Indebtedness in Rural India: The Contribution of Cognitive Skills and Personality Traits

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Abstract

Using panel dataset built on two original household surveys carried out in 2016-17 and 2020-21 in rural Tamil Nadu, South India, we analyse the relationship between personality traits (Big-5 taxonomy) & cognitive skills (Raven, literacy and numeracy scores) and financial decision-making focusing on the amount of debt and its burden (debt service ratio). First, we explore the contribution of personality traits & cognitive skills in shaping the debt. In a second step, we take advantage of the evolution of personality traits & cognitive skills to explore whether these personal characteristics are correlated with debt evolution. We find that certain personality traits such as openness and extraversion and conscientiousness are generally significantly associated with the probability of being in debt, the amount of debt and the debt service ratio. The results also suggest that the magnitude and statistical significance of the association between personality traits and debt differs across caste (dalit, non-dalit) and gender, suggesting the heaviness of these social identities. Our preliminary results call for further exploration to understand how personality traits are acquired, and how they can be leveraged to allow disadvantaged groups to have more bearable debt burden.

Keywords: Gender, caste, debt burden, panel data, Tamil Nadu.

JEL Codes: C23, D14.

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1 Introduction

Since more than a decade, there has been increasing interest in psychology in economics literature, especially through personality traits and cognitive skills (PT&CS). The relevance of such analysis in economics is well documented. Hanushek and Woessmann (2008) show that cognitive skills are correlated with individual earnings, distribution of income and economic growth (and other factors such as well-functioning economic institutions –although enter into growth and may well have stronger effects, may also amplify the effects of cognitive skills). Regarding personality traits, Borghans, Duckworth, Heckman, and ter Weel (2008) examine, for instance, the relevance of this in economics. They show that psychological variables are a good predictor of socioeconomic success and especially on the labour market[1]. Institutions, such as World Bank, collect more and more data[2] on PT&CS because it enables a better understanding of skill requirements in the labour market, backward linkages between skills acquisitions and educational achievement, personality, and social background, and forward linkages between skills acquisitions and living standards, reductions in inequality and poverty, social inclusion, and economic growth (Valerio, Sanchez Puerta, Pierre, Rajadel, & Monroy Taborda, 2014).

Used in similar studies, personality traits and cognitive skills measure two distinct skills. Cognitive skills represent the mental processes involved in the acquisition of knowledge, manipulation of information, and reasoning that include the domains of perception, memory, learning, attention, decision-making, and language abilities (Kiely, 2014) while personality is the dynamic organisation within the individual of those psychophysical systems that determine his characteristic behaviour and thought (Allport, 1961). The Big-5 model constitutes the main personality trait taxonomy[3]. It identifies five dimensions of personality: emotional stability –ES– (capacity to experience negative emotions); extraversion –EX– (capacity to experience positive emotions, the tendency to seek stimulation and company from others); openness to experience –OP– (capacity to be creative and unstructured); agreeableness –AG– (perceptions of others that are

[1] For further details see Almlund, Duckworth, Heckman, and Kautz (2011).

[2] As stated by Laajaj and Macours (2019), the World Bank alone spent 1 billion USD a year for data on PT&CS.

[3] Among the theories of personality, the traits can be defined as thought, emotion and habitual patterns of behaviour (Kassin, 2003).

caring, compassionate, and altruistic); conscientiousness –CO– (capacity to display self-discipline, act dutifully, and strive for achievement against measures or outside expectations).

Studies in economics mainly focus on the role of PT&CS on the labour market and especially on the income gap, performance at work and type of work. Other focus on education through educational attainment, course grades or standardised achievement test scores but few researchers have been interested in the relationship with household and individual finances while it is a growing area of interest.

First, households are more implicated in financial decision, partially due to the privatisation of retirement pensions, liberalisation of the loan market, increase in credit purchase. The financial innovation has enlarged the set of financial tools and complicated the choice between them (Guiso & Sodini, 2013). Second, recent financial inclusion policies focus on credit as a potential tool for business creation, improved access to education and health, enhanced decision-making and women's empowerment. It constitutes the main focus of the World Bank Group's Universal Financial Access 2020 initiative and featured as a target in eight of the 17 objectives of sustainable development goals. Nevertheless, it is a known fact that debt and credit are two sides of the same coin. If the investment goes well, debt is protective and productive (which it is called credit) but if it goes wrong (the return on investment is less than the cost of the loan, or is obtained too late), if the debt is only used to make ends meet (Guérin, Michiels, Natal, Nordman, & Venkatasubramanian, 2021), the debt can be a source of impoverishment and destruction. The choice of terms reflects this ambivalence (Peebles, 2010).

Research build a bridge between household finance and individual skills through the notion of financial literacy which measure how well an individual can understand and use personal finance-related information (Gaurav & Singh, 2012; Hastings, Madrian, & Skimmyhorn, 2013; Horn, Jamison, Karlan, & Zinman, 2021; Huston, 2010; Klapper, Lusardi, & Panos, 2012). The few studies that have focused on PT&CS and household finances mainly investigate the risk aversion, financial distress, savings and debt. Nga and Yien (2013) show that conscientiousness, openness to experience and agreeableness are correlated with risk aversion, cognitive biases and socially responsible investing for undergraduate students of Malaysia. For 4,000 individuals from Netherland, Pinjisakikool (2017) shows that all the Big-5 personality traits are good predictors of financial risk tolerance as Bucciol and Zarri (2017) whose show that agreeableness, cynical hostility and anxiety are good predictors (negative correlation) of financial risk taking for 11,000 individuals from USA. In terms of financial distress, Agarwal and Mazumder (2013) show that individuals with high math scores are less likely to make financial distress in USA. Parise and Peijnenburg (2019) are the only ones, to our knowledge, who deal with causality. They instrument conscientiousness and emotional stability with childhood trauma on Dutch dataset and they show that people in the bottom quintile of personality traits are 10 times more likely to experience financial distress than those in the top quintile. Regarding saving behaviour, Gerhard, Gladstone, and Hoffmann (2018) decompose 3,000 individuals from UK in two groups (striving and established) and find that agreeableness is negatively correlated with total household savings for both groups and the effect is stronger for the striving than for the established. Nyhus and Webley (2001) show that extraversion is negatively correlated with savings for 1,300 individuals from Netherland and that emotional stability is positively correlated with debt. Brown and Taylor (2014) find that extraversion and agreeableness are positively associated with the level of debt held while conscientiousness is negatively correlated with the level of unsecured debt for 10,000 individuals from UK and Forlicz and Rólczyński (2019) show differences between debtors and debt-free individuals in terms of conscientiousness, honesty, attitude towards money and shopping for 3,700 individuals from Poland, Spain, Romania and Italy.

To our knowledge, no articles have looked at personality traits[4] and cognitive skills on debt in India (nor even in developing countries) while understand the relationship is essential in the Indian context because of the uniqueness of indebtedness.

Since the 80s, the incidence of indebtedness increase for rural and urban households (respectively from 19 to 32% and from 17 to 22%) with an increase in the share of household indebted to formal –or institutional– sources (11 to 17%) and informal sources[5] (10 to 19%) (Rajakumar, Mani, Shetty, & Karmarkar, 2019). As we discuss in

[4]In India,Michiels, Nordman, and Seetahul (2021) are interested in the link between PT&CS and labour mobility; Dasgupta, Mani, Sharma, and Singhal (2020) are interested in the disparities in terms of personality traits between castes; Donato, Miller, Mohanan, Truskinovsky, and Vera-Hernández (2017) study how agents respond to performance incentives according to conscientiousness and neuroticism; Hafen, Singh, and Laursen (2010) examine the relations among the Big-5 personality traits, emotional intelligence, and happiness.

[5]In part due to the economic and financial sector reforms of 1991: http://indiabefore91.in/

section 2.1, the incidence of debt is largely underestimate (Jones, 1994) and micro-level studies indicates an incidence around 80-90% (Drèze, Lanjouw, & Sharma, 1997; Guérin, D'Espallier, & Venkatasubramanian, 2013; Jones, 1994; Reboul, Guérin, & Nordman, 2021). The average amount of debt per household strongly increased between 1951 and 2012 (from ₹283 to ₹33k) with an increase in the share of formal debt (from 7 to 56% for rural households) and, thus, a decreasing in the share of traditional informal debt (from 93 to 43% for rural households) (Rajakumar et al., 2019).

The situation is not homogenous among individuals, many disparities coexist between caste and gender. Guérin et al. (2013) show that caste affects borrowing strategies as amount, type and source of debt in rural Tamil Nadu, India. Dalits have a higher incidence of indebtedness but borrow smaller amounts and more frequently from ambulant lenders. They borrow less for economic reason than non-dalits but more for household expenditures. Finally, they have lower access[6] to bank loans while it offers the best conditions with low interest rate, higher amounts, and long duration (Chavan, 2007). Over gender, Reboul et al. (2021) show that the relative amount of debt is higher for females than for males while males earn much more. Moreover, females in the poorest households have the highest borrowing responsibilities and dalit females tend to face higher debt burden than non-dalits ones. In terms of uses, males borrow more for economic investment while females more for daily survival and debt repayment. Recent crises such as microfinance crisis (Nair, 2011; Sriram, 2010), demonetisation (Guérin, Lanos, Michiels, Nordman, & Venkatasubramanian, 2017) or lockdown (Guérin, Michiels, et al., 2021; Guérin, Mouchel, & Nordman, 2021) have exacerbated disparities between caste and gender to the detriment of dalits and females, making understanding individual and household debt even more essential.

In addition to residing in its incidence, the uniqueness of indebtedness in India is in his social meaning. Debt represents more than money, it is a social link closely nested in social relationship and individuals defining them and thinking of them according to their debt relationship (Guérin, 2014). Moreover, trust and reputation play a crucial role by conditioning creditworthiness (Guérin, Michiels, et al., 2021). This sociological and anthropological structuralist approach recognises that individuals cannot be considered

1991-economic-reforms - Accessed August 10, 2021.

[6] In part, because of they do not have the necessary guarantee (i) such as good land (irrigated one and good location), specific know-how (ii), or because they self-excluded themselves because dalits are persuaded to fail (iii) (Guérin et al., 2013).

outside of the social relations that make up the collective structure (Polanyi, 1944).

Disparities in terms of debt is one aspect of inequalities between caste and gender. Another important concern is finding in aspirations. Mukherjee (2017) shows that gender and caste primes can significantly affect long-run aspirations and beliefs. Alvi, Ward, Makhija, and Spielman (2019) use priming[7] to study the effect of identity salience on aspirations. They find that when females are primed on gender, they exhibit higher aspirations for their daughters and low-case female primed on caste are more aspirational for their daughters. Last, Sarkar, Chakravorty, and Lyonette (2020) show that caste and gender work as double jeopardy instead of intersectionality for aspirations. The most socially disadvantaged groups have significantly lower income aspiration when compared to other backward classes and other caste participants and female participants also have significantly lower aspiration than their male counterparts. Moreover, most socially disadvantaged female participants have lower income aspiration levels compared to other groups.

Beyond being source of inequalities, caste and gender seems to deeply impact individuals by conditioning them. In this context it appears important to investigate the role of PT&CS on indebtedness in taking into account the deepness of this social identity.

In a context marked by numerous crises, where indebtedness –and all that it represents on the social level– is predominent with growing inequalities, study the relationship with PT&CS appears full of meaning. In this article we investigate how PT&CS shape indebtedness situation? (i) and more finely, how the PT&CS vary across the indebtedness distribution? (ii). Then, we analyse how debt change over time as PT&CS change? (iii).

At the same time, we try to capture the weight of social identity by investigating the contribution of PT&CS for each social groups. Do individuals manage to differentiate themselves through their skills? By providing descriptive and econometric empirical insights, this paper contributes to furthering our understanding of the determinants of individual indebtedness –which is rare and valuable in developing countries, as well as, contributing more generally to the expanding literature exploring the implications of

[7] Priming, in cognitive psychology, is "the effect in which recent experience of a stimulus facilitates or inhibits later processing of the same or a similar stimulus." – https://dictionary.apa.org/priming. Accessed June 21, 2021.

PT&CS for economic outcomes and the literature exploring the weight of social identity. Overall, it aims to articulating behavioural (PT&CS) and structuralist approaches (social identity), two disjoint disciplinary theories. The rest of the article is organised as follow: section 2 is devoted to data and methodology, then, in section 3 we present descriptive statistics in order to give an overview of the indebtedness and the disparities between caste and gender, before exploring the relationship between PT&CS and indebtedness in section 4. We conclude this article in section 5 by providing discussion of the findings and concluding remarks.

2 Data and methodology

2.1 Data

Our empirical analysis is based on NEEMSIS-1 & NEEMSIS-2 (Networks, Employment, dEbt, Mobilities and Skills in India Survey) surveys carried out respectively in 2016-17, and 2020-21 (Nordman, Guérin, Michiels, Natal, & Venkatasubramanian, 2019; Nordman et al., 2017). These surveys are the second and third waves of a longitudinal data collection project[8] start in 2010 with RUME (RUral Microfinance and Employment survey) project in ten villages of Tamil Nadu. Located in the Cuddalore and Villupuram districts, a mostly agricultural area, economies benefits from the proximity of two large industrial towns (Neyveli and Cuddalore) and a regional business center (Panruti).

RUME randomly selected 405 households using stratified sample framework based on three dimensions: proximity to small towns (Panruti, Villupuram and Cuddalore), an agro-ecological criterion, and caste affiliation. Thus, half of villages have irrigated land (the other half is dry) and within villages, half of the sample was selected from the mostly upper and middle caste part of the village (Ur) while the other half from the Colony part, where dalits (the ex-untouchables) mainly live. NEEMSIS-1 recovered 388 households (4.19% attrition rate) and randomly selected 104 news households (for a total of 492 households) from these 10 villages, based on the same method. NEEMSIS-2 recovered 485 households (1.42% attrition rate) from 2016-17 and recovered 10 households from 2010 that were not recovered in 2016-17. Moreover, 100 news households

[8] Project took place within two broader research programmes located within the Observatory of Rural Dynamics and Inequalities (https://odriis.hypotheses.org/) at the French Institute of Pondicherry, India.

were randomly selected (for a total of 595 households).

In NEEMSIS-1 & NEEMSIS-2, two household members, called "ego 1" (mostly household questionnaire respondent) and "ego 2" (one younger household member randomly selected on a criterion of age), are directly addressed individual questionnaires that provide for instance a range of information on PT&CS.

NEEMSIS-1 & NEEMSIS-2 surveys stand out from other Indian data sources such as the All India Debt and Investment Survey (AIDIS), as it has the rare and valuable advantage of recording debt at the individual level (identifying the person who went to the lender and borrowed in her own name).

Regarding the reliability, the great expertise of the team[9] helped to formulate questions appropriately. This for instance involved using particular terms that are less degrading than the generic term "debt", lists of the main local lenders, and asking indirect questions. As stated by Reboul et al. (2021) who used the same dataset, "data accuracy is [...] reflected by an incidence of indebtedness found higher than in the estimates of the nationwide AIDIS: 99% of households are in debt in our case study, as opposed to 30% in rural Tamil Nadu in 2012 according to the AIDIS (NSSO, 2014)." Moreover, the moderate magnitude of the survey, compared to nationally representative datasets, ensures the high quality of the data and the tablet-based mode of data collection improved data quality in including constraints on answers to prevent inconsistencies.

2.2 Construction of personality traits & cognitive skills variables

As stated earlier, our survey allows us to construct measures of cognitive skills. It includes three score variables based on literacy test, numeracy test and Raven progressive matrices test[10]. These scores are constructed in adding up the correct answers of a set of four questions for literacy and numeracy test (six for numeracy in 2020-21) and 36 for Raven. Then, we standardise the score to ensure comparability of results between personality traits and cognitive skills.

[9] Some members of the research team are present since more than 20 years on the region for numerous quantitative and qualitative surveys.

[10] Raven matrix is "a nonverbal test of mental ability consisting of abstract designs, each of which is missing one part. The participant chooses the missing component from several alternatives to complete each design." – https://dictionary.apa.org/ravens-progressive-matrices. Accessed January 27, 2021.

Regarding personality traits, on the basis of 35 questions referring to Big-5 taxonomy, we averaged answers –based on a Likert scale from 1-"Almost Never" to 5-"Almost always", that belong to a determined trait after correcting for acquiescence bias[11] (see Appendix B). The resulting mean represents the score on each trait.

McDonald's Ω[12], a measure of internal consistency, are mostly satisfactory for 2016-17 data corrected from acquiescence bias: 0.81 for openness; 0.86 for conscientiousness; 0.59 for extraversion; 0.60 for agreeableness and 0.80 for emotional stability (see Figure 1). For 2020-21, the internal validity after correcting for acquiescence bias is not ideal compared to non-corrected items. It implies that results could suffer from measurement error, which would bias our results towards zero.

[Figure 1 around here]

As warned by Laajaj et al. (2019), the Big-5 taxonomy is limited in developing countries for several reasons: the enumerator-respondent interactions in face-to-face survey can induce a bias; the low education levels can make questions more difficult to understand and can induce a systematic response patterns, especially the acquiescence bias. The very good knowledge of the field (see section 2.1) allow us to collect data of high quality and avoid a bias due to misunderstanding of questions. Moreover, we implement our own factor analysis of the 35 questions by principal component with promax rotation. To avoid a bias in factor analysis, we do not recode reverse questions because it might force likeness with Big-5 taxonomy. In our dataset, acquiescence bias is measure with a set of reverse questions that are supposed perfectly opposed to another set of questions. However, the assumption of opposition is supportable only in the Big-5 taxonomy. In another layout, pairs of questions can measure different aspects of personality[13]. The resulting factors for 2016-17 data are relatively similar to the Big-5 personality traits with satisfactory McDonald's Ω: Factor 1 as Openness-Extraversion ($\Omega = 0.91$); Factor 2 as Conscientiousness ($\Omega = 0.88$); Factor 3 as *Porupillatavan* –Tamil terms for talkative, easily distracted individual– ($\Omega = 0.69$); Factor 4 as Emotional

[11] Acquiescence bias represents the tendency to answer more in one direction (agree or disagree) over the other.

[12] Literature on internal consistency estimators increasingly agrees that Cronbach's α –the widest used estimator is maybe not very efficient (Bourque, Doucet, LeBlanc, Dupuis, & Nadeau, 2019; Trizano-Hermosilla & Alvarado, 2016).

[13] Singh, Misra, and Raad (2013) show that in Hindi, the major language spoken in India, three traits different from Big-5 taxonomy firmly stood out.

stability (Ω = 0.78) and Factor 5 as Agreeableness (Ω = 0.62) (see Appendix B) while resulting factors for 2020-21 data are very different to the Big-5 taxonomy and to the 2016-17 factors. We do not present results here because we do not use it as personality traits measure (see section 2.4), however it is available on request.

To mitigate against the potential problem of life-cycle events –that might induce endogeneity through measurement error– or, in other words, to remove the effect of age on the PT&CS measures, we run univariate OLS regression with cognitive skills and personality traits as endogenous variables and age as exogenous variable. We standardised the resulting residuals and use it at as age-effect-free PT&CS (Brown & Taylor, 2014; Groves, 2005; Nyhus & Pons, 2005).

The exogeneity of PT&CS is well assumed because of stability over time while there is no consensus in psychology (Ardelt, 2000; Deary, 2014). Our data allow us to examine stability over time of PT&CS for 835 individuals of rural India.

For personality traits, according to Costa and McCrae (1997); McCrae et al. (2000) it remains stable, in part, because it is a genetic predisposition that, by definition, cannot be changed over life. Many economists follow this path and the majority of then assume stability over time after the age of 25 and other verify this stability (Cobb-Clark & Tan, 2011). However, the stability refutes sociological and psychological literature which interesting in the influence of childhood and adulthood socialisation on personality (Moen, Elder Jr., & Lüscher, 1995; Mortimer & Simmons, 1978). Ardelt (2000) state that "personality can change over the course of a person's life, particularly if age at first measurement is low or over 50, if the retest interval is large, if individual personality aspects rather than the overall personality are considered [...]." However, analysis of stability do not provide sufficient information on change in the social environment and Ardelt (2000) suggests to analyse personality before and after "unexpected, drastic changes in people's social environments". Indeed, such changes can imply a change in the individual personality to adapt to the new environment that they did not select.

Our results show stability for minor part of the population (see Appendix A). Non-corrected traits, in addition to having globally (2016-17 and 2020-21) higher internal consistency (see Table 1) are less unstable over time without being able to relate stability. Evolution of personality traits can be explained by the fact that NEEMSIS-2 data were collected after the first lockdown[14] (end of 2020) and the associated mental health consequences (Golechha, 2020; Kochhar et al., 2020) can have cause –or at least exacerbated, the non-stability.

Concerning cognitive skills, majority of individuals have higher or equal score in 2020-21 than in 2016-17 (see Appendix A) which is consistent with the lifelong learning theory –the continuing development of knowledge and skills that people experience after formal education and throughout their lives (London, 2011).

2.3 Indebtedness measures

There is no consensus in the literature to measure indebtedness but three approaches are often retained. Objective measures focus on the ability (or inability) to service or repay debts. Typically, it is the debt-to-income ratio, debt-to-asset ratio, debt service ratio. Although this is the most widely used measure, it underestimates the burden of debt in ousting personal feeling and sacrifice associated with debt (Betti, Dourmashkin, Rossi, & Yin, 2007). Subjective measure assumes that "individual households are the best judges of their own net debt/wealth position" (Betti et al., 2007). The robustness of the results are based on the degree of honesty and literacy of individuals that can make it, sometimes, less reliable (D'Alessio & Iezzi, 2013). Generally, objective measures are consistent with subjective measures at the household classification level (Keese, 2012; Rinaldi & Sanchis-Arellano, 2006). Last, administrative measures treat indebtedness as "all cases where non-payment of debts have been registered officially or declared before a court" (Betti et al., 2007). In rural Indian context, this type of measure has little meaning since most of the debt is informal.

It is recommended to analyse indebtedness at the household level because, usually, income is grouped between household members (Fondeville, Ozdemir, & Ward, 2010). However, in order to explore the role of individual characteristics such as PT&CS, we focus on two types of individual objective measures allowing us to understand the debt from two angles. First, we investigate the size of the individual debt with the total amount of individual debt taken out in her own name. Second, we investigate the burden of debt repayment with the individual debt service ratio (DSR or IDSR). It

[14]See https://thewire.in/covid-19-india-timeline for complete timeline of COVID-19 pandemy in India. Accessed August 16, 2021.

represents the share of income required to cover the repayment of interest and principal on a debt for one year. We also complete the analysis with the probability, for an individual, to be in debt to capture the incidence of debt.

2.4 Econometric framework

In order to deepen understand relationship, our analysis takes place in three steps.

How PT&CS shape individual debt? First, we use the five factors of 2016-17 factor analysis as personality traits (X_i') on individual debt of 2020-21 to understand how personality shapes individual debt. Our analysis faces non-random sample selection issues because of the nature of our dependent variables: the sample is restricted to those who declared a non-zero and non-missing debt. We therefore do not account for entry and exit in debt by only considering the total loan amount and debt service ratio. To overcome this sample selection issue, it is rigorous to use the Heckman procedure, which involves estimating a model of debt participation, where debt participation is conditioned on factors additional to those that determine the amount of debt borrowed (exclusion restriction variables). Strong theoretical background is needed to determine exclusion restriction variables that affect the participation decision to debt but not the amount. Cox and Jappelli (1993) used years of education, occupation, area income, employment status and rural-urban status and Bertaut and Starr (2002) used the proportion of household heads employed in the financial services in the region and the proportion of household heads employed in a workplace of 500 or more. In our context, such variables do not particularly make sense. Duca and Rosenthal (1993) and Crook (2001) assumed that the same variables determined the probability of having debt and the amount borrowed. However, Lennox, Francis, and Wang (2011) point out that an absence of exclusion restriction in the first stage can lead to severe multicollinearity in the second stage. del Río and Young (2006) used localisation, race and employment status. However, their results from Heckman procedures are no different from those from OLS regressions, suggested that "any corner-solution biases are small". Therefore, they focus separately on the participation equation and on debt equations (excluding non-participants). Exclusion restriction variables from literature are not relevant in our context and we do not have sufficient theoretical background. Thus, we follow del Río and Young (2006) in focusing separately on the participation equation and on debt equations in excluding non-participants. Nevertheless, we estimate a Heckman selection model as robustness check with the household debt dependency ratios – defined as the number of indebtedness individuals divided by the total number of household members, in 2016-17– as exclusion restriction variables. We also check for multicollinearity and find that the highest VIF score is 4.33, which is less than the cutoff point of 10 (Lennox et al., 2011). Results, which are available on request, are no different from those from OLS regression, suggested that the non-random sample selection issues is small, which corroborate with literature (Brown & Taylor, 2014; del Río & Young, 2006). Another way to estimate our model is to use tobit model which allows for the truncation of the dependent variables as Brown and Taylor (2014); Cox and Jappelli (1993). However, it would be unsuitable as the data are not censored or truncated, but defined on $\mathbb{R}^+$ (Maddala, 1991).

Therefore, we use, first, probit model with maximum likelihood estimation to estimate the probability for an individual of being in debt ($Indebt_i$) (eq. 1).

$$Indebt_i = \beta_0 + X_i' * \beta_1 + C_i' * \beta_2 + Z_i' * \beta_3 + \mu_i \tag{1}$$

Our control variables (C_{it}') take the existing classic controls. At individual level we use age; age square; sex; dummy variable which takes 1 if individual is the household head, 0 otherwise; main occupation[15]; number of occupations (dummy variable which takes 1 if individual declare more than one occupation, 0 otherwise); dummy variable which takes 1 if individual received formal education through school, 0 otherwise (no formal education) and a dummy variable for marital status (1 if married, 0 otherwise). At household level we use as caste; monetary value of assets[16]; sex ratio; total annual income; household size; shock exposure (dummy variable which takes 1 if the household experienced a shock[17] between 2010 and 2016-17, 0 if not). The amount of debt is estimated in $t+1$ and our independent variables in t. We therefore control for the

[15]Define as the most time-consuming activity.

[16]The monetary value of assets includes gold; land; house; livestock; agricultural equipment and consumption good (car, computer, cookgas, phone, etc.).

[17]Marriage of at least one of the household members or/and household surveyed after the demonetisation.

indebtedness situation in t in adding dummy variable which takes 1 if individual is indebted in 2016-17, 0 otherwise.

In order to investigate the amount of debt and the individual debt service ratio (Y_i), we use OLS (eq. 2). Despite the fact that DSR is a share, we do not use GLM because of the upper bound of the variable (> 1) (Cook, Kieschnick, & McCullough, 2008).

$$Y_i = \beta_0 + X_i' * \beta_1 + C_i' * \beta_2 + Z_i' * \beta_3 + \epsilon_i \tag{2}$$

To take into account the weight of social identity we investigate relationship on a pooled sample of egos with interactions variables to maximise statistical power, although splitting samples improve model specification[18]. First we do not use interaction to see the global effect (1), then we add interaction variable with sex (2), caste (3) and both (4) to test whether the effect of PT&CS differ by sex and caste:

$$\begin{array}{llll} (1) & Z_i' = 0 & (3) & Z_i' = Caste * X_i' \\ (2) & Z_i' = Sex * X_i' & (4) & Z_i' = Sex * Caste * X_i' \end{array}$$

We cluster the error at household level to take into account the fact that observations within each household are not i.i.d. Indeed, we have data for two individuals from the same household and these latter sharing resources and pooling others (incomes, assets for instance).In terms of debt, as stated by Reboul et al. (2021), data "suggests that fully pooling and sharing the household debt burden is not the norm."

To interpret our results, we compute marginal effect (ME) at representative values on the predicted values of PT&CS.We use sex (male vs female) and caste (non-dalits or middle-upper caste vs dalits) as representative values, all other variables are at mean. Thanks to our interactions variables, we obtain nine groups of ME for each PT&CS variable: average individual; average male; average female; average non-dalit; average dalit; average non-dalit male; average dalit male; average middle-upper caste female and average dalit female.

Also, we use Big-5 taxonomy as robustness check.

How the PT&CS varies across the indebtedness distribution? As OLS regression is a "mean reasoning", we supplement this analysis with "quantile reasoning" to understand

[18] The statistical power is not maximising if we use split samples.

the variation of PT&CS across the indebtedness distribution. Quantile debt regressions consider specific parts of the conditional distribution of the debt and indicate the influence of the PT&CS variables on conditional debt. Therefore, we estimate eq. 2 with quantile regression from P10 to P90 (by 10 pp) of the distribution. Control variables remain the same and we also cluster the error at household level. To fully understand the results we do not use interaction variables ($Z_i' = 0$) and we compute ME at means to investigate the relationship between debt and PT&CS for the average individual at specific percentile of the distribution.

How does debt change over time as PT&CS changes? In a last step, we fully accept the non-stability of personality traits by using one-way[19] individual fixed effect regressions (eq. 3) in order to compare within individuals over time. In other words, as PT&CS increases for an individual over time, how does the debt change over time? Unlike the previous approach, we do not use personality traits from factor analysis insofar as factors for 2016-17 are different from those for 2020-21. The resulting factor from factor analysis of 2016-17 and 2020-21 are not interpreted in the same way, therefore, we cannot analyse the evolution of a given factor. While the way we compute Big-5 personality traits allows us to analyse evolution because we use the same method in 2016-17 and 2020-21. We use the same debt measures as before –the total amount of debt and the individual DSR– as endogenous variables (Y_i).

$$Y_{it} = X_{it}'\beta_1 + C_{it}'\beta_2 + Z_{it}' * \beta_3 + \alpha_i + e_{it} \tag{3}$$

We use the same vector of control variables than before. However, as we estimate FE model, time-invariant variables are omitted from the analysis: sex; education; caste. Cluster remains the same and ME at representative values (sex and caste) are computed.

An important caveat lies in the study of causality. We do not pretend to show a causal relationship between PT&CS and indebtedness but to relate correlations because we cannot rule out the possibility of reverse causality between PT&CS variation and indebtedness variation.

[19] We choose to not compute two-way fixed effect for the many problems with maintaining assumptions and interpreting the coefficients (Imai & Kim, 2020; Kropko & Kubinec, 2020).

3 Descriptive statistics

3.1 Household unit in Table 1

Our final sample consists of 835 individuals from 473 households and almost half are dalits. Three quarters of households have 2 egos, the last quarters have only one egos –justifying the fact that we cluster the error at household level. In terms of assets, middle-upper castes households are three times richer than dalits on average –respectively ₹1,493k and ₹487k in 2016-17. 50% of middle-upper castes have less than ₹666k of assets while 50% of dalits households have less than ₹266k in 2016-17. For 50% of dalits, the monetary value of assets increased by at least 47% between 2016-17 and 2020-21 while for 50% of non-dalits, it decreased by at least 22%. However, middle-upper castes still have a higher amount of assets in 2020-21. This economic advantage of non-dalits is also found with income: the median income of middle-upper castes is 34% higher than dalits one in 2016-17 and 15% higher in 2020-21. Last, whatever the caste, we observe a reduction of total income: for 50% dalits the total income decreased by at least 4% and for 50% of non-dalits, it decreased by at least 5%.

[Table 1 around here]

3.2 Individual unit in Table 2

At egos level, 55% of our sample are males and among them, 46% are dalits (among females 50% are dalits). Males are, on average, older than females and three quarters of them are the head of the household while females are only 9% in 2016-17 and 27% in 2020-21. This increase is partly due to the life cycle: when the household head died, the wife takes over as household head. In terms of education, males are more formally educated than females.

Disparities in terms of gender are also found in the occupation. Despite the increase of the number of females in agriculture and the decreasing of the number of males in self-employment, these activities are mostly reserved for males. The reverse assessment is true for salaried jobs in agriculture. Between 2016-17 and 2020-21 the share of male increase by 47% (from 16% to 24%) but females remain relatively more numerous (27.42% in 2016-17 and 29.58% in 2020-21). Whatever gender, non-agricultural salaried job remain stable over time and the share of the male implicated is similar to the share of female (around 37%). Non-income generating work as the main occupation is overrepresented for females while even though the share fell considerably between 2016-17 and 2020-21 (from 24% to 15%). Moreover, females are more likely to have multiple occupations and the probability increases between 2016-17 and 2020-21 (from 50% to 60%). In terms of income, disparities persist between males and females. On average, males have ₹102k per year as labour income while females have ₹19k. Between 2016-17 and 2020-21, the average variation rate is higher for females than for males (respectively 173% and 163%).

Figure 2 shows the distribution of each PT&CS net of life-cycle standardised. Traits from Big-5 taxonomy (row 2) are not corrected from acquiescence bias. The distribution of personality traits from Big-5 taxonomy and factor analysis seems to match. In 2016-17, it appears that males tend to have higher score for each traits. They are more open to experience, conscientious, extroverted, agreeable and emotional stable. When we compare 2016-17 distribution with 2020-21 one, we observe that, males –taken as a whole– have slightly lower score for openness to experience and extraversion while females have slightly higher one. Distribution of conscientiousness is more platikurtic and shifted to the right in 2016-17 than in 2020-21 for males. Taken as a whole, males are less conscientious in 2020-21 compared 2016-17. The assessment is reverse for females. Distributions of agreeableness of 2020-21 are more platikurtic for males and females. Taken as a whole, a more important share of male/female is very/few agreeable in 2020-21 compared to 2016-17. Conversely, distributions of 2020-21 for emotional stability are more leptokurtic for males and females. Concerning cognitive skills, distributions of Raven score are more shifted to the left in 2016-17 than in 2020-21. Taken as a whole, a more important share of male/female has a low score at Raven test in 2020-21 compared to 2016-17. For numeracy and literacy test, distributions are more shifted to the right in 2016-17 than in 2020-21. Taken as a whole, a more important share of male/female has a high score in 2020-21 compared to 2016-17.

There are many disparities in terms of debt. While the share of individual is relatively stable through time and gender (around 75%), the path is different. Females are more vulnerable than males in the sense that the share of individuals never in debt is lower for females than for males (respectively 10% and 14%) and the share of individual who become indebted between 2016-17 and 2020-21 is higher for females than for males (respectively 14% and 8%). We also observe that more than six out of ten individuals remains indebted. Our sample of indebted individuals consists of 643 individuals in 2016-17 and 606 individuals in 2020-21 whose 516 are indebted in 2016-17 and in 2020-21. Males have a higher absolute amount of debt than females (two times more in 2016-17: ₹190k for males while ₹80k for females) despite a reduction in the amount between 2016-17 and 2020-21 (for 50% of males, debt has decreased by more than 57%). On the other hand, 50% of females saw their debt increased by more than 24% (on average, in 2016-17 a female has a debt of ₹80k, while it is at ₹90k in 2020-21). Male spend less of their annual income on debt repayment than females. In 2016-17 50% of males spend 27% of their annual income on debt repayment and 12% in 2020-21 while females spend 32% in 2016-17 and 77% in 2020-21. Furthermore, 50% of males have seen their DSR decreased by at least 0.27% while 50% of females have seen their DSR increased by at least 0.09%.

[Table 2 around here]

[Figure 2 around here]

4 Results

To interpret the results, marginal effects at representative values on the predicted value of the PT&CS are reported for the four specifications as describe previously. According to specifications, the representative values are: (1) the average individual ("All"); (2) the average male ("Male") and the average female ("Female"); (3) the average non-dalit or the average middle-upper caste ("MUC") and the average dalit ("Dalit"); (4) the average non-dalit male ("MUC male"), the average dalit male ("Dalit male"), the average non-dalit female ("MUC female") and the average dalit female ("Dalit female"). All of PT&CS are standardised to ensure comparability between them. We will therefore speak in terms of "one standard deviation (sd)" more of PT&CS.

An important caveat to acknowledge prior to exposing the findings of our empirical analysis is the magnitude of the effects. They may seem high. However, this comes from the low range of definitions of PT&CS variables. For a personality traits ranging from

-4 to 4, one more standard deviation represent a gap of 1/8. Put another way, for a variable ranging from -4 to 4, take an additional unit come back to take 12.5% in more.

4.1 How PT&CS shape individual debt?

Probability of being indebted Table 3 presents results from the multivariate probit analysis of the probability for an individual to be in debt. McFadden's pseudo R^2 indicates a very good goodness-of-fit for all the specification –they are all above 0.2 threshold (McFadden, 1979). Moreover, we observe that all p-values associated with the simultaneous coefficient nullity test (LR χ^2) are low enough to conclude that at least one of the regression coefficients in the model is not equal to zero.

The results show that 2016-17 cognitive skills –whatever the specification– are not correlated with the probability of being indebted in 2020-21 at 95% confidence level (cl) –or at 5% risk of error– except for literacy which is positively correlated for the average female at 90% cl (or at 10% risk of error).

However, three of the personality traits are correlated at 95% cl. Factor 1 as openness-extraversion is negatively correlated with the probability for the average middle-upper caste individual of being in debt and the relationship seems to be clarified for the average non-dalit female. Other things equal, when openness-extraversion increases by one standard deviation, the probability of being in debt decreases by 11.1 percentage point (pp). The magnitude of the relationship is little less strong for Factor 3 as *Porupillatavan* (-8.4 pp) for the same average individual. Last, Factor 2 as conscientiousness is positively correlated (8.5 pp) for the average middle-upper male, all else being equal.

If we accept a 10% risk of error Factor 4 and 5 becomes correlated. For the average dalit male, one more standard deviation on emotional stability is associated by a decreasing of 6.2 pp of the probability of being in debt. Regarding agreeableness, it is negatively correlated for the average non-dalit individual and especially for the average non-dalit male with lower magnitude than for conscientiousness (-6.7 pp compared to +8.5 pp). Last, when conscientiousness increase by one sd, the probability decrease by 7.7 pp for the average non-dalit female.

[Table 3 around here]

Total amount of debt Table 4 presents the results from the multivariate OLS analysis of the total loan amount. All p-values associated with the simultaneous coefficient nullity test (F-stat) are low enough to conclude that at least one of the regression coefficients in the model is not equal to zero. The goodness-of-fit is less good than previously. We are able to explain around 23% of the total variance of the total amount of debt.

Raven score is correlated with the total amount of debt at 95% confidence level for the average dalit female. All else being equal, when Raven score increases by one standard deviation, predicted total loan amount increases by ₹21k. At 90% cl, numeracy is also correlated for the average dalit female, but negatively and with lower magnitude (-₹16k). Relationship between debt and Raven is reverse for the average non-dalit female with higher magnitude than for average dalit female (+₹33k).

Regarding personality traits, Factor 1, 2 and 5 are correlated with the total amount of debt at 95% confidence level for, at least, one group. For the average individual, openness-extraversion is positively correlated. The relationship seems to be clarified for the average non-dalit individual and especially for the average non-dalit male for who, one more sd in openness-extraversion is associated by an increasing of ₹49k of the total loan amount, other things equal. Always for the average middle-upper caste male, the strength of the negative relationship with conscientiousness is high enough (-₹64k) compared to other relationships. Last, agreeableness is negatively correlated for the average dalit and especially for the average dalit female (-₹15k).

At 90% cl, new relationships appear for Factor 1 and 3. When openness-extraversion increases by one standard deviation, predicted total amount borrowed increases by ₹13k for the average dalits female, other things equal. Last, when the average individual is one sd more *Porupillatavan*, the total loan amount decreases by ₹19k, all else being equal. The relationship is stronger for the average male (-₹24k) and for the average non-dalit individual (-₹29k).

[Table 4 around here]

Individual debt service ratio Table 5 presents results for the individual debt service ratio. All p-values associated to the F-stat are low enough and the goodness-of-fit is quite low compared to previous analysis.

The results show that 2016-17 cognitive skills are not correlated with the individual DSR neither at 95% cl nor at 90%.

As for the previous analysis, Factor 1 is positively correlated with the share of the annual income dedicated to debt repayment and especially for average female and average dalit female at 95% cl. Indeed, for the average dalit female, when openness-extraversion increases by one standard deviation , the predicted DSR increases by 98 pp, all else being equal. Conscientiousness is negatively correlated for the average individual and the magnitude of the correlation is similar to Factor 1 (49 pp more for openness-extraversion and 48 pp less for conscientiousness, other things equal).

Porupillatavan and emotional stability are correlated with the DSR if we accept 10% risk of error, especially for the average non-dalit female. While the relationship is positive for *Porupillatavan*, the one with emotional stability is negative and stronger (respectively +93 pp and -136 pp).

[Table 5 around here]

4.2 How PT&CS varies across the indebtedness distribution?

Figures 3 and 4 present results from the quantile regression on the total loan amount and the individual debt service ratio.

Only Factor 4 as emotional stability, numeracy and literacy are correlated at 95% confidence level with the total loan amount (see Figure 3). Regarding emotional stability, between P10 and median (P50) correlation declining –to become more negative– but still insignificant until median. When emotional stability increases by one standard deviation, conditional distribution of total loan amount at median decreases by around ₹10k, other things equal. At P30, numeracy is also negatively correlated (around -₹10k) and between P30 and P40 correlation with literacy increasing (from +₹9k to +₹12k). At 90% cl numeracy and literacy becomes correlated at P90 (respectively +₹35k and -₹30k).

Regarding individual DSR, the coefficient of openness-extraversion varies across the distribution (see Figure 4) with ME being higher at the end of the distribution at 95% cl. ME of openness-extraversion is ₹20k at P80 and ₹45k at P90, all else being equal. Last, at 10% risk of error and at P90 emotional stability is negatively correlated (-₹50k) with higher magnitude than openness-extraversion, other things equal.

[Figure 3 around here]

[Figure 4 around here]

4.3 How does debt changes over time as PT&CS change?

Total amount of debt Table 6 presents the results from the one-way individual fixed effect regressions to understand how total loan amount changes over time as PT&CS change. The intraclass correlation (ρ) is quite high which means that around 55% of the variance is due to differences across individuals. Within-R^2 indicates that around 10% of the variation of the total loan amount within individuals (over time) are captured by our model while between-R^2 indicates that 0% of the variation of the dependent variable between individuals are captured by our model. All p-values associated with the F-stat are low enough to conclude that at least one of the regression coefficients in the model is not equal to zero.

As cognitive skills, only literacy is positively correlated with the amount of debt at 95% risk of error for the average male, average non-dalit and especially the average non-dalit male. When literacy is one more standard deviation, the predicted total amount borrowed increases by ₹81k, other things equal. If we accept 10% risk of error, Raven is positively correlated for the average female and negatively correlated for the average male (respectively +₹12k and -₹30k).

Regarding personality traits, extraversion is negatively correlated for the average dalit and especially for the average dalit male at 95% cl (-₹41k). Openness and conscientiousness are positively correlated respectively for the average non-dalit female (+₹29k) and for the average dalit female (+₹12k) if we accept 10% risk of error.

[Table 6 around here]

Individual debt service ratio Table 7 presents the results from the one-way individual fixed effect regressions to understand how individual DSR changes over time as PT&CS change. ρ is also quite high and within-R^2 and between-R^2 are similar than ones for total loan amount. All p-values associated with the F-stat are higher than 0.05 thresholds, which means that, simultaneously, all regression coefficients in the model are equal to zero. Nevertheless, it does not prevent variables taken independently of each other from being significantly differents from zero, other things equal.

At 95% confidence level , neither personality traits nor cognitive skills are correlated with the individual debt service ratio. Only extraversion is correlated at 90% cl for the average male and the average dalit female. Respectively, when extraversion is one more standard deviation, the predicted individual DSR increases by 33 pp for the average male other things equal, and it decreases by 109 pp for the average dalit female other things equal.

[Table 7 around here]

5 Discussion and conclusion

As argued in the introduction, the contribution of PT&CS remains a blind spot of current debates on indebtedness in India. The role of PT&CS is heterogenous depending on gender, caste and outcome. In what follows, we use our findings and literature on PT&CS and indebtedness to provide answers to our three questions.

5.1 How PT&CS shape indebtedness situation?

An interesting finding of this paper is that cognitive skills appear to play a limited role on individual debt, other things equal. Unlike Agarwal and Mazumder (2013) whose find that numeracy is negatively correlated with financial mistakes, neither numeracy, literacy or Raven has a significant correlation on the probability of being in debt. It illustrates the universality of debt. There is no need to have a minimum level of numeracy or literacy to get into debt in rural India. Individuals can understand how it works even if they cannot read or count.

Looking at personality traits, we have identified the crucial role of openness-extraversion and conscientiousness in shaping debt. As shown in the literature, openness and extraversion are positively correlated with the probability of holding debt and with the amount of debt (Brown & Taylor, 2014). While our results are consistent on the amount of debt (and on the debt service ratio), we find negative relationship with the probability of being in debt. This interesting pattern can be explained by the fact that the more an individual is sociable (extraversion encapsulates the concept of sociability), the more he can count on his network to avoid recourse to debt. **Travaux sur la solidarité intra caste ?** However, this lower access to debt all else being equal, does not means lower debt if individuals are indebted. Indeed, individual with higher extraversion have higher risk tolerance (Pinjisakikool, 2017), and thus they are more able to have high debt. We can also imagine that a more sociable individual can be more aware of risk of debt and therefore does not prefer to contract one, however it seems that it is not the case here. Brown and Taylor (2014); Donnelly, Iyer, and Howell (2012) find that conscientiousness is inversely associated with the level of unsecured debt. Our findings are consistent for the total loan amount and the individual DSR, but we find positive correlation with the probability of being in debt for the non-dalit males while Brown and Taylor (2014); Nyhus and Webley (2001) find negative relationship. On the one hand, it suggests that non-dalit males who are more conscientious are more able to conform (DeYoung, Peterson, & Higgins, 2002) to the debt system –and therefore are more able to establish debt– and more able to be part of social relationship. On the other hand, individuals are more able to “manage their money through greater levels of financial self-control” (Brown & Taylor, 2014). Last, regarding agreeableness, literature is not distinct. Brown and Taylor (2014) find positive correlation with debt while Nyhus and Webley (2001) find no relationship. We find negative relationship with the amount of debt for dalits, suggesting that trusted individuals (agreeableness encapsulates the concept of reliability, trust) have more facilities in their repayment and therefore we may be less inclined to borrow to repay a loan. **à vérifier avec les données**

Overall, our findings tend to show that personality traits are good predictors of future individual debt while cognitive skills, in our context, do not shape individual debt. Moreover, we observe that in each group, some individuals stand out from others thanks to their PT&CS, such as middle-upper caste females with higher openness-extraversion, middle-upper caste males with higher conscientiousness or dalit females with lower agreeableness or higher Raven.

5.2 How the PT&CS varies across the indebtedness distribution?

Another interesting finding of this paper is that the contribution of PT&CS varies across the individual debt distribution. Among the 30% least indebted, those with higher literacy level have lower amount of debt. It can be explained by the fact that individuals with higher literacy level can be the one with a better job in terms of higher income and thus individuals who need lower amount of debt to live on a daily basis. **à**

vérifier avec les données Nevertheless, we could also have thought that individuals with higher literacy level have access to a wider range of financial tools, potentially increasing their level of debt, but it seems that this is not what matters here. Findings on numeracy are surprising because they are not pairwise with literacy. Indeed, among the 30% least indebted, those with higher numeracy level have higher amount of debt. **essayer de trouver une petite piste quand même**

Emotional stability is negatively correlated at median with the amount of debt and openness-extraversion have positive relationship with individual debt service ratio at last 20-10% of the distribution. Result on emotional stability illustrate the fact that stable individuals are more able to control their debt in the image of their control of emotions. Regarding openness-extraversion, previous explanation on risk tolerance seems to be confirmed for individuals with a high individual DSR. Highly openned and extraverted individuals take more risk when they established debt potentially resulting in a higher DSR.

5.3 How does debt change over time as PT&CS changes?

When we fully accept the non-stability of PT&CS, we observe that literacy is positively correlated with the amount of debt and extraversion is negatively correlated. The pattern regarding extraversion echoes the previous intuition and seems to be clarified here. The more an individual is extroverted over time (therefore its degree of sociability), the more he is risk tolerant, but the more he is aware to debt risk, and thus his level of debt is reduced over time, other things equal. It seems that information on risk is more important than the aversion at long-term to determine debt evolution. Regarding literacy, findings seem to be consistent with our previous intuition and seems to be clarified here too. When literacy level increase through time, individuals have access to a wider range of financial tools (mobile finance with phone, formal loans, etc.) perhaps because of a better understanding of contracts, that potentially increase their level of debt, all else being equal. Another possible explanation –for female– is that an increase of literacy through time can be a sign of *empowerment*. It results a better access to microcredit, which is one of the ways, for females, to bring money into the household independently of the husband.

Thereby, our findings highlight correlation between PT&CS evolution and debt evolution through time without claiming to show causality. Also, we observe that in each group, some individuals stand out from others thanks to their PT&CS, such as non-dalit males with higher literacy or dalit males with lower extraversion.

5.4 Concluding remarks

In this paper, we have analysed financial practices of rural population using original dataset from Tamil Nadu, India, and especially their probability of being in debt, their level of debt and their debt service ratio, at individual level. We have focused on the relationship with cognitive skills (Raven, numeracy and literacy scores) and personality traits (based on Big-5 taxonomy) while taking into account the weight of social identity (caste and gender) in order to, for instance, confront two disjoint disciplinary approaches. Many studies have highlighted this weight but none has sought to distinguish individuals more finely while influence of psychological factors on economic outcomes becomes more and more attractive among academics and policymakers. Statistics recognise that behavioural and structuralist approaches are meaningful and need to be articulated to deepen understand indebtedness.

First, our findings suggest that some personality traits such as openness to experience, extraversion and conscientiousness are statistically significantly associated with the probability of being in debt, the amount of debt and the debt service ratio, with different signs and magnitude according to caste and gender. Results also suggest that cognitive skills are not a good predictor of the probability of being in debt and the individual debt service ratio but Raven is quite good predictor of the amount of debt for dalit females. Moreover, the contribution of emotional stability, numeracy and literacy are different across the total loan amount distribution and openness and extraversion are different across the DSR distribution. Last, we take advantage of the evolution of personality traits and cognitive skills through time to analyse the correlation with the evolution of debt. Results suggest that literacy is positively correlated with the amount of debt for non-dalit males and extraversion is negatively correlated for dalit males. Overall, results highlight the difference in weight of the social identity. Indeed, it seems that non-dalits are the best able to differentiate themselves through their personality traits and cognitive skills, and especially males. It echoes works on aspirations (Mukherjee, 2017; Sarkar et al., 2020). Being dalit or woman makes individuals more trapped in their social identity, with double jeopardy for dalits females.

Our paper contributes to the empirical literature on individual finances through its determinants and its disparities, in a context where understanding is essential because of the incidence of debt and the repetition of crisis that exacerbate disparities (microfinance crisis in the late 2010s, demonetisation in 2016, lockdown in 2020). We also contribute to the literature which seeks to measure the weight of social identity. Overall, it highlights the importance of taking into account individual characteristics such as personality traits when analysing debt at individual level or household level (Brown & Taylor, 2014). Last, we also contribute to the expanding literature exploring the implications of cognitive skills and personality traits for economic outcomes and it calls for further research to understand how personality traits are acquired, and how they can be leveraged to allow disadvantaged groups to have more bearable debt burden.

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Tables and figures

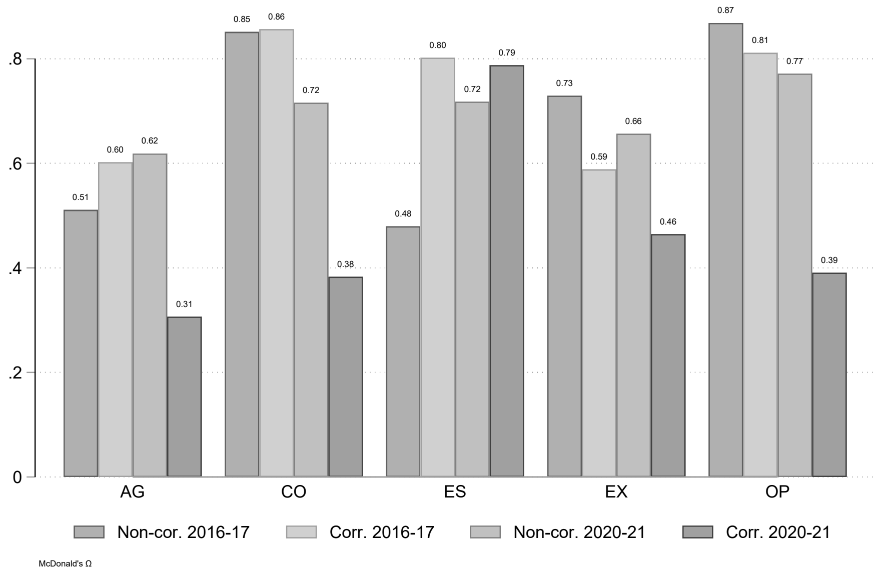

Figure 1: Internal consistency of Big-5 personality traits – Distribution of McDonald's Ω through time and correction for 953 individuals in 2016-17 and 1,316 in 2020-21 from rural Tamil Nadu, India.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

Table 1: Household-unit descriptive statistics in 2016-17

	Dalits			Middle-upper		
	2016-17	2020-21	Δ	2016-17	2020-21	Δ
Number of households	n=228	n=228	n=228	n=245	n=245	n=245
Socio-demographic characteristics						
Household size (mean)	4.93	4.94		4.46	4.41	
Number of ego (%)						
1	24.12	24.12		22.86	22.86	
2	75.88	75.88		77.14	77.14	
Sex ratio (%)						
More female	32.02	32.46		26.12	27.76	
Equal	23.68	26.32		34.29	31.84	
More male	44.30	41.23		39.59	40.41	
Location (%)						
Near Panruti	74.56	74.56		57.55	57.55	
Near Villupuram	16.23	16.23		31.84	31.84	
Near Tiruppur	0.00	0.00		2.45	2.45	
Near Chengalpattu	6.14	6.14		6.53	6.53	
Near Kanchipuram	3.07	3.07		0.82	0.82	
Near Chennai	0.00	0.00		0.82	0.82	
Wealth & finance characteristics						
Assets* (₹1k)						
Mean	487.42	458.69	192.19	1,493.35	768.25	79.93
SD	846.30	353.32	522.68	2,373.47	1,263.68	317.01
Median	266.40	360.59	47.12	666.50	447.00	-22.45
Income† (₹1k)						
Mean	179.56	146.21	59.80	193.13	191.20	85.87
SD	332.51	160.91	182.79	206.40	244.79	303.90
Median	106.35	104.71	-3.55	142.20	120.04	-5.40
Shock (=1)	57.02	26.75		56.33	17.96	
Indebted household (=1)	99.12	99.12	-	98.78	97.96	-
Household debt path (%)						
Never in debt			0.00			0.00
Out of debt			0.75			1.61
Becomes in debt			1.00			0.92
Always in debt			98.25			97.47

Note: * desc of assets † desc of income

Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

Table 2: Individual-unit descriptive statistics in 2016-17

	Male			Female		
	2016-17	2020-21	Δ	2016-17	2020-21	Δ
Number of individuals	n=463	n=463	n=463	n=372	n=372	n=372
Socio-economic characteristics						
Caste (%)	46.22	46.22		50.27	50.27	
Dalits	53.78	53.78		49.73	49.73	
Middle-upper caste						
Age (mean)	44.46	48.46		40.33	44.33	
Head of family (=1)	75.38	74.08		9.14	27.15	
Married* (=1)	80.99	86.39		84.41	81.72	
School education (=1)	68.68	68.68		52.69	52.69	
Main occupation (%)						
Agriculture	17.06	16.20		3.49	11.74	
Self-employed	16.63	12.53		5.38	8.98	
Salaried job (agri.)	15.98	23.54		27.42	29.58	
Salaried job (non-agri.)	38.66	36.72		39.78	34.85	
Unpaid working or not working	11.66	11.02		23.92	14.85	
Multiple occupation (=1)	38.01	47.27		50.27	60.00	
Labour income (₹1k)						
Mean	102.42	74.63	162.78	19.29	21.71	173.02
SD	243.22	89.33	2,405.69	41.33	45.83	538.41
Median	56.00	51.67	-0.02	7.20	9.30	0.11
Debt characteristics						
In debt (=1)						
Mean	0.78	0.71	-	0.76	0.74	-
Individual debt path (%)						
Never in debt			14.04			9.95
Out of debt			14.69			15.86
Became in debt			8.42			13.71
Always in debt			62.85			60.48
Number of indebted individuals	n=359	n=330		n=284	n=276	
Loan amount (₹1k)						
Mean	189.74	136.87	2,067.62	79.52	90.38	126.21
SD	250.40	238.64	41,296.09	97.08	94.29	934.12
Median	105.00	64.58	-56.94	44.50	69.10	23.55
DSR (%)						
Mean	93.13	134.10	251.85	173.84	253.05	91.23
SD	417.16	558.99	1,580.94	411.71	554.54	575.37
Median	27.26	11.72	-0.27	31.59	77.30	0.09

Note: *Or not (unmarried, widowed, etc.).

Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

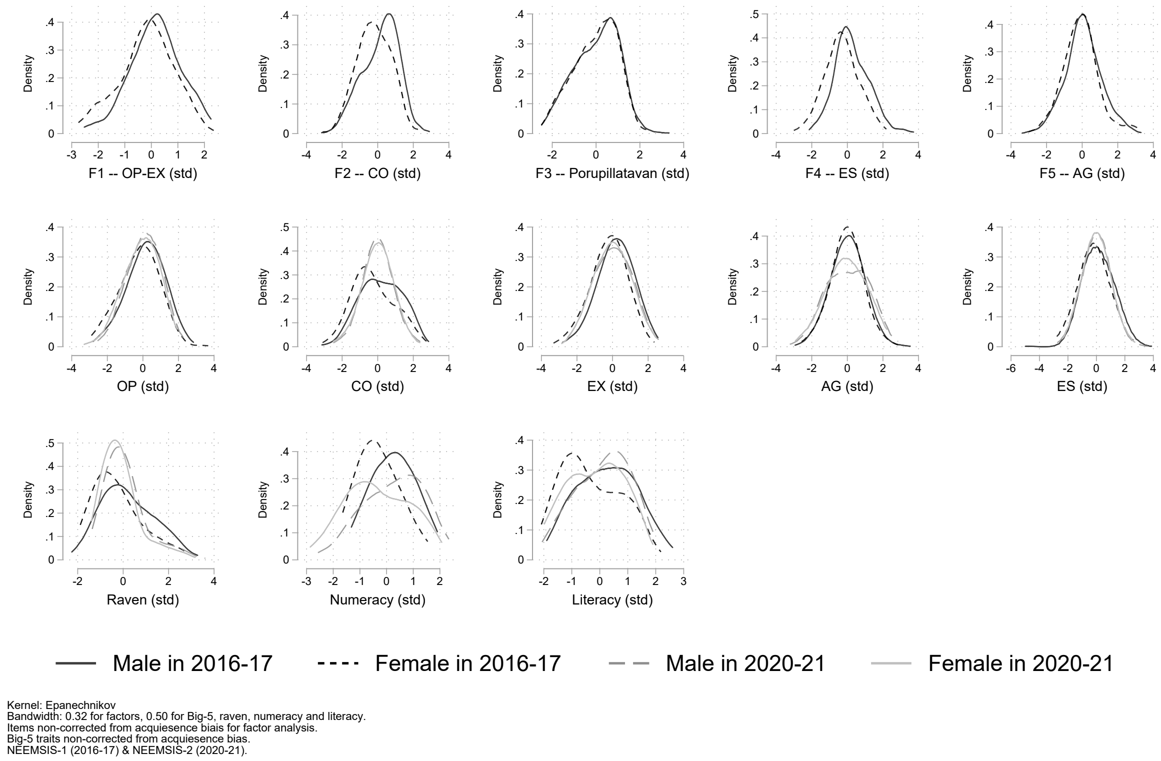

Figure 2: Distribution of PT&CS – The resulting PT&CS are based on the standardised residual from univariate OLS regression with age as exogenous variable. This is PT&CS purged from life-cycle effects.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

Table 3: ME on the probability of being in debt in 2020-21 estimated with probit model.

	(1)	(2)		(3)		(4)			
	ME/(t-stat) All	ME/(t-stat) Male	ME/(t-stat) Female	ME/(t-stat) MUC	ME/(t-stat) Dalits	ME/(t-stat) MUC male	ME/(t-stat) Dalits male	ME/(t-stat) MUC female	ME/(t-stat) Dalits female
F1 - OP-EX (std)	-0.03	-0.01	-0.05	-0.08	0.00	-0.06	0.01	-0.11	-0.00
	(-1.85)	(-0.40)	(-1.79)	(-3.05)	(0.06)	(-1.51)	(0.32)	(-2.37)	(-0.02)
F2 - CO (std)	0.00	0.04	-0.04	0.02	-0.01	0.09	-0.00	-0.08	-0.01
	(0.18)	(1.47)	(-1.52)	(0.83)	(-0.40)	(2.14)	(-0.06)	(-1.71)	(-0.42)
F3 - Porupillatavan (std)	-0.02	-0.01	-0.03	-0.04	-0.00	-0.03	-0.01	-0.08	0.01
	(-0.97)	(-0.26)	(-1.21)	(-1.61)	(-0.11)	(-0.70)	(-0.26)	(-2.02)	(0.31)
F4 - ES (std)	0.00	0.02	-0.02	-0.03	0.01	-0.04	0.06	-0.05	-0.02
	(0.05)	(0.61)	(-0.61)	(-1.09)	(0.68)	(-1.14)	(1.65)	(-1.02)	(-0.77)
F5 - AG (std)	-0.03	-0.04	-0.03	-0.05	-0.02	-0.07	-0.03	-0.06	-0.03
	(-1.51)	(-1.45)	(-1.09)	(-1.72)	(-0.72)	(-1.70)	(-0.71)	(-1.24)	(-0.80)
Literacy (std)	0.03	0.01	0.07	0.05	0.01	0.06	-0.03	0.07	0.07
	(1.13)	(0.30)	(1.77)	(1.39)	(0.34)	(1.18)	(-0.50)	(1.28)	(1.57)
Numeracy (std)	-0.01	0.00	-0.03	-0.01	-0.00	-0.05	0.05	-0.00	-0.05
	(-0.22)	(0.12)	(-0.80)	(-0.23)	(-0.06)	(-0.93)	(0.86)	(-0.06)	(-1.01)
Raven (std)	0.00	0.02	-0.03	-0.02	0.02	0.02	0.04	-0.05	-0.00
	(0.08)	(0.80)	(-0.88)	(-0.61)	(0.73)	(0.38)	(0.96)	(-1.21)	(-0.09)
Individuals controls	X	X		X		X			
Households controls	X	X		X		X			
Villages FE	X	X		X		X			
Observations	831	831		831		831			
McFadden's pseudo R^2	0.201	0.213		0.210		0.231			
Log-likelihood	-390.009	-384.098		-385.896		-375.258			
LR χ^2	222.507	223.870		278.651		256.036			
p-value	0.000	0.000		0.000		0.000			

Note: Marginal effects at representative values are reported and T-stat are in parentheses. Column 1 correspond at the average individual, column 2 at the average male, column 3 at the average female, column 4 at the average non-dalit, column 5 at the average dalit, column 6 at the average non-dalit male, column 7 at the average dalit male, column 8 at the average non-dalit female and column 9 at the average dalit female.

Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table 4: ME on the total loan amount in 2020-21 estimated with OLS model.

	(1)	(2)		(3)		(4)			
	ME/(t-stat) All	ME/(t-stat) Male	ME/(t-stat) Female	ME/(t-stat) MUC	ME/(t-stat) Dalits	ME/(t-stat) MUC male	ME/(t-stat) Dalits male	ME/(t-stat) MUC female	ME/(t-stat) Dalits female
F1 - OP-EX (std)	15.32	17.84	10.71	32.48	1.62	49.40	-7.14	12.13	12.61
	(2.20)	(1.46)	(1.63)	(2.47)	(0.26)	(2.27)	(-0.57)	(1.03)	(1.89)
F2 - CO (std)	-18.77	-31.26	-4.61	-35.50	-8.13	-64.13	-9.39	-2.17	-9.31
	(-1.82)	(-1.84)	(-0.59)	(-1.86)	(-0.81)	(-2.16)	(-0.48)	(-0.13)	(-1.57)
F3 - Porupillatavan (std)	-19.25	-23.77	-11.72	-29.31	-6.20	-32.84	-6.21	-18.43	-6.81
	(-1.96)	(-1.72)	(-1.33)	(-1.93)	(-0.80)	(-1.65)	(-0.45)	(-1.17)	(-1.08)
F4 - ES (std)	-0.61	0.06	-4.54	17.26	-13.29	37.15	-17.16	-15.76	-5.08
	(-0.05)	(0.00)	(-0.57)	(0.63)	(-1.50)	(0.76)	(-1.07)	(-1.06)	(-0.72)
F5 - AG (std)	-3.62	-1.05	-11.33	11.24	-13.01	13.25	-9.12	-13.70	-14.80
	(-0.47)	(-0.09)	(-1.77)	(0.67)	(-2.23)	(0.53)	(-1.06)	(-1.07)	(-2.44)
Literacy (std)	5.51	13.51	-5.02	5.02	13.27	2.93	18.39	-1.03	3.68
	(0.38)	(0.71)	(-0.39)	(0.25)	(0.95)	(0.11)	(0.87)	(-0.05)	(0.33)
Numeracy (std)	7.72	11.77	2.10	28.58	-8.51	26.92	3.46	23.66	-16.31
	(0.80)	(0.78)	(0.15)	(1.56)	(-0.95)	(0.93)	(0.23)	(1.07)	(-1.71)
Raven (std)	1.40	9.73	-6.23	-4.65	4.12	16.08	-7.24	-33.09	21.04
	(0.16)	(0.70)	(-0.56)	(-0.34)	(0.43)	(0.83)	(-0.41)	(-1.72)	(2.23)
Individuals controls	X	X		X		X			
Households controls	X	X		X		X			
Villages FE	X	X		X		X			
Observations	603	603		603		603			
R^2	0.263	0.273		0.288		0.315			
Adjusted R^2	0.221	0.221		0.237		0.244			
F-stat	5.404	3.244		3.768		2.453			
p-value	0.000	0.000		0.000		0.000			

Note: Marginal effects at representative values are reported and T-stat are in parentheses. Column 1 correspond at the average individual, column 2 at the average male, column 3 at the average female, column 4 at the average non-dalit, column 5 at the average dalit, column 6 at the average non-dalit male, column 7 at the average dalit male, column 8 at the average non-dalit female and column 9 at the average dalit female.

Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table 5: ME on the individual DSR in 2020-21 estimated with OLS model.

	(1)	(2)		(3)		(4)			
	ME/(t-stat) All	ME/(t-stat) Male	ME/(t-stat) Female	ME/(t-stat) MUC	ME/(t-stat) Dalits	ME/(t-stat) MUC male	ME/(t-stat) Dalits male	ME/(t-stat) MUC female	ME/(t-stat) Dalits female
F1 - OP-EX (std)	48.91	20.58	84.98	51.70	40.87	59.21	-18.27	42.95	98.66
	(2.16)	(0.62)	(3.17)	(1.46)	(1.34)	(1.00)	(-0.38)	(1.17)	(2.39)
F2 - CO (std)	-47.52	-5.56	-84.26	-41.91	-46.93	-17.30	6.61	-38.97	-105.18
	(-1.96)	(-0.26)	(-1.75)	(-1.37)	(-1.26)	(-0.54)	(0.23)	(-0.76)	(-1.47)
F3 - Porupillatavan (std)	4.46	-14.44	29.60	4.16	-0.97	-37.43	16.24	92.97	-19.39
	(0.18)	(-0.39)	(0.89)	(0.12)	(-0.03)	(-0.74)	(0.33)	(1.76)	(-0.50)
F4 - ES (std)	-26.71	-12.39	-50.70	-66.39	1.15	2.06	-18.70	-135.61	22.11
	(-1.06)	(-0.52)	(-1.18)	(-1.51)	(0.04)	(0.05)	(-0.59)	(-1.84)	(0.53)
F5 - AG (std)	11.61	18.59	2.67	-7.40	25.84	19.16	20.27	-64.07	46.58
	(0.56)	(0.77)	(0.07)	(-0.26)	(0.88)	(0.55)	(0.62)	(-1.28)	(0.90)
Literacy (std)	2.95	-12.26	18.86	-11.20	12.81	-1.01	-39.58	-58.07	51.70
	(0.10)	(-0.32)	(0.46)	(-0.28)	(0.32)	(-0.02)	(-0.84)	(-0.94)	(0.93)
Numeracy (std)	-11.55	-30.77	14.87	-1.53	-21.37	-33.48	-22.28	41.12	-5.52
	(-0.43)	(-0.99)	(0.28)	(-0.04)	(-0.62)	(-0.82)	(-0.50)	(0.49)	(-0.10)
Raven (std)	20.85	-22.95	65.26	24.45	13.46	-32.80	-12.28	109.08	36.04
	(0.81)	(-0.93)	(1.20)	(0.66)	(0.34)	(-1.25)	(-0.28)	(1.29)	(0.50)
Individuals controls	X	X		X		X			
Households controls	X	X		X		X			
Villages FE	X	X		X		X			
Observations	603	603		603		603			
R^2	0.069	0.088		0.072		0.105			
Adjusted R^2	0.016	0.023		0.006		0.011			
F-stat	2.488	1.677		1.902		1.602			
p-value	0.000	0.007		0.001		0.005			

Note: Marginal effects at representative values are reported and T-stat are in parentheses. Column 1 correspond at the average individual, column 2 at the average male, column 3 at the average female, column 4 at the average non-dalit, column 5 at the average dalit, column 6 at the average non-dalit male, column 7 at the average dalit male, column 8 at the average non-dalit female and column 9 at the average dalit female.

Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

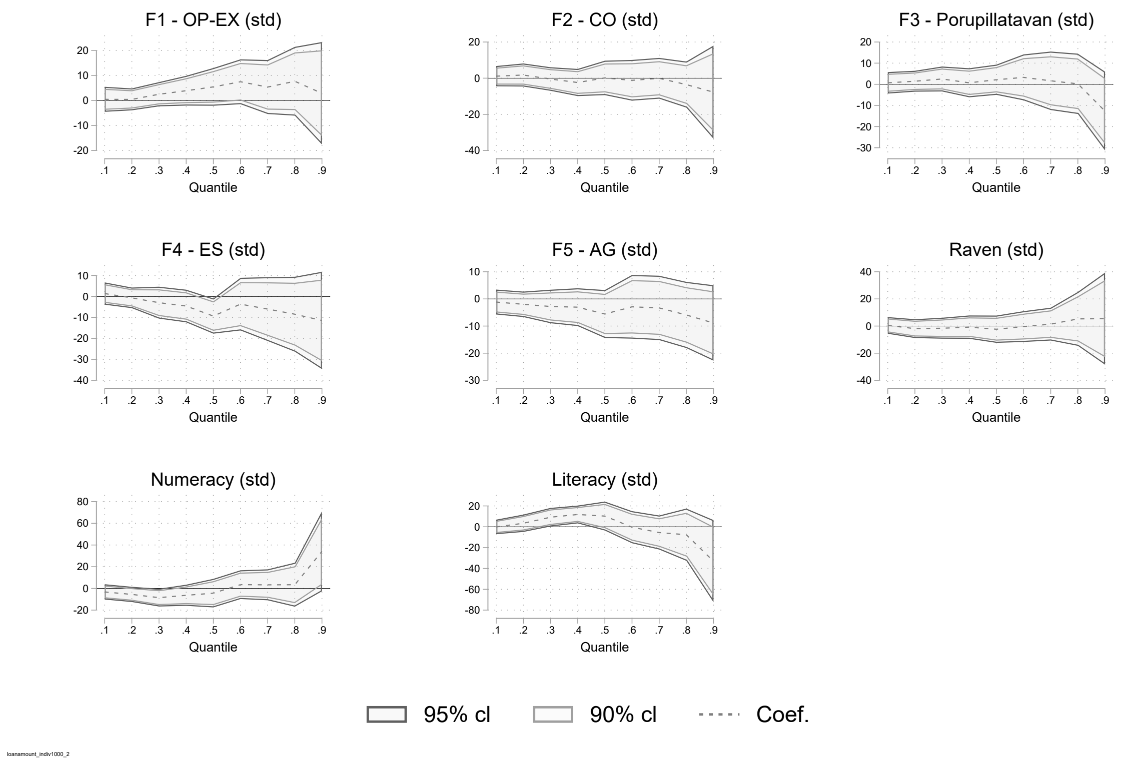

Figure 3: ME on the distribution of the total loan amount in 2020-21 estimated with quantile regression
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

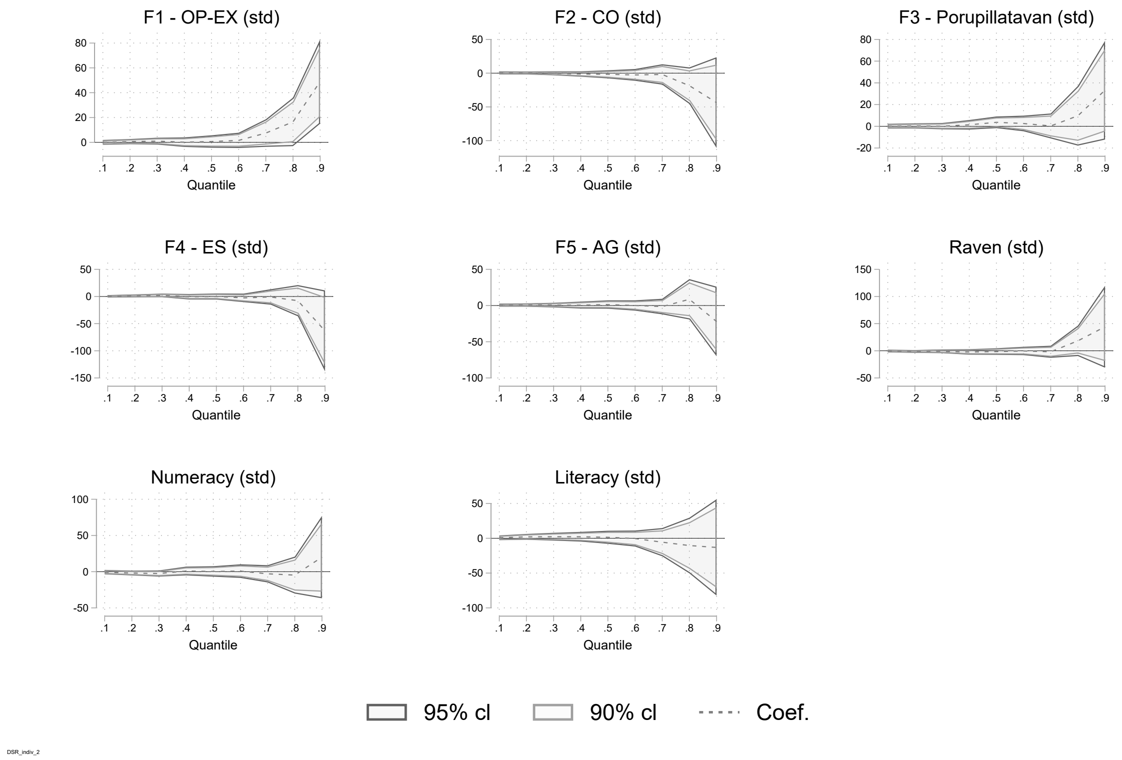

Figure 4: ME on the distribution of the individual DSR in 2020-21 estimated with quantile regression
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

Table 6: ME of the total loan amount estimated with FE model.

	(1)	(2)		(3)		(4)			
	ME/(t-stat) All	ME/(t-stat) Male	ME/(t-stat) Female	ME/(t-stat) MUC	ME/(t-stat) Dalits	ME/(t-stat) MUC male	ME/(t-stat) Dalits male	ME/(t-stat) MUC female	ME/(t-stat) Dalits female
OP (std)	7.53	-0.10	12.63	4.92	10.07	-15.78	14.94	29.13	2.01
	(0.79)	(-0.01)	(1.59)	(0.28)	(1.44)	(-0.54)	(1.39)	(1.94)	(0.26)
CO (std)	4.08	-1.49	7.94	9.71	-3.70	13.88	-24.40	1.19	11.90
	(0.47)	(-0.10)	(1.33)	(0.62)	(-0.44)	(0.52)	(-1.41)	(0.11)	(1.74)
EX (std)	-13.99	-19.61	-10.56	-3.91	-23.86	-3.67	-41.02	-14.92	-7.76
	(-1.41)	(-1.29)	(-1.24)	(-0.24)	(-2.25)	(-0.15)	(-2.29)	(-1.08)	(-0.84)
AG (std)	10.54	26.18	-2.86	0.01	23.14	13.46	47.58	-3.56	0.42
	(1.08)	(1.55)	(-0.37)	(0.00)	(1.44)	(0.71)	(1.69)	(-0.32)	(0.04)
ES (std)	-14.05	-22.88	-3.96	-32.97	4.68	-54.07	9.90	-3.41	-2.78
	(-1.11)	(-1.18)	(-0.48)	(-1.41)	(0.42)	(-1.61)	(0.59)	(-0.22)	(-0.35)
Literacy (std)	29.90	49.70	7.04	46.94	6.88	80.51	6.52	2.54	11.06
	(2.69)	(2.61)	(0.99)	(2.52)	(0.84)	(2.73)	(0.49)	(0.23)	(1.17)
Numeracy (std)	-4.46	-6.01	-3.32	-14.35	6.82	-16.78	10.61	-10.57	1.42
	(-0.71)	(-0.55)	(-0.56)	(-1.27)	(1.15)	(-0.91)	(1.01)	(-0.92)	(0.24)
Raven (std)	-12.44	-30.19	11.80	-15.84	-5.62	-37.16	-17.23	18.74	7.82
	(-1.27)	(-1.97)	(1.73)	(-0.91)	(-0.72)	(-1.51)	(-1.23)	(1.54)	(1.19)
Individuals controls	X	X		X				X	
Households controls	X	X		X				X	
Individuals FE	X	X		X				X	
Observations	1,244	1,244		1,244				1,244	
Nb of groups	733	733		733				733	
ρ	0.551	0.561		0.555				0.562	
Within R^2	0.080	0.103		0.099				0.139	
Between R^2	0.000	0.000		0.000				0.000	
Overall R^2	0.003	0.005		0.005				0.010	
F-stat	1.965	2.114		1.713				1.749	
p-value	0.006	0.001		0.012				0.002	

Note: Marginal effects at representative values are reported and T-stat are in parentheses. Column 1 correspond at the average individual, column 2 at the average male, column 3 at the average female, column 4 at the average non-dalit, column 5 at the average dalit, column 6 at the average non-dalit male, column 7 at the average dalit male, column 8 at the average non-dalit female and column 9 at the average dalit female.

Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table 7: ME on the individual DSR estimated with FE model.

	(1)	(2)		(3)		(4)			
	ME/(t-stat) All	ME/(t-stat) Male	ME/(t-stat) Female	ME/(t-stat) MUC	ME/(t-stat) Dalits	ME/(t-stat) MUC male	ME/(t-stat) Dalits male	ME/(t-stat) MUC female	ME/(t-stat) Dalits female
OP (std)	-11.00	-12.59	3.93	-6.34	-14.73	3.17	-36.52	-8.21	9.02
	(-0.63)	(-0.48)	(0.13)	(-0.26)	(-0.57)	(0.08)	(-1.59)	(-0.21)	(0.21)
CO (std)	-7.01	13.36	-25.46	8.00	-25.82	19.64	-8.45	-8.16	-24.16
	(-0.38)	(0.91)	(-0.69)	(0.31)	(-1.02)	(1.10)	(-0.44)	(-0.15)	(-0.56)
EX (std)	-2.56	33.37	-48.18	27.71	-39.86	48.06	13.92	4.89	-108.83
	(-0.14)	(1.70)	(-1.27)	(1.17)	(-1.37)	(1.38)	(0.84)	(0.12)	(-1.83)
AG (std)	5.61	-17.14	28.03	-22.07	43.16	-37.66	22.38	-6.37	70.98
	(0.24)	(-0.63)	(0.67)	(-0.73)	(1.37)	(-0.95)	(1.22)	(-0.12)	(1.01)
ES (std)	0.39	-25.31	33.28	-17.24	22.97	-39.75	-3.77	12.43	54.77
	(0.02)	(-1.36)	(0.82)	(-0.74)	(0.77)	(-1.18)	(-0.31)	(0.34)	(0.84)
Literacy (std)	15.38	28.33	3.53	14.66	19.97	40.49	8.03	-20.39	37.24
	(0.81)	(1.21)	(0.09)	(0.67)	(0.59)	(1.17)	(0.40)	(-0.39)	(0.63)
Numeracy (std)	24.82	7.96	53.36	24.83	26.48	19.40	-12.15	38.50	60.91
	(1.54)	(0.79)	(1.51)	(1.42)	(0.97)	(1.04)	(-1.00)	(1.14)	(1.19)
Raven (std)	20.50	-5.42	56.41	-4.74	45.23	-12.45	-0.93	6.88	93.60
	(1.04)	(-0.62)	(1.18)	(-0.22)	(1.31)	(-0.89)	(-0.07)	(0.13)	(1.30)
Individuals controls	X	X		X				X	
Households controls	X	X		X				X	
Individuals FE	X	X		X				X	
Observations	1,244	1,244		1,244				1,244	
Nb of groups	733	733		733				733	
ρ	0.561	0.570		0.557				0.564	
Within R^2	0.062	0.084		0.077				0.106	
Between R^2	0.007	0.009		0.007				0.009	
Overall R^2	0.009	0.012		0.013				0.018	
F-stat	1.077	0.967		0.968				0.904	
p-value	0.369	0.519		0.518				0.654	

Note: Marginal effects at representative values are reported and T-stat are in parentheses. Column 1 correspond at the average individual, column 2 at the average male, column 3 at the average female, column 4 at the average non-dalit, column 5 at the average dalit, column 6 at the average non-dalit male, column 7 at the average dalit male, column 8 at the average non-dalit female and column 9 at the average dalit female.

Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

A Stability of skills over time

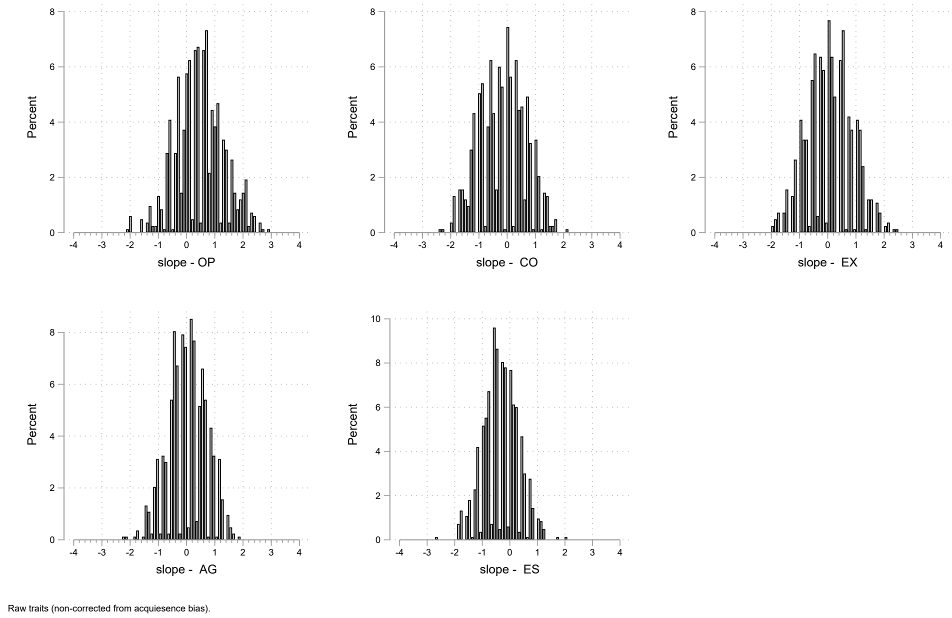

Figure 5: Stability over time of Big-5 personality traits non-corrected from acquiescence bias – Distribution of the difference of the score between 2016-17 and 2020-21 for Big-5 personality traits non-corrected from acquiescence biais for 835 individuals from rural Tamil Nadu, India. **Source**: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

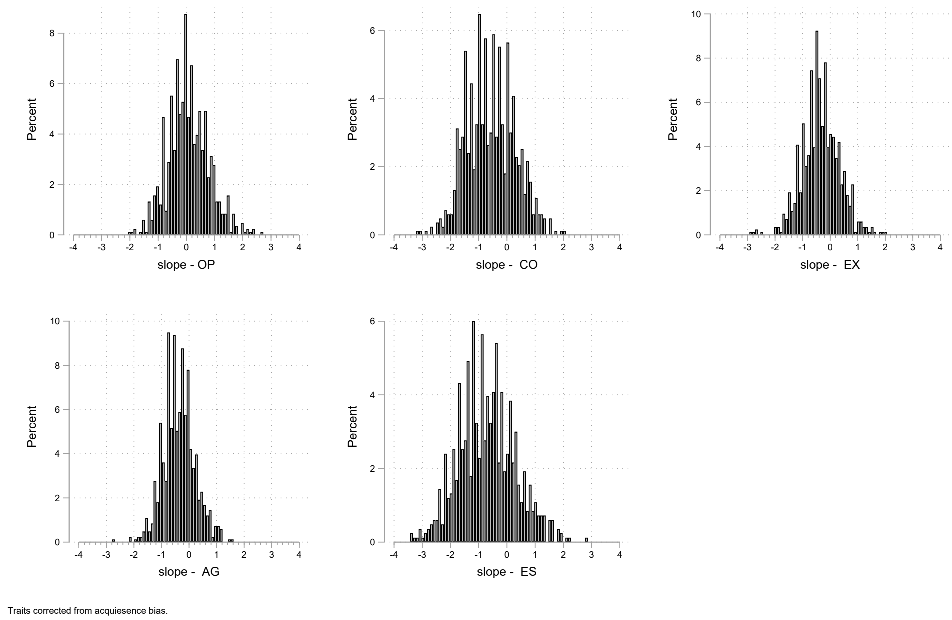

Figure 6: Stability over time of Big-5 personality traits correted from acquiescence bias – Distribution of the difference of the score between 2016-17 and 2020-21 for Big-5 personality traits corrected from acquiescence biais for 835 individuals from rural Tamil Nadu, India.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

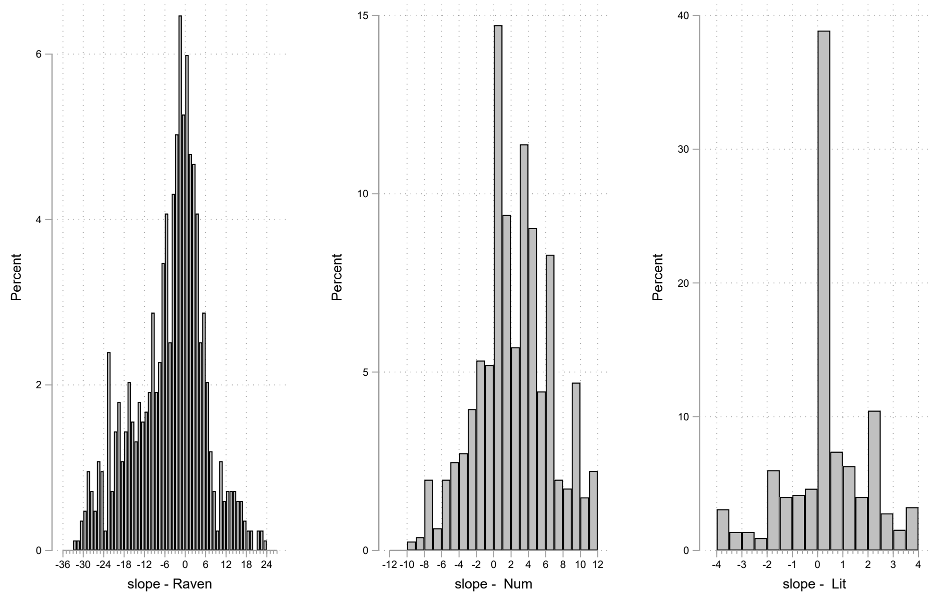

Figure 7: Stability over time of cognitive skills – Distribution of the difference of the score between 2016-17 and 2020-21 for three cognitive skills for 835 individuals from rural Tamil Nadu, India.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

B Factor analysis for personality traits

Table 8: Details for personality test questions

Variable	Question	Big-5 traits
curious	Are you curious, interested in learning new things?	OP
interestbyart	Are you interested in nature, art or music?	OP
repetitivetasks	Do you prefer work that involves repetitive tasks and routines?	OP
inventive	Are you inventive, and discover new ways of doing things?	OP
liketothink	Do you like to think a lot, and reflect about ideas?	OP
newideas	Do you come up with original or new ideas?	OP
activeimagination	Do you have an active imagination?	OP
organized	Are you organized?	CO
makeplans	Do you make plans and stick to them?	CO
workhard	Do you work hard to do things well and on time?	CO
appointmentontime	Do you get to work and appointments on time?	CO
putoffduties	Do you put off your duties in order to relax?	CO
easilydistracted	Do you get easily distracted?	CO
completeduties	Do you complete your duties on time?	CO
enjoypeople	Do you enjoy being with people?	EX
sharefeelings	Do you easily share your thoughts and feelings with other people?	EX
shywithpeople	Are you shy with people?	EX
enthusiastic	Are you enthusiastic and full of energy?	EX
talktomanypeople	In social gatherings, do you like to talk to many people?	EX
talkative	Are you talkative?	EX
expressedthoughts	Are you comfortable expressing your thoughts and opinions to others?	EX
workwithother	Do you work well with other people?	AG
understandotherfeeling	Do you try to understand how other people feel and think?	AG
trustingofother	Are you generally trusting of other people?	AG
rudetoother	Do you tend to be rude to other people?	AG
toleratefaults	Do you tolerate faults in other people?	AG
forgiveother	Do you forgive other people easily?	AG
helpfulwithothers	Are you helpful with others?	AG
managestress	Do you manage stress well?	ES
nervous	Do you get nervous easily?	ES
changemood	Do you have sudden changes in your mood?	ES
feeldepressed	Do you feel sad, depressed?	ES
easilyupset	Do you get easily upset?	ES
worryalot	Do you worry a lot?	ES
staycalm	Do you stay calm in tense or stressful situations?	ES

Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21)

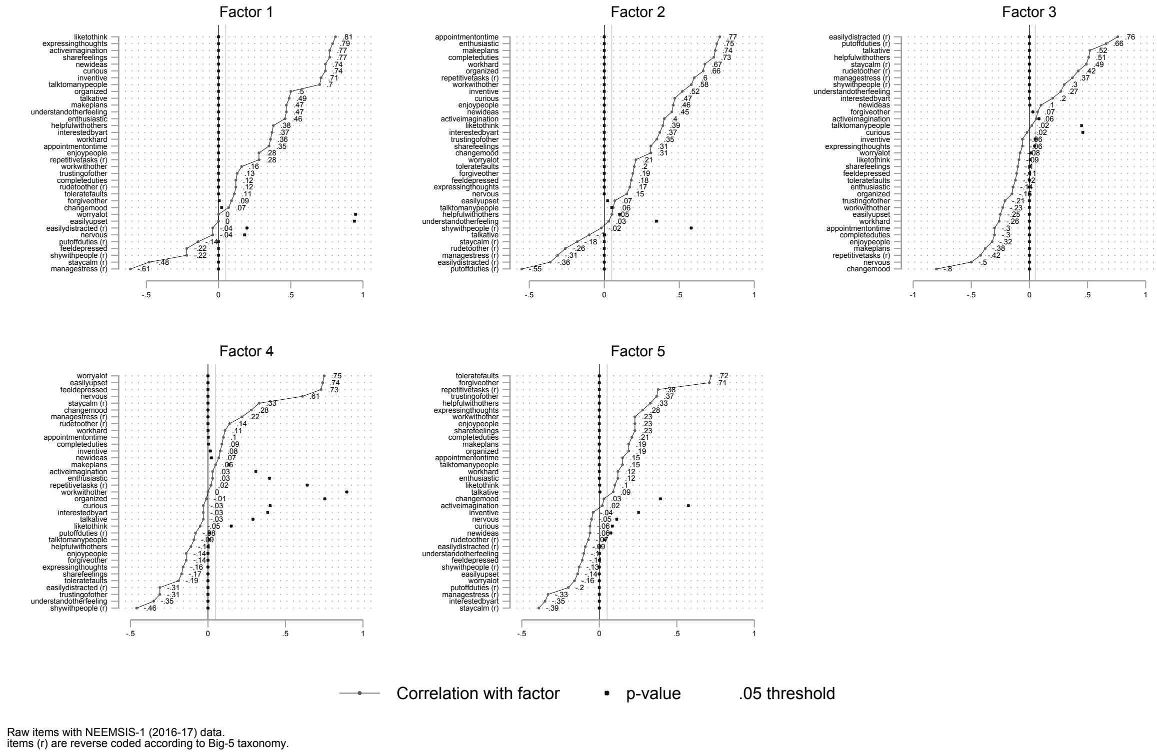

Figure 8: Results of factor analysis for 2016-17 raw items
Source: NEEMSIS-1 (2016-17); author's calculations.

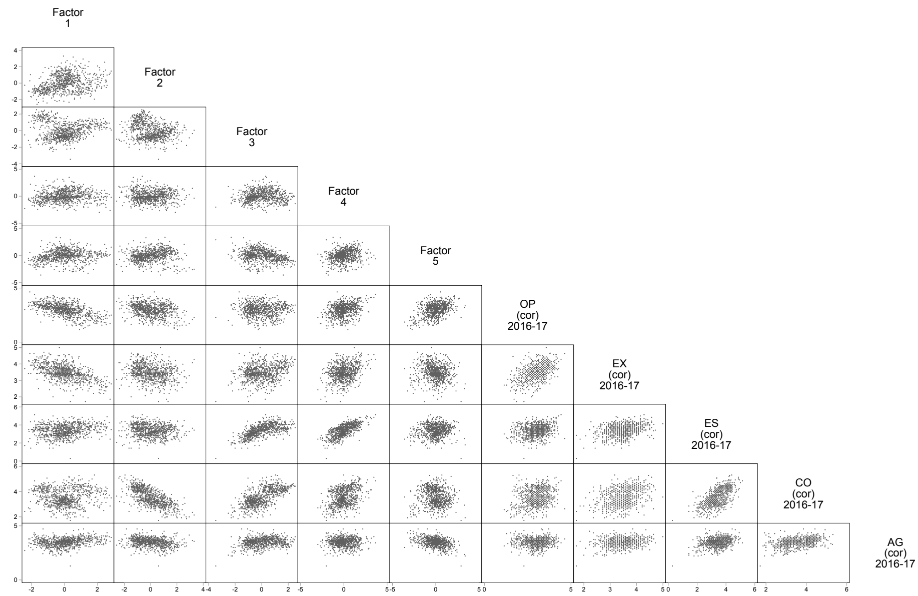

Figure 9: Correlation between Factor from EFA and Big-5 personality traits
Source: NEEMSIS-1 (2016-17); author's calculations.

Contents