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Dette, Travail et Cognition : Interactions Microéconomiques en Inde Rurale du Sud

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Doctoral Dissertation

Debt, Labour, and Cognition: Microeconomic Interactions in Rural South India

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Dette, Travail et Cognition : Interactions Microéconomiques en Inde Rurale du Sud

Résumé : Cette thèse examine divers aspects de l'endettement des ménages dans une zone rurale du Tamil Nadu, en Inde du Sud. L'objectif principal est double. D'une part, il s'agit d'analyser l'effet de la vulnérabilité financière des ménages sur l'offre de travail en accordant une attention particulière à la mesure de la vulnérabilité financière. D'autre part, il s'agit d'analyser l'endettement au niveau individuel afin d'appliquer un cadre analytique comportementaliste en étudiant la corrélation entre les traits de personnalité, les compétences cognitives et l'endettement. Cet objectif est poursuivi à travers cinq essais en économie du développement. Le premier chapitre fournit des éléments contextuels sur l'Inde et présente les données de panel de première main *NEEMSIS* utilisées tout au long de cette thèse. Le deuxième chapitre vise à faire avancer la recherche en microéconomie du développement en proposant une nouvelle mesure de la vulnérabilité financière des ménages, appelée indice de vulnérabilité financière, et en présentant ses principaux déterminants sur la décennie 2010-2020. Le troisième chapitre évalue l'effet de la vulnérabilité financière (mesurée par l'indice de vulnérabilité financière développé précédemment) sur l'offre de travail des ménages. Les quatrième et cinquième chapitres sont consacrés au comportement individuel. Après avoir détaillé la mesure des traits de personnalité à l'aide de la taxonomie du *Big Five*, le quatrième chapitre teste empiriquement l'hypothèse de la stabilité temporelle de ces traits. S'appuyant sur les résultats du chapitre précédent, le cinquième chapitre analyse la contribution des traits de personnalité et des compétences cognitives à l'utilisation, à la négociation et à la gestion de la dette.
Mots-clés : Crédit, traits de personnalité, identité sociale, genre, caste, Tamil Nadu

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Debt, Labour, and Cognition: Microeconomic Interactions in Rural South India

Abstract: This thesis examines various aspects of household indebtedness in a rural area of Tamil Nadu, South India. The main objective is twofold. The first is to analyse the effect of household financial vulnerability on labour supply, with particular attention to the measurement of financial vulnerability. The second is to analyse indebtedness at the individual level to apply a behavioural analytical framework by studying the correlation between personality traits, cognitive skills, and indebtedness. This objective is pursued through five essays in development economics. The first chapter provides background on India and presents the first-hand *NEEMSIS* panel data used throughout this thesis. The second chapter aims to advance research in development microeconomics by proposing a new measure of household financial vulnerability, called the financial vulnerability index, and presenting its main determinants over the decade 2010-2020. The third chapter assesses the effect of financial vulnerability (measured by the financial vulnerability index developed earlier) on household labour supply. The fourth and fifth chapters are devoted to individual behaviour. After detailing the measurement of personality traits using the Big Five taxonomy, the fourth chapter empirically tests the hypothesis of the temporal stability of these traits. Building on the results of the previous chapter, the fifth chapter analyses the contribution of personality traits and cognitive skills to debt use, negotiation, and management.
Keywords: Credit, personality traits, social identity, gender, caste, Tamil Nadu

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Maybe Nick Cox has written something about this error?

`. motivate`

'All models are wrong but some are useful.' George Box
Indeed but its unclear that you can take much consolation from that

`. demotivate`

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Contents

Notations

Main acronyms

SE	Standard errors
CV	Coefficient of variation
HH	Household
P1	1st percentile
P5	5th percentile
P10	10th percentile
P25	25th percentile
P50	50th percentile (median)
P75	75th percentile
P90	90th percentile
P95	95th percentile
P99	99th percentile
GDP	Gross domestic product
INR	Indian rupee (₹)
USD	United States Dollar (US$)
SHG	Self-help group

Econometrics

The notation of econometric models is based on the proposals of Karim M. Abadir and Jan R. Magnus in an article entitled "Notation in econometrics: a proposal for a standard" published in 2002 in *The Econometrics Journal* (doi: 10.1111/1368-423X.t01-1-00074).

In the rest of this manuscript:

- vectors are written are lowercase symbols;
- matrices in uppercase symbols;
- both vectors and matrices are written in bold-italic;
- a transposed matrix is denoted by a prime (');
- Greek symbols correspond to the coefficients and are written in the following order: β, γ, F, ζ, η, and ι.

General Introduction

This doctoral dissertation in applied microeconomics aims to improve the overall understanding of household debt in rural Tamil Nadu, South India, by focusing on the borrowers' side. To achieve this objective, we are proceeding in two stages. Firstly, we analyse the extent to which the debt burden drives households to work while highlighting the difficulty of accurately measuring the financial vulnerability of households. Secondly, we analyse the extent to which individual characteristics such as personality traits are correlated with financial decision-making while taking into account social identity, namely caste and gender. Before doing so, we detail the measurement and stability over time of personality traits used in analyses.

This line of research is motivated by the fact that about half of the adults worldwide have reported borrowing money in the past year (Demirgüç-Kunt et al. 2018). At the macro-level, according to the United Nations Conference on Trade and Development (2019), in 2017, the global debt stock represented 260% of the global GDP, and private debt accounted for two-thirds of global debt. "The unprecedented explosion of private debt should clearly raise the loudest alarm bells" (p.76).

According to Ramprasad (2019, p.3), "debt is the obligation that follows acceptance of a credit opportunity". The study of indebtedness is complex because of the inseparable dyad of credit and debt. Credit is "regularly lived as a kind of catalyzer, as an opportunity to reorient one's sense of the future, whereas debt is inhabited as a drag on the immediate present and its future, continually exerting a gravitational pull-of-the-past on one's sense of aspiration and mobility" (Deville and Seigworth 2015, p.619), implying a hierarchy of meanings and broad positive and negative connotations. In other words, credit refers to the financial instrument offered by a creditor to a borrower, and debt is the financial obligation adopted once the offer is formally made and accepted (Deville and Seigworth 2015). Credit and debt appear as just two sides of the same coin (Halawa 2015; Peebles 2010). In this dissertation, for the sake of overall consistency, we use the term debt while keeping in mind the dyad debt/credit.

The most important reason scholars study household debt is that behaviour in debt markets has implications for many domains (Zinman 2015). As an illustration, we find research on household debt in top leading journals in various fields of research, including finance (Bernstein 2021), environmental studies (Ho et al. 2023), health economics (Clayton, Liñares-Zegarra, and Wilson 2015), and geography economics (Walks 2013). In addition, household indebtedness underpins important macroeconomic consequences and is at the heart of development policies. Research into household debt in developing countries remains a niche area, characterised by limited exploration and a lack of diversity in the datasets used (Noerhidajati et al. 2021) while household debt is specific in many aspects (Badarinza, Balasubramaniam, and Ramadorai 2019), especially in India (Badarinza, Balasubramanian, and Ramadorai 2016). In addition, the literature in developed countries needs external validity, given that a significant portion of the knowledge pertains exclusively to WEIRD (Western, Educated, Industrialised, Rich, and Democratic societies) households, which are not representative of the global world. Therefore, studying household indebtedness in India is particularly meaningful.

Our approach is empirical, and we use the original first-hand longitudinal quantitative household survey NEEMSIS (*Networks, Employment, dEbt, Mobilities, and Skills in India Survey*) collected by a team of researchers to which the author of this doctoral dissertation belongs (see Box A.1.1 in the appendix). This survey consists of a baseline survey, RUME (*RUral Microfinance and Employment*), carried out in 2010 (Guérin, Roesch, Venkatasubramanian, et al. 2023), and two follow-up surveys, NEEMSIS-1 implemented in 2016-17 (Nordman et al. 2017), and NEEMSIS-2 conducted in 2020-21 (Nordman et al. 2021), which constitutes a three-year panel of households and individuals. NEEMSIS has been collecting a wide range of information, from financial practices and employment characteristics to education, migration, social networks, cognition, and agriculture, for more than 600 households in 10 localities in the districts of Cuddalore and Kallakurichi, in Tamil Nadu. These data allow us to analyse debt at three levels: the loan, the individual, and the household.

Beyond introducing this doctoral dissertation, this general introduction aims to show *why the study of household debt in India is crucial*.

The following two sections show why household debt has long been an area of study neglected by researchers, despite its significant macroeconomic consequences. Then, we briefly present the debate on the effectiveness of microcredit in developing countries, which has shed light on the study of household debt at the microeconomic level. Next, we provide an initial overview of household debt in India. Finally, we conclude this General Introduction by presenting the outline of this doctoral dissertation.

A neglected sub-field from a neglected field

Household finances, the field of economics that studies how households use financial instruments and markets to achieve their objectives (Campbell 2006), have received less attention than other fields of the economy, such as the labour market. However, in the last twenty years, household finances have gained increasing interest from scholars (Campbell 2006; Gomes, Haliassos, and Ramadorai 2021; Guiso and Sodini 2013) and international institutions (World Bank 2022, 2008; United Nations Conference on Trade and Development 2019). This new spotlight can be due to several factors.

Firstly, today households are more directly involved in financial decisions than in the past, partially due to the liberalisation of loan markets, the recent credit expansion experienced by many developed countries, or the financial innovation that has enlarged the set of financing and investment choices available to households (Guiso and Sodini 2013).

Secondly, household finances research requires high-quality microeconomic data (Badarinza, Campbell, and Ramadorai 2016) that were not available in the past. Before the 1990s, micro-data on household finances suffered from limited quality and lack of details (Guiso and Sodini 2013).

Lastly, the field of household finances was not well-studied because, in the last century, business-related topics were taught at elite urban universities to prepare men to deal with business careers. In contrast, consumer-related topics were taught at rural-land universities, mostly to women, as part of household studies (Tufano 2009). Tufano (2009) hypothesises that "this separation played a relevant role in slowing the emergence of household finance as a separate field" (Guiso and Sodini 2013, p.1402). This recent emergence has resulted in the creation of the "G5" JEL classification code.

Compared to other household finance subfields, "household debt" is still a peripherical subfield (Zinman 2015; Tufano 2009). However, studying household debt is crucial because household indebtedness underpins significant macro-level consequences.

Key macroeconomic implications

Mian, Sufi, and Verner (2017) show that an increase in the household debt to the GDP ratio in the medium run has predicted a lower subsequent GDP growth, higher unemployment, and negative growth forecasting error for 30 developed countries between 1960 and 2012 (Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong, Hungary, Indonesia, Ireland, Italy, Japan, Republic of Korea, Mexico, Netherlands, Norway, Poland, Portugal, Singapore, Spain, Sweden, Switzerland, Thailand, Turkey, United Kingdom, and the USA). In addition, the authors show a nonlinear effect of household debt on subsequent growth: an increase in debt leads to lower subsequent GDP, but a fall in debt does not boost GDP.

This result is confirmed for a wider set of countries over the period 1950–2016 (Alter, Feng, and Valckx 2018), and for a set of 54 countries between 1990 and 2015 (Lombardi, Mohanty, and Shim 2017). However, Lombardi, Mohanty, and Shim show that household debt boosts consumption and GDP growth in the short term (i.e., mostly within one year).

Faced with the amount of household debt (global stock of debt represented 260% of the global GDP, and private debt accounted for two-thirds of the global debt) and the experiences reported in the research, institutions have already sounded the alarm: "The unprecedented explosion of private debt should clearly raise the loudest alarm bells" (United Nations Conference on Trade and Development 2019, p.76), especially since United Nations Human Rights Council (2020) reports that massive indebtedness is a major driver in increasing inequalities.

The case of developing countries is even more *alarming* in that the household debt to GDP ratio has risen rapidly while it remained modest in the previous decades (Lombardi, Mohanty, and Shim 2017). At the same time, most household indebtedness is informal (Badarinza, Balasubramaniam, and Ramadorai 2019), which may not be included in national statistics, potentially increasing the adverse effects described above.

Despite the essential macroeconomic implications, the study of household indebtedness in developing countries has been largely understudied, even though microcredit policies have been at the centre of attention.

The spotlight of microcredit in developing countries

The development of microcredit follows the Nobel Peace Prize of Muhammad Yunus and the Grameen Bank in 2006 "for their efforts through microcredit to create economic and social development from below". Today, microfinance (and more broadly, financial inclusion) is at the heart of many Sustainable Development Goals (e.g., no poverty, zero hunger, gender equality, decent work, economic growth and industry, and innovation and infrastructure).

The original purpose of microcredit, according to Yunus and the Grameen Bank, was to provide loans to poor people to start small and often informal businesses that would be sufficient to support their families and thus lift them out of poverty. The assumption is that micro-enterprise is the best possible outcome for job creation and that lack of capital is the main barrier, meaning providing the poor with capital through microcredit to develop their entrepreneurial potential. In this view, either the poor lack capital or their only choice is informal loans, practised by moneylenders whose exorbitant fees would prevent any prospect of accumulation. The promise of microcredit to reduce poverty has been verified to a very [very] limited extent by scholars (Burgess and Pande 2005; Crépon et al. 2015; Pitt and Khandker 1998), while the methods used have rightly been heavily criticised (Roodman and Morduch 2013; Bédécarrats et al. 2021; Bédécarrats, Guérin, and Roubaud 2020). Other researchers have noted that the effects of microcredit go far beyond the fight against poverty and would improve access to education and health, improve decision-making, and empower women (Demirgüç-Kunt et al. 2018).

However, over time, the literature has become more nuanced about the effects of microcredit (Cull and Morduch 2017). Regarding the question of empowerment, several meta-analyses show that, at best, the impact of microcredit is modest, partly due to the diversity of users, contexts, and methods used to assess the impact (Garikipati et al. 2017). In addition, in the case where microcredit is used to launch an activity rather than to consolidate it, this is often done at the expense of other entrepreneurs already on the market, resulting in a drop in margins (Osmani 1989), and, therefore, a reduction in the activity's income, which is contrary to the fight against poverty. Additionally, microcredit may appear as a supplementary debt that can lead to overindebtedness, which can have significant effects in terms of health or well-being (Clayton, Liñares-Zegarra, and Wilson 2015; Guérin, Morvant-Roux, and Villarreal 2013), especially if the loan is used for immediate rather than income generating expenditure, which is quite common. Furthermore, even if the loan is used for an income-generating activity, the expected effect on poverty is uncertain and depends on local markets and demand (see, e.g., Servet 2010), meaning if local markets are saturated, entrepreneurs are unable to sell their products and find themselves even more in debt. Finally, microcredits pose a serious threat to household assets, as assets are used as collateral (i.e., guarantee for the repayment of the loan) directly affecting households' livelihoods if they fail to repay (Guérin et al. 2022).

Current debates on the effect of microcredit underpin the dyad debt/credit presented earlier in this General Introduction. Credit is favouring over debt in exteriorising poverty (Mosse 2010), making indebtedness less a factor of relationships and more a consequence of individual choices (Ramprasad 2019).

The study of household debt in India is particularly interesting because the country has one of the largest and most dynamic microfinance sectors in the world (Ghosh 2013), which is just the tip of the iceberg, given the diversity of household debt in terms of both sources and purposes.

Household debt in rural India

Among developing countries, the case of India is particularly interesting to study household indebtedness for several reasons.

Firstly, India is characterised by the coexistence of both formal and informal lenders (Badarinza, Balasubramaniam, and Ramadorai 2019). This characteristic contradicts neoclassical theory since formal lenders are less costly than informal lenders and should, therefore, replace them. Informal lenders are often viewed as usurers only there to impoverish the poor. Even if informal finance was "much maligned by scholars" (Kandikuppa and Gray 2022, p.4), it stayed a crucial player in the debt markets, in particular, because it provides credit in a timely manner with a minimum of paperwork and procedures (Guérin et al. 2012).

Secondly, debt serves a multitude of purposes. In the context of low and irregular income due to the persistence of vulnerable employment (Gammarano 2018) or global climate change (Ho et al. 2023), debt smooth incomes (Collins et al. 2009; Taylor 2012). In the face of increasing commoditisation (Bender 2017), debt provides access to essential services (e.g., water, electricity, housing, healthcare, or education). Debt is also used to finance new consumer goods driven by the adoption of urban lifestyles (Banuri and Nguyen 2023; Barba and Pivetti 2009) and allows individuals to invest in their economic activity or invest in their social relationships and status through ceremonies (Anukriti and Dasgupta 2017).

Thirdly, recourse to debt is widespread, and the amounts involved are important. All India Debt and Investment Surveys (AIDIS) national data supports that since the 1980s, the incidence of indebtedness has increased for rural and urban households (increasing from 19 to 32% and from 17 to 22% between 1980 and 2012, respectively), with an increase in the share of households indebted to formal and informal sources (Rajakumar et al. 2019). In addition, national data shows an increase in the average amount of debt per household from INR 283 to INR 33k between 1951 and 2012 (Rajakumar et al. 2019). However, this incidence is underestimated, and micro-level studies indicate a debt incidence of around 90% in villages of Tamil Nadu (Reboul, Guérin, and Nordman 2021) and 97% in Palanpur, Uttar Pradesh (Drèze, Lanjouw, and Sharma 1997). National data is often significantly underestimated due to the frequent omission or inaccurate representation of informal debt. Regarding the amount, households can spend up to 180% of their annual income to settle their debts (Reboul et al. 2019). Compared with other developing countries, the amount of debt is such that India has experienced major crises, such as the notorious microfinance one that drove some farmers to suicide in 2010 (Taylor 2011; Nair 2011). More recently, in 2018, thousands of farmers across the country took to the streets in a series of demonstrations, culminating in two huge rallies in Mumbai and Delhi to relief from debt (Menon 2018). Media coverage of the protests highlighted that farmers were under the weight of crushing debt (Menon 2018).

Fourthly, the situation is not homogeneous among individuals, and many disparities exist between caste, class, and gender. In rural India, caste shapes credit sources, segmenting local informal credit circuits, and affecting access to formal finance (Kumar 2013). Dalits, formerly called the "untouchables", the low-caste individuals, have a higher incidence of indebtedness but borrow smaller amounts (Guérin, D'Espallier, and Venkatasubramanian 2013). Across gender, the relative amount of debt to income is higher for females than for males. Females in the poorest households have the highest borrowing responsibilities, and Dalit females tend to face a higher debt burden than non-Dalit females (Reboul, Guérin, and Nordman 2021). Recent crises such as the microfinance crises of 2010 (Nair 2011), the demonetisation of November 2016 (Guérin et al. 2017), or the COVID-19 pandemic lockdowns of 2020-21 (Guérin et al. 2022) have exacerbated disparities between caste and gender, making the understanding of household and individual debt even more essential.

Outline of the dissertation

By focusing on rural South India, the purpose of this doctoral dissertation is twofold.

On the one hand, it is to pay particular attention to the measurement of household financial vulnerability to analyse its effect on labour supply, because the literature on household debt in developing countries has focused mainly on debt on the left-hand side of the equation (see, e.g., Schicks 2014) rather than on the right-hand side, and because labour supply is a key economic outcome (Blundell and Macurdy 1999).

On the other hand, it is to complement the analysis of debt at household level with an analysis at individual level to apply a behaviourist analytical framework (e.g., cognition), as has been done in developed countries (see, e.g., Brown and Taylor 2014). Thus, the purpose is also to study the correlation between personality traits, cognitive skills and individual indebtedness. However, the study of cognition, and in particular personality traits, raises a number of methodological issues (see, e.g., Laajaj and Macours 2021), especially in developing countries, which need to be carefully considered.

This objective is pursued through five essays in development economics: a chapter dedicated to presenting the context and the data used and four analytical chapters. Various tools were used, chosen for their relevance to the problem at hand (e.g., descriptive statistics, econometric models, multidimensional exploratory statistics, machine learning).

The work presented in this manuscript has been realised in accordance with the principles of honesty, integrity, and responsibility inherent to the research mission. The research work and the writing of this manuscript have been carried out in compliance with the French national charter for research integrity. In addition, in the interests of transparency and good research practice, the *Stata* codes for the analyses carried out in this doctoral dissertation are available on GitHub (https://github.com/arnaudnatal), and RUME (Guérin, Venkatasubramanian, et al. 2023) and NEEMSIS-1 (Nordman et al. 2023) data are available in Open Access on the dataverse of the *Observatory of Rural Dynamics and Inequalities in South India* (ODRIIS) (https://dataverse.harvard.edu/dataverse/odriis).

Out of habit, the entire dissertation is written in the first person plural "we". However, when a chapter is derived from a coauthored work, a footnote in the chapter title makes this clear and the CRediT is written.

The entire doctoral dissertation is based on the household survey data from the RUME survey carried out in 2010 and then the NEEMSIS waves conducted in 2016-17 and 2020-21 in rural Tamil Nadu, India. In Chapter 1, we provide key contextual elements of India, Tamil Nadu, the studied area, and present the original first-hand longitudinal household survey NEEMSIS. Since 2010 and for three points in time (2010, 2016-17, and 2020-21 for now), NEEMSIS, and its baseline survey RUME, has been collecting a wide range of information, from financial practices and employment characteristics to education, migration, social networks, cognition, and agriculture, for more than 3000 people from over 600 households in more than 10 localities in the districts of Cuddalore and Kallakurichi, Tamil Nadu. Then, descriptive statistics are used to characterise debt practices. It emerges that households are highly indebted, that they juggle a wide range of borrowing sources, and that each serves very specific purposes. Most debt is used to meet consumer spending and is contracted from informal lenders, who have the advantage of not requiring collateral and providing loans quickly.

To study the debt situation of households in greater depth, and, in particular, how it has changed over time, in Chapter 2, we develop a new simple continuous indicator of financial vulnerability adapted to developing area context, the financial vulnerability index (FVI). The proposed measure analyses different aspects of household financial vulnerability, such as the cost of debt, the debt trap, and poverty. Then, we investigate, first, the evolution of households' financial vulnerability between 2010 and 2020-21 using a machine learning method called time-series clustering algorithm. We show that upper castes are under-represented among households in vulnerable dynamics, meaning households who experienced a substantial increase in their FVI over time, while they are overrepresented in non-vulnerable dynamics. In addition, we use correlated random-effect fractional probit to analyse the determinants of household financial vulnerability.

Econometric estimates show that caste, loan amount, and income are correlated with the financial vulnerability index. This chapter serves as the initial stepping stone for delving deeper into the analysis of household financial vulnerability. Among the research to be undertaken, analysing the effects of financial vulnerability on labour supply seems to be a priority, given the importance of this economic outcome (Blundell and Macurdy 1999). However, few studies have analysed the effect of financial vulnerability and indebtedness on labour supply because of the difficulty of identification: while increased indebtedness may drive labour supply, labour shock also leads to household indebtedness. This is the subject of the next chapter.

Chapter 3 assesses the effect of household financial vulnerability on household labour supply. We use the financial vulnerability index developed in Chapter 2 and rely on a recent econometric approach called maximum-likelihood structural equation model. This approach not only protects against endogeneity arising from time-invariant unobserved heterogeneity, but also allows for reverse causality between labour supply and financial vulnerability by assuming sequential rather than strict exogeneity. The result of this chapter is that higher financial vulnerability is associated with a higher labour supply, especially for females. Despite the fact that it is necessary, analysing debt at the household level erases some of the inter-individual disparities. Among the analyses at an individual level, the behaviourist perspective can offer valuable insights into the underlying psychological factors that influence individuals' borrowing decisions (Brown and Taylor 2014) which can lead to different types of public policy (Arráiz, Bruhn, and Stucchi 2017) that must necessarily be part of broader macroeconomic and structural development policies (Bédécarrats, Guérin, and Roubaud 2020).[1] However, few researchers have investigated the relationship between cognition (i.e., personality traits and cognitive skills) and indebtedness, and even fewer in developing countries. The study of cognition, particularly personality traits, raises several methodological issues, especially in developing countries (see, e.g., Laajaj and Macours 2021; Cobb-Clark and Schurer 2012). This is the subject of the next chapter.

In Chapter 4 we analyse the universality of the Big Five personality traits (i.e., emotional stability, extraversion, openness to experience, agreeableness, and conscientiousness), the stability over time (between 2016-17 and 2020-21), and the effect of external shocks, such as the demonetisation of November 2016 and the COVID-19 pandemic lockdowns of 2020-21, on these traits. The analyses reveal a five-factor structure similar to the Big Five model in 2016-17 but different in 2020-21 and instability over time. Only 1/5 of individuals remain stable between 2016-17 and 2020-21, and upper castes are overrepresented among stable individuals. Using a covariate balancing propensity score approach, we show that individuals who experienced the Indian 2016 demonetisation are more salient in terms of openness to experience and extraversion, while those surveyed after the second COVID-19 lockdown of April 2021 are more salient in terms of neuroticism (i.e., the opposite of emotional stability) compared to the others. Overall, these results highlight the need for economists to pay more attention to the consistency of personality

1. We will not discuss public policy in this doctoral dissertation.

trait measurement to avoid measurement errors, and to the stability of traits over time to avoid double causality.

Taking into account the methodological aspects of personality trait analysis, in Chapter 5, we analyse the relationship between Big Five personality traits, cognitive skills (Raven matrices, literacy scores, and numeracy scores), and financial decision-making. We focus on the recourse, the negotiation, and the management of debt. With a multivariate probit, we find that conscientiousness is generally significantly associated with negotiating and managing debt. The magnitude and statistical significance of the association between personality traits and debt differs across social identity, meaning castes (Dalit, non-Dalit) and sex. These findings suggest the use of personality traits and cognitive skills for females as a way to overcome the weight of social identity in a rural caste-segmented patriarchal context.

Chapter 1

Analysing household debt in rural South India: Presentation of NEEMSIS data*

1.1 Introduction

The last decades have seen the achievements of a modern India. The country is the second-fastest-growing economy and the world's largest democracy (Drèze and Sen 2013). However, economic progress has to be counterbalanced by mitigated social and environmental improvements all over India, between and within Indian States, between urban and rural areas, and along different social groups in a very segmented society, making the study of socioeconomic dynamics, however diverse, necessary.

This chapter presents the original first-hand longitudinal quantitative household survey NEEMSIS (*Networks, Employment, dEbt, Mobilities, and Skills in India Survey*) used in this dissertation, which consists of a baseline survey, RUME (*RUral Microfinance and Employment*), carried out in 2010 (Guérin, Roesch, Venkatasubramanian, et al. 2023), and two follow-up surveys, NEEMSIS-1 implemented in 2016-17 (Nordman et al. 2017), and NEEMSIS-2 conducted in 2020-21 (Nordman et al. 2021), which constitutes a three-year panel of households and individuals. In addition, we offer a comprehensive overview of the main socioeconomic dynamics, along with an encompassing depiction of the

*. This chapter is derived from an article in progress with the NEEMSIS team to present the NEEMSIS survey protocol and the rural dynamics at work since 2010, in terms of employment, agriculture, debt, and migration. To better focus on the subject of this doctoral dissertation the section on rural dynamics zooms in on debt practices, compared to the article in progress. In addition, for a good overview of the role of the author of this doctoral dissertation in data collection, see Box A.1.1 from the appendix. CRediT – M. Di Santolo: Formal analysis, Writing – original draft. I. Guérin: Writing – original draft. S. Michiels: Writing – review and editing. C. Mouchel: Formal analysis, Writing – original draft. A. Natal: Formal analysis, Writing – original draft. C.J. Nordman: Writing – original draft. G. Venkatasubramanian: Writing – review and editing.

surveyed households' debt situation.

Compared to cross-sectional data, the scientific advantages of quantitative panel data are numerous. Panel data enable the observation of dynamics and changes over time, both for individual/household and social groups. Then, in addition to capturing inter-individual heterogeneity, panel data allow researchers to grasp *intra-individual* heterogeneity over time. Combining inter- and intra-individual differences enables a better understanding of the complexity of human behaviour (Hsiao 2014). Coupled with qualitative surveys (e.g., ethnography, participant observation, semi-structured interviews), quantitative panel data allow to grasp the institutional and structural dynamics and the way individuals navigate within them. Within the framework of NEEMSIS, quantitative surveys are systematically combined with qualitative data of various kinds. Qualitative data are crucial for gathering reliable data, posing innovative hypotheses, grasping realities that questionnaire surveys miss, and interpreting or illustrating quantitative results.

Several projects aim to collect longitudinal data in India. The aim is not to replace national statistical surveys but to reveal what they miss by exploring socioeconomic processes, such as the transformation of agriculture, the functioning of labour markets, and social mobility trajectories (Himanshu, Jha, and Rodgers 2016). The most famous case study of long-term data collection is the Palanpur village in Uttar Pradesh (Himanshu, Lanjouw, and Stern 2018). The whole population of Palanpur has been surveyed seven times from 1958 to 2015. Initially aimed at studying post-independence agrarian reforms and then the Green Revolution (1960-70), the objective of the Palanpur study has broadened over time, including, for example, the analysis of the social mobility of individuals and social groups (Bolazzi 2020). The special feature of the Palanpur study is the longevity and exhaustiveness of the sample, which covers the entire village population and thus enables an extremely detailed analysis of intra-village dynamics and individual trajectories in their institutional context over a long period (Himanshu, Lanjouw, and Stern 2018). Tamil Nadu has a long tradition of long-term village monographs, from the "Slater village" studied as early as 1916 (the latest study dates from 2008) to more recent initiatives, some of which have chosen a regional scale and cover several villages (Harriss 2016).

NEEMSIS is in keeping with this tradition of longitudinal studies while presenting at least three specific features. Firstly, RUME, the baseline survey of NEEMSIS, emphasised the diversity of links between urban and rural areas. Indeed, RUME started in 2010 with 405 households in 10 villages unequally integrated into the non-farm economy. The main purpose was to capture the diversity of urban-rural linkages and their interactions with household and individuals' labour, debt, skills, social networks, and social and spatial mobility. Tamil Nadu is one of the most developed, urbanised, and industrialised Indian states. However, many villages remain heavily dependent on agriculture, albeit unevenly and with rapid transformations. This creates diverse and changing urban-rural linkages that need to be studied. Secondly, NEEMSIS covers a broad spectrum of original information collected at the household and individual levels (e.g., labour episodes, indebtedness, interpersonal networks, cognitive skills or personality traits, for instance). Thirdly, NEEMSIS makes it possible to trace individuals who have permanently migrated between two survey waves to other Tamil villages for work-related reasons. Combined with a household and individual survey, migrant tracking offers a unique opportunity to better understand migration processes.

The data collection occurs within the *Observatory of Rural Dynamics and Inequalities in South India* (ODRIIS – https://odriis.hypotheses.org/), hosted at the French Institute of Pondicherry (IFP) in partnership with the French National Research Institute of Sustainable Development (IRD). The objective of the *Observatory* is to collect and share quantitative and qualitative data to better understand the region's structural changes and crises. The ODRIIS draws on the experience of researchers present in the region since 2003 and involved in various quantitative and qualitative surveys.

Long-term presence has many advantages (e.g., accumulation of data over time, good knowledge of the context, building relationships of trust with the local population). This, in turn, makes possible to improve the quality of the data collected, to combine complementary methodologies more easily, and to integrate deductive and inductive approaches (Rao 2022). However, repeated surveys raise ethical issues, such as population fatigue and legitimate questions about the direct benefits of the survey. In the manner of anthropologists, NEEMSIS team responds by forging reciprocal relationships with local populations (Guérin, Kumar, and Venkatasubramanian 2023). It includes two key aspects. On the one hand, members of the NEEMSIS team act as confidants and mediators within local communities to support their access to the world beyond the village boundaries (e.g., sharing information about welfare programs and job opportunities, assisting with paperwork). On the other hand, NEEMSIS team regularly raises funds for individual emergencies or collective hardship (e.g., food distribution support during the pandemic).

The rest of the chapter is organised as follows. Section 1.2 presents the context in which the longitudinal surveys took place. Section 1.3 details the data (i.e., sampling, questionnaires). Section 1.4 provides an overview of the data collected, and Section 1.5 focuses on debt. Section 1.6 concludes.

1.2 Context

The survey occurred in central Tamil Nadu, in the Kallakurichi and Cuddalore districts. Kallakurichi district is a newly named district derivated from the South of Viluppuram district in 2020.

1.2.1 India

With a population of over 1.2 billion, India is the second-fastest-growing large economy and the world's largest democracy (Drèze and Sen 2013).

The country is a federal republic, governed through a democratic parliamentary system, and composed of 28 States and eight union territories. The states and union territories are further subdivided into districts and smaller administrative divisions. Each state and union territory has its own institutions and the power to pass laws in certain areas.

From the nineties until 2010, India displayed an annual growth rate between 6% and 9%. However, such a sustained economic performance is offset by glooming social indicators. Economic growth has improved the standard of living of a minority of Indian citizens and has left out other disadvantaged groups who have seen their living conditions barely improving at a dismally slow pace. Economic growth was reached at the same pace as the rise of significant inequalities (Chancel and Piketty 2019), widespread corruption (Harriss-White and Michelutti 2019), and a lack of essential social services. India has been climbing up the ladder of per capita income while slipping down the slope for social indicators (Drèze and Sen 2013). Improvements in living conditions have only reached specific social groups, while others lag behind.

Drawing a general picture of the development of contemporary India by contrasting rural and urban can be misleading because of the strong interdependence between these two areas. Firstly, rural areas are facing a decline in agricultural returns with low productivity and a multiplication of livelihood sources, especially non-agricultural employment (Kumar et al. 2011). Secondly, urban and peri-urban areas tend to benefit from the development of industry and services due to large metropolises and subaltern cities with a better connection to globalised markets (Mukhopadhyay, Zerah, and Denis 2020), and connections between urban and their rural backwards have improved. Thirdly, anthropologists observe an attachment to rural ways of living despite jobs in urban areas (De Neve 2003).

1.2.2 Tamil Nadu

Located in South-East India, Tamil Nadu is one of the most socially developed Indian States (Joshi and McGrath 2015). Growth levels and per capita income are among the highest in the country, and rural and urban poverty levels are below the national average (Kalaiyarasan and Vijayabaskar 2021).

In 2011, Tamil Nadu's Human Development Index (HDI) was 0.544, ranked in 6th position, above the Indian average at 0.504 and far beyond the poorer Indian States in the Northern belt such as Bihar, Odisha or Chhattisgarh (Suryanarayana, Agrawal, and Prabhu 2016).[2]

Significant political efforts have been made to support education for all, and human development programmes have worked well compared to other states (Kalaiyarasan and Vijayabaskar 2021). Tamil Nadu was more active than other Indian States in trying to

2. HDI combines a measure of the standard of living, health and education. Variables used to calculate the standard of living is the per capita income in 2004-5 from the National Sample Survey (NSS). For health, it is the life expectancy in 2002-6 from the Sample Registration System. For education, it is the mean years of schooling in 2006 and the expected years of schooling in 2010 from the NSS.

design inclusive social policies. The government of Tamil Nadu was a pioneer in the creation of social programmes (Drèze and Sen 2013). For instance, Tamil Nadu was the first state to introduce free and universal midday meals in primary schools. It was also more creative and advanced than other States regarding the implementation standards of nationwide social programmes such as the public distribution system, which involves the distribution of food and non-food items to the poor at subsidised prices, or the national rural employment guarantee act (NREGA, now known as Mahatma Gandhi national rural employment guarantee act, i.e., MGNREGA) which guarantees employment in rural areas in the form of unskilled manual labour for at least 100 days per financial year.

Regarding employment, Tamil Nadu is an industrialised State due to the large production units in the major cities and the small industrialised urban centres (Marius-Gnanou 2010). This is leading to new forms of urbanisation and production dynamics that are redesigning the organisation of work and lifestyles in the territory (Djurfeldt et al. 2008; Amelot and Kennedy 2010). Notwithstanding the growing industrialisation and economic progress, the shift from the primary to the secondary sector and its associated implications have exhibited uneven patterns across the entirety of Tamil territory. Rural regions persistently rely on agriculture as their principal economic activity (Harriss, Jeyaranjan, and Nagaraj 2010).

The agricultural sector still employs a significant proportion of the Tamil workforce despite its low contribution to the state's GDP (Michiels 2016). The agricultural sector is characterised by low productivity, partly due to the intense fragmentation of land. The literature argues that land fragmentation in India is partly caused by the law of inheritance of paternal property, the absence of a progressive tax on inherited land, and the underdeveloped land market (Niroula and Thapa 2005). For example, in Tamil Nadu in 2019, 73% of households that own land have a surface area of less than 1 hectare, and the average is around 0.8 hectares (Government of India 2019).

As elsewhere in India, people tend to be attached to rural areas. While urban ways of living are attractive, the country is surprisingly not experiencing a rural exodus (Racine 1994). In Tamil Nadu, only half (48.4%) of the population lives in urban areas, and it appears as one of the most urban states in India (Government of India 2011).

In addition, the labour market is strongly segmented by caste and gender. Traditionally, caste implies that jobs are determined at birth (Deshpande 2000). Despite a persistent congruence between caste and occupation, this trend tends to be mitigated by the modernisation process of the Indian economy that has been deployed since the 1980s. However, facing modernisation, the caste system adapts and rearranges (Harriss-White 2002) to create new forms of employment segregation and discrimination. Consequently, individuals from the lowest castes are trapped into occupations that are more arduous, more degrading, and more unstable than others. They are twice as likely to engage in casual agricultural labour and experience poverty (Harriss-White and Gooptu 2001). Regarding gender, social and cultural factors keep females outside the labour force (Mehrotra and Parida 2017). For example, the fact that females do not work is a matter of prestige for the economically better-off households and forward castes. Additionally, females are more likely to be present in temporary and casual occupations than in more stable jobs because of barriers (e.g., not meeting educational requirements, lack of experience, insufficient social network or discrimination), and much of their time is spent on domestic work (Ratheesh and Anitha 2022).

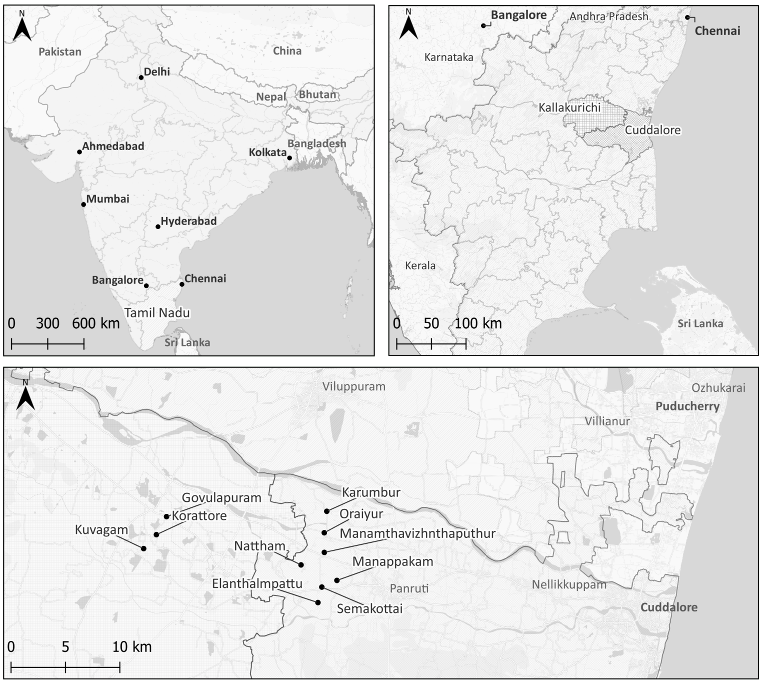

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Figure 1.1: NEEMSIS study area

1.2.3 Study area

In 2008-2009, the RUME team travelled the length and breadth of Tamil Nadu, looking for a region that encapsulates the diversity of rural dynamics on a territory small enough to facilitate the logistics of the surveys. In the end, ten villages were chosen from the South-Arcot region because it exhibits several key tendencies in the State of Tamil Nadu, such as:

- a strong diversification of rural activities;
- an important agricultural sector despite declining returns;
- the rise of subaltern medium-size cities (Denis and Zérah 2017); and
- various forms of rural-urban linkages.

The South-Arcot region is located in east-central Tamil Nadu at the border between Kallakurichi and Cuddalore districts (see Figure 1.1). Kallakurichi was previously part of the Viluppuram district and has been a separate district since 2019. South-Arcot used to be a district in the Madras presidency of British India. It no longer has an administrative existence, but it still has regional significance, and the term continues to be used. South-Arcot benefits from diversified but declining agriculture, a port, a regional market, and an industrial cluster.

The zone under study is economically dynamic, featuring a large proportion of irrigated agricultural land alongside arid pockets, two industrial towns (Neyveli and Cuddalore), and two medium-size dynamic regional business centres (Panruti and Viluppuram).

- Neyveli, around 100 00 inhabitants (Government of India 2011), is an industrial town born in the 1960s when a state-run lignite mine and a thermal power station were constructed. Today, workers in both state enterprises live on-site in purpose-built housing, enjoying considerable privileges. However, many small-scale subcontracting industries are on the site, and hire local workers and migrants.
- Cuddalore, around 170 000 inhabitants (Government of India 2011), is an industrialised urban centre formerly specialised in fishing. Today, the city is specialised in the pharmaceutical and petrochemical industries and has large agri-food production units specialised in the processing of sugar cane and cashew nuts.
- Panruti, around 60 000 inhabitants (Government of India 2011), is the nearest town in the area. Its primary source of attractiveness comes from its commercial activity (e.g., large fruit and vegetable market, sale of building materials) and its strategic geographical position (e.g., large bus station serving most of the surrounding villages and towns).
- Viluppuram, around 96 000 inhabitants (Government of India 2011). This is the second nearest town in the study area. Viluppuram is a hub for public transport at the junction of the central railways in Tamil Nadu, with a direct connection with Chennai, the capital of Tamil Nadu.

The Pennai River runs through the area, irrigating part of the villages, while remote villages have to make do with rain-fed agriculture.

As data from the Kallakurichi district is not yet available, in the following paragraph we use data from the Viluppuram district. The Viluppuram district has a low level of HDI in 2017 compared to the rest of Tamil Nadu (respectively 0.561 and 0.709), while the Cuddalore district has an average level (0.719) (Government of Tamil Nadu 2017).[3] Both districts cope with high levels of poverty. More than half of the population was living below the poverty line when we started to collect our longitudinal data. The poverty headcount ratio of Cuddalore district (50.73%) was two times higher than the Tamil Nadu

3. Variables used to calculate the standard of living is the per capita income in 2011-12 from the DOES data (Government of Tamil Nadu 2017). For health, it is the life expectancy at birth in 2011 from the State Planning Commission. For education, it is the literacy rate in 2011 from the Census of India, and the gross enrollment in primary and in secondary schools in 2013-14 from the Education Department.

level (24.90%), and the headcount ratio of Viluppuram district more than two and a half times higher (63.56%) (Mohanty et al. 2016).[4]

The *jātis* present in the region can be classified into three main categories for the sake of simplicity of analysis, which we call castes: Dalits, middle castes, and upper castes.

- Dalits, formerly called the "untouchables", the low-caste individuals, include *Paraiyar* and *Arunthathiyar*.
- Middle castes include *Asarai*, *Kulalar*, *Gramani*, *Vanniyar* (also called *Padayachi*), *Nattar*, and *Navithar*. *Vanniyars* are a farming caste with a low ritual rank but, in the villages we studied, as with many places in northeast Tamil Nadu, they control much of the land and are politically dominant. Muslims are also classified as middle castes.
- Upper castes include *Rediyar*, *Marwari* (also called *Settu*), *Naidu*, *Chettiyar*, *Mudaliar*, and *Yathavar*.

Note that the caste titles used here are simplistic. According to some anthropologists (see, e.g., Headley 2021), it is difficult or even impossible to determine the extent to which the caste histories have changed over the last two to three centuries. There are sub-castes/castes/meta-castes that have radically changed their name since the middle of the 19th century, taking with them only part of "their group", knowingly leaving aside certain sub-castes that were structurally very close. There are also cases of sub-castes that no longer know what to call themselves in the jungle of titles and denominations. Hence, further knowledge from in-depth ethnographic surveys would be needed to have certainty about the morpho-sociological units we are dealing with, and thus to be able to unravel and understand the processes of self-designation.

As in many other northeast Tamil Nadu villages, conflict often occurs between *Vanniyars* and *Paraiyars*, the two major groups in the region, over various issues, including common land usage, temple management, religious ritual organisation, local politics, and access to government schemes and resources. The upper castes of the local hierarchy account for only a small proportion of the village population. In recent decades, they have mostly moved away from the villages to nearby towns (Djurfeldt et al. 2008), adopting urban jobs and lifestyles. Their dominance has considerably declined but is by no means a thing of the past. Christians and Muslims are a minority in the area.

In addition, the studied villages still face a strong spatial segmentation that divides the space into two territories. On the one hand, the "Ur", where mostly *Vanniyar* caste households and the few remaining upper caste households live. On the other hand, the "Colony", reserved for Dalits.

4. The poverty headcount ratio is derivated from the State specific poverty line of 2009–2010 and 2011–2012 as recommended by the Rangarajan Committee and adopted by the Government of India, meaning, for Tamil Nadu, a monthly poverty line per capita at INR 1 082 for rural areas and INR 1 380 for urban areas (Government of India 2014).

1.3 Data

For an overview of the precise role of the author of this doctoral dissertation in data collection, see Box A.1.1 in the appendix.

1.3.1 Sampling, reliability and ethics

1.3.1.1 Village selection: common trends and diversity

Data collection mainly took place in 10 rural villages in Tamil Nadu, located at the border between Kallakurichi and Cuddalore districts, in the South-Arcot. Villages include Manappakam, Semakottai, Manamthavizhthaputhur, Natham, Korattore, Karumbur, Oraiyur, Govulapuram, Elamthampattu, and Kuvagam, with approximately 170 to 500 households in size (i.e., less than 5000 inhabitants).

We chose this region and the 10 villages after a long process of mapping the different Tamil regions. Although they are located in a small area, the 10 villages reflect several dynamics characteristic of the Tamil rural economy and its diversity, meaning a mix of irrigated and dry farming, two nearby industrial towns (Neyveli and Cuddalore), a regional business centre (Panruti), and varying degrees of remoteness. Villages were selected depending on ecotype systems (i.e., half irrigated villages, half dry villages) and accessibility and distance to main roads and small towns (i.e., Panruti, Viluppuram, Cuddalore).

1.3.1.2 Household selection: caste as a key factor

In rural Tamil Nadu, the influence of caste remains crucial, both spatially, economically (e.g., strong fragmentation of labour markets according to caste), socially (e.g., endogamy, making of identities, and hierarchies), and politically.

The region shows a high numerical importance of Dalits, who, in 2010, represented about half of the village population in this region. To compare the processes of change between castes (or *jātis*) and the role of caste in these changes, "middle" and "upper" castes have been overweighted. Thus, within villages, half of the sample was selected from the mostly upper- and middle-caste "Ur" part of the village, and the other half from the "Colony" part, where Dalits mainly live.

More broadly, households were selected in ten villages using a stratified sampling framework based on three criteria: proximity to small towns, agroecological, and caste.

To choose households, the random route sample method was used: enumerators, by a team of two, interviewed a household every five houses.

1.3.1.3 Unit of analysis

The household constitutes the main unit of analysis in the longitudinal data collection. This requires a clear definition of what it includes and excludes, as researchers agree that the definition of a household is essential to evaluate economic outcomes (Beaman and Dillon 2012).

To ensure comparability with national surveys, we use the definition of household and head of the household of the Government of India (2011) used in the Census of India while keeping in mind that the household boundaries move over time, both horizontally and vertically (De Vreyer et al. 2008).

A household is then a group of persons who usually live together and take their meals from a common kitchen unless the exigencies of work prevent any of them from doing so. Persons in a household may be related or unrelated or a mix of both. The important criterion in finding out whether a group of people is a household is a common kitchen.

The head of the household is a person who is recognised as such by the family members, she or he is generally the person who bears the chief responsibility for managing the household affairs and decides on behalf of the household.

1.3.1.4 Representativeness

The precise socio-demographic profile of the villages was unknown at the time of the first survey in 2010 (the last census dated from 2005, and reliability at village level is doubtful). However, thanks to qualitative monographs of each village, the approximate weight of each caste in each of the 10 villages was partially known. Given the small size of the upper castes, they were overrepresented in the 2010 sample to observe inter- and intra-caste dynamics better.

The RUME survey and then the NEEMSIS waves are small-scale data collections in rural India, and these surveys do not claim to be statistically representative of the surveyed villages. Hence, any generalisation of the survey findings to a broader population might be risky. Indeed, it is impossible to know for sure whether what one would observe in the surveyed villages would hold in other locations nearby and even less in other parts of India, as the country knows substantial regional variations in social norms, economic development, and local institutions.

Using a survey that is not representative of a broader population can still be meaningful if the survey is designed and analysed appropriately and if the limitations of the survey are clearly communicated so as to avoid making generalisations beyond the sample being studied. The RUME survey, the NEEMSIS waves, and associated analysis share then some of the characteristics one can find in monograph studies, in the sense that they allow researchers to conduct in-depth examinations of a particular socioeconomic phenomenon (e.g., indebtedness, labour trajectories, social network formation) for a particular population in a specific area. As mentioned earlier, the *Observatory of Rural Dynamics and Inequalities in South India* systematically draws on additional and complementary qualitative surveys (Hilger and Nordman 2020; Guérin, Mouchel, and Nordman 2022; Guérin et al. 2022; Guérin et al. 2017). Like all qualitative analyses, these data do not depend on representative samples in the statistical sense. They aim to illustrate a diversity of situations in relation to a given objective.

Regarding a possible extrapolation, the survey area and villages were selected because they exhibit several key tendencies in rural Tamil Nadu. There is no reason to believe that we cannot extrapolate our findings a minima to account for the dynamics of the rural areas of the Kallakurichi and Cuddalore districts, and perhaps of Tamil Nadu, given:

- the way the sample was constructed (i.e., over-weighting of upper castes) and the distribution of the 2011 Census (i.e., more Dalits in our sample) (Government of India 2011);
- the way the villages were selected (i.e., half of the villages are irrigated, and the other half has dry lands; four villages are particularly isolated, four have average accessibility, and two have relatively good accessibility); and
- the dynamics which we observed in rural South India.

1.3.1.5 Quality and reliability

Collecting reliable and quality data is the major concern of NEEMSIS. In rural areas with a low level of education, populations have their own visions and understandings of labour, finance, relationships, and the State, as anthropology has long shown. In addition, there are the usual biases, well known to statisticians (e.g., memory bias, social desirability bias, gender bias, interviewer bias).

The RUME survey and then the NEEMSIS waves were constructed to strike a balance between categories that make sense to local people and more general categories that are useful for comparison with other regions of India and abroad. Prior ethnographic work over several years has provided excellent knowledge of local contexts, terminologies used, units of measurement employed, and the functioning of labour, credit, and land markets. A major characteristic of the RUME survey and then the NEEMSIS waves is that the same researchers are involved in the questionnaire and ethnographic surveys. For example, with regard to income, it is a known fact that in contexts of high informality where people often change jobs and combine several jobs, measuring income is a challenge. Here, good knowledge of the different labour markets, prevailing wages, and seasonal variations were essential to assess the quality of the answers and to guide people in their questions. Similarly, the reliability of the data on debt comes from a good knowledge of the different sources of debt and the terminologies used (e.g., by using less shameful terms than “debt”) and the prices usually charged (Guérin, Kumar, and Venkatasubramanian 2023).

The questionnaire was designed in English and then translated into Tamil by local researchers specialised in economics, sociology, and development studies, ensuring a good understanding of the terms by the respondents. The interview took place in each household’s home or workplace, depending on the respondent’s wishes. Public spaces were avoided to ensure confidentiality as much as possible.

1.3.1.6 Ethics

Conducting surveys is time-consuming for the populations interviewed, while the benefits for them are never guaranteed. Beyond the usual ethical rules (e.g., explaining the reasons for the survey, asking for consent, allowing people to stop a questionnaire in progress, anonymising data), the NEEMSIS team is constantly asking itself how it can conduct ethical research. This is done in different ways (Guérin, Kumar, and Venkatasubramanian 2023), such as:

- financial compensation for the families surveyed (at the end of the survey);
- mobilising funds in the event of a serious crisis for the poorest people in the village;
- restitution of the results to the village communities, carefully selecting certain outcomes so as not to harm or create local conflicts;
- as in the case of ethnographic surveys, the creation of long-term reciprocal relationships based on the exchange of information, advice, and friendships; and
- using findings to advance understanding of inequalities and social policy design.

Sharing survey data in Open Access, as is already done with RUME (Guérin, Venkatasubramanian, et al. 2023) and NEEMSIS-1 (Nordman et al. 2023), is also a form of ethics.

1.3.2 RUME as a baseline survey

The baseline household survey took place within the *RUral Microfinance, and Employment* research project, which aims to explore the links between rural finance and employment to contribute to ongoing discussions and interventions in the areas of rural development, poverty, and vulnerability reduction (Guérin, Roesch, Venkatasubramanian, et al. 2023; Guérin, Venkatasubramanian, et al. 2023). Data collection began in January 2010 and ended in March 2010 in the 10 villages listed above on 405 households, representing 1928 individuals.

Household questionnaire The questionnaire is composed of modules aimed at collecting the following information:

- socio-demographic characteristics (e.g., age, sex, education, relationship to head);
- employment (e.g., details on self-employment and salaried jobs, problems at work due to the 2008 economic crisis);
- migration and remittances;
- financial practices (e.g., borrowing, lending, guarantee and recommendation, chit funds, savings, gold, insurance);
- agriculture (e.g., land, cropping, livestock, farm equipment, labourers);
- consumption and assets (e.g., main expenses, during goods);

- housing and facilities;
- public service works (e.g., president, ward member, temple committee); and
- memberships (e.g., participation to public political events, SHG).

Data collection process The questionnaire, in paper format, was administered by five local male enumerators and two fieldwork supervisors to the household head of each selected household, who answered for all members. The survey took place in each household location, and the data collection process took around two hours.

1.3.3 NEEMSIS as follow-up surveys

The *Networks, Employment, dEbt, Mobilities, and Skills in India Survey* consists of two waves of data collection carried out in 2016-17 (Nordman et al. 2017; Nordman et al. 2023) and 2020-21 (Nordman et al. 2021). The NEEMSIS survey aimed at understanding the linkages between household and individuals' labour, skills, social networks, and social and spatial mobility. This includes the investigation of various forces at play, spanning from the role of social structure (i.e., norms and institutions), the development and use of social networks, to the formation of cognitive skills.

Panel data setting NEEMSIS-1 (2016-17) recovered 388 households of RUME (2010), and NEEMSIS-2 (2020-21) recovered 485 households of NEEMSIS-1. While most households could still be found in their previous locations, some migrate seasonally for work, and some have even migrated permanently to their new workplace. Enumerators have followed a tracking methodology to search for them: meeting labour intermediaries ("maistries"), finding employers and the migration place, and being allowed by employers to interview these households at their new workplace. Most were usually accommodated around brick kiln industries in Chennai surroundings.

In addition, NEEMSIS randomly selected news households from the 10 original villages (around 10 households by village) to increase the sampled population to better reflect the village socioeconomic dynamics over time and avoid the ageing of our sample.

In 2016-17, 104 new households were added. In each village, five households were randomly selected in the "Colony" area and five in "Ur" using random route sample methods. The final sample is spread across 15 broader locations (13 villages and two "areas") in four districts and consists of 492 households, and 2696 individuals. To ensure a minimal number of observations per location, migrant households who settled in villages less than five kilometres apart were gathered together in the same area.

In 2020-21, 147 new households were added. 86 were randomly selected, and 61 were selected thanks to their link with NEEMSIS-1 households to rejuvenate the sample with young households but also to be able to observe inter-household relationships in the data. For example, a married son who had left the household between 2017 and 2020 to form a new household could be interviewed if his family house was in the same village.

Table 1.1: Sample size of the RUME survey and NEEMSIS waves

	RUME (2010)	NEEMSIS-1 (2016-17)	NEEMSIS-2 (2020-21)
Number of households			
Cross-sectional	n=405	n=492	n=632
Panel 2010 / 2016-17	n=388		
Panel 2016-17 / 2020-21		n=485	
Panel 2010 / 2016-17 / 2020-21	n=382		
Number of individuals			
Cross-sectional	n=1928	n=2696	n=3647
Panel 2010 / 2016-17	n=1826		
Panel 2016-17 / 2020-21		n=2628	
Panel 2010 / 2016-17 / 2020-21	n=1783		

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

This configuration of "nested household structure" is supposed to provide key information regarding inter-generational social mobility, interhousehold marriage, and social network formation. The final sample comprises 632 households and 3647 individuals.

Household questionnaire NEEMSIS questionnaire includes all RUME household questionnaire modules on employment, migration and remittances, financial practices, agriculture, consumption, and housing. NEEMSIS kept the same variables to observe their variation between the two time periods but has also supplemented these modules with new questions to delve deeper into certain issues that are crucial to a better understanding of social change and social mobility. For instance, the occupation module has more detailed questions about business outputs and costs to improve the calculation of business profits. It also recorded the debt at an individual level, thus differentiated by gender, identifying the person who went to the lender and borrowed in their own name, which is a rare and valuable advantage in such a context (Reboul, Guérin, and Nordman 2021).

New modules have also been added to the household questionnaire on individual migration episodes, education, marriage, and government schemes. Regarding education, NEEMSIS has added additional questions to create a complete module on education since measuring networks and skills is one of NEEMSIS's main objectives. The marriage module is also more developed. Marriage has a social and economic dimension that plays a crucial role in the life of families, their networks, and intergenerational dynamics. Public schemes represent an important share of rural households' resources, especially in Tamil Nadu. As far as government programs are concerned, they are numerous, but their use remains uncertain and uneven, hence the interest in having a dedicated module.

Individual questionnaire NEEMSIS added a new survey unit compared to RUME, the individual or "Ego" level. In 2016-17, two household members were directly addressed individual questionnaires: the respondent of the household questionnaire, called Ego 1, and one younger household member, called Ego 2, randomly selected by the software tablet into age brackets (i.e., a member of the household aged between 18 and 25 years old, if no one is available, a member aged between 26 and 35 and if no one is available, a member aged over 35). There are 953 egos in 2016-17.

Individual questionnaires provide a range of information on labour force participation and outcomes (including wages and earnings), social networks (e.g., formal and informal ties using a "name generator" methodology), cognitive skills (i.e., numeracy, literacy, and Raven's test) and personality traits (i.e., Big-Five taxonomy and the Grit). Thus, NEEMSIS survey offers a new angle of analysis of rural dynamics in South India.

In 2020-21, an additional ego (i.e., Ego 3) was added, bringing to three the number of individuals responding to the individual questionnaire. In addition, the module on participation in the labour market has been improved with questions on job satisfaction, working conditions, and discrimination at work. The personality module was completed by adding a measure of locus of control, meaning the extent to which people believe they have control over the outcome of events in their lives, as opposed to those outcomes being determined by external forces beyond their influence. A new decision-making module has also been added to understand how decisions about work are made within the household. There are 1693 egos in 2020-21.

Tracking questionnaire An individual migrant survey completes NEEMSIS household and individual surveys, called the NEEMSIS Tracking survey. This survey recovered individuals who moved from their original residential place between two survey waves. The questionnaire consists of a shortened household questionnaire and an individual questionnaire. In addition, a specific questionnaire on the migration process is asked (e.g., the reason for migration, satisfaction, help in migration, decision, cost, and working conditions).

For NEEMSIS-1 wave, the sample consists of 78 individual migrants from Chennai to Bengaluru via Tirupur, among others (Michiels, Nordman, and Seetahul 2021). For NEEMSIS-2 wave, the sample consists of 63 migrants.

Data collection process NEEMSIS used digital tablets for data collection and relied on the Survey CTO software. This tool allowed for increasing the quality of the data collected because it is meant to check quality at each stage of the data entry process (e.g., missing observations, constraints on answers to avoid aberrant answers) and to reduce the cost, time, and errors associated with data entry as this is done instantaneously on the field.

One household member, usually the head, answers the questionnaire about all household members, so we have information on each member for all modules. The individual questionnaire is directly addressed to two individuals who answer for themselves: Ego 1 and Ego 2, and Ego 3 in 2020-21. The addition of the new unit of analysis significantly increased the duration of the data collection process (three to four hours for the household questionnaire and around two hours for each individual questionnaire). Thus, the data collection for one household was regularly spread across several days to avoid disturbing household habits.

NEEMSIS-1 enumerators' team was composed of three fieldwork supervisors and six enumerators. The supervisors and three of the six enumerators participated in the 2010 RUME survey data collection, so most of them already knew the fieldwork well. The enumerator training took place during three weeks, both in the classroom and on the field during a pilot survey, using practical cases to ensure a perfect understanding of questionnaires. In 2020-21, the enumerators' team was composed of 10 persons, including two supervisors. The team of enumerators includes six females, which undoubtedly improved the quality of data collection, particularly with female respondents, by making them feel more at ease and giving them greater freedom of expression. Two supervisors and three enumerators participated in the 2010 and 2016-17 waves, so half of the fieldwork team had good experience. To reduce the duration of the data collection process, NEEMSIS-2 relies on preloaded data saved in the tablets. This method avoided asking for time-invariant information for the same individuals (e.g., education for individuals above 30 years, caste identity).

NEEMSIS-1 and NEEMSIS-2 were carried out during of dramatic shocks (i.e., demonetisation and then the COVID-19 pandemic). These shocks obviously obliged us to stop the survey and take specific measures such as sanitary precautions during the COVID-19. But in the end, this two-stage survey, before and after the shock, was like a natural experiment enabling us to understand the effects of shocks.

NEEMSIS-1: the shock of demonetisation NEEMSIS-1 was collected over two periods, from August 2016 to early November 2016 and from January to March 2017. The gap in the periods was due to technical issues with the batteries of digital tablets. The main crop in the region is paddy, and the districts in the region have a three-season pattern, meaning they harvest three times a year (i.e., July, November, and March). Therefore, our data collection took place during harvest season.

An external shock, the national demonetisation policy announced by the Indian government in November 2016, occurred during the data collection. In November 2016, Narendra Modi, the prime minister of India, announced a ban on the INR 500 and INR 1k notes, the two highest-value banknotes in circulation. Although there were two previous instances of demonetisation in India, in 1946 and 1978, the 2016 Indian demonetisation was unparalleled in its size, scope, and suddenness (Guérin et al. 2017). The implementation process involved many technical challenges, leading to severe cash shortages. Due to the importance of cash in the Indian economy (98% of transactions are estimated to be in cash), this measure had strong impacts on employment, daily financial practices, and network use for more than three months, as people relied more strongly on their networks to sustain their economic and social activities. This shock seriously disrupted local economies and livelihoods during the survey. NEEMSIS took advantage of this context to observe the effects of a macroeconomic and monetary shock on rural households (Guérin et al. 2017; Hilger and Nordman 2020). Almost half the sample (42%) was interviewed after the November 2016 demonetisation.

NEEMSIS-2: the shock of the COVID-19 pandemic NEEMSIS-2 was collected from December 2020 to October 2021, six months after the end of the first COVID-19 lockdown (March 25, 2021, to June 1, 2021). In February 2021, India was hit by the largest COVID wave, which led to a sharp rise in contamination and deaths.

Thus, from April 5, 2021, to June 15, 2021, the government of Tamil Nadu imposed a complete lockdown. Almost 60% of the households were interviewed before the second lockdown, 20% during and 20% after. NEEMSIS-2 took advantage of this timing of crisis to address its effects on rural households (Guérin et al. 2022; Guérin, Mouchel, and Nordman 2022).

1.4 Characteristics of households and individuals surveyed

When panel statistics are presented, monetary values are always deflated using the oldest year used in the analysis. For example, in the rest of this chapter, Indian rupees of 2016-17 and 2020-21 are expressed in constant INR of 2010. To deflate monetary values, we use the consumer price index of the World Bank (https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=IN). In 2010 USD 1 was equivalent to INR 45.73.

1.4.1 Socio-demographic characteristics

In the sample, due to the stratification, 48% of the households are Dalits, between 36% and 42% are middle castes and between 10% and 17% are upper castes (see Table 1.2). A household comprises five household members on average over the decade with around one child per household (i.e., household members aged between 0 and 13). The sex ratio is also stable over the survey waves, and, on average, there are 1.3 males for one female. Regarding the dependency ratio, there are around 0.4 non-active individuals for one active.

At the individual level, the average age was 29 in 2010, 32 in 2016-17 and 33 years old in 2020-21. Educational attainment is continuously increasing over the decade (see Table 1.3). For example, 21% of our sample had at least an HSC level (i.e., 12th standards, equivalent to a A-Level in the UK) in 2020-21, while this proportion was only 7% in 2010. However, more than a third of those over 25 years have less than primary education.

1.4.2 Wealth

Annual household incomes have risen since 2010, despite the demonetisation of November 2016 and the COVID-19 crisis in 2020-21 (see Table 1.2). Dalits have the lowest income growth rates, and middle castes have the highest. As a result, the gap between Dalits

Table 1.2: Household socioeconomic characteristics

	Total			Dalits			Middle castes			Upper castes		
	2010	2016-17	2020-21	2010	2016-17	2020-21	2010	2016-17	2020-21	2010	2016-17	2020-21
No. of HH	n=405	n=492	n=626	n=194	n=236	n=297	n=152	n=197	n=261	n=59	n=59	n=68
Demographic char.												
HH size (mean)	4.76	4.68	4.76	4.86	4.92	5.14	4.72	4.60	4.55	4.54	3.95	3.90
No. of child. (mean)	1.03	0.88	0.86	1.19	1.00	1.02	1.03	0.86	0.75	0.53	0.44	0.57
Sex ratio (mean)	1.37	1.33	1.29	1.37	1.36	1.30	1.31	1.27	1.31	1.51	1.43	1.21
Dep. ratio* (mean)	0.47	0.41	0.40	0.51	0.40	0.38	0.49	0.40	0.39	0.28	0.48	0.48
Economic char.												
Income:† Mean	81.31	96.12	105.52	78.75	81.42	94.52	79.74	110.07	114.10	93.80	108.35	120.65
Income: CV	0.74	1.01	1.04	0.69	0.78	1.03	0.60	1.17	1.11	1.03	0.67	0.76
Income: P50	68.00	73.90	79.02	66.00	63.48	68.48	70.00	77.91	76.83	80.00	85.44	108.15
Remittances:‡ Mean	1.87	0.56	5.10	1.78	0.28	5.25	−0.08	−0.52	4.28	7.18	5.30	7.63
Remittances: CV	8.04	21.66	3.02	4.25	40.06	2.39	−111.26	−19.49	3.95	4.70	3.57	2.62
Remittances: P50	0.00	0.00	0.27	0.00	0.00	0.27	0.00	0.00	0.27	0.00	0.00	0.00
Poor§	26.17	30.89	30.51	28.50	38.14	35.35	22.52	27.41	26.82	25.42	13.56	23.53
Assets (nl):¶ Mean	239.76	277.00	301.94	195.67	189.36	267.73	261.89	344.16	337.95	327.72	403.31	313.15
Assets (nl): CV	0.56	1.16	0.72	0.49	0.81	0.67	0.56	1.25	0.68	0.49	0.75	0.95
Assets (nl): P50	199.00	198.29	244.16	182.75	159.15	221.74	235.25	251.52	280.49	297.50	377.85	241.77
Gold:‖ Mean	0.37	0.40	0.32	0.41	0.41	0.31	0.35	0.40	0.31	0.29	0.35	0.38
Gold: CV	0.42	0.65	0.68	0.34	0.64	0.70	0.49	0.63	0.66	0.44	0.73	0.69
Gold: P50	0.37	0.36	0.27	0.41	0.38	0.28	0.35	0.37	0.26	0.28	0.27	0.33
Land owner (%)	54.32	31.30	34.98	41.97	20.76	23.23	70.20	45.18	49.43	54.24	27.12	30.88
Size land** (mean)	0.78	0.98	0.82	0.56	0.57	0.59	0.83	1.05	0.88	1.21	1.88	1.22

Note: *Dependency ratio. †Annual labour income (INR 1k). ‡Difference between transfers received and transfers sent (INR 1k). §USD 2.15 per capita per day in purchasing power parity. ¶Monetary value of assets held, without land (INR 1k). ‖Share of gold in the total assets. **For land owner.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table 1.3: Individual level characteristics

	Total			Males			Females		
	2010	2016-17	2020-21	2010	2016-17	2020-21	2010	2016-17	2020-21
No. of individuals	n=1928	n=2301	n=2979	n=1008	n=1199	n=1533	n=920	n=1102	n=1446
Age (mean)	29.30	31.77	32.71	29.81	31.96	32.58	28.74	31.57	32.85
Occupied:* Yes	66.24	72.26	70.25	77.76	78.34	76.97	53.79	65.88	63.35
Occupations†,§ (mean)	1.37	1.48	1.53	1.41	1.37	1.42	1.30	1.60	1.68
MO:† Agri self-emp	13.05	14.97	15.88	20.40	18.26	16.88	1.57	10.87	14.63
MO: Agri casual	32.62	21.24	25.36	18.90	15.67	17.74	54.05	28.18	34.84
MO: Casual	20.29	13.53	21.86	23.58	14.58	25.85	15.14	12.22	16.89
MO: Regular	13.46	25.01	19.07	19.90	33.93	26.39	3.40	13.93	9.97
MO: Self-emp	13.46	12.47	8.65	17.22	14.99	11.97	7.57	9.34	4.52
MO: MGNREGA	7.14	12.77	9.18	0.00	2.59	1.18	18.28	25.47	19.15
Edu:‡ Below primary	45.31	43.15	37.51	35.84	32.41	27.66	55.71	54.46	47.65
Edu: Primary	17.45	19.33	15.87	18.1	20.58	17.34	16.73	18	14.35
Edu: High school	30.02	24.94	25.8	35.48	31.24	31.06	24.02	18.31	20.37
Edu: HSC or more	7.22	12.59	20.84	10.57	15.77	23.94	3.54	9.23	17.64

Note: *Individual over 15. †Individual occupied over 15. ‡Individual over 25. §Average number of occupations per individual.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

and non-Dalits is widening in terms of annual income, and the middle castes tend to catch up with the upper castes. Despite the average rise in income, the proportion of poor households at the threshold of USD 2.15 per capita in purchasing power parity is increasing. In 2010, 26% of households are below the poverty line, while they are 30% in 2020-21. Dalits are more numerous below the poverty line (35% in 2020-21) than middle castes (27%) and upper castes (24%).

The wealth measured with assets is the sum of the monetary value of gold, house, livestock, and consumer goods (e.g., cars, bikes, computers, cook-gas, phones). Because of the monetary value of the land (i.e., around INR 10 lakhs per acre) and the drop in land ownership between 2010 and 2016-17 (see Table 1.2), we do not include the value of land in the measure of assets held (Singh 2016). However, in the appendix, this statistic is available in Tables A.1 and A.2. On average, the monetary value of assets has increased over the last decade (from INR 240k in 2010 to INR 302k in 2020-21, i.e., from USD 5k to USD 6.6k), especially for Dalits (from INR 196k in 2010 to INR 268k in 2020-21). This may be due, in part, to government programmes that have provided free housing and loans at preferential interest rates to low-income households for house building. Special attention should be paid to gold. In India, gold is the dominant form of saving that serves an economic, socio-cultural, and political purpose (Joseph 2018; Goedecke et al. 2018). Data indicate that gold represents around 40% of the total value of assets, and Dalits, traditionally, have a higher propensity to save in gold (Joseph 2018; Goedecke et al. 2018). However, Dalits are also those who experienced a decline in the share of gold in the total value of assets between 2016-17 and 2020-21 (on average, from 41% in 2016-17 to 31% in 2020-21) due to the COVID-19 crisis. Because of the lack of income and certainty about future income, many households lost their creditworthiness, and pledging assets became the only way to secure financial transactions (Guérin et al. 2022).

Land holding is a key issue in rural areas. Judging by the sizes of landholdings, Indian agriculture is moving towards the miniaturisation of landholdings. Our results tend to be consistent with nation-level trends. A fair percentage of the population owned a few hectares in 2010: 54% of the households owned land with an average size of 0.8 hectares (see Table 1.2). The number of households having land drops in 2016-17 at 31% while the average farm size reaches 1 hectare, and slightly increases to 35% in 2020-21 with a decreasing average farm size of 0.8 hectares. Qualitative surveys indicate that indebtedness is often an explanatory factor. While the land is rarely mortgaged, people have no other choice than to sell it when they can no longer pay their creditors (Guérin et al. 2022). Landholding inequalities are also segmented along caste groups. Dalit farmers are systematically more marginal landowners than middle-caste farmers and upper-caste farmers, no matter the collection wave.

Additional statistics are available in Tables A.1 and A.2 in the appendix.

1.4.3 Employment

Two-thirds of the sample participate in the labour market, meaning they declared at least one occupation (see Table 1.3). The occupation rate is pretty stable over the decade, slightly oscillating between 66% and 72%. On average, occupied individuals had 1.37 occupations in 2010 and more than 1.5 in 2020-21.

To present data on labour, we use seven categories of employment status:

- agricultural self-employed;
- agricultural casual workers;
- non-agricultural casual workers;
- non-agricultural regular non-qualified workers;
- non-agricultural regular qualified workers;
- non-agricultural self-employed; and
- public employment scheme workers (i.e., MGNREGA).

The proportion of casual agricultural workers tends to decrease over the decade as agricultural employment increasingly competes with jobs in other sectors, and agricultural returns are declining. On the contrary, regular workers are on the rise, suggesting potential improvements in employment forms. Nevertheless, these categories present remarkable differences in terms of annual incomes. Casual workers in agriculture and MGNREGA have systematically the lowest individual incomes, far behind other categories. For instance, in 2020-21, 50% of casual agricultural jobs enable workers to earn more than INR 600 a month (see Figure A.1 in the appendix), while 50% of regular jobs enable the worker to earn more than INR 6k.

Most females work, but systematically less than their male peers (see Table 1.3). Females are overrepresented among vulnerable occupations such as MGNREGA or casual agricultural work. These types of occupations are characterised by low incomes and a high degree of flexibility, which, on the one hand, makes it easier to take up a job but, on the other hand, maintains a latent vulnerability due to low income (see Figure A.1 in the appendix).

1.5 Household indebtedness

1.5.1 Intensity and depth

While the nationwide All India Debt and Investment Survey estimates that 36.9% of the rural households from Tamil Nadu are indebted (NSSO 2019), Figure 1.2 shows that the recourse to debt is almost systematic for all castes over the last decade (i.e., 100% of households in 2010, 99% in 2016-17, and 99% in 2020-21). In terms of debt intensity, the average amount of debt is around INR 150K, representing more than one year of income, and the amount has increased by 64% between 2010 and 2020-21. The increase is even greater for the upper castes. However, the latter also have much higher incomes than the Dalits. Thus, the financial situation is even more critical for Dalits (Guérin, D'Espallier, and Venkatasubramanian 2013).

Households have to juggle several debts, and this trend has been rising over the decade. Figure 1.3 shows that in 2010, 50% of households had at least five loans. This proportion rises to 75% in 2020-21. In addition, the 25% of households with the highest number of loans in 2010 have at least six loans, while they have at least 10 loans in 2020-21. The average loan is around INR 23k (i.e., USD 500), and 50% of loans are below INR 12k (see Table A.3 in appendix). On average, upper castes take out loans for higher amounts than middle castes, who take out loans for higher amounts than Dalits, respectively INR 32k, INR 27k, and INR 18k.

At the individual level, females are predominantly the ones who shoulder the responsibility for debt settlement (Reboul, Guérin, and Nordman 2021). This task requires skills, time, and involvement in various secondary activities to ensure repayment capacity and creditworthiness (Guérin, Kumar, and Venkatasubramanian 2023). Males also take out loans for an average amount twice that of females (Reboul, Guérin, and Nordman 2021). However, the situation is much more unfavourable for females, whose incomes are much lower than those of males. For example, for debtors with income, Reboul, Guérin, and Nordman (2021) estimate that the average debt to annual income ratio is more than three times higher for females (9.30) than for males (2.86).

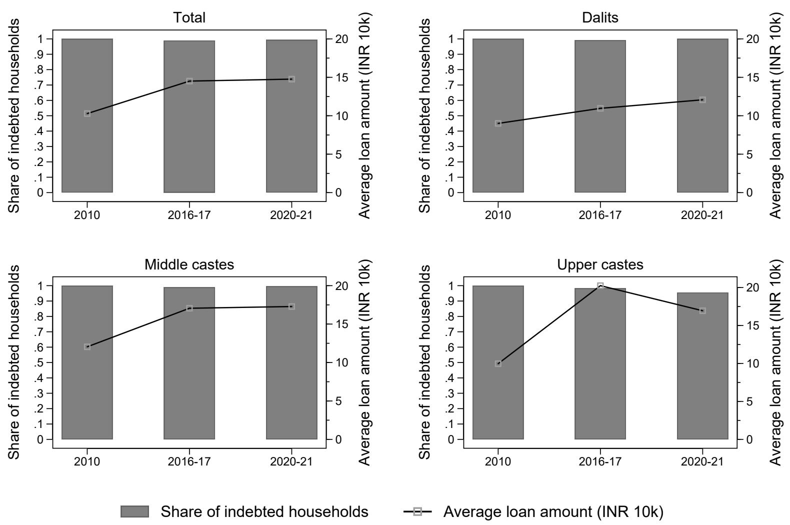

Figure 1.2: Debt trends between 2010 and 2020-21 by caste

Note: For a total of 405 households in 2010, 492 in 2016-17, and 626 in 2020-21.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

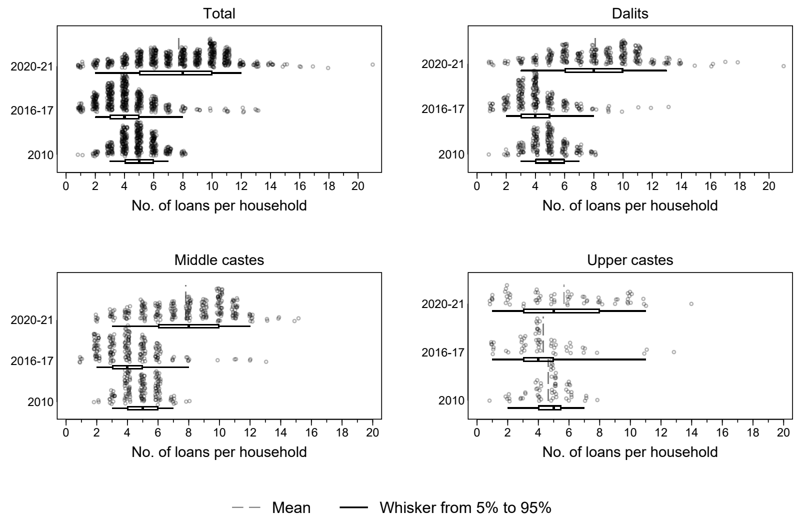

Figure 1.3: Number of loans per household between 2010 and 2021

Note: For a total of 405 households in 2010, 492 in 2016-17, and 626 in 2020-21.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

1.5.2 Purposes

The reasons for the loan have been grouped into five main categories:

- economic reason includes investment in the household business or agriculture;
- current expenditure covers expenditures directly related to the family, loans taken out to repay other loans, and expenses for relatives;
- human capital expenditure includes loans taken out for education and health;
- social expenditure includes loans for various ceremonies and festivals; and
- expenditure on housing is in a separate category.

In addition, some loans have no stated reason, and others have another reason.

In terms of use, the first purpose is to finance current expenses, such as daily consumption smoothing or family expenses (see Table 1.4). With 37% of the loans in 2010, this share rose to 56% in 2020-21, with an average amount between INR 11k and INR 18k. These amounts are largely below the average amount of loans contracted for economic reasons (INR 28k in 2010, INR 62k in 2016-17, and INR 45k in 2020-21), but the latter represents less than one-quarter of the total loans and are on a declining trend (14% in 2016-17, and 12% in 2020-21).

Additionally, housing-related reasons remain stable over time in terms of share of loans (around 10%) and amount (around INR 30k).

Human capital and social purposes are declining sharply (i.e., from 16% of loans to 11% for human capital purpose and from 23% to 11% for social reasons). In rural India, marriage is a way to signal social status (Anukriti and Dasgupta 2017), a key element in the everyday life of households, and the decline of debt for social purposes coupled with a rise in debt for current expenses reflects the deterioration of living conditions, which is well documented in the socio-anthropological literature (Lerche 2011).

Regarding caste, the economic purpose is a more frequent practice for non-Dalits, while current expenses are more frequent for Dalits (Guérin, D'Espallier, and Venkatasubramanian 2013).

By disaggregating at the individual level, economic purpose loans are largely a male practice: 10% of females debtors took out at least one of their outstanding loans for business purposes, as opposed to 27% of males (Reboul, Guérin, and Nordman 2021). Ensuring family subsistence weighs particularly heavily on female debt: 53% of females debtors took out at least one of their outstanding loans to meet daily consumption expenses, as opposed to 35% of males.

1.5.3 Lenders

In rural South India, there are three main types of lenders: informal, semi-formal, and formal.

- Informal lenders encompass loans from well-know-people (WKP), also called *Terinjavanga* (i.e., private lenders whose main activity is lending, such as village notables or influential people), relatives, labour relationships, shopkeepers, moneylenders, friends, and *Thandal* (i.e., ambulant money lenders).
- Semi-formal lenders are represented by pawnbrokers, meaning a person who lends money in exchange for mainly gold, while any asset can be pledged. Gold has the advantage of combining prestige, speculation and liquidity (i.e., gold can be pawned if needed).
- Formal debt encompass loans from bank and microcredit.

Informal lenders are often viewed as usurers only there to impoverish the poor. Even if informal finance was "much maligned by scholars" (Kandikuppa and Gray 2022, p.4), it stayed a crucial player in the debt markets, in particular, because it provides credit in a timely manner with a minimum of paperwork and procedures (Guérin et al. 2012). Informal loans are based on creditworthiness, reputation, and trust (the three terms are equivalent in Tamil, namely *nampikkai*) (Guérin et al. 2014). 70% of debt is informal in 2010, and 99.8% of the households are indebted to at least one informal lender (see Table 1.4). However, in terms of dynamics, informal debt is declining, contrary to formal debt. While in 2010, one-fifth of debt is formal, this proportion rise to almost a third in 2020-21.

The formal loan is the type of debt with the highest amount compared to informal and semi-formal. In 2020-21, an informal loan is on average at INR 12k, while semi-formal is on average at INR 19k, and formal at INR 33k. The rising of formal debt is consistent with the trend observed in national surveys (see, e.g., Rajakumar et al. 2019). In India, the development of microcredit that has been underway for the past two decades has

Table 1.4: Loan level characteristics

	%			Average amount (INR 1k)			% of household using it		
	2010	2016-17	2020-21	2010	2016-17	2020-21	2010	2016-17	2020-21
Lender									
Informal	71.38	68.39	66.87	21.45	36.14	12.65	99.75	95.48	95.34
Semi-formal	9.76	17.33	3.31	13.35	22.51	19.15	42.72	64.68	20.26
Formal	18.86	14.28	29.82	24.74	45.76	33.32	65.93	40.04	74.44
Purpose									
Economic	24.43	14.08	11.78	28.51	61.74	44.54	56.54	30.39	36.17
Current expenses	36.64	32.00	56.09	11.67	18.24	11.50	80.49	65.30	93.57
Human capital	17.94	15.95	11.51	24.19	28.04	14.66	53.33	37.78	50.00
Social expenses	11.39	23.14	10.82	25.52	40.29	26.97	39.51	44.76	38.91
Housing	9.61	13.34	9.52	29.08	37.85	26.98	29.38	28.13	39.55
No reason	0.00	0.15	0.04	0.00	33.97	28.53	0.00	0.62	0.32
Other	0.00	1.33	0.23	0.00	102.79	62.00	0.00	4.31	1.61
Total	100.00	100.00	100.00	21.13	34.79	19.03	405	487	622

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

not helped reduce the level of debt (Ghosh 2013). Contrary to expectations, microcredit, which explicitly targets females, does not always replace informal lenders but appears to be an additional source of debt (Arnold and Booker 2013) with fixed, non-negotiable repayments that are hardly compatible with low and irregular incomes, pushing many beneficiaries into situations of overindebtedness (Guérin 2014). Additionally, it seriously threatens household assets by pledging them to secure financial transactions (Guérin et al. 2022).

Regarding caste, it is an essential factor in borrowing behaviour. Dalits borrow more than other groups, but in smaller amounts and more frequently from informal ambulant lenders (Guérin, D'Espallier, and Venkatasubramanian 2013). In addition, debt is mainly "endogamous", meaning Dalits borrow more from other Dalits, middle castes from middle castes, and upper castes from upper castes (Guérin et al. 2012). For some upper castes, debt to Dalits is degrading, both to oneself and to one's own caste, as it reflects the group's inability to help its members (Guérin et al. 2012). Using the longitudinal dimension of RUME and NEEMSIS-1, Guérin et al. (2022) show that this "debt endogamy" increases over time, especially for Dalits.

At the individual level, compared to males, females are heavily indebted in relative terms, first and foremost to informal sources, alongside microcredit (Reboul, Guérin, and Nordman 2021). While females have always been excluded from formal finance, this is something genuinely new, partly due to the development of SHG that targets females (Yunus 1999).[5] However, the specific targeting of females by microcredit policies likely strengthens the association between debt and poverty for females, particularly exacerbating female responsibilities for managing scarcity (Reboul, Guérin, and Nordman 2021).

1.5.4 Lenders and purposes

Table 1.5 cross lenders and purposes of loans and provides the expected frequencies and the χ^2 contribution for the pooled sample of loans (2010 to 2020-21). The expected frequency represents the frequency if there were no dependency between the two variables.

The p-value associated with the Pearson χ^2 test is below 5%, suggesting a significant dependence between lenders and loan purposes. By investigating the χ^2 per cell and the difference between the frequency and the expected frequency, we identify which combination of lender and reason contributes more to the dependency.

With a χ^2 per cell equal to 84.8, formal loans are largely overrepresented for economic-related reasons (i.e., in the absence of dependence, formal loans for economic-related reasons should have been 316, but there are 479). On the contrary, informal loans are largely under-represented for economic-related reasons. In the absence of dependence, informal loans for economic-related reasons should have been 905, but there are 748. Re-

5. A self-help group is a financial intermediary committee usually composed of 12 to 25 local females. A SHG is generally a group of people who work on daily wages who form a loose grouping or union. Money is collected from those who are able to donate and given to members in need.

garding social expenses, they are largely financed with informal loans (χ^2 per cell equal to 15.6). Current expenditure is financed by all types of debt, with no overrepresentation of any one type, like home expenses and investment in human capital.

1.5.5 The social meaning

In India, debt is not just a material transaction governed by its monetary aspects (e.g., amount of the loan, terms of repayment, interest rate). Debt represents a significant social link between the borrower and the lender (Guérin et al. 2014). Debt "organises social life, and therefore the life of man as a social being: it makes his presence in the world a network of links, a net that imprisons him at the same time as it supports him" (Malamoud 1988, p.14). Debt is accompanied by a set of rights and obligations (e.g., provide a service, honour the debt in good time, invite the lender to ceremonies) that form a strong bond between debtors and creditors and which has consequences in terms of social belonging, status, and dignity in the village. Among the set of rights and obligations, services of debt count for a great deal. For example, following the loan, the debtor may have to do shopping or domestic work for the lender.

Services are also provided by lenders. In 2020-21, for only 3% of loans, the lender does not provide supplementary services (see Table 1.6). For 93% of loans, the lender provides financial support (e.g., financial guarantee at the organised financial companies, provide information about the various lenders and their interest rates, discuss with the lender to reduce the interest rate and get an additional loan with the existing loan, provide a good opinion to the lender about the borrower) to the borrower, and for 33% of loans, the lender provides general informant services (e.g., information regarding the various government welfare schemes, provide transport facilities, education and school information, job information, introduction to the government officials, local panchayat leaders to get the welfare schemes sanctioned priority, introduction to the labour contractors). Regarding the services rendered by the borrower, for one in two loans, the borrower does not provide service in 2020-21. For loans requiring a service, 45% of loans involved providing support as soon as the lender required it, while 5% involved working for a lower salary.

This set and, thus, the social meaning of debt are not fixed but continuously bargained and negotiated between stakeholders.

1.6 Conclusion

This first chapter presented in detail the general context of this doctoral dissertation. After giving key elements of the socioeconomic context of the study area, we presented in detail the data mobilised in the rest of this doctoral dissertation and the main dynamics, especially in terms of household indebtedness.

Regarding the population studied, half of the population are Dalits, and despite the rise in education levels, still more than a third of people over the age of 25 have not completed primary school. Despite the rise in incomes over the period, the proportion

Table 1.5: Does loan purpose differ by lender? Pooled sample

	Informal	Semi-formal	Formal	Total
Economic reason	748	100	479	1327
	905	*106*	*316*	*1327*
	(27.4)	(0.4)	(84.8)	(112.5)
Current expenses	2774	316	957	4047
	2761	*324*	*962*	*4047*
	(0.1)	(0.2)	(0.0)	(0.3)
Human capital expenses	866	117	242	1225
	836	*98*	*291*	*1225*
	(1.1)	(3.7)	(8.3)	(13.1)
Social expenses	939	96	175	1210
	826	*97*	*288*	*1210*
	(15.6)	(0.0)	(44.1)	(59.7)
Housing	625	69	220	914
	624	*73*	*217*	*914*
	(0.0)	(0.2)	(0.0)	(0.3)
No reason	3	1	1	5
	3	*0*	*1*	*5*
	(0.0)	(0.9)	(0.0)	(1.0)
Other	26	2	10	38
	26	3	9	38
	(0.0)	*(0.4)*	*(0.1)*	*(0.5)*
Total	5981	701	2084	8766
	5981	*701*	*2084*	*8766*
	(44.2)	(5.7)	(137.4)	(187.3)
Pearson $\chi^2(12)$=187.27 p-value=0.00				

Note: Frequency/*Expected frequency*/(χ^2 per cell).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table 1.6: Debt-related services

	2010	2016-17	2020-21
Lender services			
Political support	10.53	0.36	1.66
Financial support	45.58	25.56	92.96
Guarantor	11.85	1.25	6.81
General informant	16.15	18.01	33.26
None	12.98	65.64	3.34
Other	2.04	2.97	0.05
Borrower services			
Free service	27.38	5.09	1.98
Work for less wage	7.74	4.44	5.30
Provide support whenever he needs	51.56	42.13	44.73
None	9.63	53.70	52.13
Other	3.68	0.83	0.00

Note: For each service considered, percentage of loans. For example, in 2020-21, for 93% of loans the lender provided financial support to the borrower.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

of households below the USD 2.15 poverty line is increasing, and we find that 30% of households are below in 2020-21. In 2020-21, almost one in two workers are day labourers, and for one in five females, their main job are governmental schemes.

Regarding debt practices, we have outlined that households are highly indebted, that they juggle a wide range of borrowing sources and that each serves very specific purposes. Most debt is used to meet consumer spending and is contracted from informal lenders, who have the advantage of not requiring collateral and providing loans quickly. In other words, traditional informal lenders provide much more tailored loans to people's needs. However, to return to the idea of the dyad (i.e., credit and debt appear as just two sides of the same coin, and credit refers to the financial instrument offered by a creditor to a borrower, and debt is the financial obligation adopted once the offer is formally made and accepted), debt in itself is not a sign of vulnerability. In addition to sometimes being an economic investment (e.g., agriculture, self-employment) or a social investment (e.g., marriage, ceremonies), debt can be protective, can help maintain relationships of solidarity, and is a means of affirming one's social status in society (Guérin 2014). For example, taking on debt with a certain lender can facilitate access to land, work, or social programmes, and creditworthiness is a matter of self-dignity (Guérin 2014).

In the next chapter, we take a closer look at the debt situation of households and in particular, how it has changed over time.

CHAPTER 2

Hard Times: Measure and Analysis of Households' Financial Vulnerability*

2.1 Introduction

"*It is not enough to know how much a man is in debt. We must also find out, if we can, whether he is seriously involved.*" Malcolm L. Darling (1928, p.4)

As explained in the General Introduction, despite the recent interest in economic literature in the study of household debt (Zinman 2015), developing countries remain largely understudied. The literature is even more sparse if we consider not debt but financial vulnerability, a broader concept that encompasses various aspects of household debt (e.g., cost, personal feelings, type of debt) and economic situation (e.g., income, assets, poverty). There is no universally accepted definition of households' financial vulnerability; thus, there is no universally accepted way of calculating it (Fernández-López et al. 2023).

In this chapter, we propose a new way of measuring the financial vulnerability of households in developing countries and analyse *how financial vulnerability has changed in rural South India between 2010 and 2020-21*. We define household financial vulnerability as the degree of vulnerability due to the cost of debt, the debt self-reinforcing capacity, and the poverty level of the household and propose a measure called the financial vulnerability index (FVI). The proposed FVI differs from the literature in two main respects.

Firstly, an important strand of the literature approximates the financial vulnerability with a single debt ratio, meaning the total debt burden in relation to household resources such as assets or income (Van Gunten and Navot 2018). Pre-defined thresholds can also be used to create binary vulnerability variables: if a household has a ratio above the thresh-

*. We would like to thank Louis Olié for his helpful comments on an earlier version.

old, it is declared to be vulnerable or overindebted. The FVI goes beyond a simple debt ratio by considering three dimensions of vulnerability and beyond predefined threshold variables by being a continuous variable, which allows for a higher level of variance, precision and nuance. Among the key ratios, for instance, the debt service ratio (DSR) (see, e.g., Chichaibelu and Waibel 2017; Brown and Taylor 2008), meaning the proportion of gross annual income devoted to servicing annual debt, is particularly used because it is a well-precise measure of the indebtedness and it is time and space comparable. At a threshold of 0.3, 0.4, or 0.5, a household is declared to be overindebted, a situation where a household or individual has accumulated a level of debt that they cannot manage or repay comfortably given their financial resources and income. However, the DSR needs precise details about indebtedness, making field investigations more complicated in the context of developing countries where debt data are notoriously difficult to collect and prone to underreporting due to recall issues and social desirability biases (Karlan and Zinman 2008). The debt to income ratio (DIR) (see, e.g., Kandikuppa and Gray 2022; Lee and Kim 2015), that is, the ratio of the total outstanding debt to the gross annual household income, is often used to approximate the DSR because the amount of the debt is easier to calculate than its servicing. Thresholds of 0.3, 0.4, or 0.5 can also be used to classify a household as overindebted. However, the ratio is a stock of debt on a flow of income, making its intrinsic meaning complicated to interpret. Another key ratio is the debt to assets ratio (DAR) (see, e.g., Kandikuppa 2022; Bilston, Johnson, and Read 2015), the ratio of the total debt to the monetary value of assets. This ratio is easy to interpret because it is a stock of debt over a stock of wealth. However, comparing over time and space is difficult because different studies do not include the same items in wealth, making comparisons difficult (Juster, Smith, and Stafford 1999). Again, thresholds of 0.3, 0.4, or 0.5 are sometimes used to define a household as being overindebted. Financial margin (FM) is also often used as a measure of financial vulnerability (see, e.g., Leika and Marchettini 2017; Ampudia, Vlokhoven, and Żochowski 2016). It is, the difference between household income and the estimated minimum expenses and debt payments. The FM can be expressed in relative terms and used as a measure of overindebtedness at the threshold of zero. Ampudia, Vlokhoven, and Żochowski (2016, p.251) state that the "financial margin is the most popular measure of household vulnerability in the literature that exploits micro-level data on households."

Secondly, a strand of the literature analyses financial vulnerability on the basis of a set of variables grouped using factor analysis. For instance, in the USA, Azzopardi et al. (2019) assess the financial vulnerability using three variables (DSR, DAR, and household income) aggregated together using a hierarchical ascending clustering and k-means. In Indonesia, Noerhidajati et al. (2021) introduce a measure of households' financial vulnerability based on a nonlinear principal components analysis and a categorical principal components analysis, in the same vein as Anderloni, Bacchiocchi, and Vandone (2012) in Italy, and Ali, Khan, and Ahmad (2019) in Pakistan. In this study, the financial vulnerability index outperforms previous measures by focusing on reproducibility over time and space. On the one hand, it achieves this by using simple methods (weighted arithmetic mean) to combine the selected dimensions of financial vulnerability (debt trap, cost of debt, and poverty) rather than relying on principal component analysis. On the other hand, by choosing non-context specific variables. For instance, FVI does not consider assets, as can be done with the debt to assets ratio, because the boundaries for defining an asset are often blurred (Juster, Smith, and Stafford 1999).

We use the three waves of surveys (i.e., 2010, 2016-17, and 2020-21) to analyse the trends over time of the FVI and its drivers. Results show a rise in financial vulnerability between 2010 and 2020-21 and an overrepresentation of Dalits (ex-untouchable) among households in vulnerable dynamics (i.e., households who experienced a substantial increase in their FVI over time). Additionally, econometric estimates highlight that caste, loan amount, and income are correlated with the financial vulnerability index.

Thereby, by proposing a new indicator of financial vulnerability and analysing its determinants in rural South India, we contribute to several segments of the literature, ranging from the literature that analysing financial vulnerability using survey data, especially in developing countries context, to the literature that analyses household indebtedness, and especially the drivers in developing countries context.

The rest of the chapter is organised as follows. Section 2.2 introduces the new measure of households' financial vulnerability. Section 2.3 uses the data to verify the reliability of FVI. Section 2.4 presents analyses of the changes over time of FVI. Section 2.5 analyses the main drivers. Finally, we conclude in Section 2.6.

2.2 Construction of the financial vulnerability index

The proposed new measure of financial vulnerability (i.e., the financial vulnerability index) is based on three variables, aggregated together using a weighted arithmetic mean: the interest service ratio (ISR), which represents the cost of the debt; the debt trap ratio (DTR), which represents the capacity of the debt to be self-reinforcing over time; and the reverse relative gap to the poverty line (RRGPL) of the household, which describe the daily livelihood of the household. We define household financial vulnerability as the degree of vulnerability due to the three dimensions listed (i.e., the cost of debt, its self-reinforcing capacity, and the poverty level of the household).

2.2.1 Variables used

Interest service ratio The ISR is the proportion of annual gross income a household devotes to servicing its annual debt's interest obligation. The higher the ratio, the more the household is indebted.

$$\text{ISR} = \frac{\text{Interest service}}{\text{Annual income}}$$

The ISR measures the repayment burden insofar as the interest is the real burden of a loan (Yunus 1999). Indeed, interests are just additional costs for borrowers, and they can sometimes be very high, pushing households into highly vulnerable situations (Badarinza, Balasubramaniam, and Ramadorai 2019). ISR has the advantage of being time and space comparable, allowing a greater degree of replicability of the measure, compared, for instance, to the debt to assets ratio, which requires a clear understanding of what is an asset and what is not.

Debt trap ratio There is no consensus in the literature regarding the concept of the debt trap. According to Karlan, Mullainathan, and Roth (2019), a debt trap occurs when someone takes on a high-interest-rate loan and can barely repay the interest. The trap is, thus, a threshold of ISR. Yue et al. (2022) measure the debt trap with a dummy variable equal to one if a survey respondent self-reports payment difficulty, zero otherwise (i.e., debt trap is a subjective measure of overindebtedness). We propose a specific variable to measure debt trap, meaning a variable that does not already represent the debt burden (Karlan, Mullainathan, and Roth 2019) or overindebtedness (Yue et al. 2022). Thus, the debt trap is the capacity of the debt to be self-reinforcing over time, measured with the deb trap ratio, that is, the share of the total debt for the repayment of previous debt, expressed as a percentage:

$$\text{DTR} = \frac{\text{Debt to repay previous debt}}{\text{Total amount of debt}}$$

In other words, the debt trap ratio measures the vicious circle of debt. The higher the ratio, the more vulnerable the household.

Reverse relative gap to the poverty line The reverse relative gap to the poverty line measures financial vulnerability based on income and allows us to consider households' daily livelihood. We defined RRGPL as:

$$\text{RRGPL} = \frac{\text{X} - \text{PL}}{\text{PL}} * (-1)$$

PL is the measure of the international poverty line of USD 2.15 expressed in 2017 purchasing power parities per capita units (Jolliffe and Prydz 2016). While each country develops its own poverty line, the international poverty line ensures more accurate international comparisons.

X measures the *daily income per capita* expressed in 2017 USD. The *daily income* is calculated by assuming there is no seasonality of income (Alderman and Paxson 1994) to simplify the calculation and support our measure's great replicability. The *per capita* is calculated using household size instead of adult-equivalence scales (Jolliffe and Prydz 2016). Although it is important to take into account that needs vary between household members and that there are economies of scale in larger households (Jolliffe and Tetteh

Baah 2022), the use of equivalence scales is a controversial research topic (World Bank 2018), there is no consensus on the best scale to use, and adjusting income by an adult equivalence scale requires recalibrating the poverty line (Ravallion 2015).

The multiplication by "-1" ensures that the higher the ratio, the poorer the household.

2.2.2 Aggregation strategy

To aggregate ISR, DTR, and RRGPL and create the single financial vulnerability index, different strategies exist, and "there is not always a 'well-established' solution" (Mazziotta and Pareto 2013, p.71). However, four factors must be considered to aggregate variables (Mazziotta and Pareto 2013): the substitutability of the variables, the aggregation method, the type of comparisons, and the type of weights.

Substitutability Regarding substitutability, we choose to create a compensatory index, an index for which a high value can compensate for the low value in another component (OECD 2008). Compensatory indices have the advantage of "reward" on the basis of pre-defined weight, while non-compensatory indices reward on the basis of the score (p.33). Compensatory indices are, therefore, more flexible.

Thus, for the financial vulnerability index, we assume, for example, that a high proportion of debt devoted to the repayment of other debts can be balanced by a low allocation of income to the repayment of debt interest and/or by a low level of poverty. Given the nature of the variables (i.e., all linked to monetary units and all expressed as a percentage), this hypothesis seems reasonable.

Aggregation Following the compensatory approach, we use a simple method to aggregate the three components, the weighted arithmetic mean. Contrary to principal component analysis (Anderloni, Bacchiocchi, and Vandone 2012; Noerhidajati et al. 2021) or hierarchical classifications (Azzopardi et al. 2019), the arithmetic mean presents the main advantage of being easily replicated in other contexts. Additionally, the principal component analysis presents the major drawback of being "elitist" as it tends to "represent highly intercorrelated indicators and to neglect the others, irrespective of their possible contextual importance"(Mazziotta and Pareto 2016, p.107).

Comparison Regarding the comparison methods (i.e., absolute or relative), we retain the absolute comparison to be time and space comparable. Thus, we do not perform a standardisation or transformation in z-scores of our variables but restrict them to be defined between zero and one. For Y_i the real ISR, DTR, and RRGPL for a household i, $\hat{Y_i}$ is the restricted values of ISR, DTR, and RRGPL:

$$\hat{Y_i} = \begin{cases} Y_i & \text{if } Y_i \in [0;1] \\ 1 & \text{if } Y_i > 1 \\ 0 & \text{if } Y_i < 0 \end{cases}$$

This restriction allows us to control for the full range of the variables and avoid outliers. This restriction has virtually no effect on ISR and DTR, as these ratios rarely exceed 100% and cannot be less than 0%. However, for the RRGPL, the restriction is effective for households above the poverty line. For instance, a household with a daily income per capita of USD 3.00 has a reverse relative gap to the poverty line equal to -40%, but recoded to 0%.

Weight As our approach to financial vulnerability is particularly focused on household debt, we give twice as much weight to ISR and DTR in the calculation of the financial vulnerability index. RRGPL thus controls for the household's economic situation by having a weaker influence on the financial vulnerability index than ISR and DTR. As the choice of weighting may be subject to criticism, we have carried out sensitivity tests in Subsection 2.3.3. Whatever the other weights tested (i.e., a weight of 2.5 for ISR and DTR, then a weight of 1.5), results show that the distribution of the FVI is similar.

Results Given these fours steps, with ISR, DTR, and RRGPL restricted to [0;1], we estimate the households' financial vulnerability index as follows:

$$\text{FVI} = \frac{2 * \text{ISR} + 2 * \text{DTR} + 1 * \text{RRGPL}}{5} \tag{2.1}$$

FVI is interpreted as a score of financial vulnerability. FVI $\in$ [0;1], with zero representing the lowest level of financial vulnerability or the highest level of non-vulnerability in a developing country' context. On the contrary, one is the highest level of financial vulnerability for a household and represents a household with a daily income per capita equal to USD 0.00, an interest service ratio, and a debt trap ratio equal to 100%.

Despite its multidimensional nature, FVI does not claim to be an exhaustive measure of indebtedness insofar as key elements such as households' individual feelings about the sustainability of their debt and the social meaning of indebtedness are not taken into account in the index. FVI offers a new way of looking at the debt burden, one that goes beyond traditional ratios such as DSR, DAR, or DIR.

2.3 Reliability analysis of the financial vulnerability index

2.3.1 Correlations between the dimensions

Figure 2.1 presents scatter plots between each component of the FVI (i.e., ISR, DTR, and RRGPL) in the sample of pooled data. We do not observe strong correlations between the interest service ratio, the debt trap ratio, and the reverse relative gap to the poverty line. This result is desirable as it ensures no component redundancy (Salzman 2003), and thus each component measures a specific aspect of the financial vulnerability.

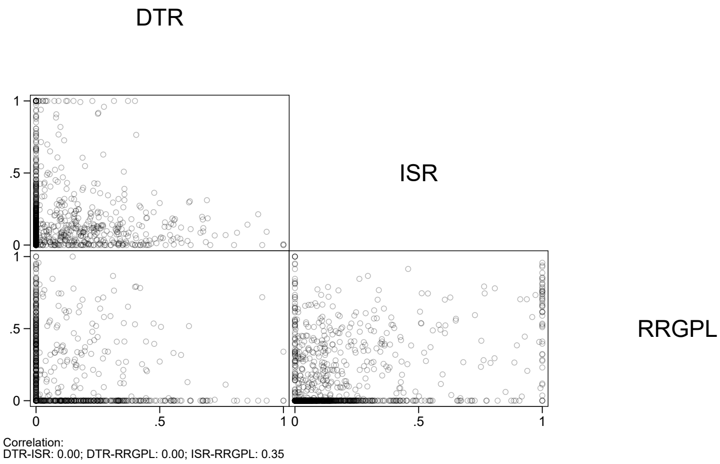

Figure 2.1: Pooled sample scatter plot of ISR, DTR, and RRGPL
Note: For 1523 households.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

2.3.2 Correlations with other measures of financial vulnerability

Figure 2.2 presents the cross-tabulation of the FVI with other classic measures of financial vulnerability presented above using the pooled data sample.

As expected, the FVI is positively correlated with the debt service ratio, the debt to income ratio, the debt to assets ratio, and negatively with the financial margin (the polarisation of the FVI is such that the highest values represent the highest cost of debt, while the polarisation of the financial margin is such that the highest values represent the highest level of non-vulnerability). However, these correlations are imperfect, suggesting that FVI is a different indicator from the other measures.

2.3.3 Sensitivity tests for weights

The proposed measure of financial vulnerability is based on a weighted arithmetic mean whith relatively arbitrary weights. In what follows, we test the sensitivity of the indicator by changing the weights. We compare the FVI distribution with alternative FVIs, meaning FVIs that are constructed with different weightings. We first increase the weight of the interest service ratio and the debt trap ratio to 2.5, leaving the weight of the reverse relative gap to the poverty line at 1 (FVI-2). We then reduce the weight of ISR and DTR to 1.5, leaving the weight of RRGPL at 1 (FVI-3). Finally, we remove the weighting in the FVI calculation, meaning ISR, DTR, and RRGPL have the same weight (FVI-4).

We plot the difference between the relative position of households in the FVI distribution and the relative position of households in the distribution of each alternative FVI (see Figure 2.3). We consider that a variation of ± 5 percentage points is acceptable,

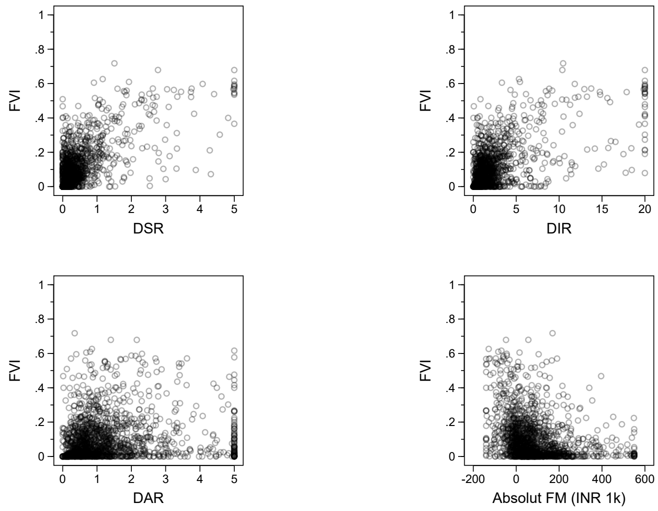

Figure 2.2: Pooled sample scatter plot of FVI with other measures of indebtedness

Note: For 1523 households.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

which means that we assume that the position of households in the two distributions is the same. When we change the weight of the interest service ratio and the debt rap ratio from 2 to 2.5 (FVI-2) or 1.5 (FVI-3), we observe that over 90% of households from the pooled sample see a change in their relative position in the FVI distribution of between -5 and +5 percentage points (i.e., they have the same position in the distributions). When we do not weight the arithmetic mean (FVI-4), we see that 75% of the households from the pooled sample have the same position in the distribution in FVI and FVI-4. However, by doing so, the weighting in favour of the direct indebtedness measure is not taken into account, and the intrinsic meaning of the measure is, therefore, different.

Overall, sensitivity analyses suggest good measurement stability.

2.4 Changes in financial vulnerability over time

2.4.1 Descriptive statistics

Table 2.1 provides descriptive statistics about the three variables used to compute the FVI, namely the interest service ratio, the debt trap ratio, and the reverse relative gap to the poverty line. In terms of level, in 2020-21, on average, 17% of the annual income is for the repayment of the debt's interest. While high, this value is probably underestimated regarding the difficulty for some households to split their repayment between interest and principal, to the detriment of interest. Regarding the debt trap ratio, on average, the stock of debt for the repayment of other debt represents 10% of the total stock of debt,

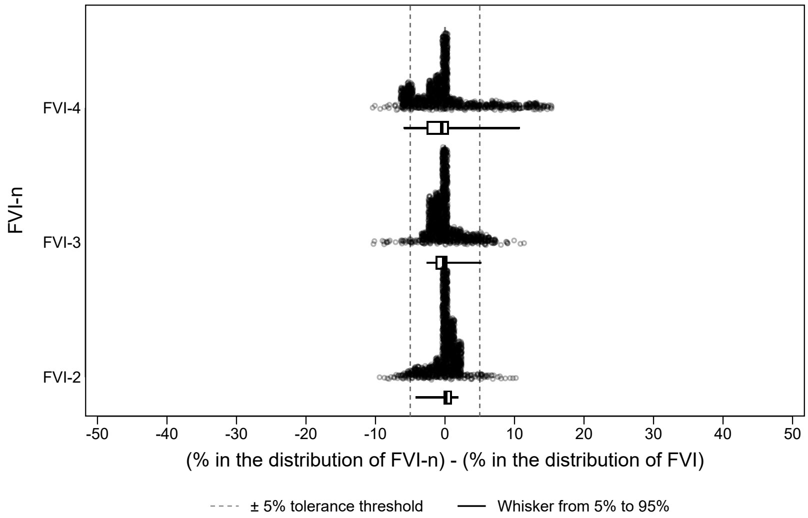

Figure 2.3: Sensitivity analyses of FVI

Note: For 1523 households.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

and for some households, the ratio is equal to 100%. In terms of the reverse relative gap to the poverty line, the average gap is equal to 13%, meaning the average daily income per capita is 13% lower than the USD 2.15 poverty line in PPP.

Regarding dynamics, we observe that the average interest service ratio increases over time (from 11% in 2010 to 17% in 2020-21), as well as the debt trap ratio (4% in 2010 to 10% in 2020-21) and the reverse relative gap to the poverty line (from 7% in 2010 to 13% in 2020-21) suggesting a degradation of the financial conditions of households.

Figure 2.4 presents the distribution of the FVI in 2010, 2016-17, and 2020-21. The distribution is more right-skewed over time, meaning that the financial vulnerability of households is increasing. In terms of level, on average, the FVI is around 0.08 in 2010 and 2016-17 and goes to around 0.14 in 2020-21. Additionally, over time, the distance between the first and the third quartile has increased, suggesting that there are more inequalities in terms of financial vulnerability. In other words, the more financially vulnerable households in 2020-21 are more vulnerable than those in 2016-17 and 2010. In addition, in 2010, the 5% of households with the highest FVI were above 0.23, 0.38 in 2016-17, and 0.47 in 2020-21. This trend is consistent with national data (Rajakumar et al. 2019) and qualitative works (Guérin et al. 2022) which point to an increasingly worrying debt situation.

2.4.2 Household time trends

While drawing a raw picture of the financial vulnerability landscape over the last decade, previous analyses do not fully exploit the panel dimension of the data. In what follows, we analyse the household time trends in the financial vulnerability index.

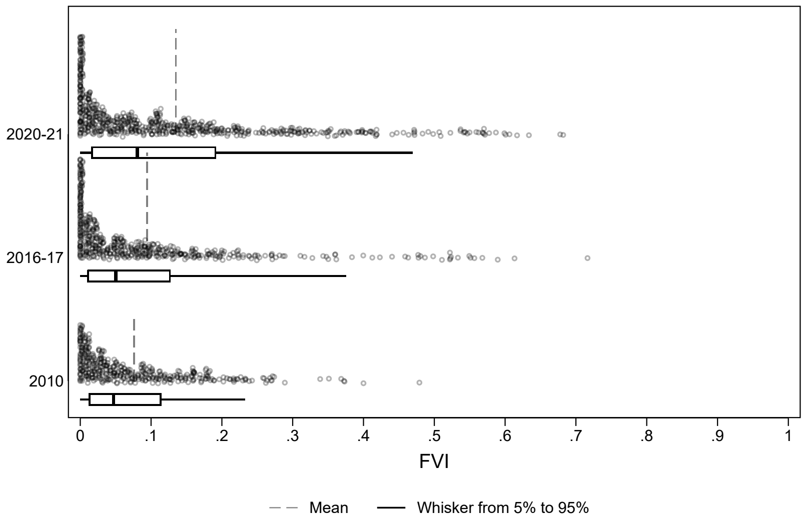

Figure 2.4: Distribution of financial vulnerability index

Note: For 405 households in 2010, 492 in 2016-17, and 626 in 2020-21.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table 2.1: Descriptive statistics of ISR, DTR, and RRGPL

	ISR			DTR			RRGPL		
	2010	2016-17	2020-21	2010	2016-17	2020-21	2010	2016-17	2020-21
Overview									
No. of HH	n=405	n=492	n=626	n=405	n=492	n=626	n=405	n=492	n=626
Mean	0.11	0.14	0.17	0.04	0.04	0.10	0.07	0.12	0.13
CV	1.22	1.66	1.56	2.40	3.08	1.71	2.11	1.87	1.87
Distribution									
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P25	0.02	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
P50	0.07	0.05	0.06	0.00	0.00	0.00	0.00	0.00	0.00
P75	0.15	0.15	0.18	0.00	0.00	0.15	0.02	0.13	0.15
P90	0.28	0.37	0.53	0.20	0.14	0.35	0.27	0.46	0.56
P95	0.38	0.71	0.97	0.32	0.29	0.51	0.41	0.65	0.73
P99	0.67	1.00	1.00	0.44	0.67	0.72	0.55	0.85	0.93
Max	1.00	1.00	1.00	0.54	1.00	1.00	0.64	1.00	1.00

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

2.4.2.1 Methodology

We use an unsupervised data mining technique, namely a time-series clustering algorithm, to classify time-series trends of the FVI. These algorithms, which require a strongly balanced panel, break down a set of dynamic data observations into subsets that are reasonably homogeneous in their characteristics.

We implement the clustering algorithm to the 382 households present in 2010, 2016-17, and 2020-21 by, firstly, using a hierarchical ascending clustering to determine the optimal number of clusters (Sardá-Espinosa 2019; Husson, Lê, and Pagès 2017). Then, we consolidate clusters with partitional clustering (Aghabozorgi, Shirkhorshidi, and Wah 2015).

For both steps, as the distance metric, we use the Euclidean distance because we deal with short time series, and it gives the best visual results with our data. We also test other algorithms, especially the dynamic time warping distance as a dissimilarity measure. However, we do not observe the minimum similarity between groups. We use Ward's method for the hierarchical ascending clustering because it performs better overall than other hierarchical methods (Ferreira and Hitchcock 2009). As centroid, we use the cluster medoid (or the prototype PAM) because it does not alter the time-series structure compared to the mean or median (Sardá-Espinosa 2019).

2.4.2.2 Results

Figure A.2 in the appendix represents the result of the hierarchical ascending clustering. The results show a clear separation of three clusters on the dendrogram.

Figure 2.5 represents the result of the time-series clustering. The clusters significantly vary from each other, whereas the trends within these clusters are homogenous, suggesting that the classification has worked rather well.

The first cluster gathers 26% of the households (98 households). This cluster contains households in a highly vulnerable dynamic, meaning households that experienced a strong increase in their vulnerability over time. The FVI of these households, on average, goes from 0.08 in 2010 and 2016-17 to around 0.4 in 2020-21 (see Figure A.3 in the appendix).

The second cluster represents households in a dynamic of high transitional vulnerability and contains about 16% of the households (62 households). These households experienced a rise in their financial vulnerability index and then a decline. The average FVI of these households goes from 0.07 in 2010 to 0.34 in 2016-17 to 0.12 in 2020-21 (see Figure A.3 in the appendix).

The last cluster covers households in a dynamic of low vulnerability, meaning households that have not experienced strong variation in their FVI across time and for whom the level of the FVI is quite low. This cluster contains 58% of the households (222 households), for whom the median FVI stays around 0.05 in 2010, 2016-17 and 2020-21 (see Figure A.3 in the appendix).

To complete the picture, we analyse the dependency between the cluster and the

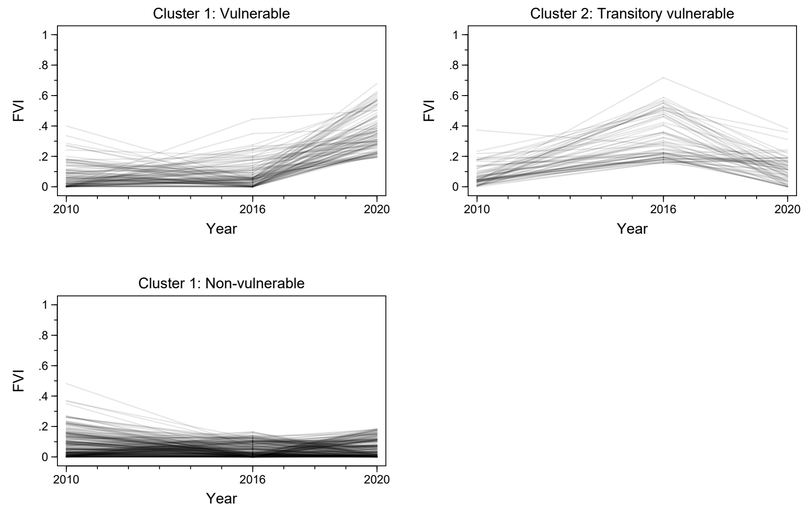

Figure 2.5: Time series clustering of FVI
Note: For 98 vulnerable households, 62 transitory vulnerable, and 222 non-vulnerable.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

caste of the household head using a Pearson χ^2 test because caste is the only household characteristic that is fully time-invariant. Table 2.2 shows that caste drives the households' financial vulnerability dynamics. The p-value associated with the Pearson χ^2 test is below 5%, suggesting a significant dependence between clusters and castes.

By investigating the χ^2 per cell and the difference between the frequency and the expected frequency, we identify which combination of caste and cluster contributes more to the dependency. With a χ^2 per cell equal to 2.6, we observe that upper castes are largely overrepresented among non-vulnerable households (i.e., in the absence of dependency, there should have been 30 high-caste households in the non-vulnerable group, but there are 39). On the contrary, with a χ^2 per cell equal to 1.4, we observe that upper castes are under-represented among vulnerable households: in the absence of dependence, there should have been 13, but there are only nine. Additionally, middle castes are overrepresented among transitory vulnerable households, meaning in the absence of dependence, there should have been 24, but there are 32. These results are consistent with the empirical literature highlighting disparities between castes in favour of the upper castes and against the Dalits (Guérin, D'Espallier, and Venkatasubramanian 2013).

2.5 Drivers of the household financial vulnerability

To complete our understanding of the financial vulnerability indicator, we analyse the determinants of FVI in what follows.

Table 2.2: Castes and trends in FVI

	Cluster			
	Vuln.	Trans. vuln.	Non-vuln.	Total
Dalits	54	26	104	184
	47.2	*29.9*	*106.9*	*184.0*
	(1.0)	(0.5)	(0.1)	(1.6)
Middles	35	32	79	146
	37.5	*23.7*	*84.8*	*146.0*
	(0.2)	(2.9)	(0.4)	(3.5)
Uppers	9	4	39	52
	13.3	*8.4*	*30.2*	*52.0*
	(1.4)	(2.3)	(2.6)	(6.3)
Total	98	62	222	382
	98.0	*62.0*	*222.0*	*382.0*
	(2.6)	(5.7)	(3.0)	(11.3)
Pearson χ^2(4)=11.3 p-value=0.02				

Note: Frequency/*Expected frequency*/(χ^2 per cell).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

2.5.1 Methodology

It is widely recognised that fixed-effects models have an advantage over random-effects models when analysing panel data because they control for time-invariant unobserved heterogeneity. However, fixed-effects models do not estimate the coefficients of time-invariant variables, as they use a within transformation to eliminate the time-invariant unobservable household effects. Thus, fixed-effects models wipe out all time-invariant explanatory variables, and no statistical inference can be made for these variables.

To go beyond this limitation, correlated random-effects models estimate the within effects in a random-effects model. As the dependent variable, FVI is continuous and defined on $[0;1]$, we use a correlated random effects fractional probit model (Bates, Papke, and Wooldridge 2022) adapted to an unbalanced panel (Wooldridge 2019). Based on the maximum-likelihood estimator, this approach models the unobserved heterogeneity as a function of the number of yearly data entries of a household and the mean of the time-varying variables. As our observations are structured with households appearing over time, we cluster the standard errors at the household level, an "obvious choice" (Bates, Papke, and Wooldridge 2022, p.19).

Using a generalised linear model with binomial distribution and probit link function with a quasi-maximum-likelihood estimator (Bates, Papke, and Wooldridge 2022) on the total unbalanced sample (i.e., 405 households in 2010, 492 in 2016-17, and 626 in 2020-21, for a total of 646 unique households), we estimate the following model:

$$E(y_{it}|\boldsymbol{X1'_{it.}}, \overline{\boldsymbol{X1'}}_{\boldsymbol{i.}}, \boldsymbol{X2'_{i.}}, \text{time}_i, \text{year}_{it}, \overline{\text{year}}_i) = \Phi(\psi_t + \boldsymbol{X1'_{it.}}\boldsymbol{\beta} + \overline{\boldsymbol{X1'}}_{\boldsymbol{i.}}\boldsymbol{\gamma} + \boldsymbol{X2'_{i.}}\boldsymbol{F} + \zeta\text{time}_i + \eta\text{year}_{it} + \iota\overline{\text{year}}_i) \quad (2.2)$$

For individual i=1 to 646, and year t=1 to 3, y_{it} is FVI. Φ represents the normal cumulative distribution function and ψ_t allows for year-specific intercepts. time$_i$ is the indicator for each number of time-observations. It is used as sufficient statistics for the dependence between the unobserved, household-level heterogeneity and the selection of time observations in our data. year$_i$ is the year indicators and $\overline{\text{year}}_i$ is the time averages of year indicators.

$\boldsymbol{X1'_{it.}}$ is composed of five vectors of explanatory time-varying variables similar to the literature (Chichaibelu and Waibel 2017; Schicks 2014). Summary statistics for all the independent variables are presented in Chapter 1, Table 1.2, and Tables A.1 and A.2 in the appendix.

- The *economic* vector refers to the variables on the economic situation of households, that is, the monetary wealth (i.e., gold, land, house, livestock, agricultural equipment, and consumer goods) and the annual income of the household, in logarithm. In the pooled settings, one household, representing 0.06% of the total sample, declared a zero value for its wealth. Given the low rate, we have recoded it to one to avoid it being dropped from the analysis. We did the same for annual income (i.e., this concerns four households, representing 0.26% of the total sample).
- The family vector refers to the socio-demographic characteristics of households, such as the household size and the number of children.
- The head vector refers to the variables of the household head as the sex, age, the main occupation (i.e., the occupation generating the most income in 2010 and the most time-consuming occupation in 2016-17 and 2020-21), the level of education (below primary, primary completed, high school or more), and the marital status (married or not).
- The shock vector includes the shock exposition as marriage, demonetisation, or second lockdown.
- The debt vector refers to the indebtedness situation of the household as the share of formal debt and the total amount of the household debt in logarithm. We recoded nine households, representing 0.59% of the total population, to a value of one because they reported a zero value in their debt, as we did for income and assets.

The vector $\overline{\boldsymbol{X1'}}_{\boldsymbol{i.}}$ represents the mean over time of each variable belonging to $\boldsymbol{X1'}$.

$\boldsymbol{X2'_{i.}}$ comprises time-invariant variables: the caste (Dalits, middle or upper castes) and the location.

To deal with the assumed heteroskedasticity, our standard errors are clustered at the household level, a common solution that has the added benefit of making standard errors robust to serial correlation (Wooldridge 2010).

To interpret our results, we present average marginal effects (AME) instead of parameter estimates because of their straightforward interpretation (Bates, Papke, and Wooldridge 2022).

2.5.2 Results

In column 1 of Table 2.3, we estimate the econometric model with the basic controls: the economic characteristics and time-invariant variables. The results show that annual income is negatively associated with households' financial vulnerability, at a 1% risk of error, which is consistent with the literature (Noerhidajati et al. 2021; Chichaibelu and Waibel 2017; Anderloni, Bacchiocchi, and Vandone 2012). In addition, the monetary value of household assets is positively associated with financial vulnerability, suggesting that the more assets the household holds, the more financially vulnerable it is. Moving ahead of the results, the correlation is no longer significant when we add the amount of debt (column 6), suggesting that the correlation between assets and vulnerability only captured the correlation between the amount of debt and financial vulnerability. Regarding the caste, other things being equal, being upper caste rather than Dalits decreases the financial vulnerability index by 0.06 points at a 99% confidence level.

Household socio-demographic characteristics can also play a key role in influencing the household's financial vulnerability. Therefore, in column 2, we control for the family characteristics, but do not observe any correlation. The previous correlation between income, castes, and FVI persist.

In column 3, we control for the head characteristics. As with family characteristics, there is no correlation between the characteristics of the head of household and the financial vulnerability of the household. Negative correlations with income and caste are still there.

In column 4, we add the shock exposition, and do not observe a significant correlation at a 5% risk of error. The previous correlation remains.

We add indebtedness covariates in columns 5 and 6. By only adding the share of formal debt (column 5), we observe a positive correlation with the financial vulnerability index, which is in line with the literature (Guérin et al. 2022). By adding the total loan amount of the household (column 6), the previous correlation is still significant, and the total loan amount is also positively correlated with the financial vulnerability index at a 1% risk of error, which is in accordance with Giarda (2013). This correlation reinforces the relevance of our debt-based measure of financial vulnerability. The previous correlation remains.

To summarise, econometric estimates highlight that income is negatively correlated with the financial vulnerability index, while the loan amount and the share of formal debt are positively correlated. Additionally, upper castes have a lower financial vulnerability

Table 2.3: AME of the financial vulnerability index

	(1) FVI AME/SE	(2) FVI AME/SE	(3) FVI AME/SE	(4) FVI AME/SE	(5) FVI AME/SE	(6) FVI AME/SE
Economic char.						
Income† (log)	−0.05***	−0.05***	−0.05***	−0.05***	−0.05***	−0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Assets‡ (log)	0.01***	0.01**	0.01*	0.01*	0.01	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time invariant variable						
Caste: Dalits	0.00	0.00	0.00	0.00	0.00	0.00
	(.)	(.)	(.)	(.)	(.)	(.)
Caste: Middles	−0.00	0.00	0.01	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Caste: Uppers	−0.06***	−0.06***	−0.05***	−0.05***	−0.05***	−0.06***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Socio-demographic char.						
HH size		0.00	0.00	0.00	0.00	−0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. of children		−0.01	−0.00	−0.00	−0.00	−0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Head char.						
Sex: Female			0.02	0.02	0.01	0.01
			(0.02)	(0.02)	(0.02)	(0.01)
Age			0.00	0.00	0.00	0.00
			(0.00)	(0.00)	(0.00)	(0.00)
MO: Unoccupied			−0.03	−0.03	−0.03	−0.04*
			(0.03)	(0.03)	(0.03)	(0.02)
MO: Agri self-emp			−0.00	−0.00	−0.01	−0.00
			(0.01)	(0.01)	(0.01)	(0.01)
MO: Agri casual			0.00	0.00	0.00	0.00
			(.)	(.)	(.)	(.)
MO: Casual			−0.02	−0.01	−0.01	−0.02*
			(0.01)	(0.01)	(0.01)	(0.01)
MO: Regular			−0.01	−0.02	−0.02	−0.02
			(0.02)	(0.02)	(0.02)	(0.02)
MO: Self-emp			−0.02	−0.02	−0.02	−0.02*
			(0.01)	(0.01)	(0.01)	(0.01)
MO: MGNREGA			−0.03	−0.03	−0.03	−0.03
			(0.02)	(0.02)	(0.02)	(0.02)
Edu: Below primary			0.00	0.00	0.00	0.00
			(.)	(.)	(.)	(.)
Edu: Primary			0.02	0.02	0.02*	0.02*
			(0.01)	(0.01)	(0.01)	(0.01)
Edu: High school or +			−0.02	−0.02	−0.02	−0.02*
			(0.01)	(0.01)	(0.01)	(0.01)
Married: No			−0.01	−0.02	−0.02	−0.01
			(0.01)	(0.01)	(0.01)	(0.01)
Shock exposition						
Marriage: Yes				0.00	0.00	−0.01
				(0.01)	(0.01)	(0.01)
Demonetisation: Yes				0.00	0.01	0.01
				(0.02)	(0.02)	(0.01)
Second lock: Before				0.00	0.00	0.00

				(.)	(.)	(.)
Second lock: During				−0.03*	−0.02	0.02
				(0.02)	(0.02)	(0.02)
Second lock: After				−0.09	−0.08	−0.13
				(0.14)	(0.14)	(0.15)
Indebtedness char.						
Share formal debt					0.00***	0.00***
					(0.00)	(0.00)
Loan amount (log)						0.03***
						(0.01)
Location controls	X	X	X	X	X	X
Observations	1523	1523	1523	1523	1523	1523

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. † Annual labour income (INR). ‡ Monetary value of assets held (INR).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

than Dalits.

2.6 Conclusion

In this study, we propose a new measure of the households' financial vulnerability in a developing area context, called the financial vulnerability index. The innovative features of this study are threefold: the variables used to analyse the financial vulnerability (debt trap, cost of debt, and poverty), the aggregation strategy (weighted arithmetic mean) that ensure a high degree of replicability, and the degree of nuance and variance of the indicator due to the continuous metric.

We then analysed the dynamic of the FVI and the main drivers at the household level. Empirical estimates show three main results.

Firstly, we note a rise in financial vulnerability between 2010 and 2020-21, with growing disparities: the 5% of households with the highest FVI have a minimum FVI that is twice as high in 2020-21 as in 2010.

Secondly, by analysing the household trends with an unsupervised data mining technique, we show that upper castes are overrepresented among households in non-vulnerable dynamics and under-represented among households in vulnerable dynamics.

Thirdly, regarding the drivers of the FVI, we highlight that income and indebtedness, particularly formal indebtedness, are correlated with financial vulnerability. Additionally, upper castes have a lower financial vulnerability than Dalits.

This study is, therefore, the starting point for two types of further analysis, which are necessary for a proper understanding of the households' financial vulnerability. On the one hand, regarding replicability, further research is needed to replicate this new measure of financial vulnerability in different developing countries' contexts where household indebtedness is high, for instance, in Thailand, Vietnam (Chichaibelu and Waibel 2017), Bangladesh (Khandker, Faruqee, and Samad 2013), or Ghana (Schicks 2014) where researchers have focused on the dichotomy of overindebtedness instead of analysing the financial vulnerability. On the other hand, further research is needed to analyse the predictive power of the financial vulnerability index on key economic outcomes, such as the labour supply. This is precisely the subject of the next chapter.

Chapter 3

She Works Hard for the Money: Financial Vulnerability and Labour Supply*

3.1 Introduction

The study of labour supply has been at the heart of traditional empirical microeconomics for over 40 years. This devotion is due to an intense interest in assessing the consequences of a wide array of public policies (e.g., tax and welfare programmes, changing institutional features of labour markets) and the curiosity of researchers to explain the factors underlying the changes in employment patterns (Blundell and Macurdy 1999). The long-standing tradition of studying labour supply and the use of various measures of labour supply (e.g., individual labour force participation, number of hours worked per year, number of days worked per year) at different levels of analysis (e.g., individual, household) has led to a good understanding of its determinants. These include, among others, human capital (Fafchamps and Quisumbing 1999), social programmes (de Brauw et al. 2015), transfers (Acosta 2020), or commodity prices (Beck, Singhal, and Tarp 2019).

Few studies have analysed the effect of debt on labour supply, partly due to the difficulty of identification: while increased indebtedness may drive labour supply (Bunn et al. 2021; Benito and Saleheen 2013), labour shock also leads to household indebtedness (Floro and Messier 2011; Karacimen 2014).

Studies that rely on correlation mainly note that mortgage commitments constrain the labour supply in Canada (Fortin 1995), the Netherlands (Aldershof, Alessie, and Kapteyn 1997), and England (Bottazzi 2004). The causal studies carried out in England confirm this. Indeed, Benito and Saleheen (2013) found that both males and females adjust their hours in response to financial shocks. Bunn et al. (2021) determined that

*. We sincerely thank Elena Reboul for her helpful comments on an earlier draft.

household heads predicted to have low debt decreased their participation in the labour force by significantly more in response to job loss, on average, than mortgagors predicted to have high outstanding mortgage balances. High-debt mortgagors subsequently increased their average hours significantly more than outright owners (conditional on being employed).

However, other studies suggest the opposite. Donaldson, Piacentino, and Thakor (2019) showed that the more the household is indebted, the more household members search for high-wage jobs, which are rare, resulting in more unemployment because individuals are not willing to work for low wages in the USA. In addition, certain negative effects of consumer credit and overindebtedness, such as anxiety and the risk of depression (Hojman, Miranda, and Ruiz-Tagle 2016), can have a negative effect on employment (Chatterji et al. 2007).

The only study in a developing country that seeks to establish the relationship between debt and labour looked at 408 small-scale manufacturing workers in Odisha, India (Kaur et al. 2021). The authors analysed the impact of financial concerns on workers' productivity by testing whether reducing financial concerns could increase productivity. The authors showed that workers who are paid earlier and receive a cash infusion, compared to those who remain liquidity-constrained, have fewer financial concerns because they immediately pay off their debts and buy household essentials. Subsequently, they become more productive at work and make fewer costly, unintentional mistakes.

This chapter builds on previous work but focuses on rural South India to analyse *how household financial vulnerability affects household labour supply* over the 2010-2020 decade. We differ significantly from the studies cited above on two essential points. Firstly, while previous studies analyse labour supply at the individual level, we analyse labour supply at the household level to consider all the household members as a single unit with a common objective. This allows us to avoid treating all individuals in the household as a single decision-making unit, assuming that the decision to work is purely an individual choice (Blundell and Macurdy 1999). More specifically, we measure household labour supply with the total number of occupations in the household. Secondly, all the studies described above have focused on household debt. None has examined the effect of financial vulnerability, a broader concept encompassing various aspects of household debt (e.g., cost, personal feelings, type of debt) and economic situation (e.g., income, assets, poverty). In this chapter, we use the financial vulnerability index developed in Chapter 2 as the variable of interest.

Using a maximum-likelihood structural equation model (ML-SEM) to control for unobserved time-invariant confounders and limits reverse causality (Moral-Benito, Allison, and Williams 2019), we find that the household's financial vulnerability increases the household's labour supply. In addition, by disaggregating the labour supply by sex, we find that the previous relationship is even stronger for females' labour supply (i.e., the total number of occupations held by females). We do not observe any difference according to caste. The main channel used to explain this result is debt repayment: financial vulnerability is an incentive to work to generate the income needed to repay the debt.

Our findings put into question, on the one hand, the specific targeting of females by microcredit policies. Contrary to expectations, microcredit has failed to replace informal debt and, instead, has added to the existing financial burden. This situation is particularly concerning, given that females must increase their labour supply to repay household debts, not just their own but also those incurred by other family members. On the other hand, the long-term sustainability of household debt by highlighting a vicious circle of debt and labour.

The rest of the chapter is organised as follows. Section 3.2 describes the methodology. Section 3.3 presents the results. Section 3.4 provides the discussion. Finally, Section 3.5 concludes.

3.2 Methodology

3.2.1 Measuring the household financial vulnerability

The measure of financial vulnerability used is the FVI developed in Chapter 2.

This measure aggregates three aspects of debt (i.e., the cost of the debt, measured with the interest service ratio, the debt trap ratio measures the extent to which debt is self-sustaining, and the daily livelihood measured with the reverse relative gap to the poverty line) with a weighted arithmetic mean.

FVI is interesting for at least three reasons. Firstly, while the literature mainly relies on binary variables (Azzopardi et al. 2019; Chichaibelu and Waibel 2017), FVI is a continuous metric. This specificity allows for a higher level of variance, precision, and nuance of the observed phenomena. Secondly, FVI is easily replicable in other contexts because it relies on a simple aggregation method (i.e., a weighted arithmetic mean), while the literature mainly relies on principal components analysis (Anderloni, Bacchiocchi, and Vandone 2012; Noerhidajati et al. 2021). Lastly, as a high debt is not in itself a sign of vulnerability (see Chapter 1), the proposed measure moves forward by taking into account three aspects described below.

Descriptive statistics relating to FVI are presented in detail in the Chapter 2, Section 2.4.

3.2.2 Measuring household labour supply

We analyse labour supply at the household level with the total number of occupations in the household.

Focusing on the household level allows us to take into account interactions and dynamics within a family unit and, thus, avoid treating all individuals in the household as a single decision-making unit (Blundell and Macurdy 1999). And with good reason: in India, participation in the labour market is often influenced by intra-household bargaining. For example, Sudarshan and Bhattacharya (2009) observed that the decision to work outside the home is commonly made at the household level in urban Delhi. In addition, Sinha (2012) demonstrated that household decision-making behaviour on labour supply in rural India results from negotiation within the household. The NEEMSIS-2 data also point in this direction: in 2020-21, 64% of the individuals who responded to the individual "ego" questionnaire declared that their participation in the labour market resulted from a collective decision within the household.

Concerning the variable itself, we use the total number of occupations in the household. Although the total number of hours worked per year is the first-best solution to measure household labour supply (Borjas 2014), this variable is unavailable in the 2010 wave. However, at least three points in time are required to get closer to a causal analysis with survey panel data (Moral-Benito, Allison, and Williams 2019). The total number of occupations in the household is the second-best choice in the specific case of this study. To support the labour supply measure used, we observe significant correlations with the number of hours worked per year with the NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21) waves at a 1% risk of error. Indeed, the correlation coefficient between the number of occupations and the number of hours worked per year for all individuals, for males and females, is respectively equal to 0.35, 0.32, and 0.46, which can be considered acceptable in social sciences (Ratner 2009) and indicates a meaningful positive relationship.

The expected effect of financial vulnerability on labour supply is uncertain. As stated above, there is no consensus on the effect of debt/financial vulnerability on labour supply. On the one hand, debt constraints (i.e., forces) people to work more (Bunn et al. 2021; Benito and Saleheen 2013; Fortin 1995; Aldershof, Alessie, and Kapteyn 1997; Bottazzi 2004). On the other hand, whether directly (Donaldson, Piacentino, and Thakor 2019) or indirectly (Hojman, Miranda, and Ruiz-Tagle 2016; Chatterji et al. 2007), debt/financial vulnerability can reduce labour supply. Given the social importance of debt and creditworthiness in rural Tamil Nadu, we believe that financial vulnerability forces households to increase their labour supply to maintain their creditworthiness.

We conduct two heterogeneity analyses to analyse the relationship between financial vulnerability and labour supply in more detail. Firstly, we distinguish between males' and females' labour supply to examine differences in labour supply responses to financial vulnerability. We, therefore, introduce two new dependent variables: females' labour supply (the total number of jobs held by females) and males' labour supply (the total number of jobs held by males). Given the level of analysis (household), this heterogeneity cannot be obtained with an interaction variable. Secondly, we examine whether the effect of financial vulnerability differs according to caste. Because caste is common to the whole household, since it is hereditary and marriage is endogamous (Vaid 2014), we can add an interaction term between financial vulnerability and caste membership to the right-hand side of the equation.

Table 3.1 presents the descriptive statistics for the dependent variables. We observe an increase in the total labour supply over time, especially for females. Indeed, in 2010, the average number of occupations females occupy is 1.23, while it is 2.02 in 2020-21. The result is the same when we consider the net labour supply of females (i.e., the total number of females' occupations divided by the number of females in the household).

Table 3.1: Descriptive statistics for dependent variables

	2010	2016-17	2020-21
No. of HH	n=405	n=492	n=626
Dependent variables			
Total occupations: Mean	3.33	3.97	4.15
Total occupations: CV	0.37	0.47	0.47
Total occupations: P50	3.00	4.00	4.00
Male occupations: Mean	2.10	2.04	2.13
Male occupations: CV	0.44	0.56	0.57
Male occupations: P50	2.00	2.00	2.00
Female occupations: Mean	1.23	1.92	2.02
Female occupations: CV	0.69	0.62	0.62
Female occupations: P50	1.00	2.00	2.00

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

This result is surprising, given India's general trend towards reducing female participation in the labour market (Mehrotra and Parida 2017). Further research needs to be conducted with the RUME survey and then NEEMSIS waves to analyse this phenomenon. For the males, the number of occupations is relatively stable over time (i.e., around four on average).

3.2.3 Econometric framework

3.2.3.1 Identification

As mentioned above, reverse causality is a concern in studying the relationship between household financial vulnerability and labour supply. Panel data can be used to limit the issue by controlling for unobserved time-invariant confounders and by including lagged endogenous regressors (Moral-Benito, Allison, and Williams 2019). Controlling for unobservables can be accomplished with fixed effects models, and causal direction may be dealt with cross-lagged panel models. However, attempting to combine fixed effects models with cross-lagged panel models leads to serious estimation problems, including error terms that are correlated with predictors (Nickell 1981). A solution is to use lagged instrumental variables with the generalised method of moments, that is, a dynamic panel data model such as the Arellano-Bond estimator (Arellano and Bond 1991). However, the Arellano-Bond estimator requires "large samples in the cross-section dimension (i.e., large N) and its finite sample performance might represent a concern when the number of units in the panel is relatively small" (Moral-Benito, Allison, and Williams 2019, p.2). To address the problems of dynamic panel data models, Moral-Benito, Allison, and Williams (2019) propose a cross-lagged panel model with fixed effects estimated by maximum-likelihood that falls within the framework of linear structural equation models, called maximum-likelihood structural equation model (ML-SEM).

3.2.3.2 Maximum-likelihood structural equation model

As the Arellano-Bond model, the ML-SEM distinguishes between strictly exogenous variables, meaning variables that are not allowed to be correlated with past, present, and future values of the idiosyncratic errors (ϵ_{it}), and predetermined variables, which are assumed to be sequentially exogenous. A predetermined variable is uncorrelated with the present and future errors but might be correlated with past errors.

ML-SEM protects against endogeneity arising from time-invariant unobserved heterogeneity as fixed effect models and allows for reverse causality by assuming sequential rather than strict exogeneity (Moral-Benito, Allison, and Williams 2019). Monte Carlo simulations show that the ML-SEM outperforms the Arellano-Bond model regarding unbiasedness efficiency and finite sample performance (Moral-Benito, Allison, and Williams 2019).

3.2.3.3 Specification

The form of our equation is based on Moral-Benito, Allison, and Williams (2019), and we estimate the following model:

$$y_{it} = \lambda y_{it-1} + \beta_1 x_{it-1} + \boldsymbol{X1'_{it.}\gamma} + \boldsymbol{X2'_{i.}F} + \alpha_i + \varepsilon_{it} \tag{3.1}$$

All variables are at the household level. y_{it} represent the measures of the labour supply at the time t (t=1 to 3), for the household i (i=1 to 646), meaning the total number of occupations in the household, the total number of occupations that females perform, and the total number of occupations that males have.

x_{it-1} represents the financial vulnerability index. To be consistent with the cross-lagged panel approach and to limit reverse causality, we use the lag of the financial vulnerability index (Moral-Benito, Allison, and Williams 2019). Good temporal lag is a well-known concern when dealing with lagged variables (Vaisey and Miles 2017). However, given the structure of our data, that is, three points in time separated by four to six years, we have to assume that changes in financial vulnerability show up in changes in the labour supply four to six years later. FVI is considered predetermined because we want to allow for the possibility that financial vulnerability is affected by earlier labour supply values. We believe that the labour supply adjustment to debt is not fully simultaneous but takes place with a time lag. The time lag corresponds, on the one hand, to the search for a job. On the other hand, to the awareness of the level of financial vulnerability. Lagging financial vulnerability to limit endogeneity may not be enough in the case where households take on debt in anticipation of future employment. The assumption of sequential exogeneity is then no longer true. However, debt for current expenditure is the primary reason for borrowing (56% of loans in 2020-21, see Table 1.4 from the Chapter 1), meaning that households take on debt primarily to live. Thus, for the majority of the debt a "debt in anticipation of a job" calculation seems illusory.

$\boldsymbol{X1'_{it.}}$ is a vector of control variables for the household i at the time t, that rely on the literature (Fafchamps and Quisumbing 1999; Acosta 2020; Matshe and Young 2004; Beck, Singhal, and Tarp 2019; Oh 2023) and are treated as strictly exogenous. It is composed of three vectors. Firstly, the vector of household economic characteristics comprises the net amount of the remittances (remittances received minus remittances sent), the monetary value of assets held (i.e., land, house, livestock, gold, and durable goods), the household labour annual income, and the exposition to shocks, namely marriage. Secondly, the vector of households' socio-demographic characteristics, composed of the log of the household size, the sex ratio (the number of males in the household divided by the number of females), the share of children (0 to 13 years old), the dependency ratio (the number dependents –0-14 and 65 years old or more– divided by the number of individuals aged to work –15-64 years old), and the share of individuals of working age, but who do not work (labour force stock). Thirdly, we control for the household head characteristics such as sex, age, and education (no formal education or at least primary completed).

With the vector $\boldsymbol{X2}'_{i.}$ we control for time-invariant variables, meaning caste (Dalits, middle, and upper castes) and location.

We add an interaction term between FVI and caste to implement the second heterogeneity analysis. As FVI is considered predetermined, the interaction term is also considered predetermined. The addition of an interaction term between a predetermined variable and a time-invariant variable is not discussed by the developers of the ML-SEM (Moral-Benito, Allison, and Williams 2019). Thus, this part of the analysis is purely exploratory, and further research needs to be undertaken to validate this strategy. For this reason, we do not perform robustness tests on these three estimates.

3.3 Econometric estimates

3.3.1 Goodness of fit

All the statistics presented in Table 3.2 attest to a good goodness of fit. The root mean squared error of approximation (RMSEA) is below 0.05 for all the estimates, and the comparative fit index and the Tucker-Lewis index are above 0.90.

3.3.2 Results

Table 3.3 provides the econometric estimates regarding the effect of financial vulnerability on labour supply.

To start with the covariates, we observe that the lag of the dependent variable is not correlated with the present value. Additionally, the result on remittances is consistent with Acosta (2020), that is, remittances tend to increase female labour supply. Without surprise, household size is positively correlated with the labour supply, meaning the larger the household, the more labour it can dispose of, in theory. Being upper caste rather than middle caste is associated with a lower labour supply while being Dalit rather

Table 3.2: Goodness of fit for econometric estimates

	(1) Total	(2) Males	(3) Females
Likelihood ratio			
Model vs saturated (p-value)	0.08	0.33	0.05
Baseline vs saturated (p-value)	0.00	0.00	0.00
Population error			
RMSEA	0.03	0.01	0.03
Baseline comparison			
Comparative fit index	0.98	1.00	0.97
Tucker-Lewis index	0.94	0.99	0.91

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

than middle caste is associated with more labour supply. This result is consistent with the well-known fact that Dalits must work more than middle and upper castes for the same income in rural India (Guérin, Venkatasubramanian, and Michiels 2014).

After controlling for endogeneity arising from time-invariant unobserved heterogeneity and protecting against reverse causality, we find that more financial vulnerability is associated with more household labour supply (see column 1 of Table 3.3). Other things being equal, at a 99% confidence level, when the financial vulnerability index increases by 0.1 unit in t, the total number of occupations increases by 0.19 in $t+1$.

3.3.3 Heterogeneity analysis

The first heterogeneity analysis suggests that females' labour supply is most sensitive to household financial vulnerability (see columns 2 and 3 of Table 3.3). All else being equal, when the FVI increases by 0.1 unit in t, the number of occupations females occupy increases by 0.13 in $t+1$, at a 1% risk of error.

Table 3.4 presents the results of the second heterogeneity analysis, that is, the contribution of the caste on the effect of financial vulnerability on labour supply. The positive effect of financial vulnerability remains, especially for females. However, we do not observe a supplementary effect of the caste on the effect of financial vulnerability on total labour supply, males' supply and females' supply. In other words, the effect of financial vulnerability on labour supply is not different for Dalits than for middle and upper castes.

3.3.4 Robustness

We implement robustness checks to confirm the relationship between household financial vulnerability and labour supply. We show that all the robustness checks confirm previous results regarding the positive impact of financial vulnerability on the labour supply, especially for females.

Table 3.3: Maximum-likelihood structural equation models for the number of occupations in the household

	(1) Total Coef./SE	(2) Males Coef./SE	(3) Females Coef./SE
Lag Y	0.04	0.04	0.00
	(0.07)	(0.06)	(0.07)
Lag FVI	1.92***	0.58	1.29***
	(0.59)	(0.36)	(0.39)
Demographic characteristics			
HH size (log)	1.73***	0.96***	0.76***
	(0.23)	(0.14)	(0.15)
Share of children	1.25	0.89	0.26
	(0.88)	(0.54)	(0.59)
Sex ratio	0.26**	0.31***	−0.05
	(0.12)	(0.07)	(0.08)
Dependency ratio	−0.20	0.02	−0.21
	(0.32)	(0.20)	(0.21)
Share of stock	0.90	0.95*	−0.08
	(0.80)	(0.50)	(0.54)
Economic characteristics			
Net remittances†	0.14**	0.01	0.12***
	(0.07)	(0.04)	(0.05)
Assets‡	0.32**	0.11	0.19**
	(0.13)	(0.08)	(0.09)
Income§	0.23***	0.18***	0.05
	(0.06)	(0.04)	(0.04)
Head characteristics			
Female	−0.22	−0.23	0.00
	(0.25)	(0.15)	(0.16)
Age	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)
Edu: Below primary	0.00	0.00	0.00
	(.)	(.)	(.)
Edu: Primary or more	−0.63*	−0.18	−0.43*
	(0.36)	(0.22)	(0.24)
Time invariant variables			
Caste: Dalits	0.26*	0.03	0.24**
	(0.15)	(0.09)	(0.11)
Caste: Middles	0.00	0.00	0.00
	(.)	(.)	(.)
Upper castes	−0.73***	−0.14	−0.60***
	(0.27)	(0.15)	(0.19)
HH FE	X	X	X
Location controls	X	X	X
Shock controls	X	X	X
Observations	646	646	646

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. †Transfers received minus transfers sent. ‡Monetary value of assets held, without land (INR 1k). §Annual labour income (INR 1k).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table 3.4: Maximum-likelihood structural equation models for the number of occupations in the household with interaction term

	(1) Total Coef./SE	(2) Males Coef./SE	(3) Females Coef./SE
Lag Y	0.04	0.03	0.01
	(0.07)	(0.06)	(0.07)
Lag FVI	2.17**	0.68	1.39**
	(0.85)	(0.52)	(0.56)
Lag FVI*Dalits	−0.27	0.04	−0.25
	(1.28)	(0.78)	(0.86)
Lag FVI*Middles	0.00	0.00	0.00
	(.)	(.)	(.)
Lag FVI*Uppers	−1.29	−0.99	−0.19
	(1.63)	(0.99)	(1.09)
Demographic characteristics			
HH size (log)	1.77***	1.01***	0.75***
	(0.23)	(0.14)	(0.15)
Share of children	1.25	0.88	0.28
	(0.88)	(0.54)	(0.59)
Sex ratio	0.24**	0.29***	−0.05
	(0.12)	(0.07)	(0.08)
Dependency ratio	−0.25	−0.04	−0.21
	(0.32)	(0.20)	(0.21)
Share of stock	0.90	0.94*	−0.07
	(0.81)	(0.50)	(0.54)
Economic characteristics			
Net remittances†	0.14**	0.02	0.12**
	(0.07)	(0.04)	(0.05)
Assets‡	0.30**	0.09	0.19**
	(0.13)	(0.08)	(0.09)
Income§	0.23***	0.19***	0.05
	(0.06)	(0.04)	(0.04)
Head characteristics			
Female	−0.18	−0.19	0.00
	(0.25)	(0.15)	(0.16)
Age	0.02*	0.01*	0.01
	(0.01)	(0.01)	(0.01)
Edu: Below primary	0.00	0.00	0.00
	(.)	(.)	(.)
Edu: Primary or more	−0.59*	−0.14	−0.43*
	(0.36)	(0.22)	(0.24)
Time invariant variables			
Caste: Dalits	0.30	0.05	0.26**
	(0.19)	(0.11)	(0.13)
Caste: Middles	0.00	0.00	0.00
	(.)	(.)	(.)
Upper castes	−0.64**	−0.08	−0.59***
	(0.30)	(0.17)	(0.21)
HH FE	X	X	X
Location controls	X	X	X
Shock controls	X	X	X

Observations	646	646	646

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. † Transfers received minus transfers sent. ‡ Monetary value of assets held, without land (INR 1k). § Annual labour income (INR 1k).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

3.3.4.1 Non-normality

In the first robustness check, we control for the non-normality of the error term. Indeed, the ML-SEM model assumes that the error term is normally distributed. However, our dependent variables are not perfectly normally distributed, suggesting that the error term is not. We correct it using a robust estimator (Williams, Allison, and Moral-Benito 2018). The results in Table A.9 in the appendix indicate that household financial vulnerability still positively affects the labour supply, especially for females.

3.3.4.2 Remove outliers

The second robustness consists of pure robustness by removing the dependent variables' 5% outliers, meaning the 5% of households with the highest labour supply. By doing so, we prevent the results of the estimates from being driven by extremes as we reason "at the mean". Results presented in Table A.10 in the appendix show that the financial vulnerability's effect on females' labour supply still holds.

3.3.5 The repayment channel

The result that more financial vulnerability is associated with more household labour supply is consistent with the literature (Bunn et al. 2021; Benito and Saleheen 2013), but two transmission channels are possible. On the one hand, this may involve debt repayment, meaning that financial vulnerability is an incentive to work to generate the income needed to repay the debt. On the other hand, an increase in the labour supply may result from a productive investment that has led to an increase in labour. To check which channel is the most convincing, we construct a new financial vulnerability variable by removing productive investment and re-estimate the model presented above. If the results are the same as before, the explanation "work to repay" dominates. If we no longer observe any effect, this implies that the "productive investment" explanation dominates.

The result in Table A.11 in the appendix show that when we remove productive investment from the financial vulnerability index, the effect on labour supply is still present, particularly for females. This result, therefore, suggests that the effect of financial vulnerability on labour supply is not the product of productive investment but is the consequence of unsustainable debt requiring additional resources to be repaid.

This interpretation is consistent with the qualitative work carried out in the study area. Firstly, with ethnographic financial diaries, Reboul et al. (2019, p.31) note that:

> As for women, debt is also an incentive to work more. While we were discussing with Lokesh's mother about the growing presence of financial

> providers in the village, she comments as follows: "now people work restless to pay these finance. Women have to work twice a day, to pay back not only finance but all moneylenders, neighbours, etc. First we started working in the morning, now we have to work twice a day. How will this end? Now all workers become regular workers. No choice".

Secondly, in a recent scientific documentary series, Nordman (2023) captured the testimony of four Dalits living in one of the study villages. In 2019, Vijaya, a Dalit mother, declared: "We have loans to repay. Also, we didn't want to burden our in-laws. So, we went to brick chambers." The same is true two years later: "I had to take up this job [worker in a sugar cane field]. My husband never goes to work. We've got loans to repay. I went to work to earn a little money."

3.4 Discussion

3.4.1 Female employment in rural India

The fact that females are increasing their labour supply to pay off household debt contracted by males and females (see Table in Chapter 1) is not insignificant, given females' place in work and society.

In addition to the fact that females' work is frowned upon in society (Mehrotra and Parida 2017), that females are confined to day-to-day activities, and bear the brunt of domestic work (Ratheesh and Anitha 2022), paid work for females is difficult. The NEEMSIS-2 wave may shed some light on this point, as it includes a module on participation in labour market, with questions on job satisfaction, working conditions, and discrimination at work for "ego". Figure 3.1 shows that casual work (agricultural or not, i.e., occupations where females are overrepresented compared to males, see Chapter 1, Table 1.3), are associated with the worst working conditions in terms of execution (e.g., standing, posture, walking, or carrying heavy loads), problem (e.g., dirtiness, humidity, or bad smells), and exposition (e.g., traffic accidents, or risk of being injured).[6] In contrast, regular occupations (qualified or not), meaning occupations where males are overrepresented compared to females (see Chapter 1, Table 1.3), are associated with better working conditions.

The testimony of Vijaya (Nordman 2023) is also telltale here. Taking a job in a brick kiln to get an advance to pay off a previous debt in 2019, she declares: "Brick-making is a tough job [...]. It was difficult with the children around. We worked in the night when they slept [...]. I didn't get time to rest or sleep [...]. I didn't even have time to eat. I had to manage my kids, cook, and also work. It was very difficult. I started getting headaches due to lack of sleep."

6. Scores are calculated by averaging nine binary questions for "execution" (e.g., do you have to stand for long periods of time as part of your job?), ten for "problem" (e.g., is dirtiness problematic in your work?), and five for "exposition" (e.g., are you exposed to smokes and dust). The score obtained is between zero and one.

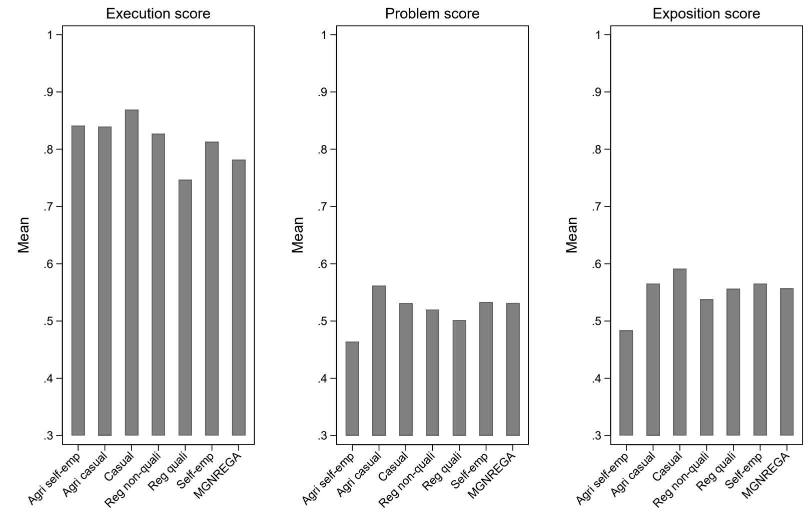

Figure 3.1: Working conditions by type of occupations

Note: For a total of 1278 occupations.

Source: NEEMSIS-2 (2020-21); author's calculations.

This result questioned the specific targeting of females by microcredit. Contrary to expectations, microcredit has not supplanted informal debt but augmented it (Arnold and Booker 2013), increasing indebtedness among females. In addition, females face the burden of augmenting their labour supply, often under arduous conditions, to repay household debts. This includes their own debts and those incurred by other family members, further entrenching them in precarious situations. This result is consistent with Reboul, Guérin, and Nordman (2021), who pointed out that females have the heaviest borrowing responsibilities. Additionally, this result highlights the work for the debt in addition to the work of the debt (Guérin, Kumar, and Venkatasubramanian 2023). In rural South India, debt management is a real job, mostly done by females. It requires time and specific skills, as it involves juggling several loans and keeping track of these loan mazes while trying to negotiate new loans well (Natal and Nordman 2022).

3.4.2 A vicious circle of debt and labour

As stated above, labour shock also leads to household indebtedness. For example, in urban Ecuador, Floro and Messier (2011) showed that low-quality jobs can lead to heavy indebtedness, while Karacimen (2014) found that employment and income insecurity are essential in determining the increased tendency to borrow in Turkey.

A vicious mechanism is thus clearly apparent. Households go into debt to meet their basic needs at date t. Then, they increase their available labour force, often females, to repay part of this debt in $t+1$. The new occupations are often flexible, low-paying, and difficult, pushing people further into debt to meet their basic needs.

This vicious debt-labour circle echoes the dichotomy of debt/credit and financial inclusion discourses. On the one hand, the supporters of financial inclusion focus on credit as a potential tool for enterprise creation, improving access to education and health, improving decision-making, and empowering females. On the other hand, financial inclusion critics have, by contrast, emphasised the debt dimension and raised concern about finance's increasing material and symbolic hold over production and daily life.

3.5 Conclusion

This study, which examined how financial vulnerability affects the labour supply in rural South India, is original in many aspects. Firstly, it is the first study to quantitatively examine the effect of financial vulnerability on labour supply in a so-called Southern country. Secondly, this study is close to a causal analysis by assuming the sequential exogeneity of the financial vulnerability. At least, we control for reverse causality and unobserved heterogeneity by relying on a maximum-likelihood structural equation model (Moral-Benito, Allison, and Williams 2019). Thirdly, the measure of financial vulnerability used goes beyond the simple amount of debt by considering the cost of debt, the debt trap and the poverty level of the household (see Chapter 2). Lastly, our results are based on panel data covering 10 years, which is rare in developing countries.

The result of this study is that greater financial vulnerability is associated with higher labour supply. When we disaggregate labour supply by gender, we find that this relationship is even stronger for females labour supply (i.e., the more financially vulnerable the household, the higher the labour supply of females). The main channel used to explain this result is debt repayment: financial vulnerability is an incentive to work to generate the income needed to repay the debt.

Given females' place in the world of work and society in India, this last result is important and raises doubts about the female-targeted approach of microcredit policies. Contrary to expectations, microcredit has not replaced informal debt but has added to the existing burden. This situation is particularly worrying because females are forced to increase their labour supply under difficult conditions to repay household debts, not only their own but also those contracted by other family members. In addition, this result highlights the labour-intensive nature of the debt. On the one hand, female labour is needed to repay the debt. On the other hand, it is needed to manage the debt. Indeed, this task requires considerable time and specific skills, as it involves juggling multiple loans and navigating complex loan agreements while trying to effectively negotiate new loans (Guérin, Kumar, and Venkatasubramanian 2023).

Additionally, this research highlights a vicious circle between debt and labour, meaning households go into debt to survive, work under difficult conditions to repay, and these occupations are not enough to create a sufficient income to live on, pushing them into debt.

This first exploratory research paves the way for other research. In particular, further research should improve the measure of labour supply to refine the estimation of the effects. We recommend using classic measures from the literature, such as the number of weeks worked in a year, or better, the number of days or hours (Fafchamps and Quisumbing 1999; Beck, Singhal, and Tarp 2019; Acosta 2020; Matshe and Young 2004). Subsequent investigations could also direct their attention toward alternative identification strategies (e.g., instrumental variables) to further enhance the causal relationship.

Despite the fact that it is necessary, analysing debt at the household level erases some of the inter-individual disparities. Among the analyses at an individual level, the behaviourist perspective can offer valuable insights into the underlying psychological factors that influence individuals' borrowing decisions (Brown and Taylor 2014) which can lead to different types of public policy (Arráiz, Bruhn, and Stucchi 2017) that must necessarily be part of broader macroeconomic and structural development policies (Bédécarrats, Guérin, and Roubaud 2020).[7] However, few researchers have investigated the relationship between cognition (i.e., personality traits and cognitive skills) and indebtedness, even fewer in developing countries. The study of cognition, particularly personality traits, raises several methodological issues, especially in developing countries (see, e.g., Laajaj and Macours 2021; Cobb-Clark and Schurer 2012). This is the subject of the next chapter.

7. We will not discuss public policy in this doctoral dissertation.

CHAPTER 4

A Change is Gonna Come: Measures and Stability of Personality Traits*

4.1 Introduction

For more than a decade, there has been increasing interest in the economics literature about personality traits. The relevance of such analyses is well documented, especially on the labour market and educational attainment in developed countries (Almlund et al. 2011).

At the same time, in the economics literature, a growing debate has emerged on the universality of the Big Five model of personality traits, which identifies five dimensions of personality (emotional stability, extraversion, openness to experience, agreeableness, and conscientiousness. This debate, already well underway in the psychological literature, highlights the fact that the non-universality of the model can generate measurement errors and hence endogeneity problems. However, another source of endogeneity has received less attention in the economic literature: reverse causality. Suppose personality traits are not stable over time. In that case, they can no longer be considered exogenous and thus become endogenous, potentially invalidating the effect of personality traits on various economic outcomes.

Developing countries have been at the heart of the debate on the universality of personality traits. However, they have been almost absent from the discussion on the stability over time of traits and whether traits are affected by shocks. While at the same time, there is a growing body of research on the relationship between traits and economic outcomes in these countries (Dasgupta et al. 2022; Donato et al. 2017; Nordman, Sarr, and Sharma 2019).

*. This study is coauthored with Christophe Jalil Nordman. CRediT – A. Natal: Conceptualisation, Formal analysis, Visualisation, Writing – original draft, Writing – review and editing. C.J. Nordman: Writing – review and editing.

By considering the case of rural Tamil Nadu, in South India, this chapter attempts to fill this knowledge gap by analysing *the extent to which the Big Five personality traits are valid and stable over time*. This context is all the more interesting because it is a caste-segmented patriarchal society that conditions many cognitive aspects of the individual (Dasgupta et al. 2023).

We employ the two NEEMSIS waves because they include longitudinal measures of individuals' Big Five personality traits (2016-17 and 2020-21). We first use descriptive statistics and econometric tools to explore the universality of the Big Five model, then the mean-level stability over time, and finally the effect of external shocks, namely the Indian demonetisation of November 2016 and the second COVID-19 lockdown of April 2021. We find that the Big Five taxonomy represents the dataset quite well in 2016-17, but we do not find strong support for it in 2020-21. We provide evidence that a significant proportion of the population faces instability over time in the Big Five trait of emotional stability. The Indian demonetisation of November 2016 positively affected the openness-extraversion trait, and the second COVID-19 lockdown of April 2021 negatively affected the emotional stability trait.

This study contributes to the psychology and economics literature on the measurement of Big Five personality traits in developing countries, the stability of these traits over time, and how they are affected by shocks. More broadly, we contribute to the economics literature on the measurement of attitudinal expectations and aspirations in a developing country context.

The chapter is organised as follows. Section 4.2 summarises the literature. Section 4.3 presents the construction of the personality traits to determine whether the Big Five taxonomy emerges from the NEEMSIS data. In Section 4.4, we analyse whether personality traits are stable over five-year time span. Section 4.5 investigates the effects of external shocks (i.e., the demonetisation of November 2016 and the second COVID-19 lockdown of April 2021) on personality traits. Section 4.6 concludes.

4.2 Literature review

The Big Five model is the central personality trait taxonomy in psychology. Based on the work of Goldberg (1981) and McCrae and Costa (1987), the Big Five model identifies five dimensions of personality:

- emotional stability (ability to feel stable and balanced emotions);
- extraversion (tendency to seek stimulation and company from others);
- openness to experience (capacity to be creative and unstructured);
- agreeableness (perceptions of others that are caring, compassionate, and altruistic); and
- conscientiousness (capacity to display self-discipline, act dutifully, and strive for achievement against measures or outside expectations).

There are several important ongoing debates regarding the Big Five in the literature. These include whether the model is universal and whether the traits are stable over time, and how they are affected by shocks.

4.2.1 Universality of the Big Five model

In psychology and economics, the literature seems to take a nuanced position on the universality of the Big Five taxonomy, that is, the idea that the Big Five model is valid for all populations. A first group of researchers, including McCrae and Costa (1997), advocates universality, while another group questions it.

For instance, in seven African countries (Botswana, the Democratic Republic of the Congo, Ethiopia, Morocco, South Africa, the United Republic of Tanzania, and Zimbabwe), Schmitt et al. (2007) found evidence of the universality of the model as do Bühler, Sharma, and Stein (2023) in rural Thailand and rural Vietnam. In addition, using data from 22 countries, Kajonius and Giolla (2017) showed that personality traits vary slightly across countries. In other words, the relationship between an individual's country of residence and personality traits is small, suggesting the universality of the Big Five taxonomy.

Conversely, Gurven et al. (2013) found no strong support for the Big Five model in indigenous Colombian tribes. However, they observed consistency among factors relating to prosociality (socially beneficial behaviour) and industriousness (the tendency for efficiency, perseverance, and thoroughness). Similarly, Thalmayer et al. (2020) observed that five-factor dimensions do not overlap with the Big Five model in two African rural communities (the Maasai in Kenya and Tanzania and the Supyire-Senufo in Mali). However, they demonstrated consistency for the Big Two model, composed of social self-regulation and dynamism (Saucier et al. 2014). Additionally, recent work by Laajaj and Macours (2021) showed that the Big Five taxonomy is of limited applicability in Kenya and Colombia because of the enumerator-respondent interactions involved in face-to-face surveys and the low education level among the population. Lastly, John et al. (2019) found no strong support for the Big Five taxonomy among young adolescents in India.

Thus, the debate regarding the universality of the model persists, and new research is essential to furthering it.

4.2.2 Stability of personality traits over time

In the economics literature, the stability of personality traits over time is often assumed, following the biological view in psychology. This assumption allows personality traits to be considered as exogenous variables in econometric analyses and thus limits endogeneity issues, the *bête noire* of econometricians.

There is no consensus in the psychology literature regarding the stability of personality traits (Ardelt 2000) because of the complexity of its study. This complexity is due to the multiplicity of types of change measures (e.g., rank-order stability, differential continuity, and mean-level stability) (Coulacoglou and Saklofske 2017).

In terms of mean level, according to Costa and McCrae (1997), personality traits remain stable partly because they are a genetic predisposition that, by definition, cannot be changed or modified over the lifespan (i.e., the biological view of personality). Roberts and DelVecchio (2000) reported a high level of test-retest stability (i.e., a correlation coefficient for values measured at two different points in time, and the higher the correlation, the more stable the traits are) for adults over seven years. Additionally, Cobb-Clark and Schurer (2012), using the Australian household income labour dynamics dataset (HILDA), determined that Big Five personality traits are stable for working-age adults over a four-year period. Other researchers obtain more nuanced findings. Elkins, Kassenboehmer, and Schurer (2017) found that unconditional changes in the mean-level of personality traits, although small, exist in Australia, except for the trait of conscientiousness.

The stability of personality traits over time contradicts the sociological and psychological literature that is interested in the influence of childhood and adult socialisation on personality (Mortimer and Simmons 1978). Bleidorn et al. (2021, p.6) showed that personality traits are "dynamic characteristics of persons that are both moderately stable and malleable across the lifespan". Besides, Caspi, Roberts, and Shiner (2005) observed a pattern of mean-level changes in personality, that is a function of both temporary and life cycle dynamics. Using the German socioeconomic panel study (GSOEP) dataset, Specht, Egloff, and Schmukle (2011) demonstrated that personality changes throughout the lifespan, with more pronounced changes at young and old ages. These changes are partly attributable to social demands and experiences. In a meta-analysis, Roberts, Walton, and Viechtbauer (2006) reported increases in social dominance (item of extraversion), conscientiousness, and emotional stability in young adulthood, increases in social vitality (item of extraversion) and openness to experience in adolescence, and decreases in both of these domains (social vitality and openness to experience) in old age.

To our knowledge, the only research on personality traits stability in developing countries was carried out by Bühler, Sharma, and Stein (2023) in rural Thailand and rural Vietnam. The authors observed small but significant differences over time in openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism (i.e., the opposite of emotional stability).

In addition to the life cycle changes described above, instability in personality traits can be due to exogenous shocks.

4.2.3 Shocks and personality traits

The psychology literature recognises external shock (e.g., illness, unemployment, or economic crises) as a potential source of instability in personality traits.

For instance, using the HILDA dataset, Cobb-Clark and Schurer (2012) found that health and labour market-related events are negatively associated with conscientiousness and emotional stability. Regarding the locus of control (i.e., the degree to which an individual perceives an outcome as being contingent on their own actions rather than those of external forces), Cobb-Clark and Schurer (2013) demonstrated that individuals who experience the birth of a child, the severe illness of a family member, or a deterioration in their finances become more externally oriented. By combining the Big Five personality traits and locus of control, Elkins, Kassenboehmer, and Schurer (2017) observed that long-term health problems, including bodily pain, are associated with an increase in external tendencies and a decline in openness to experience, conscientiousness, and agreeableness.

Using the GSOEP dataset, Boyce et al. (2015) and Anger, Camehl, and Peter (2017), showed that involuntary job loss leads to increased openness to experience and emotional stability. Marsaudon (2022) determined that individuals facing health shocks are more likely than healthy individuals to experience a reduction in their locus of control score.

In developing countries, and more specifically in Uganda, Mehra, Stopnitzki, and Alloush (2022) found that a positive shock (a poverty graduation programme) significantly increases scores on traits that represent socialisation and stability, while a negative shock (a drought) decreases scores on these traits.

In summary, this brief literature review demonstrates the various challenges facing the theory of the Big Five personality traits. Developing countries have received little attention in this area of research. However, studies are increasingly employing the Big Five taxonomy, and the issue of stability over time may raise endogeneity issues in econometrics. Using the NEEMSIS dataset, we explore the universality and stability of Big Five personality traits in rural Tamil Nadu.

4.3 Construction and universality of Big Five personality traits

The NEEMSIS module on Big Five personality traits consists of a set of 35 affirmative questions with seven questions for each trait (see Table A.12 in the appendix) (John and Srivastava 1999). Individuals respond on a Likert scale ranging from "1 – Almost never" to "5 – Almost always" for the 35 questions. Seven questions are reverse-coded, meaning they should be the opposite of seven other questions (see Table A.12 in the appendix). The inclusion of these questions allows us to measure the acquiescence bias through the acquiescence score, that is, the tendency to answer more in one direction (agree or disagree) over the other. The World Bank's STEP Skills Measurement Programme (Pierre et al. 2014) and many other researchers (Hoeschler, Balestra, and Backes-Gellner 2018) use the short Big Five inventory, which consists of two/three items per trait. The literature shows that the short inventory is associated with substantially reduced criterion validity, and Credé et al. (2012, p.886) suggest that "researchers and practitioners alike should resist the usage of very short measures of personality or at least acknowledge the inevitable reductions in construct validity associated with them".

To construct the Big Five personality traits, we use items (the 35 answers) corrected for the acquiescence bias. The correction is essential as not correcting for acquiescence bias prior to factor analysis often results in the emergence of a factor representing the response pattern (McCrae et al. 2011). Then, we compute the Big Five personality traits using two approaches. Firstly, we compute naïve personality by averaging items belonging to the same traits. The major drawback of this approach is that it does not allow us to observe whether the factors emerge naturally from the data. Secondly, we carry out factor analysis of the corrected items. Using this technique, we allow the factors to emerge endogenously from the data rather than placing an exogenous structure on them, thus improving the reliability of the trait measures. The factor analysis method is the one usually employed in psychology.

We use McDonald's ω to determine the reliability of the personality trait measurements, meaning the internal consistency. There is an increasing agreement in the literature that Cronbach's α, the widely used reliability estimator, is inefficient (Trizano-Hermosilla and Alvarado 2016). Low internal consistency implies that the results could suffer from measurement error, which would bias our results towards zero.

4.3.1 Acquiescence bias

In a self-reported survey, the acquiescence bias can affect factor structure and hence the overall validity of personality questionnaires (Danner, Aichholzer, and Rammstedt 2015) by inflating correlations among pro-trait items and con-trait items and reducing the correlations between items with opposite wording (Mavor, Louis, and Sibley 2010). In what follows, we analyse the acquiescence score and try to capture the effect of enumerators to determine the extent of their contribution to the bias (Di Maio and Fiala 2020).

To obtain the acquiescence score, we average the scores on seven pairs of questions that contain reverse items minus the modality that allows for the symmetry of the Likert scale (i.e., three, given our five-point Likert scale). Figure 4.1 presents the scores in 2016-17 and 2020-21 and shows that the acquiescence score is higher in 2020-21 than in 2016-17.

We analyse the enumerators' contribution to the acquiescence score by regressing the basic socioeconomic variables of the surveyed individuals (sex, caste, age, education, village) on their acquiescence score in the first step. Then, we add dummies for enumerators. We interpret the variation of the coefficient of determination (R^2) as the contribution of enumerators to the total variance of the score.

- In 2016-17, R^2 goes from 0.03 to 0.26, representing an increase of 0.23 percentage points.
- In 2020-21, R^2 goes from 0.06 to 0.12, representing an increase of 0.06 percentage points.

Although the acquiescence score is higher in 2020-21 than in 2016-17, the contribution of enumerators to the total variance is lower in 2020-21 than in 2016-17. This pattern suggests a limited role of enumerators in the acquiescence bias.

We use the acquiescence score to correct items for the acquiescence bias by removing the score from each item (Soto et al. 2008). We then use the corrected items to construct the Big Five personality traits using the naïve and factor analysis approaches.

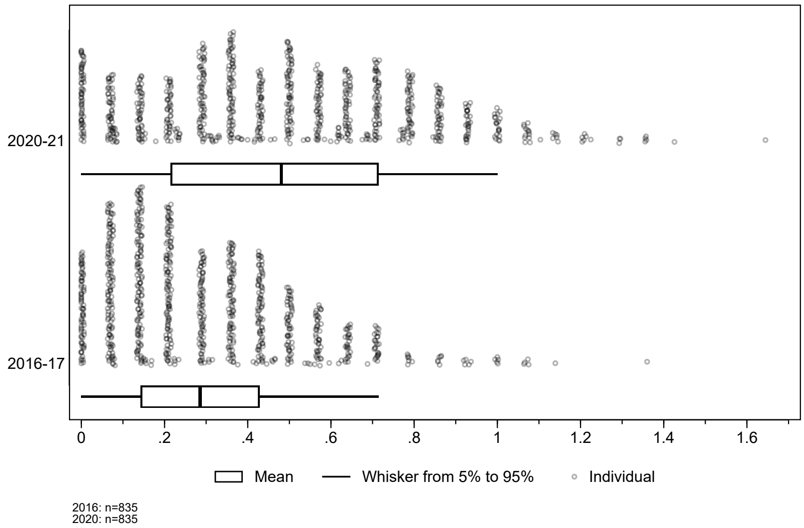

Figure 4.1: Distribution of acquiescence bias

Note: For 835 individuals in 2016-17 and in 2020-21.

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

4.3.2 Naïve approach

For the naïve Big Five approach, we average the items that constitute a determined trait. The resulting mean represents the score on each trait. This is the most commonly used method for constructing personality traits in economics (Pierre et al. 2014; Heineck and Anger 2010; Cobb-Clark and Schurer 2012). This approach is transparent and easy to understand. However, it does not consider any patterns driven by the data (i.e., it does not allow us to observe whether the factors emerge naturally from the data).

The results reflect satisfactory reliability if the internal consistency, measured with the McDonald's ω, is higher than 0.6. The results obtained from NEEMSIS-1 data (2016-17) are as follows: ω=0.81 for openness to experience, ω=0.86 for conscientiousness, ω=0.59 for extraversion, ω=0.60 for agreeableness, and ω=0.80 for emotional stability. However, for 2020-21, the internal consistency is less satisfactory for all traits except for emotional stability: ω=0.36 for openness to experience, ω=0.42 for conscientiousness, ω=0.45 for extraversion, ω=0.29 for agreeableness, and ω=0.79 for emotional stability.

These results suggest that only emotional stability is accurately measured in the panel setting. Therefore, using the naïve approach may only allow us to measure the stability over time of the emotional stability trait.

4.3.3 Factor analysis approach

The factor analysis approach "explicitly recognises that answers to the questionnaire are only imperfect proxies of the true underlying latent traits and relies on the data to uncover those latent traits" (Hilger 2018, p.26).

Before conducting the factor analysis, we compute Bartlett's test of sphericity to determine whether there is redundancy between the variables that can be summarised with a few factors. Table A.13 in the appendix provides results for 2016-17 and 2020-21. Both p-values are equal to 0.00, meaning that we reject the null hypothesis that the variables are orthogonal (i.e., uncorrelated). We also compute the Kaiser-Meyer-Olkin test to determine whether the data are suitable for factor analysis. The higher the statistic, the more suited the data are for factor analysis. The results show that 91% of the variance among the variables might be common variance in 2016-17 (86% in 2020-21), suggesting that our data are suitable for factor analysis (see Table A.13 in the appendix).

We apply factor analysis by principal component on the set of 35 questions for our two samples separately (2016-17 and 2020-21). To improve the factor's meaningfulness and reliability, we use an oblique rotation (Lee and Ashton 2007) with quartimin procedures (Attanasio et al. 2020), thus assuming that the factors can be correlated. Oblique rotation is preferred because it allows for the identification of clusters of variables that are closely linked. To quote Condon and Mroczek (2016, p.311): "Evidence for the Big Five is not predicated on orthogonality and several prominent researchers have been proponents of oblique rotations [...]. We view orthogonality as theoretically problematic for hierarchical personality inventories where the scores at one level are dependent on other levels".

The literature proposes various criteria to determine how many factors to retain from the factor analysis (see Box A.4.1 in the appendix). Although it has been argued that Velicer's minimum average partial and Horn's parallel analysis are the more reliable methods (Ledesma and Valero-Mora 2007), we retain five factors to check the complete Big Five taxonomy. All five satisfy Kaiser's criterion, which is the most widely used technique.

Then, we assume that each item proxies only one factor because "it makes the interpretation of the latent factors more transparent" (Attanasio et al. 2020, p.57). We assign items to the factor for which they have the highest factor loadings. We set to zero the factor loadings of other items (Laajaj and Macours 2021). Finally, we interpret factors based on the items with factor loadings higher than 0.30 (Attanasio et al. 2020).

The resulting factors for 2016-17 (see Table A.16 in the appendix) are relatively similar to the Big Five taxonomy. Further, the internal consistency is satisfactory: Factor 1 can be interpreted as approximately emotional stability (ω=0.89), Factor 2 as approximately conscientiousness (ω=0.85), Factor 3 as a composite of openness to experience and extraversion (ω=0.82), Factor 4 as weak emotional stability, and Factor 5 as approximately agreeableness (ω=0.55). Factor 3 is similar to the Beta factor (Digman 1997; Anusic et al. 2009), meaning the extent to which a person actively searches for new and rewarding intellectual and social experiences, also called "plasticity". Factor 4 is described as weak as it is composed of only two items, which makes it impossible to calculate ω.

For 2020-21, emerging personality traits are further away from the Big Five taxonomy (see Table A.17 in the appendix). Internal consistency is, globally, less satisfactory: Factor 1 may be interpreted as approximately emotional stability (ω=0.90), Factor 3 as approximately openness to experience (ω=0.37), and Factor 2 (ω=0.52) and Factor 4 (ω=0.35) as a mix of items from different traits. Factor 5 is composed of only one item of emotional stability.

Factor 1 from 2016-17 and Factor 1 from 2020-21 are interpreted in exactly the same way, namely emotional stability, and measure the same aspect of personality. Like the naïve approach, this result suggests that only emotional stability is accurately measured across the two waves. Therefore, using the factor approach, we are able to measure the stability over time of the emotional stability trait.

4.4 (In)stability over time of "emotional stability" trait

To analyse the stability over time of the emotional stability trait, we compute the mean-level difference between the score in 2016-17 and 2020-21. Then, we use the mean-level statistic to construct individual paths over time before analysing the extent of the instability using econometric tools. Finally, we conclude this section by analysing the contribution of the items of the emotional stability personality trait.

4.4.1 Mean-level method

The mean-level method reflects whether the personality trait score of an individual increases or decreases over time. As explained above, we only consider the emotional stability trait constructed from the factor approach. The emotional stability trait score (ESS) is defined on [0;5]. Thus, $\Delta \text{ESS}_i \in$ [-5;5], with $\Delta \text{ESS}_i = \text{ESS}_{i,2020-21} - \text{ESS}_{i,2016-17}$. We consider an absolute change of up to 10% around zero as an acceptable change and classify individuals with changes of this magnitude as stable over time, mean-level speaking. In other words, if $\Delta \text{ESS}_i \in$ [-0.5;0.5], the individual is considered as stable over time in terms of the emotional stability trait score.

Figure 4.2 presents the distribution of ΔESS. The distribution is normal left-skewed. Thus, some parts of the population are stable over time in the emotional stability trait. In addition, there is no group trajectory but rather different individual evolutions over time. Approximately 70% of individuals become less emotionally stable, while around 20% remain stable over time, and 10% become more emotionally stable.

4.4.2 Path over time

To analyse the path over time of the emotional stability trait, we split the sample in three sub-samples. Individuals with ΔESS $\in$ [-5;-0.5[are classified as decreasing over time, those with ΔESS $\in$ [-0.5;0.5] as stable over time, and those with ΔESS $\in$]0.5;5] as increasing over time. Then, we analyse the correlation between an individual's path over time and their sociodemographic characteristics (see Table 4.1).

Approximately 77% of individuals are not stable over time in terms of their emotional stability trait. 85% of these individuals become more neurotic over time, while 15% become more salient in terms of their emotional stability trait. The difference between males and females is not statistically significant, suggesting that both males and females are unstable over time. Regarding caste, the upper castes are overrepresented among

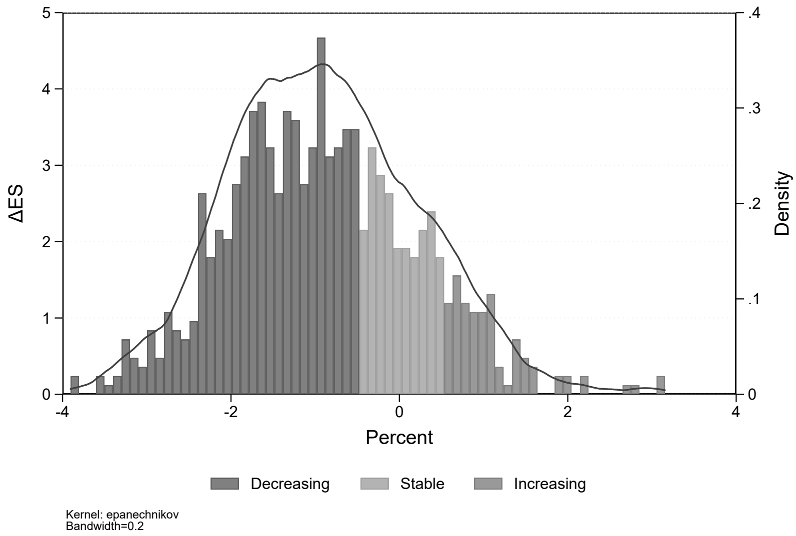

Figure 4.2: Histogram and kernel of the variable which measures the variation in the personality trait of emotional stability

Note: For 835 individuals. Δ ES is the value of the difference between emotional stability score in 2016-17 and in 2020-21. 194 individuals are considered as stable over time to 10% within (dark grey on left histogram).

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

individuals who remain stable or increase in terms of the emotional stability trait over time. Indeed, upper caste individuals represent 10% of the total sample of individuals, but they represent around 14% of stable individuals and 19% of individuals who increase in emotional stability over time. Another interesting finding relates to age. We do not observe significant differences in age between the different paths of emotional stability over time except for the slight underrepresentation of [45;55[individuals and slight overrepresentation of [25;35[individuals in increasing emotional stability. This result does not support the common assumption in economics that personality traits remain stable over time after the age of 25-30. In terms of level of education, individuals who have completed primary school are overrepresented among stable individuals over time. Regarding occupation and income, we do not observe significant differences.

Lastly, regarding the correlation between the path over time of emotional stability and acquiescence score, individuals with a stable acquiescence score over time tend to experience the least change in emotional stability. However, we qualify this relationship because two-thirds of individuals whose emotional stability remains stable over time experience a change in their acquiescence score.

Overall, our results reflect instability over time in the emotional stability trait that is not present in only one category of individuals but among almost all respondents.

Table 4.1: Descriptive statistics of Δ ES

	Path of emotional stability over time				Pearson χ^2	
	Decreasing	Stable	Increasing	Total	Prob.	p-value
No. of individuals	n=550	n=194	n=91	n=835		
Individual characteristics						
Sex: Male	55.09	59.79	47.25	55.33	3.98	0.14
Sex: Female	44.91	40.21	52.75	44.67		
Age: [18;25[	11.27	10.82	13.19	11.38	11.31	0.19
Age: [25;35[	15.27	13.40	24.18	15.81		
Age: [35;45[	26.73	27.84	23.08	26.59		
Age: [45;55[	25.09	24.74	13.19	23.71		
Age: [55;+]	21.64	23.20	26.37	22.51		
Edu: Below primary	39.27	35.57	39.56	38.44	7.41	0.28
Edu: Primary	19.45	25.77	15.38	20.48		
Edu: High school	26.55	21.13	27.47	25.39		
Edu: HSC or more	14.73	17.53	17.58	15.69		
MO: Unoccupied	9.45	12.89	15.38	10.90	9.05	0.70
MO: Agri self-emp	14.73	15.46	16.48	15.09		
MO: Agri casual	22.18	15.98	20.88	20.60		
MO: Casual	13.45	13.92	12.09	13.41		
MO: Regular	15.45	15.98	15.38	15.57		
MO: Self-emp	12.73	15.46	8.79	12.93		
MO: MGNREGA	12.00	10.31	10.99	11.50		
Income: T1	31.64	34.02	42.86	33.41	4.77	0.31
Income: T2	34.55	32.99	26.37	33.29		
Income: T3	33.82	32.99	30.77	33.29		
Household characteristics						
Caste: Dalits	50.91	44.85	37.36	48.02	18.14	0.00
Caste: Middles	41.82	40.72	43.96	41.80		
Caste: Uppers	7.27	14.43	18.68	10.18		
Acquiescence bias						
Bias: Decrease	23.22	29.38	19.78	24.28	40.57	0.00
Bias: Stable	15.72	31.96	12.09	19.11		
Bias: Increase	61.06	38.66	68.13	56.61		

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

4.4.3 Intensity of instability

4.4.3.1 Methodology

To explore the drivers of instability, we regress individuals and household characteristics on the absolute intensity of instability, that is $|\Delta\text{ESS}|$ for unstable individuals. As our dependent variable is continuous and non-negative (defined on $\mathbb{R}^+$), we use a generalised linear model (GLM) with inverse Gaussian distribution and a logarithm link function (Smyth 1989).

$$y_i = \beta_1 + \boldsymbol{X1}'_{i.}\boldsymbol{\gamma} + \boldsymbol{X2}'_{i.}\boldsymbol{F} + \varepsilon_i \tag{4.1}$$

y_i represents the absolute intensity of instability for the individual i (i=1 to 835).

The first vector of independent variables ($\boldsymbol{X1}'_{i.}$) includes variables at the individual level, namely age, sex, caste, main occupation (i.e., the most time-consuming activity for each individual using an annual calendar), income, education, and marital status. The second vector of independent variables ($\boldsymbol{X2}'_{i.}$) includes variables at the household level, namely wealth (measured by the monetary value of assets, which includes gold, land, house, livestock, agricultural equipment, and consumer goods), villages, enumerators, demonetisation exposure, and COVID-19 exposure. We do not present the statistics relating to demonetisation and COVID-19 because a separate section is devoted to them.

We cluster the standard errors at the household level to account for the fact that observations within each household are not independent and identically distributed. Indeed, we have data for two individuals from the same household, and the individuals may share some resources and pool others (e.g., assets).

In a second step, to refine the results, we split the sample between the sub-samples that increase and decrease in emotional stability over time.

4.4.3.2 Results

Table 4.2 presents the results from the multivariate GLM analysis of the intensity of instability for all unstable individuals (column 1), for the increasing sub-sample (column 2), and for the decreasing sub-sample (column 3).

For the total sample (all non-stable individuals in terms of emotional stability score), we only observe that, at a 95% confidence level, being upper caste rather than Dalit is negatively correlated with the intensity of instability. This interesting pattern can be explained by the fact that upper castes are less subject to social pressure and discrimination than Dalits and are, therefore, less likely to become anxious, worried, and fearful.

For the sub-sample that increases over time in emotional stability trait, we do not observe correlations at the 95% confidence level.

For the decreasing sub-sample, as for the total sample, we observe that caste is correlated with the intensity of instability. At a 5% risk of error, being upper caste rather than Dalit is negatively correlated with the intensity of the decrease (-0.27 points), all else being equal. We also find that having an increasing rather than a stable acquiescence bias over time is positively associated with the intensity of instability in the decreasing sample (+0.13 points) at the 95% confidence level, all other things being equal.

To complete this analysis of instability, we test whether it is due to one survey item more than another, as the emotional stability trait score is composed of 10 items.

4.4.4 Source of instability over time

To test whether the instability over time of emotional stability is homogeneous in its components and not the result of a single item characterising the trait, we analyse the stability of responses to the 10 questions in the NEEMSIS data that create the emotional stability score (see Figure 4.3).

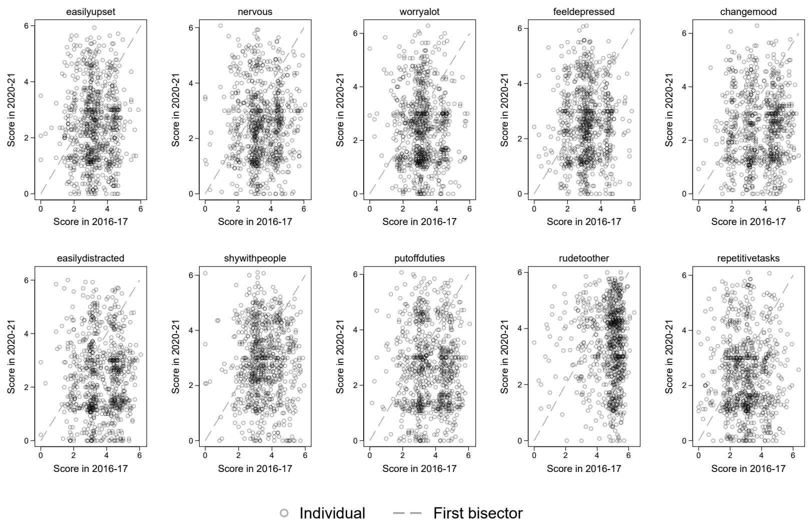

Figure 4.3: Components of emotional stability

Note: For 835 individuals.

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

Table 4.2: Generalised linear model of the intensity of "emotional stability trait" instability over time

	(1) Unstable Coef./SE	(2) Increasing Coef./SE	(3) Decreasing Coef./SE
Individual characteristics			
Sex: Female	−0.09*	−0.16	−0.07
	(0.05)	(0.13)	(0.05)
Edu: Below primary	0.00	0.00	0.00
	(.)	(.)	(.)
Edu: Primary	−0.01	0.21	−0.05
	(0.05)	(0.15)	(0.06)
Edu: High school	0.07	0.10	0.08
	(0.06)	(0.14)	(0.06)
Edu: HSC or more	−0.00	−0.13	−0.03
	(0.08)	(0.14)	(0.09)
Age: [18;25[	0.00	0.00	0.00
	(.)	(.)	(.)
Age: [25;35[	−0.01	0.24	−0.13
	(0.10)	(0.23)	(0.11)
Age: [35;45[	0.02	0.41	−0.07
	(0.10)	(0.30)	(0.11)
Age: [45;55[	0.05	0.39	−0.01
	(0.11)	(0.31)	(0.11)
Age: [55;+]	−0.03	0.21	−0.07
	(0.10)	(0.34)	(0.11)
MO: Unoccupied	0.12	0.48*	0.12
	(0.09)	(0.25)	(0.09)
MO: Agri self-emp	−0.05	−0.25	−0.02
	(0.07)	(0.19)	(0.08)
MO: Agri casual	0.00	0.00	0.00
	(.)	(.)	(.)
MO: Casual	0.02	−0.46*	0.07
	(0.07)	(0.24)	(0.07)
MO: Regular	−0.01	0.02	−0.02
	(0.09)	(0.25)	(0.10)
MO: Self-emp	0.06	0.03	0.04
	(0.08)	(0.25)	(0.08)
MO: MGNREGA	0.02	0.19	0.02
	(0.08)	(0.21)	(0.09)
Married: No	0.01	0.01	0.01
	(0.06)	(0.20)	(0.06)
Income: T1	−0.05	0.07	−0.05
	(0.07)	(0.20)	(0.07)
Income: T2	0.00	0.00	0.00
	(.)	(.)	(.)
Income: T3	−0.11*	−0.14	−0.04
	(0.06)	(0.20)	(0.07)
Household characteristics			
Assets:† T1	0.05	0.01	−0.01
	(0.06)	(0.20)	(0.06)
Assets: T2	0.00	0.00	0.00
	(.)	(.)	(.)
Assets: T3	−0.02	−0.08	−0.04

	(0.06)	(0.18)	(0.06)
Caste: Dalits	0.00	0.00	0.00
	(.)	(.)	(.)
Caste: Middles	−0.03	0.29	−0.06
	(0.04)	(0.18)	(0.05)
Caste: Uppers	−0.22**	0.30	−0.27**
	(0.11)	(0.24)	(0.12)
Acquiescence bias			
Bias: Decrease	−0.03	0.23	−0.01
	(0.07)	(0.20)	(0.07)
Bias: Stable	0.00	0.00	0.00
	(.)	(.)	(.)
Bias: Increase	0.07	−0.02	0.13**
	(0.06)	(0.16)	(0.05)
Location controls	X	X	X
Enumerator controls	X	X	X
Shock controls	X	X	X
Observations	639	91	548
Log-pseudo likelihood	−897.42	−87.91	−804.25

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. † Tercile of the monetary value of assets held, without land.
Source: NEEMSIS-1 (2016-17) & NEEMSIS-2 (2020-21); author's calculations.

Individuals above the first bisector become more salient over time on the specific dimension of emotional stability, while those below become less salient, and individuals on the first bisector are stable. The scatter plots do not show any correlation between the item scores in 2016-17 and those in 2020-21. Moreover, the 10 scatter plots are similar, suggesting that one item does not differ from the others in its contribution to explaining the instability in the emotional stability trait. In other words, all dimensions seem to be sources of positive or negative instability over time, and there is no dimension in which individuals are more stable or less stable.

To summarise this analysis of instability over time of emotional stability trait, we find that instability is not present among only one category of individuals but among almost all respondents. We also observe that the caste partly drives the intensity of the instability, and this instability is not due to one specific item on the survey but to the 10 dimensions altogether.

4.5 Effects of 2016 demonetisation and COVID-19 lockdown

We examine the effect of two exogenous shocks that occurred during the data collection on personality traits, meaning the demonetisation of November 2016 during the NEEMSIS-1 data collection and the second COVID-19 wave of April 2021 during the NEEMSIS-2 data collection (see Section 1.3.3 in the Chapter 1).

4.5.1 Empirical strategy

The demonetisation and the second lockdown fell randomly into our survey collection schedule because the chronological sequence of household data collection was random. At least, we had no clear and systematic data collection plan across the villages. However, to determine the extent to which external shocks may be a source of personality trait instability, we use propensity score to balance, on the one hand, the pre- and post-demonetisation samples and, on the other hand, the pre- and post-second lockdown samples. Indeed, naïvely comparing personality traits between the two groups (i.e., T=0 not exposed/control group, and T=1 exposed/treated group) to determine whether their traits differ would be biased. This is the case because the individuals in the group T=0 may differ from those in the group T=1 in terms of socioeconomic characteristics.

The technique most widely used with propensity scores is propensity score matching. The interest of propensity score matching lies in whether it can remove or reduce significant differences in baseline covariates. However, the estimates of propensity score matching are sensitive to the misspecification of the propensity score model and often increase imbalance, inefficiency, model dependence, and bias (King and Nielsen 2019).

We use the covariate balancing propensity score (CBPS) approach to avoid these issues (Imai and Ratkovic 2014). CBPS estimates the propensity score so that covariate balance and prediction of treatment assignment are maximised (Kainz et al. 2017). The advantage of this approach is that the CBPS estimate of the propensity score is robust to mild misspecification of the propensity score model.

CPBS is a two-stage procedure. Firstly, the probability of an individual being exposed to the treatment is estimated (CBPS estimate, equation 2). Secondly, the results of this estimation are then used to weight ordinary least squares regressions, where T_i represents the treatment and $\boldsymbol{Y}'_{i.}$ represents the vector containing all the personality traits accurately measured in 2016-17 or 2020-21 (average treatment effect [ATE] estimate, equation 3).

$$E(T_i|\boldsymbol{X'1_{i.}}) = \Phi(\boldsymbol{X'1_{i.}\gamma}) \tag{4.2}$$

$$\boldsymbol{Y}'_{i.} = \beta_1 + \beta_2 T_i + \boldsymbol{X2}'_{i.}\boldsymbol{\gamma} + \varepsilon_i \tag{4.3}$$

4.5.2 Model specification

To explore the effect of demonetisation on personality traits, we use the NEEMSIS-1 wave data. We do not limit our sample to individuals in the panel setting, but retain all egos (i.e., a sample of 953 individuals). The treatment variable is whether an individual i was surveyed before (T=0) or after (T=1) the demonetisation. In the CBPS estimate, the vector $\boldsymbol{X1}'_{i.}$ of covariates contains age, sex, caste, main occupation of the individual, education level, annual income, marital status, and household size. In the ATE estimate, the vector $\boldsymbol{X2}'_{i.}$ of covariates contains the same covariates as $\boldsymbol{X1}'_{i.}$ with the addition dummies for villages and enumerators. Indeed, we assume that these two variables are homogeneously distributed across the treatment and control groups. However, we believe they can be correlated with the personality trait score.[8] The vector of dependent variables $\boldsymbol{Y_{i.}'}$ contains all the personality traits identified as having a satisfactory McDonald's ω in the factor analysis, meaning emotional stability, conscientiousness, openness-extraversion, and agreeableness.

To explore the effect of the second lockdown of April 2021, we use the NEEMSIS-2 wave data. We keep all egos surveyed before (T=0) or after (T=1) the second lockdown. We drop from the analysis individuals surveyed during the second lockdown (i.e., 284 individuals). We then have a sample of 1409 individuals. In the CBPS estimate, the vector $\boldsymbol{X1_{i.}'}$ of covariates contains the same variables as in the demonetisation effect study. Additionally, in the ATE estimate, as covariates $\boldsymbol{X2_{i.}'}$ we use the vector $\boldsymbol{X1_{i.}'}$ with the addition of villages and enumerators dummies. The vector of dependent variables $\boldsymbol{Y_{i.}'}$ contains all the personality traits identified as having a satisfactory McDonald's ω in the factor analysis, which in this case is only emotional stability. We complete this last vector with the locus of control added in the NEEMSIS-2 wave. This concept is highly relevant in India, given the singularity of the representation of the individual in the traditional forms of Indian religions such as Hinduism. Montaut (2014, p.256) describes the difficulties of the adult ego in India "to constitute itself as a 'separate subject': responsible, autonomous, critical", "where many functions of the self are transferred [...] to social institutions (caste, clan, for example)." NEEMSIS-2 includes six questions to measure the locus of control (see Natal and Nordman 2022). We average the six items to obtain a score for the locus of control. The internal consistency of this measure is satisfactory (ω=0.8). The higher the score, the more external the locus is. In other words, the higher the score, the stronger the individual's belief that external forces (e.g., luck, fate) act on the events that affect them.

4.5.3 Results

4.5.3.1 Absolute difference of standardised means

Before considering the results of the ATE, we analyse whether the CBPS procedure succeeded in eliminating differences in baseline covariates. We compare the absolute difference of standardised means for each covariate between the treated and control groups before and after the weighting. A less than 20% difference in standardised means after weighting indicates a satisfactory weighting mechanism for achieving covariate balance (Rosenbaum and Rubin 1985).

Figures A.4 and A.5 in appendix plots for each covariate, the absolute difference of standardised means before (x-axis) and after (y-axis) weighting for each covariate. Each covariate is below the 20% threshold on the y-axis, suggesting a satisfactory reduction procedure for both the demonetisation and lockdown effects and that ATE estimates are unbiased.

8. Individuals from the same village may share common values that may be reflected in their personality traits. Regarding the effect of enumerators, see Di Maio and Fiala (2020).

4.5.3.2 Demonetisation shock

The ATE of the demonetisation exposure on personality traits is given by the treatment coefficient (*Demonetisation*) in Table 4.3. We find that exposure to demonetisation only affects the openness-extraversion trait score. All else being equal, individuals exposed to demonetisation have an openness-extraversion score 0.50 units higher than those not exposed, at a 1% risk of error.

Although surprising, this result is consistent with the literature. In Australia, Cobb-Clark and Schurer (2012) find that experiencing up to five negative employment shocks is positively correlated with openness to experience. In Germany, Anger, Camehl, and Peter (2017) find that displaced workers have a higher level of openness to experience than workers who have not lost their jobs.

In addition, our result echoes those of Hilger and Nordman (2020), who find that, in a period of demonetisation, informal social interactions are multiplied to facilitate the exchange money. Individuals need to use their networks following demonetisation may have boosted openness-extraversion. In our case, the exposure to demonetisation that increases openness-extraversion may be explained by the fact that demonetisation forced individuals to adapt to new circumstances (e.g., the banning of the INR 1k banknote, which was replaced by an INR 2k banknote). This may have required a more open and flexible mindset (i.e., more extroversion) to adapt to the new rules.

We do not find significant differences between the treated and control groups in terms of emotional stability, conscientiousness, or agreeableness.

Table 4.3: Average treatment effect of the demonetisation

	(1) ES Coef./SE	(2) CO Coef./SE	(3) OP-EX Coef./SE	(4) AG Coef./SE
Demonetisation (T=1)	0.02	0.01	0.05***	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Controls	X	X	X	X
Observations	953	953	953	953

Note: * p < 0.1, ** p < 0.05, *** p < 0.01.
Source: NEEMSIS-1 (2016-17); author's calculations.

4.5.3.3 COVID-19 second lockdown shock

The ATE of the second lockdown exposure on personality traits is given by the treatment coefficient (*COVID-19 lockdown*) in Table 4.4. We find that exposure to the second lockdown negatively affects the emotional stability score. All other things being equal, individuals exposed to the second lockdown have an emotional stability score 0.27 units lower than those not exposed, at a 1% risk of error.

This result is consistent with the literature. In Australia, Cobb-Clark and Schurer (2012) find that individuals who experience a negative external shock, meaning adverse employment or income events, become less emotionally stable. In our case, the exposure to COVID-19 second lockdown, which reduces emotional stability, may be explained by the fact that the second lockdown was more intense in terms of infections and deaths, which may have triggered feelings of distress, anxiety, fear, or sadness. These intense emotions considerably reduce emotional stability.

We do not find significant differences between the treated and control groups in terms of locus of control.

Table 4.4: Average treatment effect of the second lockdown

	(1) ES Coef./SE	(2) Locus Coef./SE
COVID-19 lockdown (T=1)	-0.27^{***}	-0.00
	(0.03)	(0.01)
Controls	X	X
Observations	1409	1408

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: NEEMSIS-2 (2020-21); author's calculations.

In summary, the two external shocks of demonetisation in November 2016 and the second COVID-19 lockdown in 2021 both have effects on personality traits but different effects. While demonetisation increased the openness-extraversion score, the second lockdown reduced the emotional stability score.

4.6 Conclusion

In this study, we analysed the universality of the Big Five model, the stability of the Big Five personality traits over time, and the effect of two external shocks on these traits, meaning the Indian demonetisation of November 2016 and the second COVID-19 lockdown of April 2021. After correcting the data for the acquiescence bias and performing factor analysis, the Big Five taxonomy emerged in 2016-17 but not in 2020-21, as only the emotional stability trait emerged in the second period. The satisfactory internal consistency of the emotional stability trait in both waves allowed us to calculate variation over time reliably.

We obtained four main results. Firstly, the Big Five taxonomy represents the dataset quite well in 2016-17, but we do not find strong support for it in 2020-21. Our results seem to partly confirm the universality of the Big Five model (Kajonius and Giolla 2017; Schmitt et al. 2007; Bühler, Sharma, and Stein 2023). Secondly, approximately 66% of individuals became more salient in neuroticism (i.e., the reverse of emotional stability), while around 11% became more salient in emotional stability, and 23% remained stable between 2016-17 and 2020-21. This instability is not driven by any of the 10 dimensions of the trait in particular. The upper castes are overrepresented in the stable-over-time sub-sample and the sub-sample that becomes more salient in the emotional stability trait. Thirdly, in terms of intensity of instability, upper caste individuals experience the smallest decreases in the emotional stability score over time. This interesting pattern can be explained by the fact that the upper castes are less subject to social pressure and discrimination than Dalits and are, therefore, less likely to become anxious, worried, and fearful. However, contrary to the economics literature (Cobb-Clark and Schurer 2012), we do not find a correlation between age and instability of personality traits over time, but a correlation between caste and instability. Fourthly, exogenous shocks affect personality traits (Boyce et al. 2015; Anger, Camehl, and Peter 2017). Individuals who experienced the 2016 Indian demonetisation are more salient in terms of openness to experience and extraversion, while those surveyed after the second COVID-19 lockdown of April 2021 are more salient in terms of neuroticism.

These results are all the more convincing given that the personality traits measured with the NEEMSIS survey have good external validity, meaning they are correlated with outcomes that they should, in theory, be correlated with. Indeed, using NEEMSIS-1 (2016-17), Michiels, Nordman, and Seetahul (2021) investigate whether individual skills and personality traits facilitate labour market mobility (measured by the income mobility) of disadvantaged groups and rural migrants. The authors show that despite strong rigidity in the area's labour market structure, personality traits are important determinants of labour mobility, enabling individuals to overcome caste and gender discrimination. In addition, using NEEEMSIS-2 (2020-21), Natal and Nordman (2022) analyse the relationship between locus of control and financial decision-making, focusing on the recourse and the negotiation of personal debt. They find that locus of control is correlated with debt negotiation and that this relationship is strongest for non-Dalit (middle and upper caste) males, suggesting that a more internal locus of control is an additional advantage in negotiation for individuals with an already favourable social position.

In conclusion, economists should pay more attention to the consistency of the measurement of personality traits to avoid measurement errors. Doing so would entail using factor analysis to ensure that personality traits emerge from the data, as well as the verification of internal consistency and external validity. Secondly, to avoid endogeneity, economists should consider that personality traits are not necessarily stable over time. Therefore, in so far as possible, researchers should test whether personality traits are stable in their data. If not, they should consider either using trait variation in a panel setting or a delayed trait measurement.

While they are considered in the debate on the universality of the Big Five model, developing countries are overlooked in the discussion regarding personality trait stability over time. Thus, this study makes a significant contribution to that debate. However, it is important for future research to explore the stability and effect of shocks on personality traits (e.g., Big Five, locus of control) in developing countries.

As stated previously, the behaviourist perspective can offer valuable insights into the underlying psychological factors that influence individuals' borrowing (Brown and Taylor 2014). However, few researchers have investigated the relationship between cognition (i.e., personality traits and cognitive skills) and indebtedness, even fewer in developing countries. This is precisely the subject of the next chapter.

Chapter 5

Psychology of Debt*

5.1 Introduction

Despite the recent growing interest in the study of cognition (i.e., personality traits and cognitive skills) developed in Chapter 4, few researchers have investigated the relationship between cognition and indebtedness.

Empirical studies focused on cognitive skills and household debt found that cognitive skills are often associated with dimensions of indebtedness in the USA. For instance, Agarwal and Mazumder (2013) observed that individuals with a higher level of cognitive skills are substantially less likely to exhibit financial distress. Furthermore, Angrisani, Burke, and Kapteyn (2023) noted that cognitive skills are an essential predictor of debt burden in older age. The authors also maintained that individuals with higher cognitive ability take on higher debt levels than individuals with lower cognitive ability. Lastly, Tang (2021) demonstrated that cognitive skills significantly affect financial behaviour.

Regarding the relationship between Big Five personality traits and debt, studies mainly note that conscientiousness, meaning the capacity to enforce self-discipline, is most often associated with debt, especially in the USA, the UK, and the Netherlands. For example, Donnelly, Iyer, and Howell (2012) determined that a higher level of conscientiousness is associated with more active financial management. Letkiewicz and Heckman (2019) found that more conscientious people are less likely to default on student loans. Additionally, Brown and Taylor (2014) observed that conscientiousness is negatively correlated with levels of unsecured debt and that extraversion, agreeableness, and openness to experience are generally associated with debt. For other Big Five personality traits, Nyhus and Webley (2001) highlighted that neuroticism (i.e., the opposite of emotional stability) is positively correlated with debt, as individuals who score high

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on neuroticism are more likely to make impulsive purchases (Youn and Faber 2000).

Thus far, to our knowledge, this research has always been conducted in developed countries, and no study has looked at the relationship between personality traits, cognitive skills, and indebtedness in developing countries. However, understanding these issues in developing countries is crucial. Firstly, microcredit as a route out of poverty (Burgess and Pande 2005) or to empower females (Demirgüç-Kunt et al. 2018) has been a strong argument in favour of financial inclusion policies, although the literature is mixed on its effects (see, e.g., de Koker and Jentzsch 2013). Secondly, research has indicated that most household debt in developing countries is informal (Badarinza, Balasubramaniam, and Ramadorai 2019), meaning that it is negotiable, and the negotiation process is conducive to the expression of individual cognition (Sharma, Bottom, and Elfenbein 2013).

By considering the case of rural Tamil Nadu, this study attempts to fill this knowledge gap by analysing, directly, *the extent to which personality traits influence indebtedness*. We use descriptive statistics and econometrics (probit with lagged explanatory variables) to explore the relationship between three aspects of personal debt (i.e., recourse, negotiation, and management), Big Five personality traits, and cognitive skills (math scores, literacy scores, and Raven matrices). In addition, to capture the weight of social identity, namely caste and gender, and the intersectionality between the two (Kannabiran 2022), we segment the analysis by caste (Dalit, non-Dalit) and gender. In rural South India, the literature indicates that interaction between cognition and social structures (i.e., caste hierarchy and gender roles) matters for various outcomes, such as job access (Carswell and De Neve 2018) and social mobility (Michiels, Nordman, and Seetahul 2021).

In this way, we contribute to economics literature on understanding indebtedness in rural India and, more broadly, to understanding household finances in developing countries. Moreover, we contribute to psychology economics literature on the role of personality traits and cognitive skills on economic outcomes, especially indebtedness, as well as the role of personality traits and cognitive skills in the negotiation process. Finally, by capturing the weight of social identity in the expression of individual cognition, we contribute to economics literature on the role of social identity in preferences and economic choices.

After controlling for important covariates (e.g., income, shock exposure, or lender characteristics), our findings suggest that a high level of conscientiousness is a strong advantage in negotiating and managing debt. In addition, as a measure of cognitive skills, the Raven score is positively correlated with debt management capacities. However, the magnitude and statistical significance of these correlations differ across caste and sex, and our results suggest that individual personality traits and cognitive skills are used as a way to overcome the weight of social identity for females.

The rest of the chapter is organised as follows. Section 5.2 reports the measures of personality traits and cognitive skills, indebtedness, and the econometric framework. Section 5.3 presents and discusses the results, and we conclude with Section 5.4.

5.2 Methodology

We analyse the relationship between three aspects of personal debt (recourse, negotiation, and management), personality traits as classified by the Big Five taxonomy, and cognitive skills (math scores, literacy scores, and Raven test scores) while taking into account the weight of social identity (caste and gender). Before presenting the estimation strategy, we present the measures of personality traits, cognitive skills, and indebtedness.

5.2.1 Construction of personality traits and cognitive skills variables

Cognitive skills Measures of cognitive skills include three score variables: literacy, numeracy, and Raven coloured progressive matrices tests (i.e., a cognitive, visual, and non-verbal test that does not require formal education and measures the ability to think and make sense of complex data and logical reasoning). Literacy and numeracy tests measure crystallised intelligence, meaning the ability to deduce secondary relational abstractions by applying previously learned primary relational abstractions (i.e., the knowledge learned). Raven's progressive matrices capture concepts of fluid intelligence, that is, the ability to solve novel reasoning problems (i.e., the rate at which people learn). These scores are constructed by summing up the correct answers for four questions for the literacy and numeracy tests and 36 for the Raven test (see Table A.20 in the appendix).

Personality traits As developed in Section 4.3 of the Chapter 4, NEEMSIS data allow us to construct Big Five personality traits from a set of 35 affirmative questions, following the Big Five long taxonomy (John and Srivastava 1999) (see Table A.12 in the appendix) and to analyse their stability over time between 2016-17 and 2020-21. Analysis of the stability over time of personality traits constructed using principal component analysis suggests stability for a small proportion of the population (see Chapter 4). Thus, to avoid endogeneity issues through reverse causality between cognition and debt, we use 2016-17 measures of cognition on debt in 2020-21 (see Section 5.2.3.1, paragraph "Reverse causality").

As a reminder, the factors resulting from the principal component analysis in 2016-17, which therefore constitute the personality traits, are as follows: Factor 1 is approximately emotional stability (ω=0.88), Factor 2 is approximately conscientiousness (ω=0.84), Factor 3 is openness-extraversion (ω=0.81), Factor 4 is weak emotional stability, and Factor 5 is approximately agreeableness (ω=0.56). As Factor 4 represents a weak measure in the sense that it captures only two items of emotional stability, we chose to exclude it from further analyses.

To remove the effect of age on the personality traits and cognitive skills measures, we run univariate ordinary least squares regressions with personality traits and cognitive skills as endogenous variables (vector $\boldsymbol{Y_{i\cdot}'}$) and age as the exogenous variable (x).

$$\boldsymbol{Y}'_{\boldsymbol{i}\cdot} = \beta_1 + \beta_2 x_i + \varepsilon_i$$

Following Brown and Taylor (2014), we standardised in z-scores the resulting residuals ε for each individual i and each personality trait and cognitive skill belonging to the vector $\boldsymbol{Y}'_{\boldsymbol{i}\cdot}$. We use the standardised residuals as age-effect-free personality traits and cognitive skills in future estimates.

5.2.2 Debt related measures

To gain a more extensive view of the role of personality traits and cognitive skills in the process of indebtedness, we analyse three aspects of debt: the recourse, negotiation, and management.

Recourse to debt We measure recourse to debt using a dummy variable that takes one if the individual is indebted, and zero otherwise.

We expect that neuroticism is positively correlated with debt, as underlined by Nyhus and Webley (2001). Indeed, emotional stability encompasses elements of self-control and planning, and "emotionally stable people are therefore more likely to be able to follow their own plans and budgets than the emotionally unstable" (p.S88).

Debt negotiation For the second aspect, we focus on debt negotiation between the lender and the borrower. We use a sample of individuals with at least one main loan. In the NEEMSIS, we have more details for the three main loans of the household. These three main loans are selected on the amount and source criterion (i.e., preferably high amount informal loan). Thus, based on the 835 individuals in our sample, 650 are indebted. Among them, 488 have at least one main loan.

To analyse debt negotiation, we use a dummy variable which takes the value one if the borrower did not have to provide services to any of his lenders to obtain his loans. The variable takes the value zero if the borrower had to provide a service to the lenders for at least one loan. Depending on the result of the negotiation process between the borrower and the lender, the borrower may have to offer services due to the loan, including numerous everyday services such as running errands or domestic work, which can be time-consuming and therefore can represent a significant loss of income for the borrower as it may imply less working (see Section 1.5.5 in the Chapter 1).

Debt negotiation can be seen as competitive (i.e., a type of negotiation where the parties involved adopt an adversarial approach and primary focus is on achieving individual goals and maximising personal gains) because, in rural Tamil Nadu, the services that accompany debt are the subject of ongoing negotiations and have repercussions on dignity and social status in the village (see Subsection 1.5.5 from the Chapter 1). Following

Barry and Friedman (1998) and Dimotakis, Conlon, and Ilies (2012), we can expect that extraversion and agreeableness tend to be liabilities in strictly competitive negotiation situations. In a competitive negotiation, strategy is more important than cooperation (a key element of extraversion) and “negotiator interests are better served by the acquisition of information from one’s opponent than by sharing information about one’s own underlying interests” (Barry and Friedman 1998, p.347). However, the contribution of certain personality traits may be limited. Indeed, as the negotiation of services of debt is of considerable importance to borrowers (e.g., social belonging, status, and dignity in the village), borrowers, and especially females, may have to take care of their appearance to give the best image of themselves to lenders (Guérin, Kumar, and Venkatasubramanian 2023). Controlling this image can involve smoothing out personality traits that are visible to others, such as extraversion and agreeableness (Penton-Voak et al. 2006).[9]

Regarding the contribution of conscientiousness, Sharma, Bottom, and Elfenbein (2013) argue that this trait is consistent with behaviours theorised to be effective in negotiations. However, many studies did not show correlations (Barry and Friedman 1998; Sharma, Bottom, and Elfenbein 2013). Only Jang, Elfenbein, and Bottom (2016) exhibit a positive contribution to conscientiousness in the negotiation process.

Debt management For the last aspect, we are interested in the management of personal debt. Using the sample of individuals with at least one main loan, we use a dummy variable, which takes one if the borrower has a problem repaying at least one loan and zero if the borrower has no problem repaying any loans.

Per Donnelly, Iyer, and Howell (2012), we can expect individuals with a higher level of conscientiousness to have a higher debt management capacity.

5.2.3 Econometric framework

5.2.3.1 Identification

Reverse causality In a context where personality traits are unstable over time, as is the case here (see Chapter 4), the possibility of reverse causality is an essential concern in the relationship between personality traits, cognitive skills, and personal indebtedness.[10] While an increase in personality trait scores may drive an increase in debt-related variables, overindebtedness might also lead to increased personality trait scores. Even if the determination of causality is not our objective, we follow the most widely used strategy in economics and replace the personality traits and cognitive skills variables with their lagged values to limit reverse causality. Although criticised in the literature (see, e.g., Reed 2015), lagged explanatory variables are a first way of limiting simultaneity

9. There is no consensus on which Big Five personality traits are most perceptible to outside observers (Alper, Bayrak, and Yilmaz 2021).

10. If traits are a stable characteristic over time, then they are considered to be exogenous and therefore do not raise any concerns about reverse causality.

in what is, to our knowledge, the first study analysing the correlation between Big Five personality traits and individual indebtedness in a developing country context.

Thus, we analyse the contribution of personality traits and cognitive skills measured in 2016-17 to individual debt measured in 2020-21.

This approach raises a well-known concern regarding the choice of a suitable temporal lag (Vaisey and Miles 2017). However, given the structure of our data (two points in time separated by four years), we assume that personality traits and cognitive skills can affect financial decision-making four years later.

Sample selection Our analysis faces non-random sample selection issues because, for the measure of debt negotiation and debt management, the sample is restricted to individuals who declared a non-zero and non-missing main loan. We can rely on the Heckman procedure to overcome this sample selection issue, but a solid theoretical underpinning is needed to identify exclusion restriction variables that may affect the participation decision to debt but not the other dependent variables.

Nonetheless, exclusion restriction variables from the literature are not relevant in our context. Cox and Jappelli (1993) used the years of education, employment status, and rural-urban status as exclusion restriction variables. We do not have urban employment, and occupation and education are supposed to be correlated with negotiating and managing debt. Bertaut and Starr (2002) used the proportion of household heads employed in financial services in the region and the proportion of household heads employed in a workplace of 500 or more as exclusion restriction variables. However, in the context of the study, there is no workplace of 500 or more, and very few people work in financial services.

Therefore, we follow Río and Young (2006) and exclude non-participants to debt from our subsequent regressions. Indeed, using location, race, and employment status as exclusion restrictions, the authors find that results from Heckman procedures are no different from the ordinary least squares regressions without non-participants, suggesting that "any corner-solution biases are small" (p.1125).

5.2.3.2 Specification

To analyse the multivariate correlations between personality traits, cognitive skills and personal indebtedness, we estimate the following probit models:

$$E(\boldsymbol{Y'_{i.}}|\boldsymbol{X1'_{i.}}, \boldsymbol{X2'_{i.}}) = \Phi(\boldsymbol{X1'_{i.}}\boldsymbol{\beta} + \boldsymbol{X2'_{i.}}\gamma) \tag{5.1}$$

$\boldsymbol{Y'_{i.}}$ represents the vector of dependent variables measured in 2020-21, that is, the probability of an individual being in debt, the probability that the borrower does not need to provide services to the lender to obtain a loan, and the probability that the borrower has a problem repaying the loan.

$\boldsymbol{X1}_i'$ contains the age-effect-free personality traits and cognitive skills measured in 2016-17, that is, emotional stability, conscientiousness, openness-extraversion, agreeableness, numeracy score, literacy score, and Raven score.

$\boldsymbol{X2}_{i.}'$ represents the vector of control variables measured in 2016-17. At the individual level, it includes age; sex; a dummy variable which takes one if the individual is the household head, and zero otherwise; main occupation, defined as the most time-consuming activity (agricultural self-employed, agricultural casual worker, casual worker, regular worker, self-employed, MGNREGA worker); a dummy variable which takes one if the individual received formal education through school, and zero otherwise; and a dummy variable which takes one if the individual is married, and zero otherwise. At the household level, in 2016-17, $\boldsymbol{X2}_{i.}'$ includes caste (Dalit or not); monetary value of assets, which is a continuous variable proxying gold, land, house, livestock, agricultural equipment, and consumer goods; total annual income; household size; and shock exposure as a dummy variable which takes one if the household experienced marriage of at least one of the household members between 2016-17 and 2020-21 and/or if the household has been surveyed after the demonetisation of November 2016, and zero if not. Finally, $\boldsymbol{X2}_{i.}'$ includes the indebtedness situation in t with a dummy variable that takes one if the individual is indebted in 2016-17, and zero otherwise.

We cluster the standard errors at the household level to consider that observations within each household are not independent and identically distributed. Indeed, we observe two individuals in the same household who may share resources such as income or assets.

Given that in rural South India, the literature indicates an interaction between cognition and social structures (Michiels, Nordman, and Seetahul 2021; Carswell and De Neve 2018), we refine the results by estimating the model according to individuals' social identity, namely caste and gender, and the intersectionality of the two (Kannabiran 2022). Firstly, we establish an interaction between personality traits, cognitive skills and gender. Secondly, between cognition variables and caste. Finally, between cognition variables, gender, and caste. Although splitting samples by social identity may improve the model specification, using the entire sample can maximise statistical power.

Interaction effects are difficult to interpret in nonlinear models because the magnitude of the coefficient depends on all the covariates in the model. Additionally, interaction effects can have different signs for different observations, making simple summary measures of the interaction effect challenging to interpret (Greene 2010). Thus, we compute marginal effects (MEs) at representative values of gender and caste and all other variables at the mean to determine how the effects of personality traits and cognitive skills vary according to individual characteristics. This allows us to create nine groups of MEs for each personality trait and cognitive skill variable: average individual (no interaction); average male and average female (gender interaction); average Dalit and non-Dalit (caste interaction); and average non-Dalit male, Dalit male, non-Dalit female and Dalit female (gender and caste interaction).

5.3 Results

5.3.1 Descriptive statistics

The final sample of panel egos consists of 835 individuals from 473 households.

Figure 5.1 shows the distribution of each standardised personality trait and cognitive skill, net of the life cycle. We do not observe any difference in terms of emotional stability and agreeableness between males and females. However, in terms of conscientiousness and openness-extraversion, males tend to have a higher score. Concerning cognitive skills, males also tend to have higher scores for Raven, numeracy, and literacy than females.

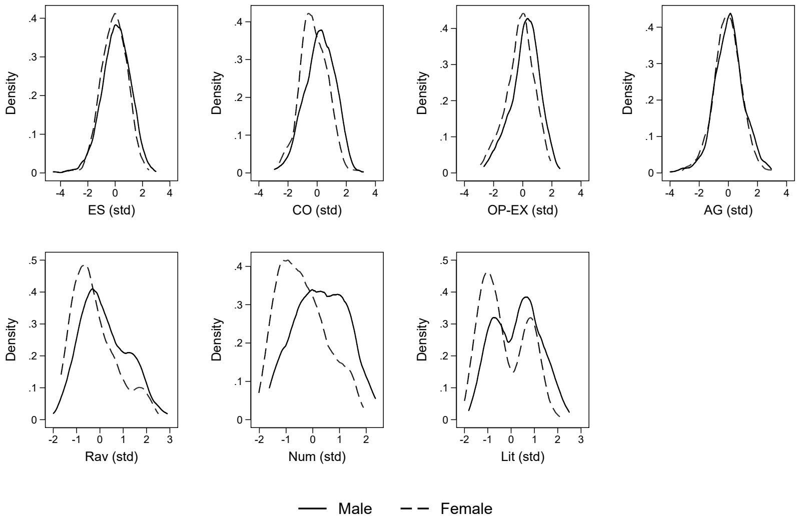

Figure 5.1: Distribution of personality traits and cognitive skills in 2016-17
Note: For 835 individuals. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy. The resulting personality traits and cognitive skills are based on the standardised residual from univariate OLS regression with age as exogenous variable. This is personality traits and cognitive skills purged from life-cycle effects.
Source: NEEMSIS-1 (2016-17); author's calculations.

Among our total sample of 835 individuals, 650 are indebted, 338 males and 312 females, representing 73% of males and 84% of females (see Table 5.1). We observe small disparities between males and females regarding debt amount to the disadvantage of males. However, the situation is much more disadvantageous for females, as their income is four times lower than males'. Regarding services rendered by the borrower due to the loan, females are more likely than males not to have to provide any services (69% versus 45%, respectively). Interestingly, we observe almost no differences in terms of the repayment problem between males and females, even though females have the heaviest borrowing responsibilities and manage the highest proportions of household debt (Reboul, Guérin, and Nordman 2021).

Table 5.1: Descriptive statistics of dependent variables in 2020-21

	Total	Males	Females
No. of individuals	n=835	n=462	n=373
In debt: Yes	0.78	0.73	0.84
Debt amount:* Mean	139.45	150.23	127.77
Debt amount: CV	1.28	1.45	0.95
Debt amount: P50	89.15	69.90	100.00
No need to provide services:† Yes	0.54	0.45	0.69
Have a problem to repay:† Yes	0.47	0.45	0.49

Note: *For individuals in debt. †For individuals with at least one main loan.
Source: NEEMSIS-2 (2020-21); author's calculations.

5.3.2 Econometric results

Tables A.21, A.22, and A.23 in the appendix present the full results of the probit regressions. Marginal effects at representative values are reported in Tables 5.2, 5.3, and 5.4. Thanks to the interactions with sex and caste, the representative values are the average individual (no interaction, column 1); the average male and the average female (gender interaction, column 2); the average non-Dalit and the average Dalit (caste interaction, column 3); the average non-Dalit male, the average Dalit male, the average non-Dalit female, and the average Dalit female (gender and caste interaction, column 4). All personality traits and cognitive skills are standardised. Therefore, we speak in terms of a one standard deviation increase in personality traits and cognitive skills. In analysing the results, we focus on coefficients that are significantly different from zero at a 5% risk of error. However, we also discuss results that are significantly different from zero at a 10% risk of error if the relationship has been discussed beforehand.

5.3.2.1 Recourse to debt

Using Table A.21 in the appendix, we observe that the McFadden's pseudo R^2 indicates a suitable goodness-of-fit for all the specifications (i.e., all are above the threshold of 0.2). Moreover, to see if one of our predictors could be linearly predicted from the other covariates with a substantial degree of accuracy, we use a linear probability model and compute the variance inflation factor (VIF). For each specification, the statistic of VIF is below 10, suggesting no multicollinearity in our estimations.

At a 10% risk of error, we observe that emotional stability is positively correlated with the recourse to debt for the average female (see Table 5.2). All other things being equal, at a 10% risk of error, when emotional stability increases by one standard deviation, the predicted probability of being in debt increases by 3 percentage points. This relationship is Dalit-driven (+3 percentage points for the average Dalit female). This finding is contrary to Nyhus and Webley (2001)'s result but can be explained as follows. As stated previously, within the context of Tamil Nadu, debt is not just a financial relationship. It is, above all, a social relationship between two individuals that can be protective and have non-negligible importance in terms of social status inside the village, and psychology literature highlights the contribution of emotional stability in social relationships. For example, Lopes, Salovey, and Straus (2003) demonstrated that emotional stability is positively correlated with self-perceived satisfaction with social relationships for 103 students from the USA. In other words, more emotionally stable individuals are more likely to enter into a social debt relationship.

Additionally, we find that the Raven score is negatively correlated with the recourse to debt, especially for the average non-Dalit female. Indeed, at a 5% risk of error, the predicted probability of being in debt decreases by 5 percentage points when the Raven score increases by one standard deviation. This result is consistent with the literature. In rural India, Gaurav and Singh (2012) found that cognitive ability predicts financial aptitude and debt literacy, the two components of financial literacy (i.e., the capacity to analyse economic information and make well-informed decisions pertaining to financial planning, accumulation, and debt management) and individuals with higher levels of financial literacy are less likely to engage in high-cost borrowing and less likely to use informal financial service providers (see, e.g., Disney and Gathergood 2013).

5.3.2.2 Debt negotiation

Table A.22 in the appendix features the McFadden's pseudo R^2. It indicates a suitable goodness-of-fit for all the specifications. Moreover, the statistic of VIF is below 10, suggesting no multicollinearity in our estimations.

Examining at the results from Table 5.3, we do not observe a correlation between extraversion and negotiation of debt at the 95% or 90% confidence level. This surprising result contradicts Barry and Friedman (1998)'s and Dimotakis, Conlon, and Ilies (2012)'s finding that extraversion and agreeableness are disadvantages in a competitive negotiation. The non-correlation between extraversion, agreeableness, and debt negotiation may suggests that negotiation is of such importance to borrowers that, to give the best image of themselves to lenders, they smooth out their personality traits that can be perceived by others, meaning extraversion and agreeableness (Penton-Voak et al. 2006).

Table 5.3 corroborates Jang, Elfenbein, and Bottom (2016)'s finding, meaning conscientiousness is the common thread in the success of each phase of a negotiation. For the average female, at a 5% risk of error, conscientiousness is positively correlated with the probability of not having to provide services, and the relationship seems to be non-Dalit-driven. All other things being equal, at a 1% risk of error, when conscientiousness increases by one standard deviation, the predicted probability of not having to provide services increases by 17 percentage points for the average non-Dalit female.

In contrast, for the average female, at a 1% risk of error, the Raven score is negatively correlated with the negotiation of debt (-14 percentage points), and the relationship seems more salient for the average non-Dalit female (-24 percentage points). Similarly, we observe a negative correlation between numeracy and the predicted probability of not having to provide services. In other words, a high level of cognitive skills is a liability in the negotiation process. Although surprising, this result may be explained

Table 5.2: Marginal effects at representative values of the probability of being in debt

	(1) Recourse ME/SE	(2) Recourse ME/SE		(3) Recourse ME/SE		(4) Recourse ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.02	0.01	0.03*	0.03	0.03	−0.00	0.02	0.03	0.03*
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.05)	(0.04)	(0.03)	(0.02)
CO (std)	0.00	0.02	−0.01	0.01	−0.00	0.04	−0.00	−0.03	−0.00
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.05)	(0.04)	(0.03)	(0.02)
OP-EX (std)	0.01	−0.00	0.02	−0.01	0.02	−0.02	0.01	0.01	0.03
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.02)
AG (std)	−0.02	−0.03	−0.01	−0.03	−0.02	−0.04	−0.02	−0.02	−0.01
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.05)	(0.03)	(0.03)	(0.02)
Rav (std)	−0.02	0.00	−0.03*	−0.03	0.00	−0.01	0.03	−0.05**	−0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)
Num (std)	0.00	0.01	−0.01	−0.01	0.01	−0.05	0.06	0.03	−0.03
	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.06)	(0.05)	(0.03)	(0.03)
Lit (std)	0.01	0.01	0.02	0.05	−0.03	0.07	−0.05	0.05	0.00
	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. †When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *ME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

by self-confidence, which may positively correlated with cognitive skills (Stankov 2013). Excessive self-confidence is a well-known cognitive bias in negotiation that can lead individuals to believe their judgments to be infallible, which "reduces concessionary behavior and negotiator success in reaching agreement"(Neale and Bazerman 1985, p.37). However, further studies are needed to analyse the correlation between cognitive intelligence and self-confidence, particularly in a developing country context.

This analysis reveals that non-Dalit females are more able to use the personality trait of conscientiousness during the negotiation of debt to obtain the best conditions. Our interpretation is that females know that their social condition (being a female rather than a male) can be a disadvantage in negotiations and then use their personality traits to overcome this burden. Conversely, males know they do not need to mobilise their skills because their male identity has a positive and intrinsically important weight in the negotiation process in the context of rural South India. This assumption corroborates the findings of Michiels, Nordman, and Seetahul (2021), who used the same dataset: females' personality traits are generally better predictors of income mobility than males' personality traits.

Regarding caste, we only observe a correlation between personality traits, cognitive skills, and debt negotiation for non-Dalit females. Our interpretation is that although females can overcome their social gender identity by using their personality traits and cognitive skills, the added weight of caste puts them in a situation where they cannot mobilise their personality traits and cognitive skills. This interpretation is consistent with Deshpande (2002)'s findings. Indeed, the author revealed that Dalit females suffer from the double jeopardy of their gender-caste identity, meaning they suffer from both material deprivation and immurement, putting them in a situation of greater vulnerability than non-Dalit females, who suffer less from material deprivation.

5.3.2.3 Debt management

McFadden's pseudo R^2 indicates a relatively low goodness-of-fit (see Table A.23 in the appendix). In addition, the VIF statistic is below 10, suggesting no multicollinearity in our estimations.

The results exposed in Table 5.4 illustrate that, at a 5% risk of error, conscientiousness is negatively correlated with the predicted probability that the average borrower has problems repaying the debt (-7 percentage points). The correlation seems to be female-driven (-14 percentage points) and, more precisely, non-Dalit female-driven. Other things being equal, when conscientiousness increases by one standard deviation, the predicted probability that the average non-Dalit female has problems repaying the debt decreases by 22 percentage points at a 99% confidence level. Thus, this result corroborates Donnelly, Iyer, and Howell (2012)'s findings that conscientious individuals have greater financial self-control, partly because of their positive financial attitudes and future orientation.

Another interesting finding of this analysis is that emotional stability is positively correlated with the predicted probability that the average borrower has problems repaying the debt at a 5% risk of error (+7 percentage points). This correlation is clearer for

Table 5.3: Marginal effects at representative values of the probability of not providing a service to lender

	(1) Negociation ME/SE	(2) Negociation ME/SE		(3) Negociation ME/SE		(4) Negociation ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.00	0.02	−0.04	0.03	−0.04	0.09	−0.07	−0.09	0.02
	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)	(0.07)	(0.07)
CO (std)	0.05	0.02	0.11**	0.07	0.03	0.01	0.05	0.17***	0.04
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)	(0.06)	(0.07)
OP-EX (std)	−0.01	−0.04	0.05	−0.03	0.01	−0.07	0.00	0.00	0.03
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)
AG (std)	0.02	−0.00	0.06	0.05	0.00	0.02	−0.01	0.06	0.03
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)	(0.04)	(0.07)	(0.06)
Rav (std)	−0.03	0.03	−0.14***	−0.02	−0.07	0.09	−0.08	−0.24***	−0.03
	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.08)	(0.07)
Num (std)	−0.08*	−0.10**	0.01	−0.03	−0.13**	−0.13*	−0.09	0.16*	−0.16*
	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.09)	(0.10)
Lit (std)	0.08	0.10*	0.02	0.05	0.13**	0.13*	0.11	−0.03	0.15
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)	(0.10)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. †When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *ME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

the average female. All other things being equal, when emotional stability increases by one standard deviation, the predicted probability that the average female has problems repaying the debt increases by 13 percentage points at a 5% risk of error. This result is inconsistent with Fan, Chatterjee, and Kim (2022). We do not have a clear interpretation of this result, but it is possible that certain behaviours of emotionally unstable individuals, such as anxiety, lead them to be more cautious in managing their debts while keeping in mind that debt management also depends on a variety of structural factors that are difficult to measure (e.g., storm, accident). Further studies in developing countries are needed to see whether a new model could emerge in this respect.

Furthermore, the more individuals have a high level of fluid intelligence (measured with Raven matrices), the fewer problems they have repaying the debt. This correlation is male-driven (-10 percentage points at a 1% risk of error), Dalit-driven (-12 percentage points at a 5% risk of error), and non-Dalit male-driven (-10 percentage points at a 5% risk of error). This result is not surprising and is consistent with the literature. For example, Konig, Buhner, and Murling (2005) demonstrated that fluid intelligence is an important predictor of management skills measured with multitasking. Additionally, cognitive abilities are predictors of financial literacy (Gaurav and Singh 2012), and literature supported that individuals with higher levels of financial literacy are more likely to avoid financial mistakes (see, e.g., Gaudecker 2015).

As for the negotiation of debt, females are more able to use their personality traits to manage debt. Our interpretation is that females know that their social condition can be a disadvantage and thus use their personality traits to overcome this burden, corroborating Michiels, Nordman, and Seetahul (2021)'s findings.

Lastly, regarding caste, we only observe a correlation between debt management, personality traits, and cognitive skills for non-Dalit females. Our interpretation is the same as for the negotiation of debt. Although females can overcome their social gender identity by using their personality traits and cognitive skills, the added weight of caste puts them in a situation where they cannot mobilise their personality traits and cognitive skills. This interpretation is consistent with the literature (see, e.g., Deshpande 2002).

5.3.3 Robustness check

5.3.3.1 COVID-19 exposure and income constraints

The whole sample was surveyed between December 2020 and September 2021, after the first lockdown of March to May 2020 and during the second lockdown of April to June 2021. As the lockdown had important economic and social consequences (see, e.g., Guérin et al. 2022; Guérin, Mouchel, and Nordman 2022), we add a control for the degree of exposure to the COVID-19 shock for the second robustness check: a dummy variable to indicate if the household had to sell assets to cope with the difficulties of the lockdown or not. In addition, as loan repayment difficulties may be due to contemporaneous income constraints, we control for income constraints using a dummy variable which takes one if the individual's household experienced a declined in income between 2016-17 and

Table 5.4: Marginal effects at representative values of the probability to have problem to repay the debt

	(1) Management ME/SE	(2) Management ME/SE		(3) Management ME/SE		(4) Management ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.07**	0.04	0.13**	0.07	0.07	0.01	0.03	0.15*	0.13*
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.09)	(0.07)
CO (std)	−0.07**	−0.04	−0.14***	−0.07	−0.08*	0.02	−0.09*	−0.22***	−0.06
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.05)	(0.08)	(0.07)
OP-EX (std)	0.04	0.02	0.09*	0.06	0.03	0.03	0.02	0.14**	0.04
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.05)
AG (std)	−0.00	0.01	−0.02	0.01	−0.00	0.07	−0.01	−0.05	0.03
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)	(0.07)	(0.06)
Rav (std)	−0.07**	−0.10***	0.01	−0.03	−0.12**	−0.10**	−0.12*	0.10	−0.12
	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)
Num (std)	0.03	0.03	0.00	0.04	0.02	0.03	0.03	−0.02	−0.01
	(0.04)	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)	(0.06)	(0.10)	(0.10)
Lit (std)	0.01	0.05	−0.06	−0.01	0.05	0.04	0.08	−0.08	−0.01
	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.09)	(0.10)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. † When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *ME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

2020-21, and zero otherwise.

Results presented in Tables A.24, A.25, and A.26 in the appendix show no differences with the main findings, suggesting good robustness of previous results.

5.3.3.2 Debt contract terms

The terms of the debt contract (e.g., lenders, cost, amount) are particularly important when it comes to negotiating and managing debt. The terms of the debt contract can strongly affect the direction and strength of the relationship between debt negotiation, debt management and personality traits, and may even question the use of the probability of not providing a service as a proxy for negotiation skills if there is a trade-off between the cost of the loan and the services to be provided for example.

Thus, as second robustness check, we conduct additional analyses at the loan level (not at the indidivual level) to control for the debt contract terms in the regression of each loan. The dependent variable for debt negotiation becomes a dummy variable which takes one if the borrower does not need to provide services to the lender to obtain a specific loan, and zero otherwise. The dependent variable for debt management becomes a dummy variable which takes one if the borrower has a problem repaying a specific loan, and zero otherwise. The variables controlling the debt contract terms for each loan are the amount of the loan, the type of lender (WKPs, relatives, labour relationship, pawn broker, moneylenders, friends, microcredit, and bank), the reason for the loan (economic, current expenses, human capital, social expenses, and housing), the amount of interest, and the collateral (required or not). When considering the negotiation of debt, we add two supplementary control variables: a dummy variable which takes one if the borrower and the lender have the same sex and a dummy variable which takes one if the borrower and the lender have the same caste level. Our intuition is that caste solidarity (Guérin, Mouchel, and Nordman 2022) and gender solidarity may facilitates negotiation. When considering debt management, we add the total amount of debt by individual as a control variable because we believe that the higher the total debt, the more difficult it is to manage each specific debt, especially in terms of repayment. By doing so, we obtain estimates of the correlations between personality traits, cognitive skills, and negotiation and loan management, for, among other things, a given amount, lender, loan purpose, interest amount, and collateral.

Results presented in Tables A.27 and A.28 in the appendix confirm the relationships found in Section 5.3.2 and the intensity of the effects is stronger, which implies that the effects observed previously are minimal effects. The only relationship we observed that is no longer statistically different from zero is the relationship between debt management and openness-extraversion for the average non-Dalits female.

5.4 Concluding remarks and implications

This study analyses the financial practices of a rural population from Tamil Nadu, India, in terms of their recourse to debt, negotiation of debt, and management of debt. In the context of this study, debt appears as a set of rights and obligations that are continuously bargained and negotiated between stakeholders, and complex forms of power and dominance are encompassed in debt relationships. We focus on the correlation between the three aspects of debt and cognitive skills (Raven, numeracy, and literacy scores) and personality traits (based on the Big Five taxonomy) while taking into account the weight of social identity (caste and gender).

After controlling for important covariates (e.g., income, shock exposure, or lender characteristics), our findings suggest that a high level of conscientiousness is a strong asset in the negotiation and management of debt. Furthermore, regarding cognitive skills, Raven score, used as a proxy for fluid intelligence, is negatively correlated with the negotiation of debt and the management of debt. Lastly, we highlight the use of personality traits and cognitive skills to overcome the weight of social identity, especially for females.

Our study contributes to the growing literature on individual and household finances, furthering our understanding of the determinants of debt negotiation and management. It also contributes more generally to the expanding literature on the implications of personality traits for economic outcomes and the interaction between social identity and economic choices.

Overall, while we rely on correlation, this research is the first attempt to examine the relationship between cognition, such as personality traits, cognitive skills, and indebtedness in a rural developing country context where households are highly indebted.

General Conclusion

What was the idea?

The main idea of this doctoral dissertation in applied microeconomics was to improve the overall understanding of household debt in rural South India by focusing on the borrowers' side. While microcredit has had its day in the sun in academic literature, its counterpart, the debt, has not received much attention from researchers despite the "unprecedented explosion of private debt" that "should clearly raise the loudest alarm bells" (United Nations Conference on Trade and Development 2019, p.76), and the key macroeconomic consequences such as lower GDP growth and higher unemployment (see, e.g., Mian, Sufi, and Verner 2017; Alter, Feng, and Valckx 2018; Lombardi, Mohanty, and Shim 2017).

Firstly, we wanted to look not just at household debt but at household financial vulnerability to get a better picture of the debt burden. We then set out to examine household vulnerability not as an end in itself but as a determinant of economic outcomes. Indeed, the literature on household debt in developing countries has focused mainly on debt on the left-hand side of the equation (see, e.g., Chichaibelu and Waibel 2018; Schicks 2014) rather than on the right-hand side, meaning analysing its consequences.

Secondly, the idea was to complement the analysis of debt at the household level with analysis at an individual level and to apply a behaviourist analytical framework (e.g., cognition), as has been done in developed countries (Brown and Taylor 2014). However, the study of cognition, and in particular personality traits, raises several methodological issues (see, e.g., Laajaj and Macours 2021; Cobb-Clark and Schurer 2012), especially in developing countries, which need to be carefully considered.

What have we really done?

After providing key contextual elements regarding India, Tamil Nadu, and the studied area (i.e., more than 10 villages in the districts of Cuddalore and Kallakurichi), in the Chapter 1, we present the original first-hand longitudinal household survey NEEMSIS (*Networks, Employment, dEbt, Mobilities, and Skills in India Survey*) used in this doctoral dissertation, which consists of a baseline survey, RUME (*RUral Microfinance and Employment*), carried out in 2010 (Guérin, Roesch, Venkatasubramanian, et al. 2023), and two follow-up surveys, NEEMSIS-1 implemented in 2016-17 (Nordman et al. 2017), and NEEMSIS-2 conducted in 2020-21 (Nordman et al. 2021), which constitutes a three-year panel of households and individuals (see https://neemsis.hypotheses.org/). Then, with descriptive statistics, we characterise debt practices. It emerges that households are highly indebted, that they juggle a wide range of borrowing sources, and that each serves specific purposes. Most debt is used to meet consumer spending and is contracted from informal lenders, who have the advantage of not requiring collateral and providing loans quickly.

To study the debt situation of households in greater depth, and in particular how it has changed over time, in Chapter 2, we develop a new simple continuous indicator of financial vulnerability called the financial vulnerability index that combines the cost of debt, the debt trap, and poverty of the household. Using a time-series clustering algorithm, we investigate household time trends in financial vulnerability between 2010 and 2020-21. We show that 42% of households are in a highly vulnerable situation (either temporary or permanent), and upper castes are under-represented among households who experienced a substantial increase in their FVI over time, while they are overrepresented among households who experienced a substantial decrease in their FVI over time. Then, by analysing the determinants of household financial vulnerability, we find that caste, loan amount, and income are correlated with the financial vulnerability index.

We then examined household vulnerability not as an end in itself but as a potential determinant of household labour supply in Chapter 3. We rely on a recent econometric approach called the maximum-likelihood structural equation model, which not only protects against endogeneity arising from time-invariant unobserved heterogeneity as fixed effect models but also allows for reverse causality between labour supply and financial vulnerability by assuming sequential rather than strict exogeneity. We find that higher financial vulnerability is associated with a higher labour supply, especially for females. This interesting result calls into question the specific targeting of females in financial inclusion policies through microcredit, given that microcredit has not eliminated informal debt but added to it (Arnold and Booker 2013), thereby increasing females indebtedness. In addition, females have to increase their labour supply, often in difficult conditions, to repay their debts, but also those contracted by other family members, which plunges them further into precariousness.

To achieve the second objective (i.e., complement the analysis of debt at the household level with analysis at an individual level and to apply a behaviourist analytical framework), we first turn our attention to methodological aspects. Thus, in Chapter 4, we analyse the universality of the Big Five personality traits (i.e., emotional stability, extraversion, openness to experience, agreeableness, and conscientiousness), the stability over time (between 2016-17 and 2020-21), and the effect of external shocks, such as the demonetisation of November 2016 and the lockdown, on these traits. The analyses reveal a five-factor structure similar to the Big Five model in 2016-17 but different in 2020-21 and instability over time. Only 1/5 of individuals remain stable between 2016-17 and 2020-21, and upper castes are overrepresented among stable individuals. Then, we show that individuals who experienced the Indian 2016 demonetisation are more salient in terms of openness to experience and extraversion, while those surveyed after the second COVID-19 lockdown of April 2021 are more salient in terms of neuroticism compared to the others. Overall, these results highlight the need for economists to pay more attention to the consistency of personality trait measurement to avoid measurement errors and to the stability, or otherwise, of traits over time to avoid double causality.

Secondly, in Chapter 5, we actually analyse indebtedness with a behaviourist analytical framework by studying the relationship between Big Five personality traits, cognitive skills (Raven matrices, literacy, and numeracy scores), and financial decision-making. We focus on the recourse, the negotiation, and the management of individual debt. We find that conscientiousness is generally significantly associated with negotiating and managing debt. The magnitude and statistical significance of the association between personality traits and debt differs across social identity, meaning castes (Dalit, non-Dalit) and sex. These findings suggest the use of personality traits and cognitive skills for females as a way to overcome the weight of social identity in a rural caste-segmented patriarchal context. By doing so, in this chapter, we bring together two disjoint strands of the literature to analyse the various mechanisms that explain the individual debt process. On the one hand, behavioural economics approach, which provides evidence that cognitive and socioemotional skills are likely to affect individual choices and outcomes (Brown and Taylor 2014). On the other hand, sociological and anthropological structuralists approach in our field of investigation (Guérin 2014), which recognises that individuals are embedded in social relations that make up the collective structure (Polanyi 1944).

What will happen next?

The answers provided by this doctoral dissertation to the various questions raised are only the tip of the iceberg, paving the way for studying the submerged part.

Firstly, regarding Chapter 2, further research is needed to replicate this new measure of financial vulnerability in other developing countries where household indebtedness is high, such as Thailand, Vietnam, Bangladesh, or Ghana. This chapter also raised the issue of the debt trap. This phenomenon has received too little attention in the literature even though it is a good indicator of the financial situation of households. Therefore, an in-depth study of the debt trap will be the subject of specific research. The idea is to carry out a panel analysis at two levels (household and individual) of the extent of the debt trap, its evolution, and its determinants. It also involves a detailed analysis of this type of debt (e.g., lender, price).

Secondly, concerning Chapter 3, further research is needed to improve the measure of labour supply to refine the estimation of the effects. For this purpose, we recommend using classic measures from the literature, such as the number of weeks worked in a year or, better, the number of days or hours. This work can be conducted using NEEMSIS data once the NEEMSIS-3 wave has been carried out (within two to three years), as we will then have the benefit of the three waves required to apply the maximum-likelihood structural equation model. Variables, such as the number of hours worked per year are already available in NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21).

Thirdly, further research needs to be undertaken regarding Chapter 5 to determine the causal impact of personality traits and cognitive skills on debt to corroborate our findings. In addition, to fully understand the psychological mechanisms at work in the debt process, future research could look at other individual characteristics such as socio-emotional skills (e.g., self-awareness, personal initiative, perseverance, or self-esteem).

Finally, beyond household debt, further research is needed to analyse household livelihoods and the rural dynamics at work in a context where recent economic growth has not benefited everyone and where the caste system is adapting and rearranging to create new forms of discrimination (Harriss-White 2002). For example, the author of this doctoral dissertation and co-authors will seek to analyse the multifaceted role of marriages. To do so, they will study how marriages (and matrimonial transfers such as the dowry) are both shaped and constitutive of local political and sexual economies. In addition, they will analyse how marriages compensate for economic volatility (e.g., declining agriculture, uncertain non-agricultural labour markets, costly and risky investments in education, and high housing expenditures) and how they contribute to the intensification of patriarchal norms ■

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Appendix

A
Appendix

A.1 Analysing household debt in rural South India: Presentation of NEEMSIS data

Box A.1.1: My role in the data collection

The RUME survey, and then the NEEMSIS waves, are the fruit of the work of a whole team of researchers, including the author of this doctoral dissertation, and coordinated by Isabelle Guérin, Christophe Jalil Nordman and Govindan Venkatasubramanian. Let's move from "we" to "I" to explain the role I played in the data collection.

As a doctoral student, my first task was to produce the statistical report on the NEEMSIS-1 data, that is, to examine the dataset as a whole and produce descriptive statistics. I have also converted all the RUME data from *Access* format to *Stata* format to make the data accessible to the whole team, formatted the questionnaire (i.e., converting the questionnaire from an *Excel* file to an easy-to-read *PDF* file), and produced the survey manual and the statistical report.

Then, I have organised the data from the NEEMSIS-1 migrant tracking survey and formatting the questionnaires (i.e., converting the data collected from *CSV* format to *Stata* format, then merging all the "sub-datasets" to form a coherent set of datasets).

Once the NEEMSIS-2 data collection was complete, I have organised the data, produced the survey manual, the statistical report, and formatted the questionnaires. With the help of Cécile Mouchel, I took part in the creation of a unique longitudinal identifier (RUME / NEEMSIS-1 / NEEMSIS-2) for households and individuals, to make longitudinal data easier to handle.

More recently, I monitored the progress of the NEEMSIS-2 migrant tracking survey,

then organised the data, questionnaires, and wrote the survey manual.
I have also coded, in *XLSFormat*, and monitored the NEEMSIS-GPS survey (collection of the GPS position of households surveyed in NEEMSIS-2).
More recently, I anonymised the RUME and NEEMSIS-1 data and made them freely available on the Harvard Dataverse of the *Observatory of Rural Dynamics and Inequalities in South India* (https://dataverse.harvard.edu/dataverse/odriis).
I am also in charge of the animation of the NEEMSIS (https://neemsis.hypotheses.org) and ODRIIS (https://odriis.hypotheses.org) websites.

Table A.1: Other household socioeconomic characteristics, part. 1

	Total			Dalits		
	2010	2016-17	2020-21	2010	2016-17	2020-21
No. of HH	n=405	n=492	n=626	n=194	n=236	n=297
HH head char.						
Age (mean)	47.88	51.13	51.42	46.71	50.23	50.29
Sex: Male	93.33	90.85	77.80	91.24	88.14	75.08
Sex: Female	6.67	9.15	22.20	8.76	11.86	24.92
MO: Unoccupied	2.96	4.47	7.83	2.06	4.24	9.09
MO: Agri self-emp	25.93	21.14	19.65	15.98	12.29	10.44
MO: Agri casual	24.94	20.33	27.96	35.57	32.20	37.71
MO: Casual	19.26	14.84	19.81	25.26	18.64	22.90
MO: Regular	7.90	18.09	8.95	7.22	15.25	7.07
MO: Self-emp	19.01	16.46	12.30	13.92	12.29	10.44
MO: MGNREGA	0.00	4.67	3.51	0.00	5.08	2.36
Edu: Below primary	47.41	44.11	44.25	55.15	57.20	54.21
Edu: Primary	19.26	23.17	21.09	19.07	18.64	17.85
Edu: High school or more	33.33	32.72	34.66	25.77	24.15	27.95
Married: Yes	100.00	88.01	86.58	100.00	86.02	84.85
Married: No	0.00	11.99	13.42	0.00	13.98	15.15
Shocks						
Marriage: No	100.00	61.38	73.48	100.00	60.17	68.35
Marriage: Yes	0.00	38.62	26.52	0.00	39.83	31.65
Demonetisation: No	100.00	71.14	100.00	100.00	72.88	100.00
Demonetisation: Yes	0.00	28.86	0.00	0.00	27.12	0.00
Demographic char.						
S.o. stock* (mean)	0.75	0.82	0.82	0.71	0.81	0.81
S.o. child.† (mean)	0.21	0.15	0.15	0.23	0.16	0.17
Economic char.						
Assets:‡ Mean	1272.84	721.77	735.67	769.53	355.28	464.37
Assets: CV	1.24	1.84	1.52	1.23	1.78	1.23
Assets: P50	709.00	268.50	324.46	241.50	182.58	247.01
Formal debt:§ Mean	0.15	0.34	0.69	0.10	0.32	0.72
Formal debt: CV	1.57	1.42	0.82	1.79	1.41	0.76
Formal debt: P50	0.00	0.00	0.70	0.00	0.00	0.74

Note: *Share of individuals in age to work, but who do not work (labour force stock). †Share of children in the household. ‡Monetary value of assets, with land (INR 1k). §Share of formal debt in the total debt.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table A.2: Other household socioeconomic characteristics, part. 2

	Middle castes			Upper castes		
	2010	2016-17	2020-21	2010	2016-17	2020-21
No. of HH	n=152	n=197	n=261	n=59	n=59	n=68
HH head char.						
Age (mean)	47.92	51.67	52.39	51.63	52.88	52.63
Sex: Male	94.08	93.40	80.46	98.31	93.22	79.41
Sex: Female	5.92	6.60	19.54	1.69	6.78	20.59
MO: Unoccupied	2.63	2.03	5.75	6.78	13.56	10.29
MO: Agri self-emp	37.50	32.49	30.65	28.81	18.64	17.65
MO: Agri casual	17.76	10.66	21.46	8.47	5.08	10.29
MO: Casual	17.76	14.21	16.86	3.39	1.69	17.65
MO: Regular	8.55	19.80	7.66	8.47	23.73	22.06
MO: Self-emp	15.79	16.75	13.03	44.07	32.20	17.65
MO: MGNREGA	0.00	4.06	4.60	0.00	5.08	4.41
Edu: Below prim	40.79	36.55	38.31	38.98	16.95	23.53
Edu: Primary	19.08	26.90	24.14	20.34	28.81	23.53
Edu: HS or +	40.13	36.55	37.55	40.68	54.24	52.94
Married: Yes	100.00	91.88	89.66	100.00	83.05	82.35
Married: No	0.00	8.12	10.34	0.00	16.95	17.65
Shocks						
Marriage: No	100.00	63.45	78.16	100.00	59.32	77.94
Marriage: Yes	0.00	36.55	21.84	0.00	40.68	22.06
Demo: No	100.00	68.53	100.00	100.00	72.88	100.00
Demo: Yes	0.00	31.47	0.00	0.00	27.12	0.00
Demographic char.						
S.o. stock* (mean)	0.76	0.82	0.82	0.82	0.85	0.84
S.o. child.† (mean)	0.21	0.15	0.13	0.10	0.08	0.11
Economic char.						
Assets:‡ Mean	1648.52	1048.34	1004.93	1959.92	1097.27	887.15
Assets: CV	0.94	1.60	1.40	1.30	1.53	1.54
Assets: P50	1258.75	465.19	490.00	847.50	399.05	317.47
Form debt:§ Mean	0.21	0.32	0.69	0.20	0.37	0.62
Form debt: CV	1.38	1.44	0.82	1.32	1.46	1.12
Form debt: P50	0.06	0.05	0.69	0.11	0.00	0.20

Note: *Share of individuals in age to work, but who do not work (labour force stock). †Share of children in the household. ‡Monetary value of assets, with land (INR 1k). §Share of formal debt in the total debt.
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

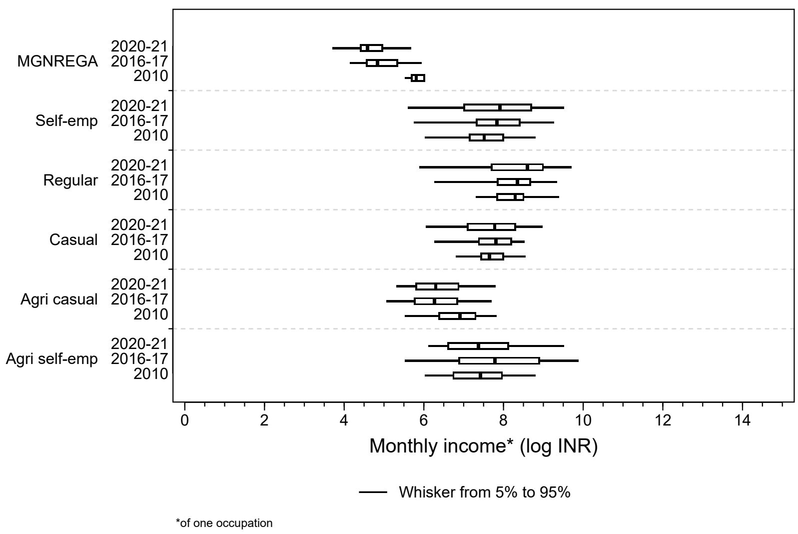

Figure A.1: Monthly income per occupation

Note: For 1343 occupations in 2010, 1766 in 2016-17, and 2339 in 2020-21.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table A.3: Amount of loans between 2010 and 2020-21

	N	Mean	CV	P25	P50	P75	P90	P95
Total								
2010	1957	18.58	2.48	5.00	10.00	20.00	30.00	50.00
2016-17	2031	26.53	1.36	6.33	15.82	31.65	63.29	94.94
2020-21	4778	14.85	1.67	2.72	9.78	19.02	27.17	54.35
Dalits								
2010	940	18.58	2.48	5.00	10.00	20.00	30.00	50.00
2016-17	967	26.53	1.36	6.33	15.82	31.65	63.29	94.94
2020-21	2389	14.85	1.67	2.72	9.78	19.02	27.17	54.35
Middle castes								
2010	738	24.65	1.80	6.00	10.00	20.00	50.00	100.00
2016-17	813	40.92	1.36	12.66	25.32	47.47	94.94	126.58
2020-21	2022	22.13	2.15	2.72	10.87	24.46	54.35	81.52
Upper castes								
2010	279	21.44	1.60	7.50	10.00	20.00	40.00	50.00
2016-17	251	46.79	1.50	10.13	31.65	63.29	94.94	145.57
2020-21	367	29.12	2.23	1.63	5.43	27.17	81.52	108.70

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

A.2 Hard Times: Measure and Analysis of Households' Financial Vulnerability

Table A.4: Descriptive statistics for the financial vulnerability index (FVI)

	FVI		
	2010	2016-17	2020-21
Overview			
No. of HH	n=405	n=492	n=626
Mean	0.08	0.09	0.14
CV	1.07	1.32	1.11
Distribution			
Min	0.00	0.00	0.00
P1	0.00	0.00	0.00
P5	0.00	0.00	0.00
P10	0.00	0.00	0.00
P25	0.01	0.01	0.02
P50	0.05	0.05	0.08
P75	0.11	0.13	0.19
P90	0.18	0.24	0.36
P95	0.23	0.38	0.47
P99	0.37	0.56	0.60
Max	0.48	0.72	0.68

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table A.5: Descriptive statistics for others measure of household financial vulnerability – Part. 1

	DSR			DIR		
	2010	2016-17	2020-21	2010	2016-17	2020-21
Overview						
No. of HH	n=405	n=492	n=626	n=405	n=492	n=626
Mean	0.33	0.44	0.61	1.63	2.79	3.55
CV	1.41	1.80	2.20	3.00	1.94	2.65
Distribution						
Min	0.00	0.00	0.00	0.10	0.00	0.00
P1	0.00	0.00	0.00	0.12	0.00	0.00
P5	0.00	0.00	0.00	0.23	0.20	0.13
P10	0.01	0.01	0.01	0.29	0.33	0.24
P25	0.07	0.07	0.07	0.59	0.67	0.62
P50	0.19	0.20	0.21	0.99	1.31	1.30
P75	0.44	0.50	0.54	1.79	2.75	2.98
P90	0.82	1.05	1.50	2.83	6.50	6.54
P95	1.07	1.78	2.63	3.57	10.47	11.59
P99	2.00	3.32	5.92	8.38	24.31	48.99
Max	4.82	11.38	15.02	95.20	86.49	134.39

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table A.6: Descriptive statistics for others measure of household financial vulnerability – Part. 2

	DAR			Absolut FM (INR 10k)		
	2010	2016-17	2020-21	2010	2016-17	2020-21
Basic statistics						
No. of HH	n=405	n=492	n=626	n=405	n=492	n=626
Mean	1.23	2.98	1.48	4.64	7.69	11.14
CV	1.87	3.77	2.11	1.72	1.79	1.50
Distribution						
Min	0.07	0.00	0.00	−32.73	−24.30	−26.56
P1	0.09	0.00	0.02	−11.94	−16.29	−12.83
P5	0.21	0.22	0.12	−4.45	−6.00	−9.02
P10	0.30	0.38	0.21	−2.27	−3.46	−5.95
P25	0.47	0.66	0.48	0.63	0.31	−0.07
P50	0.72	1.23	0.94	3.79	5.13	8.24
P75	1.26	2.26	1.49	8.05	11.20	17.66
P90	2.12	4.39	2.58	12.58	22.06	30.53
P95	3.19	7.05	3.61	16.77	31.12	41.85
P99	9.44	37.15	11.04	24.95	55.61	77.99
Max	35.52	184.40	61.84	74.80	122.04	105.83

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

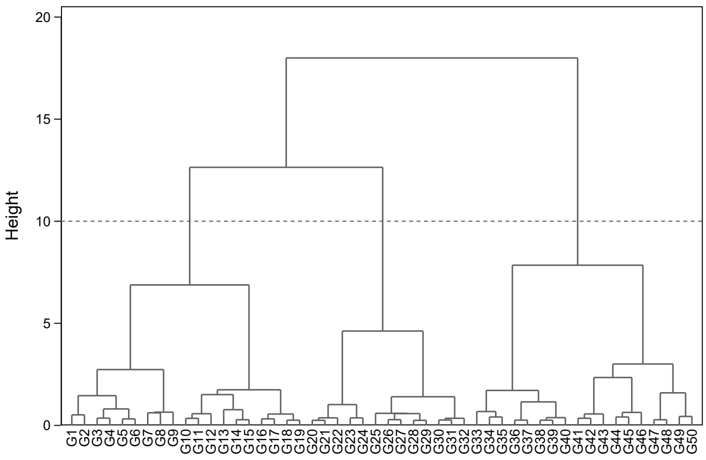

Figure A.2: Dendrogram of the hierarchical ascending clustering of financial vulnerability index trends

Note: For 382 households.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

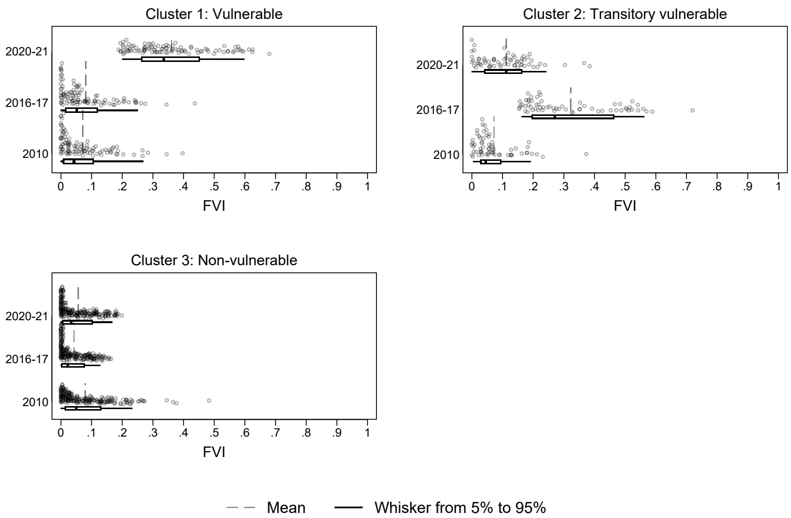

Figure A.3: Distribution of the financial vulnerability index across time and cluster

Note: For 98 vulnerable households, 62 transitory vulnerable, and 222 non-vulnerable.

Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

A.3 She Works Hard for the Money: Financial Vulnerability and Labour Supply

Table A.7: Correlation between hours worked per year and the number of occupations

	Number of occupations		
	Total	Males	Females
Hours a year			
Total	0.35***		
Males		0.32***	
Females			0.46***

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: NEEMSIS-2 (2020-21); author's calculations.

Table A.8: Who decides whether to take a job?

	N	Percent
Who has the most say in decisions about your work?		
Yourself	461	36.04
Husband/wife	697	54.50
Parents or step-parents	103	8.05
Children	18	1.41
Total	1279	100.00

Source: NEEMSIS-2 (2020-21); author's calculations.

Table A.9: Maximum-likelihood structural equation models for the number of occupations in the household with robust standard errors

	(1) Total Coef./SE	(2) Males Coef./SE	(3) Females Coef./SE
Lag Y	0.04	0.05	0.01
	(0.08)	(0.07)	(0.08)
Lag FVI	1.85***	0.52	1.28***
	(0.61)	(0.38)	(0.37)
Demographic characteristics			
HH size (log)	1.78***	1.01***	0.75***
	(0.23)	(0.14)	(0.15)
Share of children	1.23	0.86*	0.28
	(0.88)	(0.50)	(0.60)
Sex ratio	0.25**	0.31***	−0.05
	(0.11)	(0.08)	(0.07)
Dependency ratio	−0.27	−0.05	−0.21
	(0.31)	(0.23)	(0.22)
Share of stock	0.87	0.93*	−0.08
	(0.79)	(0.49)	(0.52)
Economic characteristics			
Net remittances†	0.14*	0.01	0.12**
	(0.08)	(0.05)	(0.05)
Assets‡	0.31**	0.10	0.19*
	(0.13)	(0.10)	(0.10)
Income§	0.24***	0.19***	0.05
	(0.07)	(0.04)	(0.04)
Head characteristics			
Female	−0.20	−0.20	0.00
	(0.25)	(0.15)	(0.18)
Age	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)
Edu: Below primary	0.00	0.00	0.00
	(.)	(.)	(.)
Edu: Primary or more	−0.60*	−0.14	−0.43*
	(0.36)	(0.21)	(0.26)
Time invariant variables			
Caste: Dalits	0.28*	0.05	0.24**
	(0.15)	(0.09)	(0.11)
Caste: Middles	0.00	0.00	0.00
	(.)	(.)	(.)
Caste: Uppers	−0.74***	−0.14	−0.61***
	(0.24)	(0.13)	(0.19)
HH FE	X	X	X
Location controls	X	X	X
Shock controls	X	X	X
Observations	646	646	646

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Transfers received minus transfers sent. ‡ Monetary value of assets held (INR 1k). § Annual labour income (INR 1k).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table A.10: Maximum-likelihood structural equation models for the number of occupations in the household without outliers (95%)

	(1) Total Coef./SE	(2) Females Coef./SE
Lag Y	0.01	−0.06
	(0.07)	(0.07)
Lag FVI	1.17**	1.11***
	(0.52)	(0.34)
Demographic characteristics		
HH size (log)	1.50***	0.68***
	(0.20)	(0.13)
Share of children	1.43*	0.35
	(0.77)	(0.50)
Sex ratio	0.26**	0.00
	(0.10)	(0.07)
Dependency ratio	−0.16	−0.15
	(0.28)	(0.19)
Share of stock	1.21*	0.07
	(0.70)	(0.46)
Economic characteristics		
Net remittances†	0.10	0.10**
	(0.07)	(0.04)
Assets‡	0.27**	0.19**
	(0.12)	(0.08)
Income§	0.09*	0.00
	(0.06)	(0.03)
Head characteristics		
Female	−0.04	0.11
	(0.22)	(0.15)
Age	0.02	0.00
	(0.01)	(0.01)
Edu: Below primary	0.00	0.00
	(.)	(.)
Edu: Primary or more	−0.21	−0.20
	(0.32)	(0.21)
Time invariant variables		
Caste: Dalits	0.11	0.21**
	(0.13)	(0.10)
Caste: Middles	0.00	0.00
	(.)	(.)
Caste: Uppers	−0.78***	−0.69***
	(0.23)	(0.18)
HH FE	X	X
Location controls	X	X
Shock controls	X	X
Observations	575	606

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. †Transfers received minus transfers sent. ‡Monetary value of assets held (INR 1k). §Annual labour income (INR 1k).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

Table A.11: Maximum-likelihood structural equation models for the number of occupations in the household without debt for economic investment

	(1) Total Coef./SE	(2) Males Coef./SE	(3) Females Coef./SE
Lag Y	0.03	0.03	0.01
	(0.07)	(0.06)	(0.07)
Lag FVI	1.57***	0.47	1.06***
	(0.59)	(0.36)	(0.39)
Demographic characteristics			
HH size (log)	1.71***	0.95***	0.75***
	(0.23)	(0.14)	(0.16)
Share of children	1.31	0.91*	0.30
	(0.88)	(0.54)	(0.59)
Sex ratio	0.26**	0.31***	−0.05
	(0.12)	(0.07)	(0.08)
Dependency ratio	−0.19	0.02	−0.21
	(0.32)	(0.20)	(0.21)
Share of stock	0.97	0.97**	−0.03
	(0.80)	(0.49)	(0.54)
Economic characteristics			
Net remittances†	0.14**	0.01	0.12***
	(0.07)	(0.04)	(0.05)
Assets‡	0.30**	0.10	0.18**
	(0.13)	(0.08)	(0.09)
Income§	0.24***	0.18***	0.06
	(0.06)	(0.04)	(0.04)
Head characteristics			
Female	−0.25	−0.24	−0.01
	(0.25)	(0.15)	(0.16)
Age	0.02	0.01	0.01
	(0.01)	(0.01)	(0.01)
Edu: Below primary	0.00	0.00	0.00
	(.)	(.)	(.)
Edu: Primary or more	−0.62*	−0.17	−0.43*
	(0.36)	(0.22)	(0.24)
Time invariant variables			
Caste: Dalits	0.25	0.03	0.23**
	(0.15)	(0.09)	(0.11)
Caste: Middles	0.00	0.00	0.00
	(.)	(.)	(.)
Caste: Uppers	−0.74***	−0.14	−0.61***
	(0.27)	(0.15)	(0.19)
HH FE	X	X	X
Location controls	X	X	X
Shock controls	X	X	X
Observations	646	646	646

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Transfers received minus transfers sent. ‡ Monetary value of assets held (INR 1k). § Annual labour income (INR 1k).
Source: RUME (2010), NEEMSIS-1 (2016-17), and NEEMSIS-2 (2020-21); author's calculations.

A.4 A Change is Gonna Come: Measures and Stability of Personality Traits

Table A.12: Details of personality traits questions

Item	Question	Trait
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

Note: *For a given trait, first pair of reverse-coded variables. **For a given trait, second pair of reverse-coded variables. The order of the questions is random in the questionnaire.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21).

Table A.13: Pre-factor analysis tests

	2016-17	2020-21
Bartlett test of sphericity		
χ^2	14960.96	12774.47
Degree of freedom	595	595
p-value	0.00	0.00
Sampling adequacy		
KMO	0.91	0.86

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

Table A.14: Factor analysis results with 2016-17 wave

	Eigenvalue	Difference	Proportion	Cumulative
Factor1	8.12	3.62	0.23	0.23
Factor2	4.50	1.89	0.13	0.36
Factor3	2.61	0.76	0.07	0.44
Factor4	1.86	0.15	0.05	0.49
Factor5	1.71	0.35	0.05	0.54
Factor6	1.36	0.24	0.04	0.58
Factor7	1.12	0.11	0.03	0.61
Factor8	1.01	0.19	0.03	0.64
Factor9	0.82	0.03	0.02	0.66
Factor10	0.79	0.07	0.02	0.68
Factor11	0.71	0.04	0.02	0.70
Factor12	0.67	0.03	0.02	0.72
Factor13	0.64	0.05	0.02	0.74
Factor14	0.59	0.00	0.02	0.76
Factor15	0.59	0.01	0.02	0.77
Factor16	0.57	0.03	0.02	0.79
Factor17	0.55	0.02	0.02	0.81
Factor18	0.53	0.02	0.02	0.82
Factor19	0.51	0.02	0.01	0.84
Factor20	0.49	0.02	0.01	0.85
Factor21	0.47	0.01	0.01	0.86
Factor22	0.46	0.02	0.01	0.88
Factor23	0.45	0.03	0.01	0.89
Factor24	0.42	0.01	0.01	0.90
Factor25	0.40	0.02	0.01	0.91
Factor26	0.38	0.01	0.01	0.92
Factor27	0.37	0.02	0.01	0.93
Factor28	0.34	0.01	0.01	0.94
Factor29	0.34	0.01	0.01	0.95
Factor30	0.32	0.01	0.01	0.96
Factor31	0.31	0.03	0.01	0.97
Factor32	0.29	0.02	0.01	0.98
Factor33	0.27	0.04	0.01	0.99
Factor34	0.23	0.03	0.01	0.99
Factor35	0.19	0	0.01	1.00

Source: NEEMSIS-1 (2016-17); author's calculations.

Table A.15: Factor analysis results with 2020-21 wave

	Eigenvalue	Difference	Proportion	Cumulative
Factor1	5.91	3.05	0.17	0.17
Factor2	2.85	1.46	0.08	0.25
Factor3	1.39	0.12	0.04	0.29
Factor4	1.27	0.06	0.04	0.33
Factor5	1.21	0.05	0.03	0.36
Factor6	1.16	0.02	0.03	0.39
Factor7	1.14	0.02	0.03	0.43
Factor8	1.12	0.02	0.03	0.46
Factor9	1.10	0.01	0.03	0.49
Factor10	1.09	0.05	0.03	0.52
Factor11	1.03	0.04	0.03	0.55
Factor12	0.99	0.02	0.03	0.58
Factor13	0.97	0.02	0.03	0.61
Factor14	0.95	0.02	0.03	0.63
Factor15	0.93	0.01	0.03	0.66
Factor16	0.91	0.03	0.03	0.69
Factor17	0.88	0.04	0.03	0.71
Factor18	0.84	0.05	0.02	0.74
Factor19	0.79	0.04	0.02	0.76
Factor20	0.75	0.02	0.02	0.78
Factor21	0.73	0.01	0.02	0.80
Factor22	0.72	0.02	0.02	0.82
Factor23	0.70	0.01	0.02	0.84
Factor24	0.69	0.03	0.02	0.86
Factor25	0.66	0.07	0.02	0.88
Factor26	0.59	0.02	0.02	0.90
Factor27	0.57	0.06	0.02	0.91
Factor28	0.50	0.04	0.01	0.93
Factor29	0.47	0.03	0.01	0.94
Factor30	0.44	0.04	0.01	0.95
Factor31	0.39	0.06	0.01	0.96
Factor32	0.34	0.01	0.01	0.97
Factor33	0.33	0.00	0.01	0.98
Factor34	0.32	0.05	0.01	0.99
Factor35	0.28	0	0.01	1.00

Source: NEEMSIS-2 (2020-21); author's calculations.

Table A.16: Factor analysis with 2016-17 wave

Item	Trait	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
easilyupset	ES	0.85				
nervous	ES	0.83				
feeldepress	ES	0.81				
worryalot	ES	0.80				
changemood	ES	0.69				
easilydistr	CO	0.68				
shywithpeop	EX	0.64				
putoffdutie	CO	0.51				
rudetoother	AG	0.51				
repetitivet	OP	0.41				
makeplans	CO		0.73			
appointment	CO		0.71			
completedut	CO		0.66			
enthusiasti	EX		0.64			
organized	CO		0.62			
workhard	CO		0.60			
workwithoth	AG		0.47			
liketothink	OP			0.74		
expressedth	EX			0.73		
activeimagi	OP			0.72		
sharefeelin	EX			0.70		
newideas	OP			0.64		
inventive	OP			0.60		
curious	OP			0.58		
talktomanyp	EX			0.55		
talkative	EX			0.37		
understando	AG			0.30		
interestbya	OP			0.29		
staycalm	ES				0.73	
managestres	ES				0.56	
forgiveothe	AG					0.70
toleratefau	AG					0.69
trustingofo	AG					0.56
enjoypeople	EX					0.35
helpfulwith	AG					0.24

Source: NEEMSIS-1 (2016-17); author's calculations.

Table A.17: Factor analysis with 2020-21 wave

Item	Trait	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
worryalot	ES	0.82				
easilydistr	CO	0.81				
feeldepress	ES	0.80				
easilyupset	ES	0.80				
changemood	ES	0.78				
nervous	ES	0.77				
repetitivet	OP	0.76				
putoffdutie	CO	0.74				
shywithpeop	EX	0.60				
rudetoother	AG	0.46				
understando	AG	0.23				
talkative	EX		0.56			
helpfulwith	AG		0.47			
inventive	OP		0.46			
staycalm	ES		0.45			
trustingofo	AG		0.42			
liketothink	OP		0.41			
sharefeelin	EX		0.37			
organized	CO		0.35			
appointment	CO		0.28			
enthusiasti	EX			0.58		
talktomanyp	EX			0.44		
completedut	CO			0.43		
forgiveothe	AG			0.36		
expressedth	EX			0.35		
activeimagi	OP			0.32		
makeplans	CO			0.29		
workwithoth	AG			0.25		
curious	OP				0.66	
interestbya	OP				0.47	
workhard	CO				0.36	
enjoypeople	EX				0.28	
newideas	OP				0.24	
toleratefau	AG				0.21	
managestres	ES					0.67

Source: NEEMSIS-2 (2020-21); author's calculations.

Box A.4.1: How many factors to retain?

For more details see Ledesma and Valero-Mora (doi: 10.7275/WJNC-NM63).
Kaiser's criterion keeps all factors with eigenvalues greater than or equal to one. The eigenvalue represents the amount of variance accounted for by the factor. An average single item contributes one to the total eigenvalue, while a factor with an eigenvalue less than one would account for less information than a single item.
Velicer's proposes the minimum average partial test. A method based on "the application of principal component analysis and in the subsequent analysis of partial correlation matrices. This rule employs the exploratory factor analysis concept of 'common' factors to determine how many components to extract. The method seeks to determine what components are common, and is proposed as a rule to find the best factor solution, rather than to find the cutoff point for the number of factor." (Ledesma and Valero-Mora, 2007, p.3).
Horn's Parallel Analysis is a sample-based alternative to the Kaiser criterion, taking into account that under Kaiser's criterion, some factors might have an eigenvalue greater than or equal to one simply due to sampling error.
Cattell's scree plot suggests to keep all factors before a discontinuity in the plot. The scree plots depict the eigenvalues on the y-axis in descending order against their factor numbers on the x-axis. The scree plots then rely on visual inspections to determine the point at which the slope levels off, which indicates the number of factors to retain.

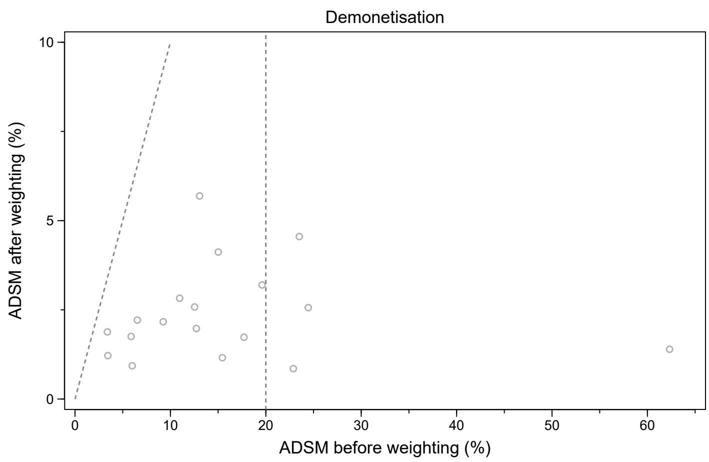

Figure A.4: Absolute difference in standardised means for the exposition to demonetisation as treatment

Note: For a set of 18 variables.

Source: NEEMSIS-1 (2016-17); author's calculations.

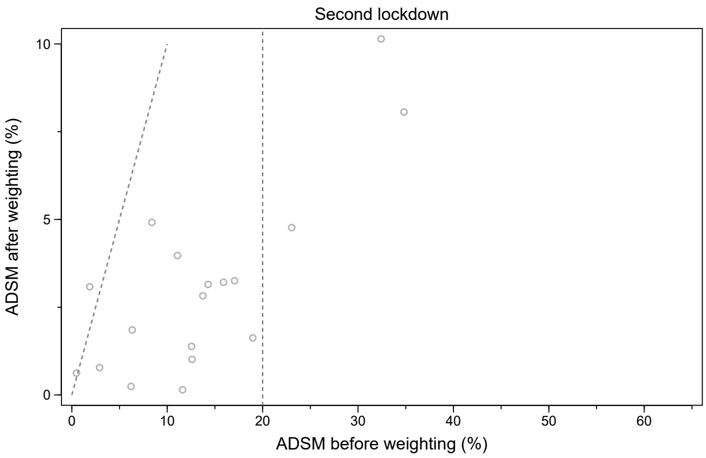

Figure A.5: Absolute difference in standardised means for the exposition to second COVID-19 lockdown as treatment

Note: For a set of 18 variables.

Source: NEEMSIS-2 (2020-21); author's calculations.

Table A.18: Mean test between pre- and post-demonetisation samples before and after weighting

	Before weighting			
	T=0	T=1	Diff	t-stat
No. of individuals	n=679	n=274		
Age	42.19	40.36	−1.84*	−1.83
Caste: Middles	0.39	0.45	0.06*	1.75
Caste: Uppers	0.12	0.09	−0.03	−1.53
Sex: Female	0.48	0.38	−0.10***	−2.75
MO: Unoccupied	0.13	0.15	0.02	0.84
MO: Agri self-emp	0.16	0.10	−0.06**	−2.48
MO: Casual	0.10	0.18	0.08***	3.44
MO: Regular non-qualified	0.08	0.29	0.22***	9.07
MO: Regular qualified	0.03	0.02	−0.02	−1.29
MO: Self-emp	0.14	0.09	−0.04**	−1.78
MO: MGNREGA	0.13	0.08	−0.05**	−2.10
Edu: Primary	0.20	0.18	−0.01	−0.47
Edu: High-School	0.26	0.28	0.02	0.48
Edu: HSC/Diploma	0.09	0.14	0.05**	2.16
Edu: Bachelors	0.07	0.09	0.02	0.91
Married: No	0.20	0.22	0.02	0.82
Income†	44.17	63.18	19.00***	3.30
HH size	4.85	4.39	−0.46***	−3.21

	After weighting			
	T=0	T=1	Diff	t-stat
No. of individuals	n=679	n=274		
Age	41.36	40.56	−0.80	−0.74
Caste: Middles	0.40	0.42	0.01	0.32
Caste: Uppers	0.11	0.10	−0.01	−0.36
Sex: Female	0.44	0.42	−0.02	−0.40
MO: Unoccupied	0.14	0.14	0.00	0.13
MO: Agri self-emp	0.14	0.14	−0.01	−0.22
MO: Casual	0.12	0.13	0.01	0.37
MO: Regular non-qualified	0.14	0.14	0.00	0.20
MO: Regular qualified	0.03	0.03	0.00	0.23
MO: Self-emp	0.12	0.13	0.01	0.24
MO: MGNREGA	0.12	0.10	−0.01	−0.53
Edu: Primary	0.19	0.18	−0.01	−0.24
Edu: High-School	0.27	0.28	0.01	0.15
Edu: HSC/Diploma	0.11	0.11	0.00	0.15
Edu: Bachelors	0.08	0.08	0.01	0.28
Married: No	0.21	0.22	0.01	0.21
Income†	50.29	53.97	3.68	0.52
HH size	4.77	4.76	−0.02	−0.11

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Annual individual labour income (INR 1k).
Source: NEEMSIS-1 (2016-17); author's calculations.

Table A.19: Mean test between pre- and post-second lockdown samples before and after weighting

	Before weighting			
	T=0	T=1	Diff	t-stat
No. of individuals	n=1031	n=377		
Age	46.92	41.56	−5.37***	−5.85
Caste: Middles	0.39	0.42	0.03	1.07
Caste: Uppers	0.14	0.10	−0.04**	−2.38
Sex: Female	0.50	0.49	−0.01	−0.47
MO: Unoccupied	0.15	0.22	0.07***	2.83
MO: Agri self-emp	0.17	0.14	−0.02	−1.04
MO: Casual	0.17	0.13	−0.04**	−2.09
MO: Regular non-qualified	0.01	0.04	0.03**	2.28
MO: Regular qualified	0.04	0.07	0.02	1.39
MO: Self-emp	0.09	0.09	0.00	−0.03
MO: MGNREGA	0.04	0.07	0.03**	2.09
Edu: Primary	0.23	0.15	−0.08***	−3.81
Edu: High-School	0.26	0.26	−0.01	−0.32
Edu: HSC/Diploma	0.09	0.14	0.06***	2.64
Edu: Bachelors	0.07	0.14	0.07***	3.15
Married: No	0.35	0.30	−0.05*	−1.85
Income†	39.42	51.05	11.63*	1.92
HH size	4.18	4.80	0.62***	5.43

	After weighting			
	T=0	T=1	Diff	t-stat
No. of individuals	n=1031	n=377		
Age	41.52	40.28	−1.24	−1.25
Caste: Middles	0.42	0.43	0.01	0.30
Caste: Uppers	0.10	0.09	−0.01	−0.47
Sex: Female	0.48	0.49	0.00	0.13
MO: Unoccupied	0.23	0.24	0.01	0.51
MO: Agri self-emp	0.14	0.14	0.00	0.03
MO: Casual	0.11	0.12	0.00	0.19
MO: Regular non-qualified	0.04	0.05	0.01	0.46
MO: Regular qualified	0.09	0.07	−0.01	−0.92
MO: Self-emp	0.09	0.09	0.00	−0.06
MO: MGNREGA	0.08	0.08	0.00	0.16
Edu: Primary	0.15	0.13	−0.02	−0.66
Edu: High-School	0.23	0.25	0.01	0.46
Edu: HSC/Diploma	0.15	0.16	0.01	0.51
Edu: Bachelors	0.17	0.16	−0.01	−0.28
Married: No	0.31	0.30	−0.02	−0.61
Income†	56.51	56.62	0.11	0.02
HH size	4.77	4.96	0.19*	1.79

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † Annual individual labour income (INR 1k).
Source: NEEMSIS-2 (2020-21); author's calculations.

A.5 Psychology of Debt

Table A.20: Details of cognitive skills questions

Item	Question	Skill
canreadcard1a	Can you please read the letters on this card?	Literacy
canreadcard1b	Can you please read the word on this card?	Literacy
canreadcard1c	Can you please read the sentence on this card?	Literacy
canreadcard2	Can you please write the following sentence?	Literacy
numeracy1	Please tell me the answer to the calculation (5+9=14)	Numeracy
numeracy2	Please tell me the answer to the calculation (33-7=26)	Numeracy
numeracy3	Please tell me the answer to the calculation (7*8=56)	Numeracy
numeracy4	Please tell me the answer to the calculation (42/6=7)	Numeracy

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

Table A.21: Multivariate probit of the probability that individual is in debt

	(1) Recourse Coef./SE	(2) Recourse Coef./SE	(3) Recourse Coef./SE	(4) Recourse Coef./SE
Indebted in 2016-17	0.49^{***}	0.50^{***}	0.48^{***}	0.50^{***}
	(0.13)	(0.14)	(0.14)	(0.14)
Sex: Female	0.84^{***}	0.86^{***}	0.85^{***}	0.78^{***}
	(0.16)	(0.16)	(0.16)	(0.21)
Caste: Dalits	0.18	0.16	0.18	0.05
	(0.12)	(0.12)	(0.12)	(0.17)
Age	−0.00	−0.00	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Head: Yes	0.48^{***}	0.49^{***}	0.47^{***}	0.47^{**}
	(0.18)	(0.18)	(0.18)	(0.19)
MO: Unoccupied	-0.85^{***}	-0.91^{***}	-0.86^{***}	-0.93^{***}
	(0.24)	(0.24)	(0.24)	(0.24)
MO: Agri self-emp	−0.08	−0.13	−0.06	−0.12
	(0.24)	(0.24)	(0.24)	(0.24)
MO: Casual	−0.22	−0.25	−0.21	−0.26
	(0.21)	(0.21)	(0.21)	(0.21)
MO: Regular	0.11	0.08	0.15	0.11
	(0.23)	(0.22)	(0.23)	(0.23)
MO: Self-emp	−0.10	−0.15	−0.06	−0.11
	(0.23)	(0.23)	(0.23)	(0.23)
MO: MGNREGA	-0.37^{*}	-0.41^{*}	−0.35	-0.39^{*}
	(0.23)	(0.23)	(0.23)	(0.23)
Edu: Primary or more	−0.01	−0.01	−0.01	−0.03
	(0.18)	(0.18)	(0.18)	(0.18)
Married: Yes	0.99^{***}	0.98^{***}	1.01^{***}	1.03^{***}
	(0.15)	(0.15)	(0.15)	(0.15)
Assets†	0.00^{*}	0.00^{*}	0.00^{*}	0.00^{*}
	(0.00)	(0.00)	(0.00)	(0.00)
HH size	−0.03	−0.02	−0.02	−0.02
	(0.03)	(0.03)	(0.03)	(0.03)

Income[‡]	−0.00*	−0.00	−0.00*	−0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
ES (std)	0.08	0.02	0.09	−0.00
	(0.06)	(0.09)	(0.10)	(0.13)
CO (std)	0.01	0.05	0.02	0.11
	(0.07)	(0.09)	(0.10)	(0.14)
OP-EX (std)	0.03	−0.01	−0.03	−0.06
	(0.06)	(0.08)	(0.09)	(0.11)
AG (std)	−0.08	−0.07	−0.11	−0.11
	(0.06)	(0.08)	(0.10)	(0.13)
Raven (std)	−0.06	0.01	−0.12	−0.03
	(0.07)	(0.09)	(0.09)	(0.11)
Numeracy (std)	0.01	0.03	−0.02	−0.16
	(0.09)	(0.11)	(0.12)	(0.16)
Literacy (std)	0.04	0.02	0.18	0.19
	(0.09)	(0.11)	(0.11)	(0.15)
Female*ES		0.17		0.19
		(0.14)		(0.21)
Female*CO		−0.12		−0.26
		(0.14)		(0.21)
Female*OP-EX		0.12		0.10
		(0.13)		(0.19)
Female*AG		−0.00		−0.03
		(0.12)		(0.20)
Female*Rav		−0.21		−0.28
		(0.14)		(0.19)
Female*Num		−0.08		0.30
		(0.18)		(0.25)
Female*Lit		0.13		0.08
		(0.16)		(0.23)
Dalits*ES			0.02	0.07
			(0.13)	(0.18)
Dalits*CO			−0.02	−0.12
			(0.13)	(0.18)
Dalits*OP-EX			0.12	0.10
			(0.12)	(0.16)
Dalits*AG			0.04	0.04
			(0.12)	(0.16)
Dalits*Rav			0.13	0.12
			(0.14)	(0.18)
Dalits*Num			0.06	0.33
			(0.18)	(0.23)
Dalits*Lit			−0.29*	−0.33
			(0.16)	(0.21)
Female*Dalits				0.14
				(0.26)
Female*Dalits*ES				0.00
				(0.29)
Female*Dalits*CO				0.23
				(0.29)
Female*Dalits*OP-EX				0.07
				(0.26)
Female*Dalits*AG				0.04
				(0.26)
Female*Dalits*Rav				0.05
				(0.28)

Female*Dalits*Num				−0.69*
				(0.35)
Female*Dalits*Lit				0.09
				(0.34)
Location controls	X	X	X	X
Shock controls	X	X	X	X
Observations	831	831	831	831
Pseudo R^2	0.25	0.26	0.26	0.27
LPM VIF§	1.86	2.29	2.43	4.11

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. †Monetary value of assets held, without land (INR 1k). ‡Annual labour income (INR 1k). §Variance Inflation Factor (VIF) statistic computed using a Linear Probability Model (LPM). ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21).

Table A.22: Multivariate probit of the probability of not providing a service to lender

	(1) Negociation Coef./SE	(2) Negociation Coef./SE	(3) Negociation Coef./SE	(4) Negociation Coef./SE
Indebted in 2016-17	0.34*	0.41**	0.30	0.35*
	(0.19)	(0.19)	(0.19)	(0.20)
Sex: Female	0.56**	0.62**	0.62***	0.55*
	(0.23)	(0.25)	(0.24)	(0.31)
Caste: Dalits	−0.33**	−0.36**	−0.33**	−0.47**
	(0.16)	(0.17)	(0.16)	(0.20)
Age	0.00	−0.00	−0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Head: Yes	0.17	0.17	0.22	0.18
	(0.23)	(0.25)	(0.24)	(0.26)
MO: Unoccupied	−0.41	−0.24	−0.52	−0.12
	(0.40)	(0.38)	(0.40)	(0.38)
MO: Agri self-emp	−0.34	−0.43*	−0.35	−0.44*
	(0.24)	(0.24)	(0.24)	(0.25)
MO: Casual	−0.21	−0.24	−0.22	−0.22
	(0.23)	(0.24)	(0.24)	(0.24)
MO: Regular	−0.78***	−0.85***	−0.79***	−0.85***
	(0.24)	(0.24)	(0.24)	(0.25)
MO: Self-emp	−0.42*	−0.41*	−0.48**	−0.39
	(0.24)	(0.24)	(0.24)	(0.25)
MO: MGNREGA	0.55**	0.63**	0.53*	0.64**
	(0.27)	(0.30)	(0.28)	(0.29)
Edu: Primary or more	0.26	0.28	0.23	0.23
	(0.20)	(0.20)	(0.20)	(0.21)
Married: Yes	−0.00	0.03	0.00	0.04
	(0.23)	(0.23)	(0.23)	(0.25)
Assets†	0.00**	0.00**	0.00**	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)
HH size	0.03	0.03	0.04	0.04
	(0.04)	(0.04)	(0.04)	(0.04)
Income‡	−0.00	−0.00	−0.00	−0.00

	(0.00)	(0.00)	(0.00)	(0.00)
ES (std)	0.00	0.04	0.08	0.24
	(0.09)	(0.12)	(0.15)	(0.18)
CO (std)	0.13	0.06	0.18	0.03
	(0.08)	(0.10)	(0.13)	(0.16)
OP-EX (std)	−0.02	−0.10	−0.07	−0.19
	(0.07)	(0.09)	(0.11)	(0.13)
AG (std)	0.05	−0.01	0.14	0.06
	(0.08)	(0.09)	(0.14)	(0.18)
Raven (std)	−0.09	0.08	−0.04	0.23
	(0.09)	(0.10)	(0.12)	(0.14)
Numeracy (std)	−0.20*	−0.26**	−0.07	−0.33*
	(0.11)	(0.13)	(0.15)	(0.19)
Literacy (std)	0.20	0.25*	0.13	0.32*
	(0.12)	(0.14)	(0.15)	(0.18)
Female*ES		−0.16		−0.51**
		(0.17)		(0.26)
Female*CO		0.26*		0.49**
		(0.16)		(0.24)
Female*OP-EX		0.23*		0.19
		(0.14)		(0.21)
Female*AG		0.18		0.12
		(0.15)		(0.27)
Female*Rav		−0.48***		−0.99***
		(0.17)		(0.25)
Female*Num		0.28		0.84**
		(0.21)		(0.35)
Female*Lit		−0.21		−0.40
		(0.21)		(0.29)
Dalits*ES			−0.17	−0.43*
			(0.19)	(0.24)
Dalits*CO			−0.10	0.09
			(0.16)	(0.20)
Dalits*OP-EX			0.11	0.19
			(0.14)	(0.18)
Dalits*AG			−0.13	−0.08
			(0.16)	(0.21)
Dalits*Rav			−0.13	−0.44**
			(0.17)	(0.22)
Dalits*Num			−0.25	0.09
			(0.21)	(0.26)
Dalits*Lit			0.20	−0.04
			(0.19)	(0.24)
Female*Dalits				0.16
				(0.30)
Female*Dalits*ES				0.76**
				(0.34)
Female*Dalits*CO				−0.51
				(0.33)
Female*Dalits*OP-EX				−0.11
				(0.29)
Female*Dalits*AG				−0.03
				(0.32)
Female*Dalits*Rav				1.12***
				(0.37)
Female*Dalits*Num				−1.05**

				(0.46)
Female*Dalits*Lit				0.53
				(0.42)
Location controls	X	X	X	X
Shock controls	X	X	X	X
Observations	485	485	485	485
Pseudo R^2	0.21	0.23	0.23	0.27
LPM VIF§	1.94	2.33	2.64	4.41

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. †Monetary value of assets held, without land (INR 1k). ‡Annual labour income (INR 1k). §Variance Inflation Factor (VIF) statistic computed using a Linear Probability Model (LPM). ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21).

Table A.23: Multivariate probit of the probability to have problem to repay the debt

	(1) Management Coef./SE	(2) Management Coef./SE	(3) Management Coef./SE	(4) Management Coef./SE
Indebted in 2016-17	0.22	0.17	0.21	0.25
	(0.19)	(0.18)	(0.19)	(0.19)
Sex: Female	0.23	0.23	0.26	0.30
	(0.24)	(0.25)	(0.25)	(0.29)
Caste: Dalits	−0.05	−0.05	−0.04	0.06
	(0.14)	(0.14)	(0.15)	(0.18)
Age	0.00	−0.00	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Head: Yes	0.14	0.21	0.18	0.21
	(0.24)	(0.24)	(0.24)	(0.25)
MO: Unoccupied	−0.01	0.12	−0.07	−0.03
	(0.38)	(0.38)	(0.38)	(0.39)
MO: Agri self-emp	−0.42*	−0.42*	−0.40	−0.38
	(0.24)	(0.24)	(0.25)	(0.25)
MO: Casual	−0.04	−0.07	−0.06	−0.09
	(0.23)	(0.23)	(0.23)	(0.24)
MO: Regular	−0.24	−0.26	−0.26	−0.27
	(0.23)	(0.23)	(0.23)	(0.24)
MO: Self-emp	−0.06	−0.03	−0.07	−0.03
	(0.23)	(0.23)	(0.23)	(0.23)
MO: MGNREGA	−0.29	−0.36	−0.27	−0.32
	(0.23)	(0.24)	(0.24)	(0.25)
Edu: Primary or more	−0.13	−0.15	−0.14	−0.19
	(0.18)	(0.19)	(0.19)	(0.19)
Married: Yes	0.70***	0.71***	0.75***	0.84***
	(0.24)	(0.25)	(0.25)	(0.26)
Assets†	0.00	0.00	0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
HH size	−0.03	−0.03	−0.03	−0.04
	(0.03)	(0.03)	(0.04)	(0.04)
Income‡	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)

ES (std)	0.19**	0.09	0.18	0.04
	(0.09)	(0.11)	(0.13)	(0.17)
CO (std)	−0.18**	−0.10	−0.17	0.04
	(0.08)	(0.10)	(0.12)	(0.15)
OP-EX (std)	0.11	0.05	0.15	0.07
	(0.07)	(0.08)	(0.10)	(0.12)
AG (std)	−0.01	0.04	0.02	0.18
	(0.07)	(0.09)	(0.12)	(0.16)
Raven (std)	−0.17**	−0.27***	−0.09	−0.25**
	(0.08)	(0.10)	(0.10)	(0.13)
Numeracy (std)	0.08	0.08	0.10	0.07
	(0.10)	(0.12)	(0.15)	(0.18)
Literacy (std)	0.02	0.12	−0.03	0.10
	(0.10)	(0.12)	(0.13)	(0.16)
Female*ES		0.23		0.33
		(0.16)		(0.26)
Female*CO		−0.24		−0.60***
		(0.15)		(0.23)
Female*OP-EX		0.17		0.29
		(0.13)		(0.20)
Female*AG		−0.09		−0.30
		(0.14)		(0.22)
Female*Rav		0.28*		0.51**
		(0.16)		(0.21)
Female*Num		−0.08		−0.12
		(0.20)		(0.29)
Female*Lit		−0.27		−0.29
		(0.19)		(0.26)
Dalits*ES			−0.01	0.05
			(0.17)	(0.23)
Dalits*CO			−0.02	−0.27
			(0.15)	(0.20)
Dalits*OP-EX			−0.09	−0.02
			(0.13)	(0.17)
Dalits*AG			−0.03	−0.21
			(0.15)	(0.20)
Dalits*Rav			−0.22	−0.05
			(0.16)	(0.21)
Dalits*Num			−0.05	0.01
			(0.20)	(0.24)
Dalits*Lit			0.16	0.11
			(0.18)	(0.23)
Female*Dalits				−0.18
				(0.27)
Female*Dalits*ES				−0.09
				(0.35)
Female*Dalits*CO				0.69**
				(0.32)
Female*Dalits*OP-EX				−0.24
				(0.27)
Female*Dalits*AG				0.41
				(0.30)
Female*Dalits*Rav				−0.50
				(0.33)
Female*Dalits*Num				0.01
				(0.42)

Female*Dalits*Lit				0.07
				(0.39)
Location controls	X	X	X	X
Shock controls	X	X	X	X
Observations	485	485	485	485
Pseudo R^2	0.07	0.09	0.08	0.11
LPM VIF§	1.94	2.33	2.64	4.41

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. † Monetary value of assets held, without land (INR 1k). ‡ Annual labour income (INR 1k). § Variance Inflation Factor (VIF) statistic computed using a Linear Probability Model (LPM). ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21).

Table A.24: Marginal effects at representative values of the probability of being in debt with COVID-19 exposure and income constraints

	(1) Recourse ME/SE	(2) Recourse ME/SE		(3) Recourse ME/SE		(4) Recourse ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.02	0.00	0.03*	0.02	0.02	−0.00	0.02	0.03	0.04*
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.05)	(0.04)	(0.03)	(0.02)
CO (std)	0.01	0.02	−0.01	0.01	0.00	0.04	0.01	−0.02	−0.00
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.05)	(0.04)	(0.03)	(0.02)
OP-EX (std)	0.01	−0.00	0.02	−0.01	0.02	−0.02	0.01	0.01	0.03*
	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.04)	(0.04)	(0.03)	(0.02)
AG (std)	−0.02	−0.03	−0.01	−0.03	−0.02	−0.03	−0.03	−0.02	−0.01
	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)
Raven (std)	−0.02	0.00	−0.03*	−0.03	0.00	−0.01	0.03	−0.06**	−0.02
	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)	(0.02)
Numeracy (std)	−0.00	0.00	−0.01	−0.01	0.00	−0.06	0.06	0.03	−0.03
	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.06)	(0.05)	(0.03)	(0.03)
Literacy (std)	0.01	0.01	0.02	0.05*	−0.03	0.07	−0.05	0.05	0.00
	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *AME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table A.25: Marginal effects at representative values of the probability of not providing a service to lender with COVID-19 exposure and income constraints

	(1) Negociation ME/SE	(2) Negociation ME/SE		(3) Negociation ME/SE		(4) Negociation ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.01	0.02	−0.04	0.04	−0.03	0.10	−0.07	−0.09	0.02
	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.07)	(0.06)	(0.07)	(0.07)
CO (std)	0.05	0.02	0.11**	0.07	0.03	0.01	0.05	0.17**	0.03
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.05)	(0.07)	(0.07)
OP-EX (std)	−0.01	−0.04	0.05	−0.03	0.02	−0.08	0.01	0.01	0.03
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.06)
AG (std)	0.02	−0.00	0.06	0.05	0.01	0.02	−0.00	0.05	0.03
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.07)	(0.04)	(0.07)	(0.06)
Raven (std)	−0.03	0.04	−0.14***	−0.01	−0.07	0.10*	−0.08	−0.25***	−0.03
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.08)	(0.08)
Numeracy (std)	−0.08*	−0.10*	0.00	−0.03	−0.13**	−0.13*	−0.09	0.16*	−0.18*
	(0.04)	(0.05)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)	(0.09)	(0.10)
Literacy (std)	0.07	0.09*	0.01	0.04	0.13**	0.12*	0.11	−0.03	0.15
	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)	(0.10)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. † When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *AME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table A.26: Marginal effects at representative values of the probability to have problem to repay the debt with COVID-19 exposure and income constraints

	(1) Management ME/SE	(2) Management ME/SE		(3) Management ME/SE		(4) Management ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.07**	0.04	0.12**	0.07	0.06	0.02	0.03	0.14	0.12*
	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.07)	(0.06)	(0.09)	(0.07)
CO (std)	−0.07**	−0.04	−0.13**	−0.07	−0.07*	0.01	−0.09	−0.22***	−0.05
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.06)	(0.08)	(0.07)
OP-EX (std)	0.05*	0.02	0.09**	0.06	0.03	0.02	0.03	0.15**	0.04
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.07)	(0.05)
AG (std)	−0.01	0.01	−0.02	0.01	−0.01	0.06	−0.02	−0.04	0.03
	(0.03)	(0.04)	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)	(0.07)	(0.06)
Raven (std)	−0.07**	−0.11***	0.00	−0.03	−0.13***	−0.10*	−0.13*	0.10	−0.12
	(0.03)	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)	(0.08)
Numeracy (std)	0.03	0.03	0.01	0.04	0.01	0.02	0.03	0.00	−0.01
	(0.04)	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)	(0.07)	(0.10)	(0.10)
Literacy (std)	0.01	0.05	−0.06	−0.01	0.05	0.05	0.08	−0.08	−0.01
	(0.04)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.07)	(0.09)	(0.10)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. †When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *AME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table A.27: Marginal effects at representative values of the probability of not providing a service to lender with debt contract

	(1) Negociation ME/SE	(2) Negociation ME/SE		(3) Negociation ME/SE		(4) Negociation ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	−0.05	−0.01	−0.13**	−0.00	−0.08**	0.02	−0.06	−0.10	−0.14**
	(0.03)	(0.04)	(0.05)	(0.06)	(0.04)	(0.07)	(0.05)	(0.08)	(0.07)
CO (std)	0.09***	0.05	0.18***	0.11**	0.06	0.08	0.04	0.24***	0.14*
	(0.03)	(0.04)	(0.06)	(0.05)	(0.04)	(0.07)	(0.05)	(0.08)	(0.08)
OP-EX (std)	−0.03	−0.03	−0.04	−0.06	−0.00	−0.08	0.03	−0.06	−0.07
	(0.03)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)	(0.07)	(0.07)
AG (std)	0.02	−0.01	0.06	0.01	0.02	−0.00	−0.01	0.04	0.07
	(0.03)	(0.04)	(0.05)	(0.05)	(0.03)	(0.07)	(0.04)	(0.07)	(0.06)
Raven (std)	−0.02	0.03	−0.14**	−0.02	−0.03	0.05	−0.03	−0.26***	−0.04
	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.06)	(0.06)	(0.10)	(0.08)
Numeracy (std)	−0.10**	−0.13**	0.06	−0.08	−0.11**	−0.18**	−0.10	0.22*	−0.09
	(0.04)	(0.05)	(0.08)	(0.07)	(0.05)	(0.08)	(0.06)	(0.12)	(0.10)
Literacy (std)	0.09*	0.09*	0.02	0.11*	0.08	0.16**	0.05	0.01	0.10
	(0.04)	(0.05)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.10)	(0.10)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. † When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *AME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Table A.28: Marginal effects at representative values of the probability to have problem to repay the debt with debt contract

	(1) Management ME/SE	(2) Management ME/SE		(3) Management ME/SE		(4) Management ME/SE			
	Total	Male†	Female	Non-Dalit	Dalit	Non-Dalit male	Dalit male	Non-Dalit female	Dalit female
ES (std)	0.07**	0.06**	0.09	0.10**	0.04	0.07	0.05	0.13	0.06
	(0.03)	(0.03)	(0.06)	(0.04)	(0.04)	(0.05)	(0.04)	(0.08)	(0.08)
CO (std)	−0.08***	−0.06**	−0.14**	−0.11***	−0.06	−0.05	−0.08**	−0.24***	−0.05
	(0.03)	(0.03)	(0.06)	(0.04)	(0.04)	(0.05)	(0.04)	(0.08)	(0.07)
OP-EX (std)	0.02	−0.01	0.08*	0.03	0.02	−0.01	0.00	0.12*	0.02
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)
AG (std)	0.01	0.02	−0.01	0.02	0.01	0.03	0.02	−0.01	0.00
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.05)	(0.03)	(0.06)	(0.06)
Raven (std)	−0.05*	−0.07**	0.02	−0.02	−0.10**	−0.05	−0.11**	0.07	−0.05
	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.07)	(0.07)
Numeracy (std)	0.00	0.03	−0.08	0.03	−0.01	0.03	0.03	−0.08	−0.10
	(0.04)	(0.04)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)	(0.11)
Literacy (std)	0.03	0.04	−0.01	0.02	0.05	0.06	0.06	−0.04	0.04
	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.11)

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. †When a personality traits/cognitive skills increases by one standard deviation, the probability that $Y = 1$ increases/decreases by *AME* percentage point, for the average *male*, all else being equal. ES: Emotional stability, CO: Conscientiousness, OP-EX: Openness-Extraversion, AG: Agreeableness, Rav: Raven, Num: Numeracy, Lit: Literacy.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.