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

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Abstract

Using individual 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. 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 XXX are generally significantly associated with XXX. The results also suggest that the magnitude and statistical significance of the association between personality traits and debt differs across caste and gender, suggesting the heaviness of these social identities. Our preliminary results call for further exploration of the nature and the variety of socioeconomic barriers facing disadvantaged groups in rural India.

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 personality traits in economics. They show that psychological variables are a good predictor of socioeconomic success and especially on labour market[1]. Institutions –such as World Bank– collect more and more data[2] on PT&CS because it enable a better understanding of skill requirements in the labor market, backward linkages between skills acquisition and educational achievement, personality, and social background, and forward linkages between skills acquisition and living standards, reductions in inequality and poverty, social inclusion, and economic growth (Valerio, Sanchez Puerta, Pierre, Rajadel, & Monroy Taborda, 2014).

Often 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 organization within the individual of those psychophysical systems that determine his characteristics behavior and thought (Allport, 1961). The Big-5 model constitute the main personality trait taxonomy[3]. It identifies five dimensions of personality: neuroticism or emotional stability –ES– (the capacity to experience negative emotions); extraversion –EX– (the 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 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 focuses on the role of PT&CS on labour market and especially on income gap, performance at work and type of work or education through educational attainment, course grades or standardised achievment test scores but few researcher have been interested in the relationship with household finances while it is a growing area of interest.First, household are more implicated in financial decision such as privatization of retirement pension, liberalization of loan market, increase in credit purchase, which are more complicated because of financial innovation (Guiso & Sodini, 2013). Second, financial inclusion policies focus on credit as a potential tool for business creation, improved access to education and health, enhanced decision-

[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.

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

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 –if 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 source of impovrishment and destruction. The choice of terms reflects the 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 predictor of financial risk tolerance as Bucciol and Zarri (2017) whose show that agreeableness, cynical hostility and anxiety are good predictor of financial risk taking for 11,000 individuals from USA (negative correlation). 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 one of the only who deal with causality. Using instrumental variable[4] on Dutch dataset, 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 of UK and Forlicz and Rólczyński (2019) show differences between debtors and debt-free individuals in terms of conscientiousness, honesty, attittude towards money and shoppping for 3,700 individuals from Poland, Spain, Romania and Italy.

To our knowledge, no articles has looked at personality trait[5] and cognitive skills on debt in India (nor even in developing countries) while understand the relationship is essential in the

[4]They instruments conscientiousness and emotional stability with childhood trauma.

[5]Michiels, Nordman, and Seetahul (2021) interesting in the link between PT&CS and labour mobility. Dasgupta, Mani, Sharma, and Singhal (2020) interesting 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) examined the relations among the big five personality traits, emotional intelligence, and happiness.

indian context because of the uniqueness of indebtedness.

Since the 80's, the incidence of indebtedness increase for rural and urban households (respectively from 19 to 32% and from 17 to 22%) with an increasing in the share of household indebted to formal (or institutional) sources (11 to 17%) and informal sources[6] (10 to 19%) (Rajakumar, Mani, Shetty, & Karmarkar, 2019). As we discuss in section 2.1, the incidence of debt is largely under-estimate (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 83 INR to 32,522 INR) with an increasing 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 the caste affect borrowing strategies as amount, type and source of debt in rural Tamil Nadu, India. Dalits, have 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 the lower access[7] to bank loans while it offer 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 female than for male while male earn much more. Moreover, female in the poorest households have the highest borrowing responsibilities and dalit female tend to face higher debt burdens than non-dalit one. In terms of use, male borrow more for economic investment while female more for daily survival and debt repayment (Reboul et al., 2021). Recents 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 exacerbate disparities between caste and sex to the detriment of dalits and female, 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 represent more than money, it is a social link closely nested in social relationship and individual defining them and thinking of them according to their indebtedness (Guérin, 2014). Moreover, trust and reputation play a crucial role by conditioning creditworthiness (Guérin, Michiels, et al., 2021). This sociological and anthropological structuralist approcahes recognises that individuals cannot be considered 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 concerns is find in aspirations. Mukherjee (2017) show that gender and caste primes

[6] In part due to the economic and financial sector reforms of 1991: http://indiabefore91.in/1991-economic-reforms - Accessed August 10, 2021.

[7] In part, because of they does not have 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 (Guérin et al., 2013).

can significantly affect long run aspirations and beliefs. Alvi, Ward, Makhija, and Spielman (2019) use priming[8] to study the effect of identity salience on aspirations. They find that when female 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. Indeed, the most socially disadvantaged groups have significantly lower income aspiration when compared to Other Backward Class and Other Caste participants and female participants also have significantlty lower aspiration than their male counterparts. Moreover, most socially disadvantaged female participants have lower income aspiration levels compared to other groups.

Beyond being a source of inequality, caste and gender seems to deeply impact individuals by conditionning them. In this context it appears important to investigate the role of PT&CS on indebtedness in take 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 varies across the indebtedness distribution? (ii). Then, we analyse how does debt change over time as PT&CS changes? (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 PT&CS for economic outcomes and aim to articulating behavioural and structuralist approcahes, disjoint disciplinary approaches. The rest of the article is organised as follow: section 2 is devoted to data and methodology, then, in section 3 we discuss some descriptive statistics to highlight the weight of social identity before exploring and discussing the relationship between PT&CS and indebtedness in section 4.

[8]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.

2 Data and methodology

2.1 Data

Our empirical analysis is based on the 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). This survey was the second and third waves of a longitudinal data collection project 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 are irrigated (the other half have dry lands) 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 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's surveys stands 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 data sets) "data accuracy is [...] reflected by an incidence of indebtedness found higher than in the estimates of the nation-wide 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.

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

2.2 Construction of personality traits & cognitive skills variables

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

Regarding Big-5, on the basis of 35 questions, 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 represent the score on each traits.

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 acquiesence 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-Five 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 recoded reverse questions beause it might force likeness with Big-5 taxonomy. In our dataset, acquiesence 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 stability ($\Omega = 0.78$) and Factor 5 as Agreeableness ($\Omega = 0.62$) (see Appendix B) while resulting factors for 2020-21 data

[10] Raven test 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.

[11] Acquiescence bias represent 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 most wide 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 differents from Big-5 taxonomy firmly stood out.

are very different to the Big-5 taxonomy and to the 2016-17 factors[14].

To mitigate against the potential problem of life-cycle events –that might induce endogeneity through measurement error– [or 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 or net of life cycle influences (Brown & Taylor, 2014; Groves, 2005; Nyhus & Pons, 2005).

The exogeneity of PT&CS is well assume 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 economist[15] 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). The stability refutes sociological and psychological literature which interesting in the influence of childhood and adulthood socialization on personality (Moen, Elder Jr., & Lüscher, 1995; Mortimer & Simmons, 1978). Following this path, 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, and if personality aspects other than the big five [...] traits are assessed." Our results show a 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.

Concerning cognitive skills, majority of individuals have higher –or equal– score in 2020-21 than in 2016-17 (see Appendix A) which coroborate with the lifelong learning theory. It is 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 under-estimate the burden of debt in ousting personal feeling and sacrifice associated with debt (Betti, Dourmashkin, Rossi, & Yin, 2007).

Subjectives measure assume 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 &

[14] We do not present results here because we do not use it as personality traits measure, however it is available on request. See section 2.4.

[15] But not all, see Almlund et al. (2011); Borghans et al. (2008); Heckman (2011). As stated by Heckman (2011), "Personality traits are not set in stone. They change over the life cycle. They are a possible avenue for intervention and policy."

Iezzi, 2013). As stated by Rinaldi and Sanchis-Arellano (2006) and Keese (2012), in general, objective measures align quite well with subjective measures at the household classification level.

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 measures have little meaning since most of the debt is informal.

It is recommended to analyse indebtedness at household level because generally 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 three 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). It represent 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 being in debt to capture the incidence of debt.

2.4 Econometric framework

In order to better understand the relationship, our analysis take place in three step.

How PT&CS shape individual debt? In a first step, we use the five factor 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 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 this 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 but not the amount of debt. 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. 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. Duca and Rosenthal (1993) and Crook (2001) assumed that the same variables determined the probability of having debt and the amount borrowed. del Río and Young (2006) used localisation, race and employment status. However, their results from Heckman procedure are no different from those from OLS regressions, suggested that "any corner-solution biases are small". Therefore, they focus separatly on the participation equation and on debt equations (excluding non-participants). As exclusion restriction variables from literature are not relevant in our context and as we do not have the sufficient theoretical background, we follow del Río and Young (2006) in focusing separatly on the participation equation and on debt equations in excluding non-participants. We also 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 [available on request] are no different from those from OLS regression, suggested that the non-random sample selection issues is small, which coroborate with literature (Brown & Taylor, 2014; del Río & Young, 2006). Another way to estimate our model is to use tobit model which allow 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:

- Individual level variables as age; age square; sex; dummy variable which take 1 if individual is the household head, 0 otherwise; main occupation[16]; number of occupation (dummy variable which take 1 if individual declare more than one occupation, 0 otherwise); dummy variable which take 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).
- Household level variables as caste; monetary value of assets[17]; sex ratio; total annual income; household size; shock exposure (dummy variable which take 1 if the household experienced a shock[18] 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 indebtedness situation in t in adding dummy variable which take 1 if individual is indebted in 2016-17, 0 otherwise.

In order to investigate the amount of debt and the burden of repayment (Y_i), we use OLS (eq. 2). Despite the fact that DSR is a share, we do not use GLM because of the upper bond 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 strength of social identity we investigate relationship on a pooled sample of egos with interactions variables to maximize statistical power, although splitting

[16] Define as the most time-consuming activity.
[17] The monetary value of assets includes gold; land; house; livestock; agricultural equipment and consumption good (car, computer, cookgas, phone, etc.).
[18] Marriage of at least one of the household members or/and household surveyed after the demonetisation.

samples improves model specification[19] . 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 wether 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 choose to cluster the error at households 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.In terms of debt, as stated by Reboul et al. (2021), "our data is limited, [but] it 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 obtains nine groups of ME for each PT&CS variable: average individual; average male; average female; average non-dalits; average dalits; average non-dalits male; average dalits male; average middle-upper caste female and average dalits female.

We use Big-5 taxonomy as robustness check.

How the PT&CS varies across the indebtedness distribution? As OLS regression is mean reasoning, we supplement this analysis with quantile reasoning to understand 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 respectively at P10, P25, P50, P75 and P90 of the distribution. Controls variables remain the same and we also cluster the error at households 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[20] individual fixed effect regressions (eq. 3) in order to compare within individual 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 factor 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 allow 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).

[19] The statistical power is not maximize if we use split samples.

[20] 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).

$$Y_{it} = X'_{it}\beta_1 + C'_{it}\beta_2 + Z'_{it} * \beta_3 + \alpha_i + e_{it} \tag{3}$$

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 relationshipt 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.

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. The sex ratio is different through caste: in 24% of dalits households the sex ratio is equal to 1 which mean that they are as many men as women while in middle-upper caste, it is 34% of households in 2016-17. In terms of assets, middle-upper caste households are three times richer than dalits on average –respectively 1,493k INR and 487k INR in 2016-17. 50% of middle-upper caste have less than 666k INR of assets while 50% of dalits households have less than 266k INR 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 households, it decreased by at least 22%. However, middle and upper caste still have higher amount of assets in 2020-21. This economic advantage of non-dalit households is also found with income: the median income of middle-upper caste 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 households the total income decreased by at least 4% and for 50% of non-dalits households, 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 male and among them, 46% are dalit (among female 50% are dalit). Male are, on average, older than female and three quarters of them are the head of household while female 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, is the wife who takes over as household head. In terms of education, male are more formal educated than female.

Disparities in terms of gender are also found in the occupation. Despite the increasing of the number of female in agriculture and the decreasing of the number of male in self-employment, this activities are mostly reserved for male. The reverse assessment is true for salaried job in agriculture: between 2016-17 and 2020-21 the share of male increase by 47% (from 16% to 24%) but female remain relatively more numerous (27.42% in 2016-17 and 29.58% in 2020-21). Whatever the gender, non-agricultural salaried job remain stable over time and the share of male implicated is similar to the share of female (around 37%). Non-income generating work as the main occupation is over-represented for female while even though the share fell considerably between 2016-17 and 2020-21 (from 24% to 15%). Moreover, female are more likely to have multiple occupations and this probability increase between 2016-17 and 2020-21 (from 50% to 60%). In terms of income, disparities persist between male and female. On average, male have 102,000 INR per year as labour income while female have 19,000 INR. Between 2016-17 and 2020-21, the average variation rate is higher for female than for male (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 acquiesence bias. The distribution of personality traits from Big-5 taxonomy and factor analysis seems to corroborate. Indeed, in 2016-17, it appear that male tend to have higher score for each traits: they are more open to experience, conscientious, extraverted, agreeable and emotional stable. When we compare 2016-17 distribution with 2020-21 one, we observe that, male –taken as a whole– have slightly lower score for openess to experience and extraversion while female have slightly higher one. Distribution of conscientiousness is more platikurtic and shifted to the right in 2016-17 than in 2020-21 for male: taken as a whole, male are less conscientious in 2020-21 than in 2016-17. The assessment is reverse for female. Distributions of agreeableness of 2020-21 are more platikurtic for male and female: taken as a whole, a more important share of male/female is very/less agreeable in 2020-21 than in 2016-17. Conversely, distributions of 2020-21 for emotional stability are more leptokurtic for male and female. Concerning cognitive skills, distributions of RPM are more shifted to the left in 2016-17 than in 2020-21: taken as a whole, a more important share of male/female have a low score at RPM in 2020-21 than in 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 have a high score in 2020-21 than in 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. Female are more vulnerable than male in the sense that the share of individual never in debt is lower for female than for male (respectively 10% and 14%) and the share of individual becomes in debt between 2016-17 and 2020-21 is higher for female than for male (respectively 14% and 8%). To finish with the path, we observe that more than six out of ten individuals remains indebted. Our sample of indebted individual consists of 643 individuals in 2016-17 and 606 individuals in 2020-21 whose 516 are indebted in 2016-17 and in 2020-21. Male have a higher absolute amount of debt than female (two times more in 2016-17: 190,000 INR for male while 80,000 INR for female) despite a reduction in the amount between 2016-17 and 2020-21 (for 50% of male, debt has decreased by more than 57%). On the other hand, 50% of female saw their debt increased by more than 24% (on average, in 2016-17 a female has a debt of 80,000 INR, while it is at 90,000 INR in 2020-21. Male spend less of their annual income on debt repayment than female: in 2016-17 50% of male spend 27% of their annual income on debt repayment and 12% in 2020-21 while female spend 32% in 2016-17 and 77% in 2020-21. Furthermore, 50% of male have seen their DSR decreased by at least 0.27% while 50% of female 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 (ME) at representative values on the predicted value of the PT&CS are reported for the four specifications as describe previously. According to specifications, the representatives values are: (1) the average individual (“All”); (2) the average male (“Male”) and the average female (“Female”); (3) the average non-dalits (“MUC”) and the average dalits (“Dalits”); (4) the average non-dalits male (“MUC male”), the average dalits male (“Dalits male”), the average non-dalits female (“MUC female”) and the average dalits female (“Dalits female”). All of PT&CS are standardised to ensure comparability between them. We will therefore speaks 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 come from the low range of definitions of PT&CS variables. For personality traits, ranging around 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 the results from the multivariates probit analysis of the probability for an individual to be indebtedness. McFadden's pseudo R^2 indicate 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 skill –whatever the specification– are not correlated with the probability of being indebted in 2020-21 at 95% confidence level (cl), except for literacy which is positively correlated for the average female at 90% cl.

However, three of the personality traits are correlated at the 95% cl. Factor 1 as OP-EX 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 OP-EX increase by one standard deviation, the probability of being in debt decrease 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 CO 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 ES is associated by a decreasing of 6.2 pp of the probability of being in debt. Regarding AG, it is negatively correlated for the average non-dalit individual and especially for the average non-dalit male with lower magnitude than for CO (-6.7 pp compared to +8.5 pp). Last, when CO 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 multivariates OLS analysis of the first outcome of the burden of debt, 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 the previous one: 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 dalits female: all else being equal, when Raven score increase by one standard deviation, predicted total loan amount increase by 21,000 ₹. At 90% cl, numeracy is also correlated for the average dalits female, but positively and with lower magnitude (-16,000 ₹). Relationship between debt and Raven is reverse for the average non-dalit female with higher magnitude than for dalit female (+33,000 ₹).

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, OP-EX 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 OP-EX is associated by a increasing of 49,000 ₹ of the total loan amount, other things equal. Always for the average middle-upper caste male, the strengh of the negative relationship with CO is high enough (-64,000 ₹) compared to other relationship. Last, AG is negatively correlated for the average dalits and especially for the average dalit female (-15,000 ₹).

At 90% cl, new relationship appears for Factor 1 and 3. When OP-EX increase by one standard deviation, predicted total amount borrowed increase by 13,000 ₹ other things equal, for the average dalits female. Last, when the average individual is one sd more *Porupillatavan*, the total loan amount decrease by 19,000 ₹, all else being equal. The relationship is stronger for the average male (-24,000 ₹) and for the average non-dalit individual (-29,000 ₹).

[Table 4 around here]

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

The results show that 2016-17 cognitive skill are not correlated with the individual DSR at 95% cl neither at 90%.

As for the previous analysis, Factor 1 is positively correlated with the share of the annual income dedicated to debt (capital and interest) repayment and especially for average female and average dalits female at 95% confidence level. Indeed, for the average dalit female, when OP-EX increase by one standard deviation , the predicted DSR increase by 98 pp, all else being equal. CO is negatively correlated for the average individuals and the magnitude of the correlation is similar to that of Factor 1 (49 pp in more for OP-EX and 48 pp in less for CO, other things equal).

Porupillatavan and ES are correlated with the amount of debt if we accept a 10% risk of error, especially for the average non-dalit female. While the relationship is positive for Factor 3, the one with Factor 4 is negative and stronger (respectively +93,000 ₹ and -136,000 ₹).

[Table 5 around here]

4.2 How PT&CS varies across the indebtedness distribution?

Figures 3 and 4 presents the results from the quantile regression on the total loan amount and DSR.

Only Factor 4 as Emotional stability, numeracy and literacy are correlated at 95% confidence level with the total loan amount (see Figure 3). Regarding ES, between P10 and median (P50) correlation declining –to become more negative– but still insignificant untile median: when ES increase by one standard deviation, conditional distribution of total loan amount at median decrease by around 10,000 ₹, other things equal. At P30, numeracy is also negatively correlated (around -10,000 ₹) and between P30 and P40 correlation with literacy increasing (from +9,000 to +12,000 ₹). At 90% cl numeracy and literacy becomes correlated at P90 (respectively +35,000 ₹ and +30,000 ₹).

Regarding individual DSR, the coefficient of OP-EX varies across the distribution (see Figure 4) with ME being higher at the end of the distribution at 95% cl. ME of OP-EX is 20,000 ₹ at P80 and 45,000 ₹ at P90, all else being equal. Last, at 10% risk of error and at P90 ES is negatively correlated with higher magnitude than OP-EX, other things equal (-50,000 ₹).

[Figure 3 around here]

[Figure 4 around here]

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

Total amount of debt Table 6 presents the results from the one-way individual fixed effect regressions to understand how does total loan amount change over time as PT&CS changes. ρ (the intraclass correlation) is quite high which mean 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 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.

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 increase by 81,000 ₹, 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 +12,000 ₹ and -30,000 ₹).

Regarding personality traits, EX is negatively correlated for the average dalit and especially for the average dalit male at 95% cl (-41,000 ₹). OP and CO are positively correlated respectively for non-dalit female (+29,000 ₹) and for dalit female (+12,000 ₹) 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 does individual DSR change over time as PT&CS changes. ρ (the intraclass correlation) 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 simultaneous coefficient nullity test (F-stat) are higher than 0.05 threshold, which mean that, simultaneously, all regression coefficients in the model are equal to zero, however, this does not prevent variables taken independently of each other from being significantly different from zero, other things equal.

At 95% confidence level , neither personality traits, neither cognitive skills are correlated with the total loan amount. Only EX is correlated at 90% cl for the average male and the average dalit female. Respectively, when EX is one more sd, the predicted individual DSR increase by 33 pp for the average male other things equal, and it decrease 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 statistics reveal a number of important insights and recognize that behavioural and structuralist are meaningful and need to be articulated to deepend understand indebtedness. The role of PT&CS is heterogenous depending on the gender and the caste of individuals, and magnitude differs across skills, groups and output. In what follows, we use our findings and literature on PT&CS and indebtedness to provide answers to our 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 mistake, neither numeracy, literacy or Raven have a significant correlation on the probabilty of being in debt. This result illustrate the universality of debt: there is no need to have minimum level of numeracy or literacy to get into debt

Looking at personality traits, we have first identifies the crucial role of OP-EX and CO in shaping debt. As shown in the literature (Brown & Taylor, 2014), OP-EX is positively correlated with the probability of holding debt and positively correlated with the amount of debt. Our results suggest negative relationship with the probabilty of being in debt only for non-dalit female and positive relationship with the level of debt (total amount and DSR) for non-dalit male and dalit female. This interesting pattern can be explained by **what?**. Brown and Taylor (2014); Donnelly, Iyer, and Howell (2012) find that conscientiousness is inversely associated with the level of unsecured debt. Our findings corroborate for the total loan amount and the individual DSR, but we find positive correlation with the probability of being in debt while Brown and Taylor (2014); Nyhus and Webley (2001) find negative relationship. It **suggest that** individuals who are more conscientious are more able to "manage their money through greater levels of financial self-control." Last, regarding AG, 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 **suggesting that**

More globally, it seem that in our context, cognitive skills not shape indebtedness situation while personality traits such as OP-EX and CO are a good predictor of future debt.

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

Quantile regression results show that Raven is correlated (positively) with the total amount of debt for dalit female, all else being equal, and numeracy and literacy are negatively correlated with the amount of debt in the first 30-40% of the distribution and positively correlated in the last decile. In terms of personality traits, it appear that ES is negatively correlated at median with the amount of debt and OPEX have positive relationship with individual debt service ratio at last 20-10%. Findings illustrate **what?**

We can therefore conclude that

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 amount and EX is negatively correlated. This pattern can be explained by **what?**.

Thereby to answer to our question,

5.4 Do individuals manage to differentiate themselves through their skils?

The last key result of our analysis lies in the disparities between caste and sex. Among female, dalits with higher AG and Raven have higher amount of debt than other, other things equal. Also, those with higher OP-EX have higher individual DSR. It **suggest that** Among non-dalit, those with higher OP-EX and more *Porupillatavan* differ from others because they have lower probability of being in debt. This interesting finding illustrate **what?**.

Regarding dalit male, those with higher EX have lower amount of debt than other, all else being equal, **suggesting that**. Non-dalit male are the group in which individuals stand out the most by their PT&CS, other things equal. Indeed, those with higher CO are more likely to be indebted, but among indebted one, those with higher CO tend to have a lower amount of debt. This pattern can be explained by **what?**. Moreover, for them, OP-EX and literacy are positively correlated with the amount of debt.

Oui, certaines se démarquent, en bien ou en mal, mais dans tous les groupes, certains individus arrivent à mieux s'en sortir que d'autres graces à leurs compétences.

5.5 Concluding remarks

This paper reveal a number of important insights. Personality traits and cognitive skills are correlated with the probability of being in debt, the amount of debt and the burden of debt in rural India at different magnitude according to caste and sex. Another findings, effect of OP-EX, ES, numeracy and literacy varies across the debt distribution.

As Brown and Taylor (2014) on montre l'importance des PT&CS dans l'analyse des finances

Numerous study reveal the gravity of the burden of debt for female and dalits, with double-jeopardy phenomenom. Here we highlight the fact that in this social identity, there is considerable differences.

Numerous study have highlighted disparities in terms of debt between caste and gender. Nous sommes les seules à avoir creusé encore plus précisément pour savoir si des gens s'en sortaient mieux que d'autres à l'intérieur de ces identités sociales.

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Tables and figures

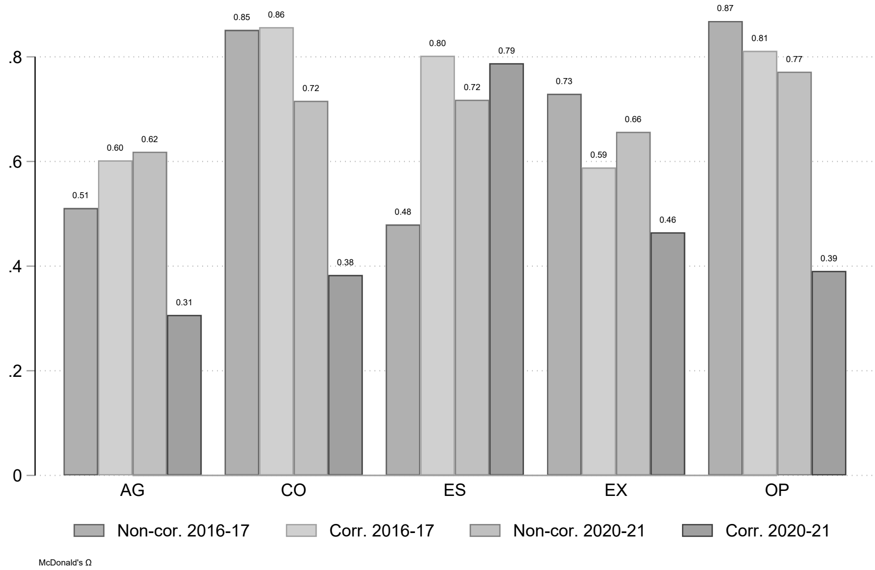

Figure 1: Internal consistency of Big-5 personality traits – Distribution of McDonald's Ω through time and correction for 953 individuals in 2016-17 and 1,316 in 2020-21 from rural Tamil Nadu, India.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

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* (1,000 INR)						
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† (1,000 INR)						
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 (1,000 INR)						
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 (1,000 INR)						
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.

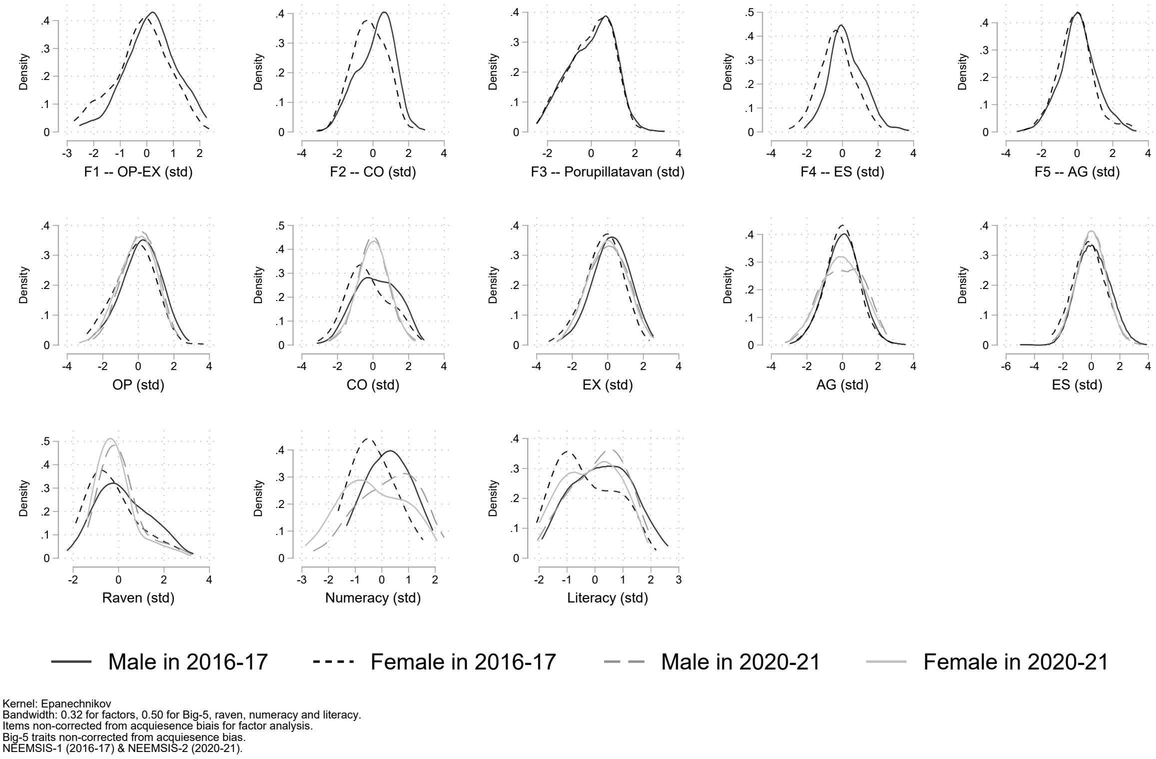

Figure 2: Distribution of PT&CS – The resulting PT&CS are based on the standardised residual from univariate OLS regression with age as exogenous variable. This is PT&CS purged from life-cycle effects.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

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.

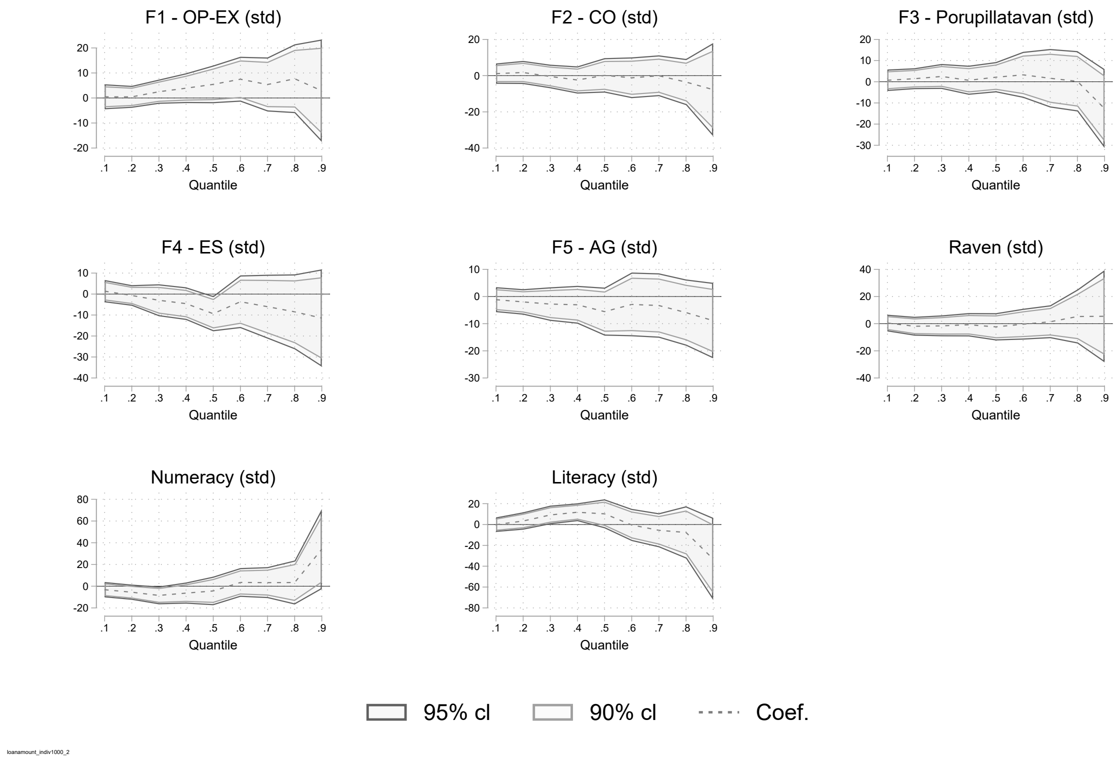

Figure 3: ME on the distribution of the total loan amount in 2020-21 estimated with quantile regression
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

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.

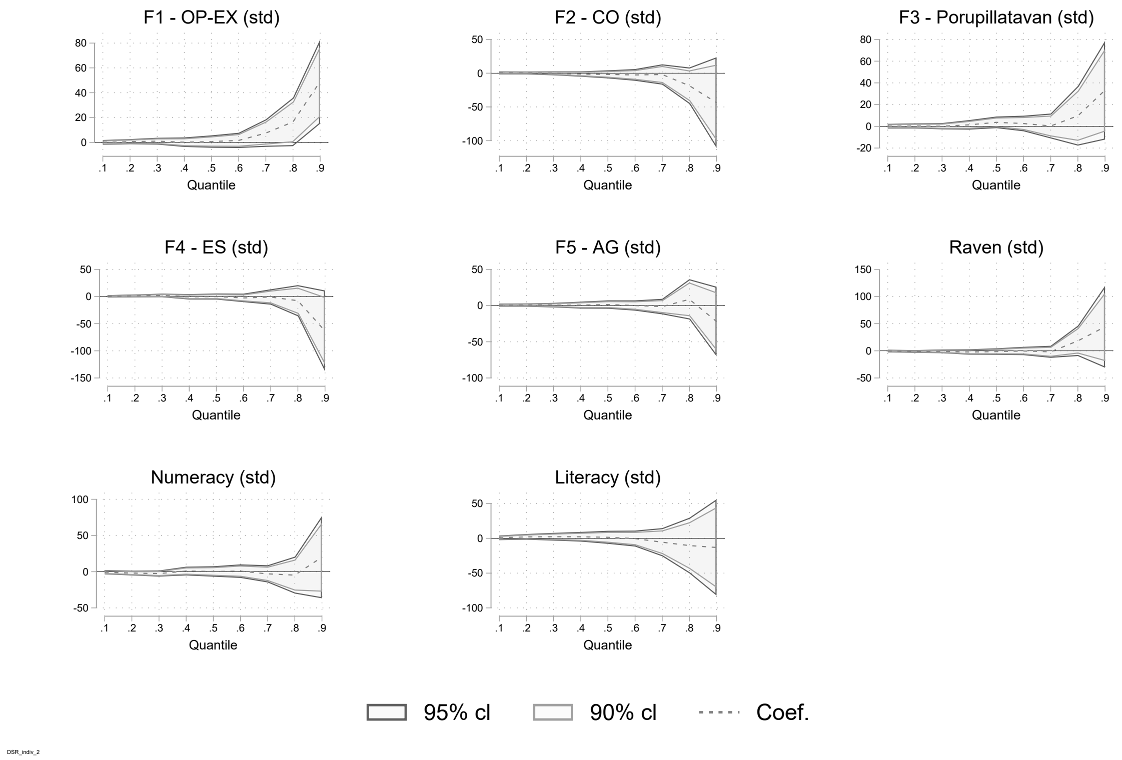

Figure 4: ME on the distribution of the individual DSR in 2020-21 estimated with quantile regression
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

Table 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

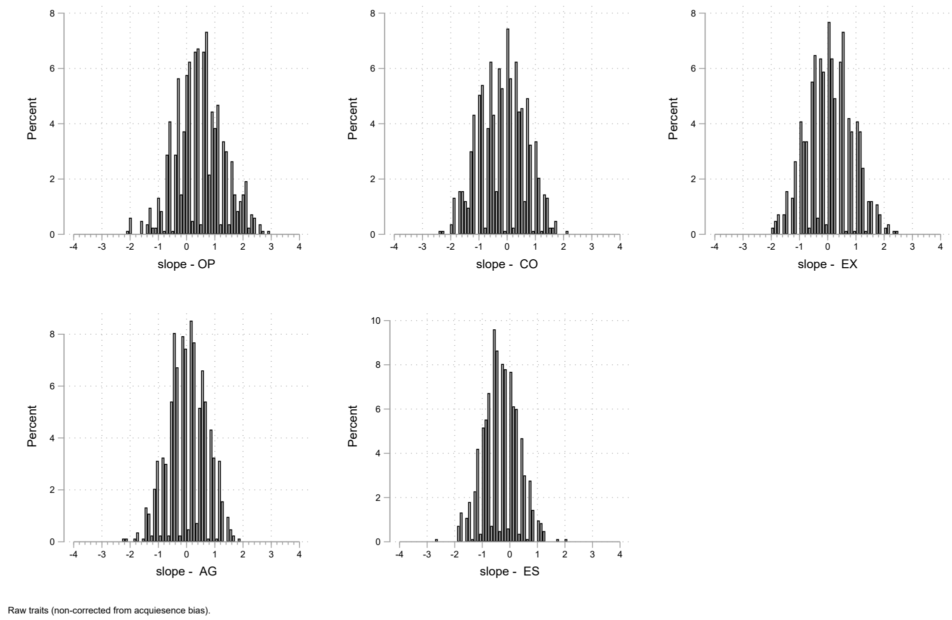

Figure 5: Stability over time of Big-5 personality traits non-corrected from acquiescence bias – Distribution of the difference of the score between 2016-17 and 2020-21 for Big-5 personality traits non-corrected from acquiescence biais for 835 individuals from rural Tamil Nadu, India.
Source: NEEMSIS-1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

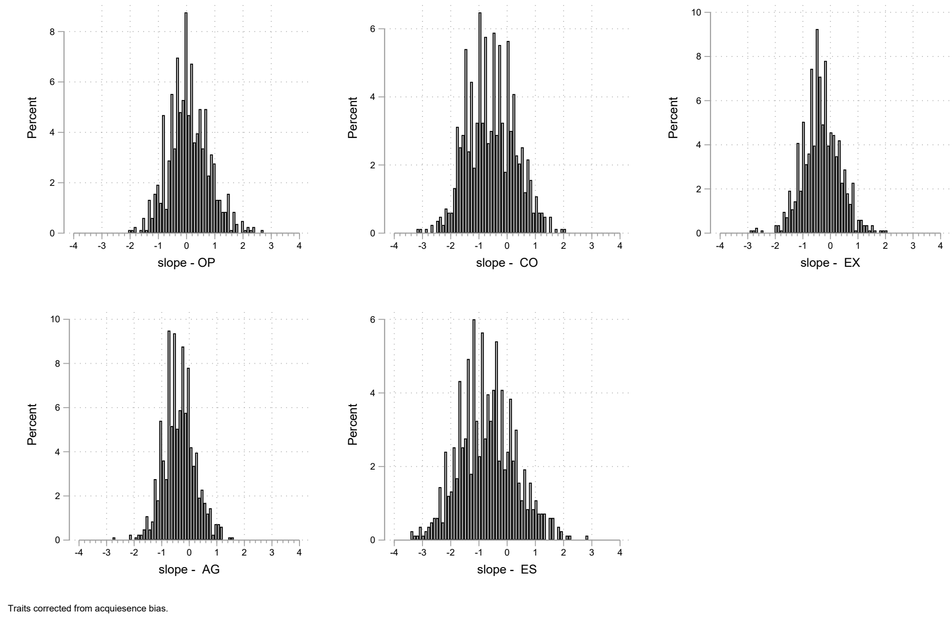

Figure 6: Stability over time of Big-5 personality traits correted from acquiescence bias – Distribution of the difference of the score between 2016-17 and 2020-21 for Big-5 personality traits corrected from acquiescence biais for 835 individuals from rural Tamil Nadu, India.
Source: NEEMSIS-1 (2016-17)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

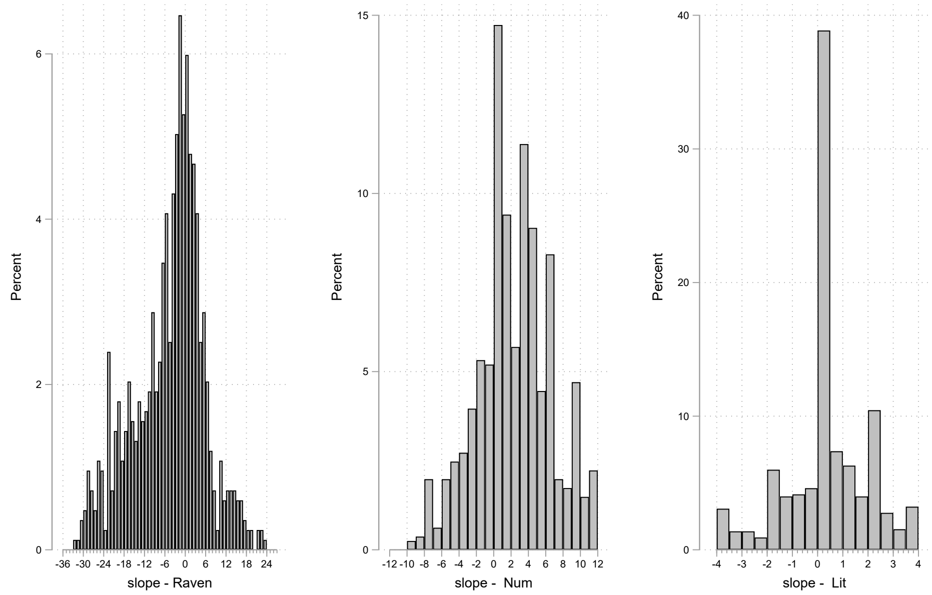

Figure 7: Stability over time of cognitive skills – Distribution of the difference of the score between 2016-17 and 2020-21 for three cognitive skills for 835 individuals from rural Tamil Nadu, India.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

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)

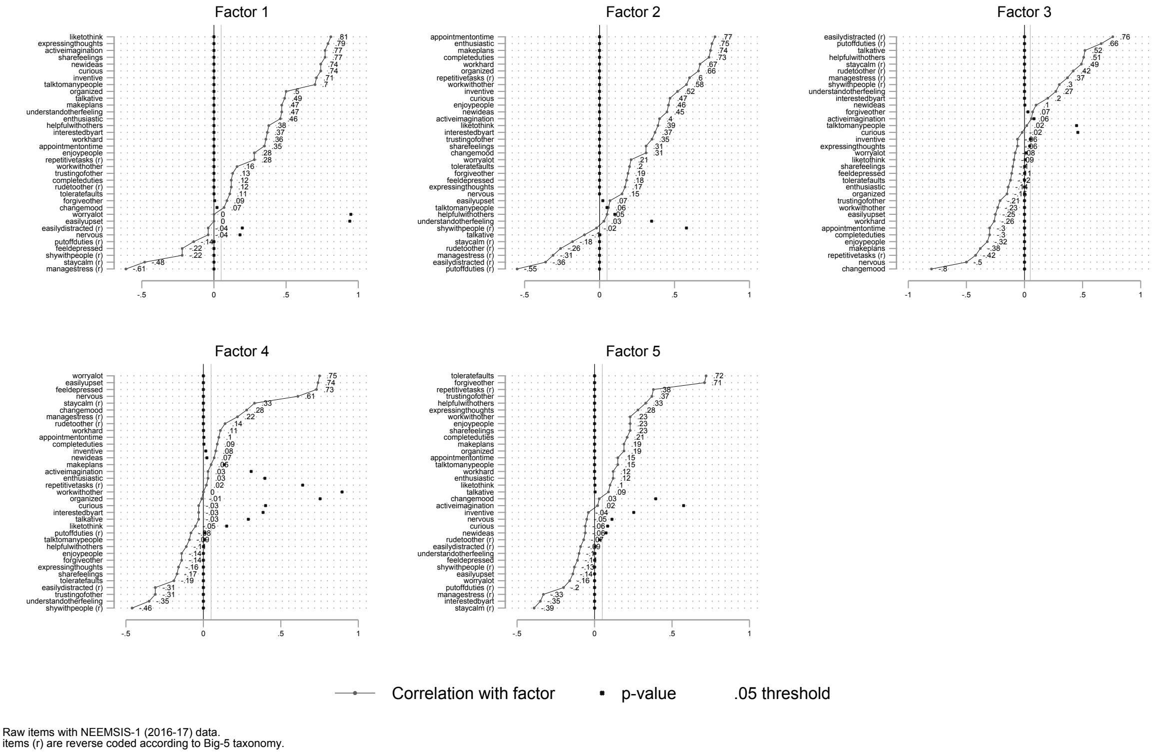

Figure 8: Results of factor analysis for 2016-17 raw items
Source: NEEMSIS-1 (2016-17); author's calculations.

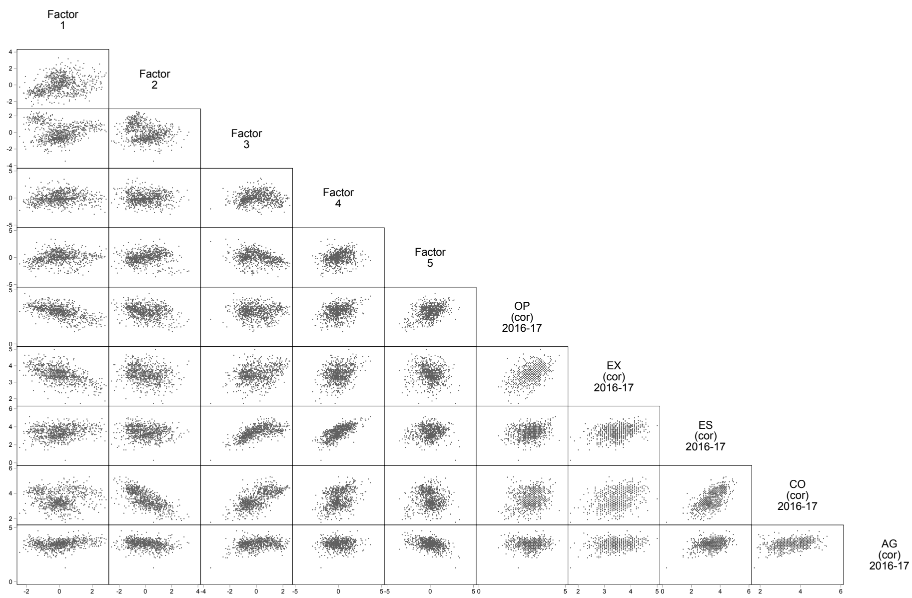

Figure 9: Correlation between Factor from EFA and Big-5 personality traits
Source: NEEMSIS-1 (2016-17); author's calculations.

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