.0232	—
Senior-inclusive	0.0100	0.0383	—
Education (Ref: Primary/No education)			
Middle (Matriculate)	-0.0924***	0.0172	—
Higher (Graduate+)	-0.6414***	0.0262	—
Occupation (Ref: Unemployed/Casual)			
Self-employed	0.1005***	0.0139	—
Salaried	-0.2012***	0.0202	—
Farmer	0.1255***	0.0243	—
Retired/Other	-0.5451***	0.0265	—
Constant (_cons)	-7.8200***	0.2252	—

Note. ***1%, ** 5%, * 10% levels of significance. Robust standard errors clustered at hh_id level. Number of observations = 1,174,263; Number of groups (hh_id) = 178,513; Wald chi2(34) = 9163.22 (p < .001); Log pseudolikelihood = -147,772.09; rho = .8616; sigma_u = 2.4952. Wave fixed effects (waves 21–30, 31–33) were included in the estimation but are omitted from this table for brevity; all wave indicators from wave 22 onwards were highly statistically significant (p < .001) except wave 21 (p = .440). AME = Average Marginal Effects calculated only for non-mean focal variables using the 'nose' option.

The model 1 (lagged specification) has an estimated rho (p) equivalent to 0.86 which is the proportion of total residual variance attributed to unobserved household-level heterogeneity and implies that approximately 86 percent of the unexpected variation in debt cycling behaviour originates from time-invariant household-specific characteristics rather than within-household variation across waves. This finding further implies that the panel approach, that is, a pooled cross-sectional estimator that ignores household heterogeneity would give severely biased estimates because it attributes the variation in dependent variable to the observed regressors which actually belongs to fixed household characteristics. Also, this high rho value tells that the presence of deep structural heterogeneity in household financial condition like some households are persistently debt-prone for reasons not fully captured by the observable covariates, including unobserved cultural norms, family histories of indebtedness, and local credit market conditions. Then the Mundlak correction terms, that is, time-means of time-varying regressors are included in the model to relax the random effects assumption that the unobserved heterogeneity is uncorrelated with the regressors. The regression gives large and highly significant coefficients on the Mundlak terms which leads us to the conclusion of rejecting the standard random effects assumption. This indicates that the standard random effects probit model would attribute to the within-household effect of the key regressors. The chosen regression model (CRE Probit) helps us correctly separate the within-household effect from the between-household permanent heterogeneity (Bates et al., 2024; Papke & Wooldridge, 2022). The estimates obtained by the original model cannot be directly interpreted to come to a valid conclusion, so we obtain the Average Marginal Effects (AMEs) which shows the actual impact of the regressors on the dependent variable (Wei & Zhang, 2022; Bates et al., 2024).

In model 1, the lagged log of social expenditure variable in positive and highly significant indicating that a one-unit increase in the log of social obligation expenditure in the previous period increases the probability of debt cycling in the current period. The corresponding average marginal effect is 0.0015, implying that one log unit increase in the lagged social expenditure raises the probability of debt cycling by approximately 0.15 percentage points at the margin. The data shows only 6.18 percent of positive cases of debt cycling, so as this is a small value it tends to compress the AMEs downward. Therefore, we are interpreting them in relative terms. This value might seem very modest in absolute terms, but this effect is very meaningful economically as the distribution of social expenditure zero to the 75th percentile of log social expenditure (approximately 4.84 log units) translates into an increase in the probability of debt cycling by 0.73 percentage points which is ultimately equivalent to an 11.8 percent increase over the sample mean recycling rate of 6.18 percent. Also, relative to this baseline probability of debt cycling of 6.18 percent a one percent increase in lagged social expenditure increases the probability of debt cycling by 2.39 percent. These values are significant and social obligation events in period t-1 generate large lump-sum outflows that deplete household liquidity. In the following period t, the household faces its regular debt service obligations without getting the time to replenish its liquidity buffer (Ganong & Noel, 2018). The result is that the household must borrow to repay the existing debt obligations.

We further interpret the other independent variables. The lagged log of income is statistically insignificant in this model, indicating that the level of household income in the previous period does not independently predict debt cycling when the household fixed effects and other covariates are controlled for. The variable income volatility is the single most powerful predictor of debt cycling with 0.0456 AME, indicating that one unit increase in the coefficient of variation of income raises the probability of debt cycling by 4.56 percentage points. Using the results we can say that the social obligation expenditure creates debt cycling risk through its interaction with income volatility. The log of expenditure on food carries a large positive and highly significant coefficient with 0.017 AME value, indicating that this expenditure increases the probability of debt cycling. But this does not imply that eating more causes debt cycling, rather, within-household increases in food expenditure relative to a household's own mean controlling for oncome level. This signal financial distress, that is, a household spending proportionally more on food than its own historical norm is likely facing consumption compression, where basic necessities consume an increasing share of a shrinking discretionary budget (Hu et al., 2021; Kane et al., 2023). This is consistent with the within-household interpretation of the CRE Probit means the coefficient captures the effect of deviations from the household's own average food expenditure on probability of debt cycling. The Mundlak term for food expenditure has the opposite sign to the within coefficient meaning that households with a persistently high average food expenditure proxies for higher permanent household consumption capacity which further implies a higher permanent income, while transitory increases in food expenditure signal consumption stress. Therefore, the separation of within and between effects by the Mundlak device is essential for correctly identifying this pattern.

Contrary to this, the expenditure on health is statistically insignificant. This may be due to the fact that health expenditure while severe in absolute terms are either being covered by insurance or community support networks in ways that social obligations are not. The expenditure on EMIs on house and consumer durables are negative and significant. This implies that the EMI burdens increase probability of debt cycling. However, within the CRE framework, within-household increases in housing and durable EMIs signal access to formal and structured credit. These are the household which are having mortgages and loan agreements, and represent the disciplined formal borrowing rather than distressed informal debt cycling. Thus, the households servicing housing

EMIs have demonstrated creditworthiness to formal institutions and are embedded in formal repayment structures with fixed schedules, making opportunistic debt cycling less necessary (Ganong & Noel, 2018; Purcell, 2021). The model accounts for the asset ownership through the number of houses owned by the household. The houses owned variable carries a significant negative coefficient indicating increase in number of houses owned reduces the probability of debt cycling. This confirms that asset ownership provides a financial buffer that absorbs social obligation shocks without borrowing to repay existing debt. This mechanism is likely twofold. First, the additional housing assets provide collateral for formal credit at lower interest rates, enabling households to address liquidity needs originated from social obligations without resorting to informal credit sources (Ganong & Noel, 2018). Second, the asset acts as emergency liquidity through rental income or asset liquidation.

Furthermore, the Mundlak terms in the model captures the household's permanent average level of each time-varying regressor relates to its baseline propensity to recycle debt, that is the net of the within-period effects captured by the raw coefficients. The mean log social expenditure shows that households with persistently high social obligation expenditure over the panel are substantially more likely to recycle debt. The permanent effect is larger than the within-period effect, indicating that the between-household dimension of the social obligation expenditure which reflects the deep cultural embeddedness, caste obligations, or community status is a far stronger predictor than any single period's spending deviation. The mean log income has opposite sign that of log income. This shows that the households with higher permanent income are more likely to recycle debt which reflects the fact that such households face a status amplification effect. Households with higher income face greater social obligation pressure meaning larger weddings, more community commitments and higher gift expectations and hold more formal debt such as mortgages and business loans that must be serviced, making them structurally more exposed to debt cycling (Liu et al., 2025; Woldehanna et al., 2022). The between-household income effect operates through a fundamentally different channel than the within-period income effect.

Similarly, interpreting the mean log food and health expenditure. The households with high permanent food expenditure which acts as proxy for permanent consumption capacity are less likely to recycle debt. This result is consistent with the permanent income hypothesis, that is, there is permanent wealth buffers against social obligation shocks (Ganong & Noel, 2018). The large coefficient for this variable suggests that permanent consumption capacity is a stronger protector from the risk. Also, the households with permanent higher health expenditure are marginally less likely to recycle debt. This could be due to the fact that such household are already occupied with the expenditure on the health that they cannot afford to spend on social obligations and thus they are protected against those social shocks.

Other than the focal variables discussed above, the household characteristic variables are also revealing systematic variation in debt cycling propensity across household types, education levels, and occupations. These characteristics moderate the relationship between social obligation expenditure and debt cycling, identifying which groups face the highest structural vulnerability. The prime-age households with refence to the young-inclusive households carry the highest risk premium. These households are dominated by the working-age adults who are at their life-cycle stage of maximum social obligation exposure while simultaneously servicing the largest active loan portfolios. This combination creates the highest structural vulnerability to debt cycling (di Falco & Bulte, 2011). On the other hand, mixed households have slightly lower risk premium and the senior-inclusive households are not any statistically difference from the reference category of young-inclusive households which is consistent with the reduced social obligation exposure and lower active debt loads among households with heads from senior population group.

As noted in the literature, the education variable exhibits a strong negative gradient. The household with middle (matriculate) level of education shows lower probability of debt cycling in reference to primary or no education. While the household with higher (graduate) education shows far less probability of debt cycling. So, middle education provides only minimal protection and higher education provides great protection. This is consistent with the literature which shows that financial literacy and the social bargaining capacity to resist or renegotiate social obligation demands require education level to increase (Hu et al., 2021; Agyepong et al., 2024). Also, basic literacy alone is insufficient to protect from social pressure.

The last characteristic variable included in the model is occupation, the coefficients of which confirm that relative to the unemployed or casual labour group, the self-employed households and farmers household face higher risk of debt cycling. This is because households may face irregular business income due to market fluctuations, customer payment delays, and seasonal demand which makes it difficult to guarantee debt servicing after a social obligation outflow (Kane et al., 2023; Woldehanna et al., 2022). The farmers face risk due to agricultural income cycle which is concentrated at the harvest period and the timing of social obligation outflow mismatch. A debt incurred after a wedding in the pre-harvest period may persist unresolved in the next harvest period, initiating a multi-wave recycling. On the other hand, the salaried workers and retired households face significantly less risk and are showing a decreasing probability of debt cycling with reference to the base category. This is somewhat self-explanatory as predictable monthly salary income permits continued EMI servicing even after outflows due to obligations. These households are capable of planning and absorbing spending shocks. And, the households with stable pension or transfer income combined with reduced social obligation exposure are the least vulnerable to debt cycling.

Model 2: Random-Effects Probit Regression Results (Contemporaneous Independent Variables)

Variable	Coefficient	Robust SE	AME (dy/dx)
ln_social (Contemporaneous)	0.0139***	0.0015	0.0006
ln_inc (Contemporaneous)	-0.0227***	0.0065	-0.0010
ln_food	0.3285***	0.0183	0.0145
ln_health	0.0036	0.0036	0.0002
income_cv	1.0891***	0.0305	0.0480
m_exp_emi_for_house	-0.00005***	0.00000	-0.000002
m_exp_emi_for_durables	-0.00002**	0.00001	-0.000001
houses_owned	-0.1357***	0.0249	-0.0060
mean_ln_social	0.3026***	0.0046	—
mean_ln_inc	0.9866***	0.0197	—
mean_ln_food	-1.1869***	0.0346	—
mean_ln_health	-0.2153***	0.0085	—
Household Type (Ref: Young-inclusive)			
Prime-age	0.3041***	0.0190	—

Mixed	0.2636***	0.0189	—
Senior-inclusive	-0.0075	0.0315	—
Education (Ref: Primary/No education)			
Middle (Matriculate)	-0.0881***	0.0141	—
Higher (Graduate+)	-0.5612***	0.0206	—
Occupation (Ref: Unemployed/Casual)			
Self-employed	0.0703***	0.0115	—
Salaried	-0.2075***	0.0167	—
Farmer	0.0962***	0.0201	—
Retired/Other	-0.5350***	0.0218	—
Constant (_cons)	-6.4935***	0.1975	—

Note. ***1%, ** 5%, * 10% levels of significance. Robust standard errors clustered at hh_id level. Number of observations = 1,163,399; Number of groups (hh_id) = 184,829; Wald chi2(35) = 12,819.76 ($p < .001$); Log pseudolikelihood = -189,724.80; rho = .8374; sigma_u = 2.2690. Wave fixed effects (waves 20–33) were included in the estimation but are omitted from this table for brevity; all wave indicators were highly statistically significant ($p < .001$). AME = Average Marginal Effects calculated only for non-mean focal variables using the 'nose' option.

In this paper we have modelled another regression with the contemporaneous independent variables. This model 2 acts as a robustness and consistency check for the model 1. Comparing both the models we can see that there is remarkable stability across the specification. All the variables except the log income are stable in both sign and approximate magnitude while being significant. The log income variable was insignificant in model 1 but becomes significant in model 2. This indicates that the only systematic difference is in the timing-dependent variables where different temporal specifications, that is, lagged or contemporaneous, produce different estimates.

In model 2, the contemporaneous log social obligation expenditure displays a smaller coefficient and lower AME, suggesting that the impact of a social obligation shock takes time to materialise into debt cycling. When a ceremony occurs in the same period as borrowing for repayment, the household has already begun borrowing to repay, therefore, the coefficient only captures the marginal within-period effect. On the other hand, the lagged coefficient captures the full post-shock repayment stress that increases in the following period. Using the results we can say that social obligation expenditure increases debt cycling probability both contemporaneously and with one period lag. The persistent significance across models despite the inclusion of household fixed effects via the Mundlak device confirms that this is a within-household effect. The high obligation households are not merely structurally different but that increases in social expenditure within a household's own history predictably elevate debt cycling risk.

In both the models, coefficient of variation of income variable has nearly identical coefficients despite the different sample sizes and compositions, confirming that income volatility is playing dominant role. The stability of time-invariant characteristics (household composition, education, and occupation) coefficients across models and consistent effects across different wave samples and different social obligation timing assumptions confirm that the structural vulnerability patterns identified in the study are robust of Indian households. In addition to the above-mentioned variables, the wave fixed effects are also included in the models to capture common temporal shocks affecting all households simultaneously. The wave coefficients show an increasing pattern which is exactly what we see in the figures in descriptive analysis. These wave effects capture the macro-level forces such as rising credit market penetration, post-COVID ceremony catch-up, inflationary pressure on ceremony costs, and evolving social norms around social expenditure. Even after controlling for the household fixed effects and time-varying covariates implies that structural macroeconomic and social forces which are not captured in the model are driving a portion of the observed rise in debt cycling. This finding is consistent with the structural interpretation of worsening household financial fragility.

7. Conclusion and Policy Implications

In this study we have examined whether expenditure on socially mandated obligations causes household debt cycling in India, using longitudinal dataset from the CMIE CPHS and using CRE Probit model with the Mundlak device to control for unobserved household heterogeneity. The results obtained consistently support a positive and statistically robust causal effect of a social obligation expenditure on the probability of debt cycling. This effect works mainly through a delayed repayment stress mechanism. Further, findings suggest that social obligation expenditure and income volatility interact to determine debt cycling trap. This is because ceremonial shocks are most damaging when they are combined with unpredictable income streams. Also, the 74.18 percent wave to wave persistence rate among recycling households confirms that once a household enters the debt trap. The study has traced increasing trend in debt cycling during the time period covered across waves. It has more than doubled from the pre-pandemic baseline in wave 19 to its peak in wave 30 and has not reverted back to pre-pandemic levels. This points to a structural deterioration in Indian household financial conditions rather than transitory shocks (Hu et al., 2021; Agyepong et al., 2024). The natural experiment of the COVID-19 in which both social expenditure and debt cycling collapsed simultaneously during the lockdown period and subsequently recovered provides compelling evidence of a causal link before it was confirmed by the econometric results.

We have obtained findings for a heterogeneity analysis from the empirical results. Here, self-employed and farming households are facing higher risk related to salaried workers which reflects the mismatch between irregular income and fixed debt service schedules. Higher levels of education provide protection against debt trap as it enables financial literacy and social bargaining power to resist obligatory spending and debt obligations. Asset ownership in the form of additional housing reduces vulnerability suggesting that collateral access and liquidity buffers absorb ceremonial shocks. The above findings lead us to their direct policy implications. These implications can be understood across three levels. At the community level, the arms race in social obligation spending identified in this study driven by Veblen pecuniary emulation and Akerlof's social norm enforcement represents a collective below optimal position in which individual households cannot exit unilaterally. Community level resolutions that establish publicly visible spending caps such as in Uttarakhand for weddings and ceremonies have successfully reduced ceremonial expenditure. Also, engaging community and religious leaders, self-help groups, and local governance institutions as norm entrepreneurs could reduce the social penalty attached to modest ceremonies and shift the spending downward. At the household level, financial counselling and literacy programmes that specifically address ceremonial savings planning for major life events could help reduce households' reliance on debt due to presence of liquidity buffers ahead of predictable social obligation shocks (Ganong & Noel, 2018). At the macro level, the income volatility acts as the major driver of debt cycling points toward the importance of income stabilisation mechanisms such as crop insurance and minimum support price reforms for agricultural households, social protection schemes with income smoothing properties for informal workers.

This study has several limitations which leaves gap to be filled by future research. First, the dependent variable is self-reported which may be subject to recall bias and social desirability effects even after the effort taken in this paper to minimise it. Second, this study relies on the data from 2020 to 2024, a period that includes the exceptional distortion of the COVID-19 pandemic and its aftermath. A replication of this study over a longer and pre-pandemic baseline would allow cleaner separation of structural from cyclical forces. Third, the CRE Probit framework used here addresses time-invariant omitted variable bias but does not fully resolve the potential for time-varying endogeneity. In the future research, incorporating exogenous variation in social obligation expenditure, for example, through religious calendar variation in auspicious ceremony dates would provide a sharper causal link. Finally, disaggregating the analysis by caste, gender of household head, and geographical region would establish a more detailed storyline of how debt cycling burden is distributed across India's most structurally vulnerable sections.

In conclusion, this study provides panel data econometric evidence that socially mandated ceremonial expenditure is a significant and structurally embedded cause of household debt cycling in India. The debt trap that culturally obligate spending initiates is not merely a product of individual financial irrationality, but it is predictable outcome of community enforced norms interacting with volatile income and limited formal credit access (Kane et al., 2023; di Falco & Bulte, 2011). Addressing all these problems require interventions that simultaneously target the norms, income risk, and the credit environment.

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