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She Works Hard for the Money: Debt Burden and Labour Supply in India[*]

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Abstract For over 40 years, labour supply has been at the heart of empirical microeconomics, but few studies have examined the impact of household debt burdens on labour supply, and almost none on countries of the Global South. This research fills this gap by examining how debt burden - measured by the debt service ratio - affects labour supply, in particular hours worked, among more than 3200 individuals in rural Tamil Nadu, India, between 2016-17 and 2020-21. Using a Heckman correction with lagged debt ratios and fixed effects to account for unobserved factors and limit reverse causality, the study highlights a striking result: women increase their labour supply to repay household debt, regardless of which household member incurred it. Our results challenge the commonly held view in the South that women's work is synonymous with empowerment, suggesting that it may be the result of economic pressures rather than a move towards autonomy.

Keywords Caste, gender, empowerment, labour supply, microcredit.

JEL Codes D13, G51, J21.

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1. Introduction

Over the past two decades, household indebtedness has drawn increasing attention, driven in part by its profound macroeconomic implications (Mian, Sufi, & Verner, 2017). However, the literature on household indebtedness in the Global South remains a niche area, characterised by limited exploration and a need for more diversity in the datasets used (Noerhidajati, Purwoko, Werdaningtyas, Kamil, & Dartanto, 2021). Much of the literature on the Global South has focused on the factors leading to debt accumulation, leaving a significant gap in understanding its consequences, and particularly on labour-related outcomes. This gap is surprising, given that labour supply is a fundamental determinant of economic well-being for individuals, households, and society at large (De Neve et al., 2018).

Studies carried out in developed countries mainly indicate that mortgage commitments force individuals to increase their labour supply to repay the loan (Aldershof, Alessie, & Kapteyn, 1997; Benito & Saleheen, 2013; Bottazzi, 2004; Bunn, Chadha, Lazarowicz, Millard, & Rockall, 2021; Fortin, 1995). However, Donaldson, Piacentino, & Thakor (2019) also show that, in the USA, 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 addition, specific adverse effects of consumer credit and overindebtedness, such as anxiety and the risk of depression (Hojman, Miranda, & Ruiz-Tagle, 2016), can have a negative effect on labour market participation (Chatterji, Alegría, Lu, & Takeuchi, 2007).

The only study on a developing country that seeks to establish the relationship between debt and labour looked at 408 small-scale manufacturing workers in Odisha, India (Kaur, Mullainathan, Oh, & Schilbach, 2025). 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 and unintentional mistakes.

In this study, we build on previous work but focus on rural South India to analyse how the household debt burden (i.e., the financial strain that households may experience due

to the debt obligations) affects labour supply. We differ significantly from the studies cited above on one essential point: the measurement of debt. Indeed, unlike Bunn et al. (2021) or Kaur et al. (2025), we do not examine the effect of a specific shock, but the effect of the debt burden, which is more encompassing in terms of the type of debt (i.e., secured or unsecured) and therefore provides a more holistic view of a household's financial situation. In so doing, this study is the first to analyse the effect of household debt on labour supply in the context of a developing country.

We use an original first-hand panel dataset collected by the authors of this paper, which covers ten years (2010, 2016-17, 2020-21) and contains precise measures of debt and labour supply (Nordman, Venkatasubramanian, Guérin, Natal, et al., 2025). We use a two-stage sample selection model with lagged debt service ratio and fixed effects to control for unobserved time-invariant confounders and limit reverse causality. We find that the household debt service ratio increases individuals' labour supply. By disaggregating the labour supply by sex, we find that the previous relationship is stronger for women' labour supply. We do not observe any difference according to caste status of the household.

The rest of the study is organised as follows. In Section 2, we present credit and labour markets in rural South India. In Section 3, we present the data while, in Section 4, we describe the main variables. In Section 5, we explain the methodology, present the results in Section 6 and discuss them in Section 7. Conclusion is in Section 8.

2. Credit and labour markets in rural South India

2.1. Credit market

Even if informal finance is often viewed as usurers only there to impoverish the poor, it is the key feature of the rural credit market in South India, because it provides credit promptly with a minimum of paperwork and procedures (Guérin, Roesch, Venkatasubramanian, & D'Espallier, 2012). However, sources of debt have changed considerably and diversified over the second half of the last century, with the emergence of SHGs (i.e., a group of 15 to 20 women who circulate money among themselves and are then eligible for loans provided by NGOs, banks or non-bank financial companies) and microcredit. These new players have the particularity of mainly targeting women, which is a novelty given that women have always

been excluded from formal finance. Contrary to the neoclassical theory, formal lenders have not replaced informal lenders and using both formal and informal loans is very common.

National data from the All-India Debt and Investment Surveys (AIDIS) indicate that, since the 1980s, the incidence of debt among rural households has risen from 19% to 32% and that there has been an increase in the use of both informal and formal debt (Rajakumar, Mani, Shetty, & Karmarkar, 2019). However, it should be noted that these trends are largely underestimated because the AIDIS data do not capture informal finance well. For instance, several household micro-surveys conducted in Uttar Pradesh and Tamil Nadu indicate that the incidence of debt is around 90% (Himanshu, Lanjouw, & Stern, 2018; Reboul, Guérin, & Nordman, 2021).

In South 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, Kumar, & Venkatasubramanian, 2023). 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) and, more precisely, creditworthiness has consequences in terms of social belonging, status, and dignity in the village (Guérin et al., 2023).

Caste remains a powerful regulator of borrowing relationships by segmenting local informal credit circuits and affecting access to formal finance (Kumar, 2013). Dalits (formerly called "untouchables"), the low caste, have a higher incidence of indebtedness but borrow smaller amounts (Guérin, D'Espallier, & Venkatasubramanian, 2013). At the individual level, both men and women borrow. However, the relative amount of debt to income is higher for women than for men (Reboul et al., 2021).

2.2.Labour market

The employment structure in rural India has changed considerably over the last few decades, particularly in Tamil Nadu, where the study is taking place. Tamil Nadu is an industrialised State due to the large production units in the major cities and the small industrialised urban centres that constitute new forms of urbanisation and production dynamics. The latter are redesigning the organisation of work and lifestyles in the territory (Djurfeldt et al., 2008). 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 Tamil territory. Rural regions persistently rely on agriculture as their principal economic activity (Harriss, Jeyaranjan, & Nagaraj, 2010). The agricultural sector is characterised by low productivity, partly due to the intense fragmentation of land. This low productivity, combined with the development of connections between rural and urban areas, is leading to an increase in the number of sources of income for individuals in rural areas, particularly non-agricultural jobs (Di Santolo et al., 2024). The seasonality of employment due to agricultural cycles, monsoons, and crop patterns also leads to the multiplication of sources of income and accentuates circular migration that also fuels the multiplication of sources of income.

The labour market is strongly segmented by caste and gender. Traditionally, caste implies that jobs are determined at birth (Deshpande, 2000). But despite the process of modernisation of the Indian economy since the 1980s, 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 & Gooptu, 2001). Regarding gender, social and cultural factors keep women outside the labour force (Mehrotra & Parida, 2017). For example, the fact that women do not work is a matter of prestige for the economically better-off households and forward castes (Eswaran, Ramaswami, & Wadhwa, 2013). In addition, women are more likely to be present in temporary and casual occupations than in more stable jobs because of entry 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 & Anitha, 2022).

3. Data

Empirical analyses rely on longitudinal data collected through three survey rounds: the "RUral Microfinance and Employment survey" (RUME) carried out in 2010, followed by the two waves of the "Networks, Employment, dEbt, Mobilities and Skills in India Survey" (NEEMSIS), conducted in the same area in 2016-17 (NEEMSIS-1) and 2020-21 (NEEMSIS-2) (Nordman et al., 2025).

The RUME survey was conducted in ten villages in coastal/central Tamil Nadu in the Cuddalore district and Kallakurichi district, mostly agricultural areas. The villages benefit from the proximity of two large industrial towns (Neyveli and Cuddalore) and a regional business centre (Panruti). The RUME survey randomly selected 405 households using a stratified sample framework based on three dimensions: proximity to small towns (Panruti, Viluppuram, and Cuddalore), an agroecological criterion, and caste affiliation. Thus, half of the villages have irrigated land (the other half is dry) and, within villages, half of the sample was selected from the most upper and middle caste part of the village, "Ur". By contrast, the other half comes from the "Colony" part, where Dalits mainly live. The random route sample method was implemented to choose households: enumerators, by a team of two, interviewed a household every five houses.

The NEEMSIS surveyed population has been built from the RUME survey. NEEMSIS has two waves carried out in 2016-17 (NEEMSIS-1) and 2020-21 (NEEMSIS-2). Of the 405 households surveyed in 2010, 388 were re-surveyed in 2016-17 with NEEMSIS-1 (i.e., 4.2% attrition rate), and 104 new households were randomly added, using the same method as RUME, to refresh the sample. The sample in 2016-17 consists of 492 households. The NEEMSIS-2 (2020-21) wave is the third wave of data collection. The survey recovered 485 households from the NEEMSIS-1 wave (i.e., 1.4% attrition rate), and selected 147 new households to increase the sampled population. The 2020-21 sample consists of 632 households. The very low attrition observed is explained by the specific context of the rural areas of South India. In fact, in this area, the population shows a strong attachment to rural areas, and although the urban lifestyle may seem attractive, South India is not experiencing any significant rural exodus (Racine, 1994). Moreover, attrition does not affect any particular segment of the distribution of income and debt (see Table A1 in the appendix). These two elements therefore allow us to assert that attrition is random and therefore does not bias the results of subsequent analyses.

Compared to existing literature, the added value of this study lies in five main aspects. Firstly, this is rich, first-hand, individual panel data collected by a relatively small research team, including the author of this study. From the beginning of the data collection process (2010), the research team fully controlled the quality of the main socio-economic variables, such as income or caste affiliation. Secondly, the data cover a broad spectrum of household and individual information over a reasonably long time (10-11 years). They also benefit from a relatively homogeneous population coverage because the interviews were conducted in ten

nearby localities in rural Tamil Nadu. This specificity ensures the diversity of the observed family and professional situations without reducing the observed population homogeneity. Thirdly, the tablet-based mode of data collection improved data quality by including constraints on answers to prevent inconsistencies. Fourthly, this survey stands out from other Indian data sources, such as AIDIS, as it has the rare and valuable advantage of recording debt at the individual level by identifying the person who went to the lender and borrowed in her own name. Finally, the NEEMSIS data have the advantage of capturing informal loans relatively well, which results in a much higher incidence of debt than the national data indicate, but which is consistent with the work of anthropologists and ethnologists (Guérin et al., 2023).

Regarding the reliability of the collected information, the long expertise of the fieldwork team (i.e., some research team members are present in the region for numerous quantitative and qualitative surveys for more than 20 years) helped formulate questions appropriately. This involved using specific terms that are less degrading than the generic term "debt" or asking indirect questions (Guérin et al., 2023). Data accuracy is reflected by an incidence of indebtedness higher than in the estimates of the nationwide AIDIS: 99% of households are in debt in our case study, as opposed to 36.9% in rural Tamil Nadu in 2019, according to the AIDIS (NSSO, 2019).

These detailed data make it possible to quantify the indicators of household debt burden and supply used in the existing literature. These are presented below.

4. Measuring the debt burden and labour supply

The debt burden is measured by the debt service ratio (DSR), that is the proportion of gross annual income that households must devote to servicing their debt obligations, principal and interest. The higher the ratio, the heavier the debt burden. DSR has the advantage of being time and space comparable, and it is an objective measure of the debt burden, in the sense that DSR is a quantitative variable based on monetary amounts. Objective measures have the advantage of being more precise and reliable, as they are based on quantifiable data and allow easy comparisons between different individuals and periods. The DSR is traditionally analysed at the household level because, within a household, income is generally shared between its members. High debt servicing may make households more sensitive to economic and socio-economic shocks than otherwise, and given that the DSR represents the percentage

of a household's income allocated to servicing its existing debt, it exerts a direct impact on the resources available for current spending. Holding other factors constant, an increase in the DSR may be correlated with a reduction in household immediate consumption expenditure. Conversely, a fall in the DSR allows households to devote a greater proportion of their income to current consumption and savings.

Labour supply is measured by the total number of monthly working hours for an individual, which is known as the most precise labour supply variable (Blundell & Macurdy, 1999).

The expected effect of financial vulnerability on labour supply is uncertain. As stated above, there is no consensus on the effect of debt on labour supply. On the one hand, debt forces people to work more (Aldershof et al., 1997; Benito & Saleheen, 2013; Bottazzi, 2004; Bunn et al., 2021; Fortin, 1995). On the other hand, whether directly (Donaldson et al., 2019) or indirectly (Chatterji et al., 2007; Hojman et al., 2016), debt can reduce labour supply. However, given the social importance of debt in rural Tamil Nadu, we believe that individuals will increase their labour supply to maintain a certain creditworthiness and, thus, a status, dignity, and reputation in their village.

5. Empirical strategy

Estimating the effect of debt burden on hours worked is tricky for at least two reasons. Firstly, identifying the effect is sensitive because an increase in debt can lead to a rise in labour supply, but a low level of labour supply can also increase household debt. Thus, this creates a simultaneity issue. Secondly, the analysis faces non-random sample selection issues because the sample is restricted to labour force participants.

5.1. Identification

Regarding the identification problem, panel data can be used to circumvent it by controlling for unobserved and time-invariant confounders using fixed-effects models, and by including lagged endogenous regressors. Although criticised in the literature (Reed, 2015), lagged explanatory variables are a first way of limiting simultaneity. This method raises a well-known concern regarding the choice of a suitable temporal lag (Vaisey & Miles, 2017).

However, given the structure of our data, we assume that household indebtedness can still affect working hours four years later.

To accurately identify the effect of debt burden on labour supply, we exclude from the debt service ratio any debt used for productive purposes. Productive debts—such as loans taken to finance household micro-enterprises or family farming operations—have the potential to increase income or create jobs within the household. Including this type of debt in the analysis could distort the results, as an increase in labour supply in these cases may be due to the job creation potential of productive investments rather than financial constraints linked to debt repayment. By excluding loans taken for productive purposes, the debt service ratio is adjusted to capture only the proportion of household annual income allocated to non-productive debt service, that is, debt that does not directly generate income or employment opportunities. This refined debt service ratio allows us to specifically focus on how households respond to the pressure of repaying debt that does not enhance their economic capacity. Consequently, any observed increase in labour supply can be more accurately attributed to the burden of non-productive debt, rather than to the potential economic benefits of productive investments.

5.2. Selection bias

The total number of hours worked per month per individual is censored at zero due to a selection process that selects individuals into two groups: those who work and those who do not (i.e., the labour supply at the extensive margin). A two-stage sample selection model is commonly used to correct this issue (Heckman, 1979). A probit equation is fitted for all survey respondents to predict the labour force participation status using covariates and exclusion restriction variables that may affect the participation in the labour market but not the labour supply. Then, an inverse Mills ratio that accounted for the effect of selectivity is entered into the second-stage equation to predict the working hours, that is, the labour supply at the intensive margin.

However, this framework encounters challenges when extending it to panel data models with fixed effects. Indeed, the initial equation, responsible for depicting the selection process, is a non-linear binary choice model. Unlike linear models, where consistency is maintained when the fixed effect is treated as an estimable parameter, non-linear models generally lack consistency under such circumstances.

Wooldridge (1995) and Semykina & Wooldridge (2010) propose a method for applying the two-stage sample selection model with fixed effects based on a correlated random effects model. The procedure consists of (i) performing a probit on the selection equation for each time period t to obtain T inverse Mills ratios; (ii) estimating the hours worked equation using the inverse Mills ratios as instruments by pooled two-stage least squares (2SLS). We implement the Semykina & Wooldridge (2010) method using the routine of Rios-Avila (2020).

5.3. Model specification

Applying the framework defined above, in the first stage, we estimate labour market participation using a probit for each time period t:

$$s_{it} = 1[z_{it}\lambda_t + \mathrm{DSR}_{it-1}\beta_t + x_{it}\gamma_t + c_i + u_{it} > 0]$$

s_{it} is a selection indicator that equals one if the total number of hours worked per individual y_{it}, is observed, and zero otherwise. z_{it} is the instrument used for restriction exclusion, that is, the number of non-workers in a household divided by the number of workers. This ratio is inspired by Comola & Mello (2013), who use the dependency ratio (i.e., the number of aged under 14 and over 65 divided by the number of people of working age aged between 15 and 64), and Kuepie, Nordman, & Roubaud (2009), who use the household's inverse dependency ratio (number of working individuals divided by the total number of individuals in the household). In India, where the social protection system is not optimal (Drèze & Khera, 2017), the non-worker ratio is preferred because the elderly have to work to meet their basic needs. As the choice of instrument is important, we tested other instruments used in the literature (see Section 6.3). The use of the worker ratio is justified by the fact that a greater number of dependents per worker can lead to greater financial responsibilities for workers (e.g., financing health costs, education, festivals), which can influence the decision to participate in the labour market for non-workers. However, this ratio is unlikely to affect the quantity of work done by workers, as the amount of work is more influenced by job requirements, the dynamics of demand on the labour market, seasonal and agricultural cycles, weather conditions and other contextual factors.

DSR_{it-1} is the lagged debt service ratio. Good temporal lag is a well-known concern when dealing with lagged variables (Vaisey & Miles, 2017). However, given the structure of

the data, that is, three points in time separated by four to six years, we have to assume that changes in the debt service ratio show up in changes in the labour supply four to six years later.

x_{it} is a vector of control variables that rely on the literature (Acosta, 2020; Beck, Singhal, & Tarp, 2019; Fafchamps & Quisumbing, 1999; Matshe & Young, 2004; Oh, 2023). It is composed of two vectors. Firstly, the vector of individual characteristics comprises age, education level (i.e., below primary, primary completed, high school, or HSC or more), relationship to head, sex, and marital status (married, unmarried, or other, i.e., separated, divorced, widowed). Secondly, the vector of household characteristics comprises monetary value of assets, which is a continuous variable proxying gold, land, house, livestock, agricultural equipment, and consumer goods, net remittances (i.e., the difference between remittances received and remittances sent), household size, the number of children in the household, sex ratio, caste, and villages.

After retrieving the inverse Mills ratios from the first stage, at the second stage, we estimate the following equation for all individuals who work non-zero hours by 2SLS:

$$y_{it} = \alpha + \mathrm{DSR}_{it-1}\beta + x_{it}\gamma + \mathrm{IMR}_{it}\mathfrak{f} + \varepsilon_{it}$$

y_{it} represent the measures of the labour supply at the time t, for the individual i, meaning the total number of monthly working hours for an individual. DSR_{it-1} and x_{it} are the same variables as in the previous equation. IMR_{it} is the inverse Mills ratios from the first stage. α is the intercept and ε_{it} is the idiosyncratic error.

Heterogeneity

To introduce heterogeneity into the analysis, we examine differences in labour supply responses to debt burden by gender and caste. Thus, we first introduce two new dependent variables (women' and men' working hours) and then include an interaction term between the debt service ratio and caste.

6. Results

6.1. Descriptive statistics

The final pooled sample consists of 1467 individuals in 2016-17 from 388 households (which corresponds to the households observed in 2010 and 2016-17) and 1875 individuals in 2020-21 from 485 households (which corresponds to the households observed in 2016-17 and 2020-21). As our sample is restricted to longitudinal households, the effect of attrition on the results may be a source of concern. However, as noted in section 3, the attrition rate has been very low (4.2% in 2016 and 1.4% in 2020-21) and these households do not have distinctive characteristics on key variables such as income and debt service ratio, which leads us to believe that attrition is random.

Table 1 provides descriptive statistics at the household level. To ensure the comparison between monetary values, Indian rupees of 2016-17 are expressed in constant rupees of 2020-21 using the consumer price index of the World Bank.[2] On average, a household consists of four to five members, with around 1.3 men for one woman. Regarding economic characteristics, half of the households have positive net remittances, and half have zero or negative net remittances. The average household annual labour income is 180k rupees (around 2000 euros), and the monetary value of assets is relatively stable over time, averaging 1300k rupees.

[TABLE 1 AROUND HERE]

For the variable of interest, we show the distribution in 2010 and 2016-17 in Figure 1 because this variable is lagged in the regressions. Debt service in 2010 is therefore associated with labour supply in 2016-17 and debt service in 2016-17 is associated with labour supply in 2020-21. We observe that the proportion of household income devoted to repaying debt capital and interest increases over time. Whereas in 2010, households spent an average of 24% of their income on repaying the capital and interest on their non-productive debt, they spent 33% in 2016-17. This proportion may seem relatively small, but it is only non-productive debt. When productive debt is added, the ratios are much higher: on average,

[2] https://data.worldbank.org/indicator/FP.CPI.TOTL?locations=IN (Accessed on February 27, 2025).

households spend 35% of their income on repaying the capital and interest of their debts in 2010, 48% in 2016-17, and 68% in 2020-21 (see Guérin et al., 2023, p. 39).

[FIGURE 1 AROUND HERE]

Table 2 provides descriptive statistics at the individual level. Half of the sample is woman, and the average age is 39. Roughly two-thirds are married. A third of people have less than primary education, but there are significant gender disparities: in 2020-21, this will be the case for 21% of men but 36% of women. The gap between men and women is reversed at higher levels of education. There is a difference of more than ten percentage points between men and women over the age of 14 in terms of employment status in 2020-21. While more than 75% of men work, this is the case for 64% of women.

[TABLE 2 AROUND HERE]

Regarding labour supply, measured by the number of hours worked per month, there are significant disparities between men and women (see Figure 2). In 2020-21, the 25% of men who work the most will work more than 200 hours a month, or more than 50 hours a week, which is the excessive working time defined by the International Labour Organisation. It is also important to note that in 2020 50% of men will be working no more than 130 hours a month (i.e., 32 hours a week), equivalent to working part-time. Excessive working hours, on the other hand, affect around 7% of women, while more than 75% of them work part-time.

[FIGURE 2 AROUND HERE]

Even if these are not explanatory or explained variables, presenting the individuals' main occupations is essential to have a precise idea of the population studied. The main occupation is defined as the most time-consuming activity. Table 3 shows the types of occupation by sex. Women are more present in vulnerable occupations such as Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA, a national programme that offers guaranteed employment in rural areas by conducting unskilled manual labour for at least 100 days per financial year) employment or casual agricultural work than men. In fact, 53% of women in 2016-17 and 51% in 2020-21 have casual agricultural work or MGNREGA as their main occupation, whereas these activities concern only 18% of men in 2016-17 and 20% in 2020-21. These types of occupations are characterised by 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. The corollary is also true: men are over-represented in regular activities.

[TABLE 3 AROUND HERE]

6.2.Econometric estimates

To remain concise, the full results of the estimates (first and second stages) are not discussed here, but are presented in Tables A2 and A3 in the appendix.

Table 4 provides the econometric estimates regarding the effect of debt service ratio on labour supply (the full table is available in the appendix, Table 4). After controlling for endogeneity arising from time-invariant unobserved heterogeneity and protecting as far as possible against reverse causality, results show that a higher non-productive debt service ratio is associated with more labour supply (see column 1 of Table 4). Other things being equal, at a 95% confidence level, when the household debt service ratio increases by one percentage point in t, the number of hours worked per person per month increases by 0.09 hours in $t + 1$.

When the labour supply of men and women is separated, the analysis results suggest that only the labour supply of women responds to household debt (see columns 2 and 3 of Table 4). All else being equal, when the household debt service ratio increases by one percentage point in t, the number of hours worked per woman per month increases by 0.11 hours in $t + 1$.

[TABLE 4 AROUND HERE]

Table 5 presents the results of the heterogeneity analysis, that is, the contribution of the caste on the effect of household debt service ratio on labour supply. The positive effect of the debt service ratio remains, especially for the labour supply of women. However, caste has no additional effect on the effect of DSR on total labour supply. In other words, the effect of the household debt service ratio on labour supply is no different for Dalits than for middle and upper castes.

[TABLE 5 AROUND HERE]

Although the magnitude of the observed effect on labour supply appears as small, it is essential to put it into perspective in the light of the identification strategy adopted. Indeed, our analysis focuses on the effect of the debt burden, but we measure it with a time lag of four years. However, it is very likely that the debt burden has a much stronger impact on labour supply from the first year following the measure. Consequently, by not taking this

immediate effect into account, we probably significantly underestimate the true magnitude of the relationship between the debt burden and labour supply and propose here a lower bound effect. Moreover, the effect is indeed present, and the fact that the debt burden only has an effect on women's labour supply raises important questions addressed in the discussion section.

This result confirms the literature that debt forces people to work more (Aldershof et al., 1997; Benito & Saleheen, 2013; Bottazzi, 2004; Bunn et al., 2021; Fortin, 1995). And, thanks to the deletion of productive debt in the debt service ratio, the effect observed is not the result of productive investment potentially creating jobs but is the result of too much debt requiring additional work to repay the capital and interest. This interpretation is consistent with certain testimonies gathered as part of qualitative studies in the survey area. For example, in the context of a collection of ethnographic financial diaries conducted by Reboul, Guérin, Raj, & Venkatasubramanian (2025, p.31), a surveyed woman stated that "now people work restless to pay these finances. Women have to work twice a day, to pay back not only finance but all moneylenders, neighbours, etc." In the same vein, as part of a feature length documentary, Nordman (2024) has gathered the testimony of a Dalit woman who declares: "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."

6.3. Robustness

We implement robustness checks to confirm the relationship between debt service and labour supply. All the robustness checks confirm previous results regarding the positive impact of debt service on the labour supply of women.

Other instruments

The first robustness test involves changing exclusion restriction used to select the sample. As explained in section 5.3, we tested other instruments used in the literature, such as the number of adults, the number of children, and whether an individual is married or not (Hussain & Mukhopadhyay, 2023); the couple's age and age squared (Hwang, Lee, & Lee, 2019); the income, the underemployment of household members, education of the household head, the number of children by age group, and the presence of in-law parents (Klasen & Pieters, 2015); the ownership of land, the average monthly per capita consumption expenditure and

whether an individual is the head or married child of the head (Abraham, 2017). Whatever the instrument chosen, the results are stable (Table 6).

[TABLE 6 AROUND HERE]

Cragg

Given the difficulty of finding a valid and convincing instrument, we estimate a Cragg (1971) model as a second robustness test. The Cragg model uses a two-part estimation approach, where the first part uses a binary choice model to determine whether an individual participates in the labour market, while the second part uses a truncated regression model to analyse the extent of participation among those who are active. The Cragg model therefore does not require the calculation of an inverse Mills ratio like the Heckman model, as it directly models the two processes separately. The results presented in Table 7 are the same as with the two-stage sample selection model with fixed effects: women increase their labour supply to pay off household debt.

[TABLE 7 AROUND HERE]

Outliers

The third robustness check consists of removing the dependent variables' 5% outliers, meaning the 5% of individuals with the highest labour supply and the 5% of individuals with the lowest labour supply. In this way, we avoid the results of the estimates being influenced by extremes when we reason "on average". The results presented in Table 8 show that the effect of the household debt service ratio on woman labour supply is maintained.

[TABLE 8 AROUND HERE]

Household or individual debt?

The final robustness test aims to determine whether the observed effect is specifically due to the household debt burden rather than the individual debt burden. It is possible that the previously established relationship (that household debt increases women's labour supply) could be driven by individual women with high levels of personal debt. Conversely, if this is not the case, this would suggest that women are increasing their labour supply to help repay debts incurred by all household members.

To investigate who owns the debt in the household, we re-estimate the previous model by replacing the lagged debt service ratio with the individuals' share of the lagged debt service ratio. The underlying intuition is as follows: if we do not observe any significant effect, it indicates that an individual's share of the debt does not impact their ability to increase their labour supply. In other words, any increase in an individual's labour supply is not a response to their personal debt but rather to the household's overall debt burden. Due to the lack of information on individual indebtedness in 2010, we re-estimate the previous model using a standard two-stage sample selection Heckman procedure. We focus solely on the sample of women and estimate the impact of the share of the debt service ratio held by women in 2016-17 on their labour supply in 2020-21.

Table 9 presents the econometric estimates. Our findings indicate no effect from the share of the debt service ratio held by women. This implies that women increase their labour supply not in response to their personal debt burden but in reaction to the household debt burden, which includes debts incurred by all household members, both men and women.

[TABLE 9 AROUND HERE]

7. Discussion

The fact that women are increasing their labour supply to pay off household debt contracted by both men and women is not insignificant, given the place of women in rural India's work world. In addition to the fact that women' work can be frowned upon in society (Mehrotra & Parida, 2017) and that women bear the brunt of domestic work (Ratheesh & Anitha, 2022), they are also the ones who are confined to day-to-day activities, such as casual agricultural work or MGNREGA, characterised by low pay and difficult working conditions. Indeed, the average hourly wage for agricultural casual work and MGNREGAs is around 25 rupees per hour in 2020-21 (around 0.28 euros), compared with 45 rupees for non-agricultural casual work and over 70 rupees for regular qualified work (see Figure 3).

[FIGURE 3 AROUND HERE]

Regarding working conditions, NEEMSIS-2 data shed some light as it includes a module on working environmental conditions for certain individuals called "egos". In 2020-21, three household members were directly addressed an individual questionnaire: the respondent of the household questionnaire, Ego 1, and two younger household members, Ego

2 and Ego 3, randomly selected by the software tablet into age brackets (i.e., two members of the household aged between 18 and 25 years old, if no one is available, two members aged between 26 and 35 and if no one is available, two members aged over 35). Working conditions are assessed using a scoring system and are classified in three categories: execution (e.g., standing, posture, walking, or carrying heavy loads), problems (e.g., dirtiness, humidity, or bad smells), and exposure (e.g., traffic accidents, or risk of being injured). The scores are derived by averaging responses to a set of binary questions: nine for execution (e.g., "Does your job require you to stand for extended periods?"), ten for problems (e.g., "Is cleanliness a significant issue in your workplace?"), and five for exposure (e.g., "Are you exposed to smoke or dust?"). The resulting score ranges from zero to one. Figure 4 shows that casual works (agricultural or not) are associated with the worst working conditions in terms of execution, problem, and exposure. In contrast, regular occupations (qualified or not), meaning occupations where men are overrepresented compared to women, are associated with better working conditions.

[FIGURE 4 AROUND HERE]

Moreover, the fact that it is women who are increasing their labour supply is all the more striking, given that a significant proportion of men do not work full-time. Indeed, 50% of men work less than 32 hours a week (see Figure 2), and almost one man in two has a casual job as the main occupation (see Table 2).

Our results therefore call into question the interpretation often given in the Global South that women's work is synonymous with agency. Indeed, this increase in the labour supply may sometimes be more the result of a constraint imposed by the economic situation (as here with the repayment of household debts), rather than a genuine choice or desire for autonomy. From this perspective, women's increased economic participation may not translate into increased decision-making power within the household or in the public sphere. The increase in their workload could even lead to physical and mental overload, without any real improvement in their living conditions or social status. This forced participation could well reflect further exploitation, where women are seen as flexible resources to respond to household economic crises, often to the detriment of their well-being and health. Politically, this means reconsidering the way in which the State and public policies perceive and support women's involvement in the labour market, particularly in rural areas where gender norms remain strong. The emphasis must be on guaranteeing better working conditions, fair pay and

the creation of opportunities that enable real and lasting empowerment of women, rather than simply seeing them as a flexible and temporary workforce. This issue is particularly important when considering the specific targeting of women by microfinance institutions. Indeed, the rigid repayment requirements of microcredit can be difficult to meet in a context of low and irregular incomes. To meet these obligations, many women resort to borrowing from informal lenders, which can increase their repayment burden and therefore their workload. In addition, in the event of default, microfinance institutions can seize the household's collateral, directly jeopardising their livelihoods (Guérin, Michiels, Natal, Nordman, & Venkatasubramanian, 2022). The risk of default also places significant social pressure on women, as household solvency is closely linked to social status, position and dignity within the village (Guérin et al., 2023).

More broadly, the fact that women increase their labour supply to repay household debt has notable implications for the general well-being of individuals and households. On the one hand, higher debt has effects on physical and mental health (Hojman et al., 2016; Keese & Schmitz, 2014), which significantly reduces the well-being of the households concerned. On the other hand, the work necessary to repay debts is carried out in tough conditions, which has a negative effect on the well-being of individuals (De Neve et al., 2018) and is added to the domestic tasks already carried out by women (Ratheesh & Anitha, 2022), which increases the mental burden and worsens well-being.

8. Conclusion

In this study, we analysed how the household debt burden measured with the debt service ratio affects labour supply in rural South India. To answer this question, we used an original first-hand panel dataset collected by the authors of this paper, which covers a ten-year period (2010 to 2020-21) and contains precise measures of debt and labour supply. We used a two-stage sample selection model with lagged debt service ratio and fixed effects to control for unobserved time-invariant confounders and limits reverse causality. We find that only woman labour supply responds to an increase in the household debt service ratio. In other words, only women increase their labour supply to repay the debt incurred by all the household members. We do not observe any difference according to caste status.

The results call into question the idea commonly accepted in the Global South that women's work is synonymous with empowerment, by suggesting that the increase in the labour supply may be the result of economic constraints rather than a genuine move towards autonomy. This finding highlights the need for public policy to focus on improving working conditions and creating genuine empowerment opportunities for women, particularly in rural areas. India already has programmes such as the MGNREGA programme, which provides employment to rural households. While this programme is proving effective in improving women's empowerment (Rodriguez, 2022), it needs to be expanded to address the specific challenges of the female labour market, ensuring that women get sustainable and dignified jobs, and not just a safety net in times of economic crisis. This is all the more important as budgetary allocations to the programme have been considerably reduced in recent years.[3]

This article paves the way for further research in other developing country contexts where household indebtedness is very high, as well as for further research aimed at analysing the specific process of taking on debt to repay debts, a phenomenon that has been little studied in the literature. It also calls for specific research analysing the effects of microcredit on gender norms relating to financial responsibility.

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Tables

Table 1: Descriptive statistics at the household level

	2016-17 n=388	2020-21 n=485
Household size (mean)	4.6	4.6
Sex ratio (mean)	1.3	1.3
Number of children (mean)	0.9	0.7
Non-workers ratio (mean)	0.3	0.3
Net remittances* (mean)	1.8	7.6
Monetary value of assets (mean)	1248.4	1353.4
Annual income (mean)	177.2	181.9

Note: *Remittances received minus remittances sent.

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

Table 2: Descriptive statistics at the individual level

	Total		Men		Women	
	2016-17	2020-21	2016-17	2020-21	2016-17	2020-21
	n=1467	n=1875	n=748	n=946	n=719	n=929
Age (mean)	37.8	39.1	38.6	39.5	37.3	38.6
Relation: Head	25.6	25.4	45.7	38.6	4.7	12.0
Relation: Wife/husband	23.3	19.2	0.1	0.3	47.4	38.3
Relation: Parents	3.8	3.4	2.0	2.3	5.7	4.5
Relation: Children	34.8	35.7	46.5	48.7	22.7	22.5
Relation: Child-in-law	8.3	9.7	0.9	0.7	16.0	18.8
Relation: Grandchild	2.2	1.5	2.7	2.0	1.7	1.0
Relation: Other	1.9	5.1	2.0	7.3	1.8	2.9
Married: Yes	64.1	64.4	62.6	63.2	65.7	65.7
Married: No	30.1	28.1	36.2	34.0	23.8	22.0
Married: Other	5.8	7.5	1.2	2.8	10.6	12.4
Education: Below primary	31.6	28.3	23.0	20.7	40.6	36.1
Education: Primary	14.8	13.8	15.5	14.8	14.1	12.8
Education: High school	29.0	27.4	34.5	32.6	23.4	22.2
Education: HSC or more	24.5	30.5	27.0	31.9	22.0	29.0
Working status: Non-worker	28.6	30.3	22.3	24.6	35.2	36.1
Working status: Worker	71.4	69.7	77.7	75.4	64.8	63.9

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

Table 3: Main occupation for workers (%)

	Total		Men		Women	
	2016-17	2020-21	2016-17	2020-21	2016-17	2020-21
	n=1047	n=1307	n=581	n=713	n=466	n=594
Agricultural self-employed	13.9	15.7	16.9	16.1	10.3	15.2
Agricultural casual	21.6	26.4	15.8	18.9	28.8	35.4
Casual	12.8	24.1	13.9	27.6	11.4	19.9
Regular non-qualified	18.6	6.9	23.9	8.7	12.0	4.7
Regular qualified	8.2	10.8	12.4	15.7	3.0	4.9
Self-employed	12.7	8.3	14.6	11.6	10.3	4.2
MGNREGA	12.1	7.9	2.4	1.3	24.3	15.8

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

Table 4: Estimated labour supply measured by the number of hours worker per month per individual

	(1) Total Coef./Std Err.	(2) Men Coef./Std Err.	(3) Women Coef./Std Err.
Lagged DSR (%)	0.09**	0.06	0.11**
	(0.04)	(0.07)	(0.05)
Controls for individual characteristics	Yes	Yes	Yes
Controls for household characteristics	Yes	Yes	Yes
Controls for villages	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Bootstrap replications	200	200	200
Observations	3342	1694	1648

Note: Heckman two-stage sample selection model with fixed effects following Semykina and Wooldridge (2010).

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

Table 5: Estimated labour supply measured by the number of hours worked per month per individual interacts with caste

	(1) Total Coef./Std Err.	(2) Men Coef./Std Err.	(3) Women Coef./Std Err.
Lagged DSR (%)	0.18***	0.09	0.19***
	(0.05)	(0.08)	(0.07)
Dalits (ref)			
Middle castes	0.59	2.40	-2.57
	(5.16)	(7.38)	(6.07)
Upper castes	23.50**	26.84*	32.53**
	(10.00)	(14.23)	(14.22)
Lagged DSR x Dalits			
Lagged DSR x Middle castes	-0.08	-0.07	-0.04
	(0.09)	(0.17)	(0.10)
Lagged DSR x Upper castes	-0.17	-0.05	-0.16
	(0.12)	(0.22)	(0.19)
Controls for individual characteristics	Yes	Yes	Yes
Controls for household characteristics	Yes	Yes	Yes
Controls for villages	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Bootstrap replications	200	200	200
Observations	3342	1694	1648

Note: Heckman two-stage sample selection model with fixed effects following Semykina and Wooldridge (2010).

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

Table 6: Estimated labour supply measured by the number of hours worked per month per individual using different instruments

	(1)	(2)
	Total	Total
	Coef./Std Err.	Coef./Std Err.
Lagged DSR (%)	0.10***	0.09**
	(0.04)	(0.04)
IMR	Abraham (2017)	Hussain and Mukhopadhyay (2023)
Controls on individual charact	Yes	Yes
Controls on household charact	Yes	Yes
Controls for villages	Yes	Yes
Individual FE	Yes	Yes
Bootstrap replications	200	200
Observations	3342	3342

	(3)	(4)
	Total	Total
	Coef./Std Err.	Coef./Std Err.
Lagged DSR (%)	0.09**	0.09**
	(0.04)	(0.04)
IMR	Hwang et al. (2019)	Klasen and Pieters (2015)
Controls for individual characteristics	Yes	Yes
Controls for household characteristics	Yes	Yes
Controls for villages	Yes	Yes
Individual FE	Yes	Yes
Bootstrap replications	200	200
Observations	3342	3342

Note: Heckman two-stage sample selection model with fixed effects following Semykina and Wooldridge (2010).

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

Table 7: Estimation of individual labour supply using the Cragg (1971) model with fixed effects

	(1)	(2)
	Total	
	LFP	Hours a month
	Coef./Std Err.	Coef./Std Err.
Lagged DSR (%)	0.00	0.12**
	(0.00)	(0.05)
Controls for individual characteristics	Yes	Yes
Controls for household characteristics	Yes	Yes
Controls for villages	Yes	Yes
Individual FE	Yes	Yes
Observations	3342	2354

	(3)	(4)
	Men	
	LFP	Hours a month
	Coef./Std Err.	Coef./Std Err.
Lagged DSR (%)	-0.00	0.07
	(0.00)	(0.08)
Controls for individual characteristics	Yes	Yes
Controls for household characteristics	Yes	Yes
Controls for villages	Yes	Yes
Individual FE	Yes	Yes
Observations	1694	1294

	(5)	(6)
	Women	
	LFP	Hours a month
	Coef./Std Err.	Coef./Std Err.
Lagged DSR (%)	0.00*	0.17***
	(0.00)	(0.06)
Controls for individual characteristics	Yes	Yes

Controls for household characteristics	Yes	Yes
Controls for villages	Yes	Yes
Individual FE	Yes	Yes
Observations	1648	1060

Note: LFP is the Labour Force Participation.

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

Table 8: Estimated labour supply measured by the number of hours worked per month per individual without 5% outliers

	(1) Total Coef./Std Err.	(2) Men Coef./Std Err.	(3) Women Coef./Std Err.
Lagged DSR (%)	0.12***	0.03	0.09**
	(0.03)	(0.07)	(0.04)
Controls for individual characteristics	Yes	Yes	Yes
Controls for household characteristics	Yes	Yes	Yes
Controls for villages	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Bootstrap replications	200	200	200
Observations	3128	1572	1556

Note: Heckman two-stage sample selection model with fixed effects following Semykina and Wooldridge (2010).

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

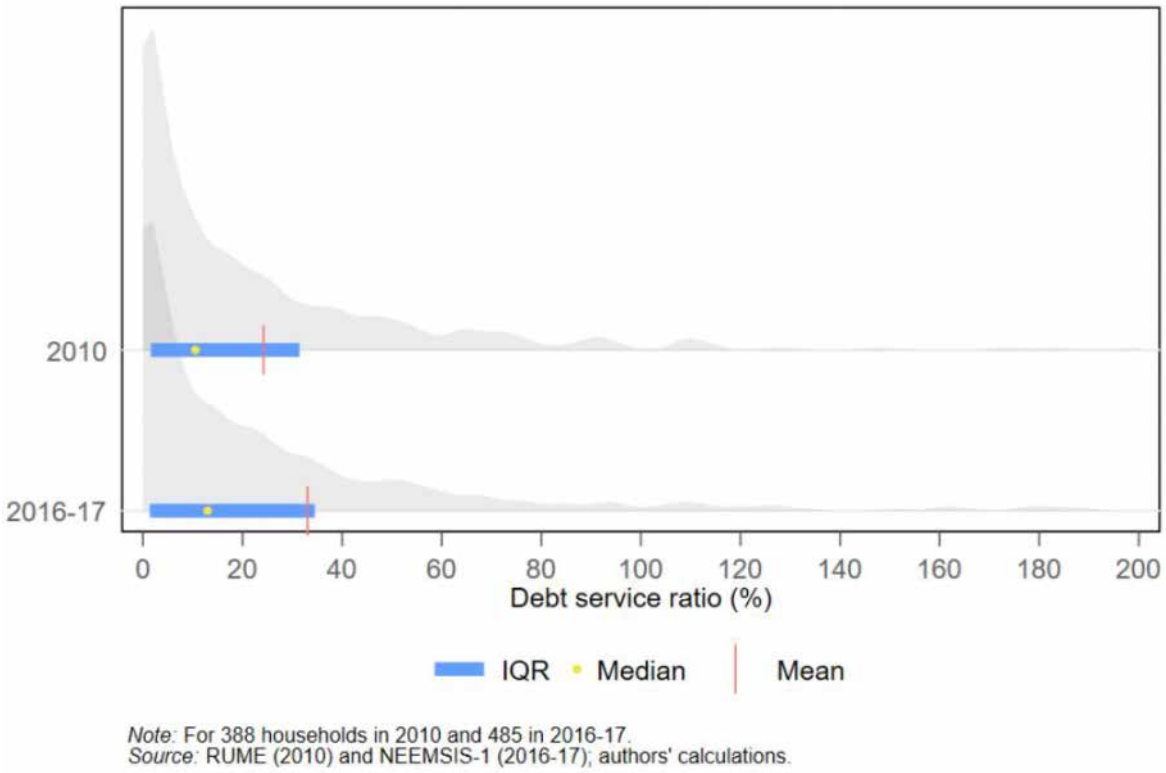
Table 9: Estimated labour supply measured by the number of hours worked per month per individual

	(1) Total Coef./Std Err.	(2) Men Coef./Std Err.	(3) Women Coef./Std Err.
Lag share DSR (%)	0.06	0.13	0.02
	(0.09)	(0.11)	(0.06)
Controls for individual characteristics	Yes	Yes	Yes
Controls for household characteristics	Yes	Yes	Yes
Controls for villages	Yes	Yes	Yes
Observations	1384	632	752

Note: Heckman (1979) two-stage sample selection model.

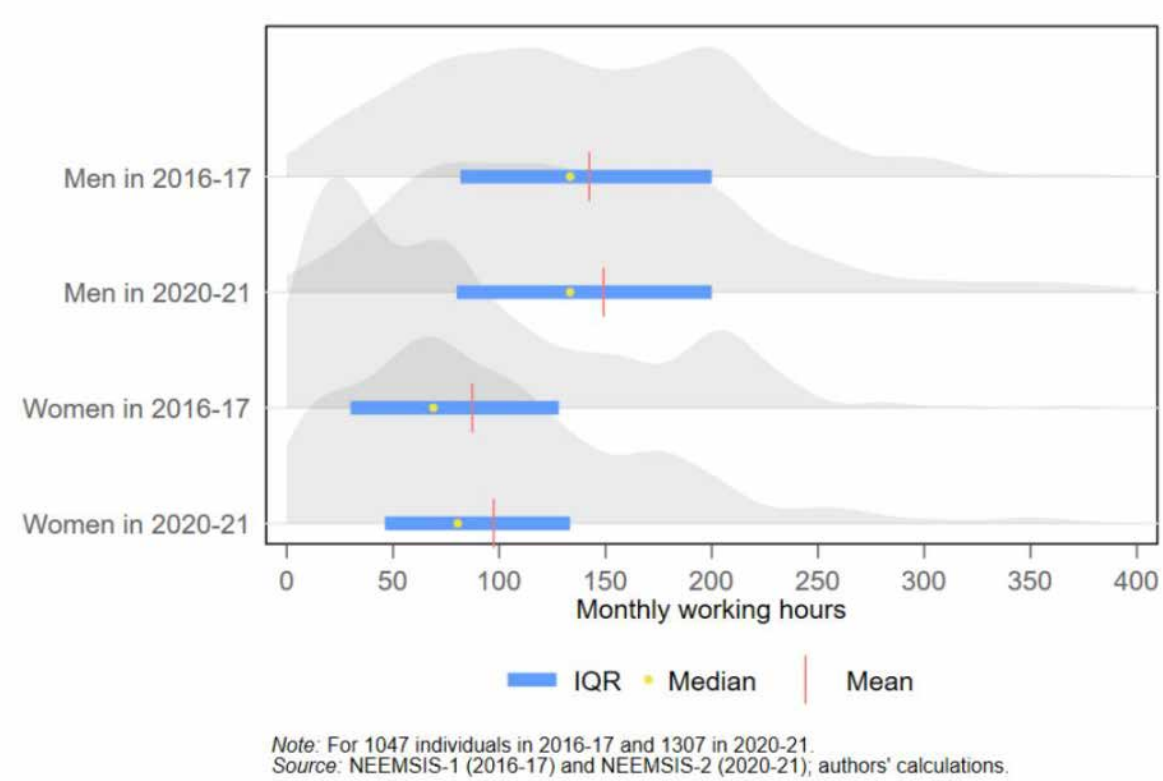
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); author's calculations.

Figures



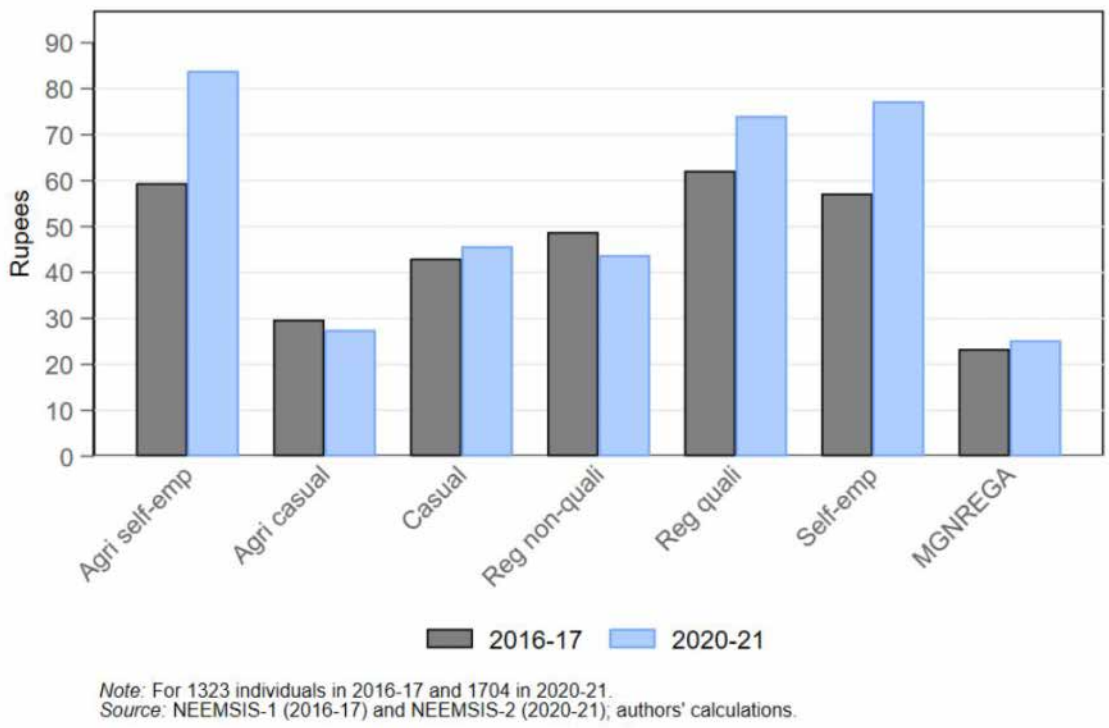
Note: For 388 households in 2010 and 485 in 2016-17.
Source: RUME (2010) and NEEMSIS-1 (2016-17); authors' calculations.

Figure 1: Distribution of the debt service ratio



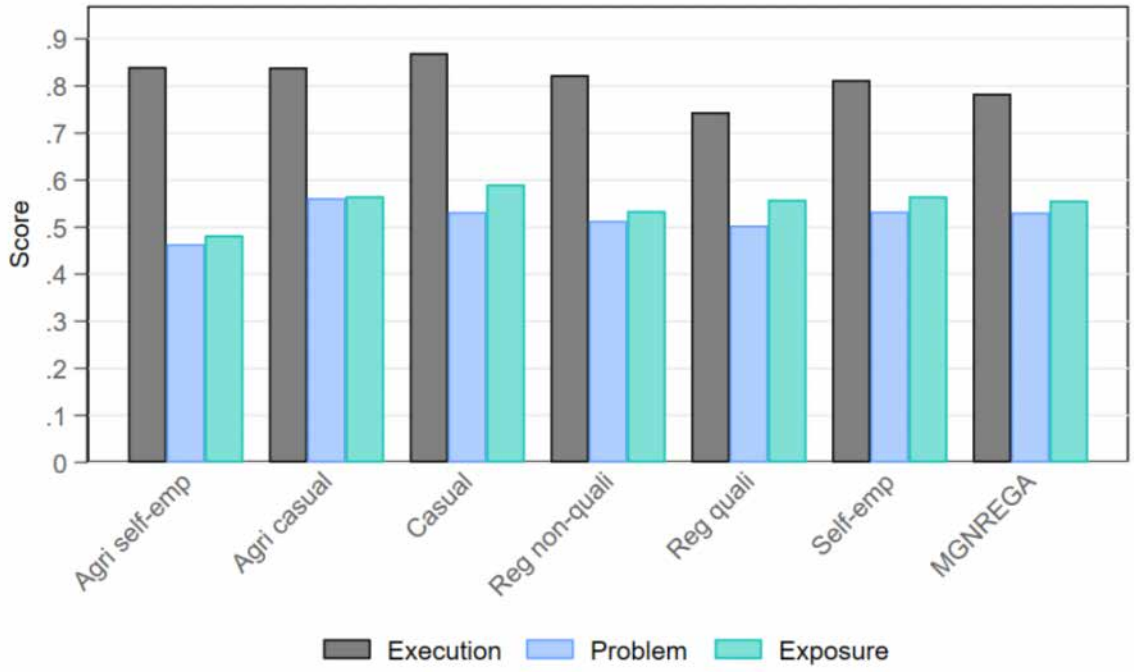
Note: For 1047 individuals in 2016-17 and 1307 in 2020-21.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); authors' calculations.

Figure 2: Distribution of the labour supply



Note: For 1323 individuals in 2016-17 and 1704 in 2020-21.
Source: NEEMSIS-1 (2016-17) and NEEMSIS-2 (2020-21); authors' calculations.

Figure 3: Average hourly income of individual's main occupation



Note: For 1272 individuals in 2020-21.
Source: NEEMSIS-2 (2020-21); authors' calculations.

Figure 4: Average working environmental condition scores of individual's main occupation

Appendix

Table A1: Difference in household income and debt by attrition (household found or lost between two dates)

	Recovered in t+1	Lost in t+1	|diff|	t-stat
2010				
Annual income: N	n=388	n=17		
Annual income: Mean (1k rupees)	150.7	144.7	5.9	0.21
Annual income: Median (1k rupees)	126.7	111.0		
Debt service: N	n=382	n=17		
Debt service: Mean (%)	24.6	26.9	2.3	0.23
Debt service: Median (%)	10.8	23.7		
2016-17				
Annual income: N	n=485	n=7		
Annual income: Mean (1k rupees)	177.2	102.0	75.3	1.11
Annual income: Median (1k rupees)	135.5	103.7		
Debt service: N	n=454	n=7		
Debt service: Mean (%)	35.3	58.3	23.0	0.74
Debt service: Median (%)	14.5	18.7		

Source: RUME (2010) and NEEMSIS-1 (2016-17); authors' calculations.

Table A2: First step of the Heckman two-stage sample selection model with fixed effects of Semykina and Wooldridge (2010)

	(1) Total 2016-17 Coef./Std Err.	(2) Total 2020-21 Coef./Std Err.	(3) Men 2016-17 Coef./Std Err.	(4) Men 2020-21 Coef./Std Err.	(5) Women 2016-17 Coef./Std Err.	(6) Women 2020-21 Coef./Std Err.
Lagged DSR (%)	0.00	-0.00	0.00	-0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Individual characteristics						
Age	0.01	0.24***	-0.01	0.23***	-0.01	0.24***
	(0.06)	(0.05)	(0.11)	(0.09)	(0.09)	(0.07)
Education: Below primary (ref)						
Education: Primary	15.55***	2.07	10.22*	10.60**	15.89**	0.74
	(2.22)	(5.07)	(5.86)	(4.34)	(6.33)	(6.50)
Education: High school	13.98***	2.42	8.78*	10.27***	14.51***	1.84
	(2.08)	(5.14)	(4.79)	(3.59)	(5.31)	(7.68)
Education: HSC or more	15.04***	0.32	9.46**	8.16**	16.04***	-0.28
	(2.13)	(5.19)	(4.80)	(3.58)	(5.31)	(7.66)
Relation: Head (ref)						
Relation: Wife/husband	0.96**	-0.35	0.00	0.00	2.24	0.16
	(0.48)	(0.43)	(0.00)	(0.00)	(1.81)	(1.34)
Relation: Parents	-0.51	-0.48	-2.68	-0.98	0.19	0.17
	(0.68)	(0.65)	(5.30)	(2.78)	(1.62)	(1.30)
Relation: Children	1.73**	-1.54***	1.04	-0.51	5.49	-6.05
	(0.80)	(0.53)	(1.17)	(1.02)	(4.52)	(6.70)
Relation: Child-in-law	1.97***	-1.22*	-3.78	-0.53	4.67**	-2.19
	(0.67)	(0.62)	(4.21)	(3.63)	(2.05)	(2.25)
Relation: Grandchild	1.89	-2.14**	1.54	-1.32	-3.37	-4.07
	(1.49)	(0.96)	(2.47)	(1.42)	(3.82)	(5.57)
Relation: Other	0.25	-0.78	-0.34	-0.49	1.41	-0.18
	(0.87)	(0.66)	(1.81)	(1.14)	(2.58)	(1.80)

Sex: Man (ref)						
Sex: Woman	-0.66***	-0.51***				
	(0.16)	(0.13)				
Married: Yes (ref)						
Married: No	0.48	-1.08***	0.36	-1.84***	0.08	1.00
	(0.38)	(0.40)	(0.56)	(0.68)	(1.24)	(1.09)
Married: Other	0.62	-1.64***	-0.40	-1.34	1.70	-2.06**
	(0.62)	(0.59)	(3.32)	(2.76)	(1.10)	(0.99)
Household characteristics						
Net remittances (std)	0.06	0.24**	0.04	0.28	0.09	0.35**
	(0.08)	(0.10)	(0.14)	(0.17)	(0.15)	(0.17)
Assets (std)	0.15	0.02	0.15	0.43	0.02	-0.25
	(0.15)	(0.17)	(0.25)	(0.42)	(0.26)	(0.32)
Household size	-0.01	-0.04	-0.19	-0.06	0.17	-0.04
	(0.10)	(0.10)	(0.17)	(0.19)	(0.18)	(0.17)
Number of children	0.22	0.20	0.32	0.36	0.36	0.00
	(0.19)	(0.18)	(0.36)	(0.35)	(0.31)	(0.30)
Sex ratio	-0.01	0.14	-0.12	0.30	0.05	0.08
	(0.16)	(0.19)	(0.25)	(0.25)	(0.33)	(0.36)
Dalits (ref)						
Middle castes	0.13	0.24**	0.33	0.39***	0.01	0.19
	(0.12)	(0.10)	(0.21)	(0.15)	(0.17)	(0.14)
Upper castes	-0.25	-0.43**	0.16	0.29	-0.76	-0.95***
	(0.28)	(0.20)	(0.59)	(0.47)	(0.51)	(0.36)
Non-workers ratio	-1.18***	-0.71	-0.95	-0.74	-2.02**	-0.71
	(0.45)	(0.47)	(0.86)	(0.72)	(0.79)	(0.77)
Controls for villages	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3342		1694		1648	

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

Table A3: Second step of the Heckman two-stage sample selection model with fixed effects of Semykina and Wooldridge (2010)

	(1) Total	(2) Men	(3) Women
	Coef./Std Err.	Coef./Std Err.	Coef./Std Err.
Lagged DSR (%)	0.09**	0.06	0.11**
	(0.04)	(0.07)	(0.05)
Individual characteristics			
Age	-1.57	-2.76	-5.11**
	(1.89)	(2.92)	(2.18)
Education: Below primary (ref)			
Education: Primary	117.99	140.13**	104.63
	(84.13)	(60.13)	(80.18)
Education: High school	86.03	134.68**	-1.79
	(86.75)	(52.73)	(97.97)
Education: HSC or more	59.25	113.50**	-35.69
	(88.50)	(51.72)	(109.01)
Relation: Head (ref)			
Relation: Wife/husband	9.04	120.60	10.81
	(11.06)	(97.11)	(11.83)
Relation: Parents	-30.17	-19.50	-29.61
	(22.65)	(43.93)	(23.74)
Relation: Children	44.34**	42.51*	79.90**
	(21.05)	(22.16)	(40.36)
Relation: Child-in-law	-1.60	76.54**	-1.50
	(23.29)	(35.72)	(28.57)
Relation: Grandchild	49.06	45.29	110.54
	(40.92)	(42.13)	(106.94)
Relation: Other	8.77	14.61	15.71
	(13.02)	(15.57)	(64.13)
Sex: Man (ref)			
Sex: Woman	-42.52***		

	(6.73)		
Married: Yes (ref)			
Married: No	-0.74	-2.91	48.33
	(12.70)	(15.49)	(38.83)
Married: Other	16.34	14.45	30.77*
	(15.10)	(37.09)	(16.62)
Household characteristics			
Net remittances (std)	2.96	3.46	-1.51
	(2.26)	(2.93)	(3.81)
Assets (std)	20.71***	24.93**	14.78
	(7.11)	(10.57)	(9.09)
Household size	-5.50*	-8.64**	-1.72
	(2.83)	(4.05)	(3.49)
Number of children	-1.05	2.39	-5.35
	(4.50)	(6.55)	(5.38)
Sex ratio	-4.00	-3.84	-3.63
	(4.74)	(6.83)	(6.79)
Dalits (ref)	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Middle castes	3.35	5.73	-1.34
	(4.00)	(5.73)	(4.74)
Upper castes	22.43**	26.42**	29.29*
	(8.91)	(12.29)	(14.96)
Inverse Mills ratio in 2016-17	21.87*	-16.96	5.10
	(11.73)	(17.27)	(13.45)
Inverse Mills ratio in 2020-21	27.26**	-0.53	-6.07
	(11.21)	(16.84)	(13.05)
Controls for villages	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Bootstrap replications	200	200	200
Observations	3342	1694	1648

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