I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14807

Many Rivers to Cross: Social Identity, Cognition and Labour Mobility in Rural India

Sébastien Michiels
Christophe Jalil Nordman
Suneha Seetahul

OCTOBER 2021

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14807

Many Rivers to Cross: Social Identity, Cognition and Labour Mobility in Rural India

Sébastien Michiels
CNRS, CREST and French Institute of Pondi-cherry

Christophe Jalil Nordman
IRD, PSL University, French Institute of Pondicherry and IZA

Suneha Seetahul
World Bank, School of Social and Political Sciences and University of Sydney

OCTOBER 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Many Rivers to Cross: Social Identity, Cognition and Labour Mobility in Rural India*

By considering the case of rural South India, this study analyses whether individual skills and personality traits are able to facilitate labour market mobility of disadvantaged groups in the presence of constraining social structures. We use an individual panel dataset built on two household surveys carried out in 2010 and 2016-2017 in Tamil Nadu. We explore the relationship between individual cognitive skills (Raven, literacy and numeracy scores), personality traits (Big Five Inventory) and earnings mobility. We first assess the extent of gender and caste-based labour market segmentation using transition matrices. Then, we take advantage of intra-group heterogeneity in terms of cognitive skills and personality traits to explore whether these personal characteristics can enable individuals to overcome rigid social structures. Results show that personality traits are important determinants of labour mobility. Nonetheless, we observe a strong rigidity of the labour market structure in terms of gender and caste, and its relative stillness over time.

JEL Classification: J24, J31, J71, O12

Keywords: occupational transition, income mobility, cognitive skills, personality, Tamil Nadu, India

Corresponding author:
Christophe Jalil Nordman
PSL University
60 Rue Mazarine
75006 Paris
France
E-mail: nordman@dial.prd.fr

* The authors are grateful to Anne Hilger for fruitful discussions, to the participants of the 7th GREThA-DIAL seminar 2019, and to the participants of the Paris Cognition and Migration Workshop 2020 for their comments and suggestions on presentations of this study. We thank especially our discussant Flore Gubert for her constructive comments.

1. Introduction

Over the past decades, India has experienced rapid changes that have reshaped the labour structure throughout the country. Tamil Nadu, one of the most developed, urbanised, and industrialised Indian states, is no exception. The exodus of higher castes, from rural areas to the cities has initiated substantial transformations of land distribution and labour organisation (Djurfeldt et al., 2008), leading to a decline of agriculture in the last twenty years. Despite this significant drop, agriculture remains one of the sectors providing a large share of employment, especially in remote areas. Conversely, development of connections between rural and urban areas has led to a significant rise in rural non-farm employment which has provided new job opportunities (Guérin et al., 2015). At the same time, political changes have created a fertile ground for social policies targeted at the poor, thus improving access to employment for disadvantaged groups, namely women and lower castes (Vijayabaskar, 2010). Yet, these vulnerable groups remain disadvantaged in both absolute and relative terms (Papola and Kanan, 2017). In this changing economic, social and political landscape, studying the dynamics of the labour market is essential to understand social mobility, and thus to provide empirical insights for public policies aiming at reducing group-based inequalities. Given the strong structural changes India has witnessed in the last decades, detecting generalised income gains and occupational transitions (especially in rural areas) allows to assess whether socio-economic changes and pro-poor targeted public policies have led to a reduction of caste and gender segmentation in the labour market or, alternatively, to a strengthening of social and economic inequalities.

Labour mobility is an essential dimension of social mobility and represents an 'avenue to long-term equality' (Rama et al. 2014), especially in the context of developing countries. Labour mobility can occur either at an intergenerational or intragenerational level. The first refers to mobility between two generations (Jäntti and Jenkins, 2015) and the latter to "observed differences in the economic circumstances of individuals over time" (Burkhauser et al., 2012). If occupational mobility is a common metric for the measurement of social stratification and its rigidity through time (Long and Ferrie, 2013; Rama et al., 2014), income mobility (i.e. income loss or income gain) provides complementary information on welfare. An important literature has explored the determinants of labour mobility across generations given the significant caste-based occupational path-dependency in India, which traps households in specific occupations and income brackets. Traditionally, the caste system implies that jobs are determined at birth (Deshpande, 2000), making hereditary occupational specialisation one of its inherent characteristics (Béteille, 1991). Yet, 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 deploying since the 1980s. Modernisation does not only weaken barriers of entry into specific occupations, but it also creates new forms of employment. The rapid and substantial development of the service sector in urban and peri-urban areas has created new types of occupations out of the traditional caste-based job assignment system. However, facing modernisation, the caste system adapts and rearranges (Harriss-White, 2003) to create new forms of employment segregation. Various studies, focusing on the evolution of the employment structure of specific groups with an intergenerational perspective, have shown a large occupational path-dependency across generations (Motiram and Singh, 2012). Individual (intra-generational) labour mobility, on the other hand, remains only scarcely analysed, all the more so, using longitudinal individual level data (i.e. panel data). Studying intra-generational income mobility by analysing both absolute and relative measures, Azam (2016) has shown that individuals belonging to the disadvantaged groups (Scheduled Castes and Other Backward Castes) are less likely to experience an upward mobility and more likely to experience a downward one compared to individuals belonging to the Upper Castes.

The Indian labour market is also strongly segmented on the lines of gender which limits women's occupational and income mobility. Women are more likely to be present in temporary and casual occupations than in more stable ones because of barriers of entry (e.g. not meeting educational requirements, lack of experience, insufficient social network or discrimination), and they are also likely to remain in those occupations (Sundari, 2020). Moreover, self-selection of women into specific jobs linked to beliefs regarding "male" and "female" jobs (Goldin, 2014) strengthens labour market segregation and leads to reduced mobility across occupations and income brackets. Women's labour market mobility can have interesting implications at the household level, but it may also attenuate the sharp contrasts between socio-religious groups. To our knowledge, only a recent published article by Sarkar et al. (2019) uses panel data (India Human Development Survey) to analyse Indian women's labour market mobility by focusing on female exit and entry into the labour market. They found that an income increase of household members leads to lower entry and higher exit probabilities of women, explaining why, despite economic growth, a household income effect can decrease female labour force participation over time.

If socio-cultural structures such as caste and gender play an important role in limiting mobility across occupations and income brackets, individual skills can allow workers to overcome these barriers by providing them with resources to seize labour market opportunities. In Western countries, individual endowments, such as cognitive and personality traits, have received significant attention as determinants of labour performance in the past two decades (Heckman et al., 2006; Almlund et al., 2011). In fact, personality traits, referring to qualities such as motivation, leadership, self-esteem or social skills have in some cases been shown to be at least as important as cognitive skills (such as numeracy and literacy) for earnings and employment prospects. Theoretically, personality traits can have both direct and indirect effects on labour market integration and success. They can directly affect employability and productivity by being considered as part of an individual's set of endowments or serve as incentive enhancing preferences (Acosta et al., 2015). Additionally, they can indirectly affect individuals' social inclusion, for instance, through effects on aspirations, occupational choice and educational attainment. Labour market mobility, both in terms of income or occupations, is hence likely to be shaped by these individual differences. Studies in psychology show that individuals with higher cognitive skills and those with certain personality traits (openness to experience, extraversion, and emotional stability) have access to broader and more diverse social networks (Wu et al., 2008; Pollet et al., 2011), which in turn influence labour market transitions (see for instance Granovetter, 1985; Bramoullé and Saint-Paul, 2010). In India, social structure, institutions and norms affect individual labour, mobility, trajectories, and other individual choices, oftentimes by constraining them. Up to now, in economics, the role of cognitive and personality traits has been evaluated in isolation from the external environment, by purely focusing on their effects on individual choices and preferences, thereby neglecting the social structures in which individuals evolve. Hence, to our knowledge, the extent to which the effects of skills and traits on labour mobility are intertwined with these social structures, namely gender roles and the caste system, is rather unexplored. Anthropological studies in India show that the interaction between skills and social structures matters for job access (Carswell and De Neve, 2018). But empirical knowledge on this is meagre in economics, especially in the context of developing countries, and all the more so in India where information on personality traits and cognitive skills are rarely collected in population surveys.

Labour market mobility across time in India is usually studied through the prism of social groups, mainly due to the cross-sectional nature of available data. Individual data can nevertheless provide a more precise understanding of the determinants of labour market mobility by providing insights on both group and individual characteristics. This article follows this approach with a broader look at income mobility and occupational transitions using first-hand panel data from rural Tamil Nadu in 2010 and 2016. This dataset allows us to simultaneously observe whether occupational and income mobility are restricted for vulnerable groups (i.e. low caste groups and women) and if individual endowments in terms of personality traits and cognitive skills play a role in labour market mobility.

Our research questions ask: are personality traits and cognitive skills determinants of income mobility and occupational transitions? How do gender and caste interact with heterogeneous personality traits and cognitive skill endowments in this process?

This paper contributes to the emerging literature on intra-generational social mobility in India by providing insights from rich first-hand panel data collected by the authors and containing information that is seldom present in the context of developing countries (i.e. cognitive skills and personality traits). We combine a thorough description of mobility patterns using transition matrices and Heckman estimations of determinants of income mobility and occupational transitions which control for selection bias. We also discuss the relevance of a Five Factor Model (FFM) of personality traits to study rural women's labour market mobility and compare the estimates to alternative gender-specific factors. Our results show that in rural Tamil Nadu, cognitive skills (i.e. literacy, numeracy and Raven score) are hardly related to labour mobility. However, psychological traits, namely emotional stability, are enhancers of income and occupational mobility. Moreover, we observe a strong rigidity of the labour market structure in terms of gender and caste, and its relative stillness over time

2. Data and Methodology

2.1. Data

To study the dynamics of labour market transitions, this paper relies on a panel database built on two original first hand surveys: *RUral Microfinance & Employment* (RUME) and *Networks, dEbt, Employment, Mobilities and Skills in India Survey* (NEEMSIS), respectively carried out in 2010, and 2016-2017. The first wave (RUME) has been conducted among 405 households in ten villages located in coastal/central Tamil Nadu in the Cuddalore and Villupuram districts (see Appendix 1). In this area, the economy is dominated by agriculture but benefits from the proximity of two industrial towns (Neyveli and Cuddalore) and a regional business centre (Panruti). The survey used a stratified sample framework based on three dimensions: an agro-ecological criterion (dry or irrigated villages), urban proximity, and caste affiliation (Dalits, middle castes, upper castes). The second wave of the survey (NEEMSIS) was collected in the same 10 villages plus 9 additional localities where migrant households had settled since 2010.[1] Using a tracking procedure for migrant households allowed limiting the attrition rate between both waves to 4.8 percent. The balanced panel dataset (i.e. individuals observed in both waves) contains 1400 adults (15+), with 52 percent of men and 48 percent of women. Jatis[2] affiliation has been clubbed in three categories: the Dalits community which are at the bottom of the Caste system represents around 48 percent of the sample, the Middle Caste group represents 37 percent, and the Upper Caste constitutes the last 15 percent of the sample. 749 adults had an occupation in both waves.

2.2. Methodology

This article analyses two main dimensions of labour market mobility: income mobility and occupational transitions, analysed in two steps: a first exploratory one consisting in uncovering the patterns of labour market mobility and a second inferential one proposes to detect the determinants of mobility.

[1] For further detail, see the survey's dedicated website, https://neemsis.hypotheses.org/ and the NEEMSIS user guide and statistical report (Nordman et al., 2017, 2019).

[2] *Jatis*, sub-division of the Indian caste system, are hereditary social groups stratified according to ritual purity. There are thousands of jatis throughout India, traditionally associated to a specific occupation.

2.2.1. The detection of labour market mobility

We measure income mobility in absolute and relative terms. Absolute income mobility is measured by the logged value of the difference of income between 2010 and 2016 (after controlling for inflation). Relative income mobility is detected by a variable measuring the number of percentiles of mobility (percentile rank change) that a worker experienced across the distribution of annual wages between the 2010 and 2016-2017 waves. The variable can take the values [-100; 100].

We detect movements across occupational groups using transition matrices. These matrices allow computing the row percentages of movers and stayers between the two dates. In the case of a two-wave dataset (*t=1*; *t=2*) with two professional categories A and B, the workers who kept the same status in both periods are the stayers and the workers who changed statuses are the movers.

Table 1. Transition matrix

Status in t=2 / Status in t=1	A	B
A	Stayers	Movers (Upward mobility)
B	Movers (Downward mobility)	Stayers

Source: Authors

By establishing this type of matrix for general occupational categories, we can compare the mobility patterns of different socio-demographic groups.

2.2.2. Cognitive skills and personality traits

Individual endowments, such as educational background, are known to be important determinants of labour opportunities. However, the effects of other individual differences on the labour market are much more complex to assess. Cognitive skills are identified in our study by three dimensions. Literacy tests (reading and writing basic sentences), numeracy tests (four basic calculation tests) and the Raven Colored Progressive Matrices (CPM), meant to capture "fluid intelligence"[3]. The Raven CPM consists of three sets of 12 questions of increasing difficulty which are cognitive, visual, non-verbal tests that do not require any level of formal education. It captures the ability to think and make sense of complex data and logical reasoning. The Raven CPM have been previously used in economics for cognitive skills assessment in low-literacy populations in developing countries (e.g.

[3] The concept of "fluid intelligence" introduced by Cattell (1987) refers to basic processes of reasoning and other mental activities that depend only minimally on prior learning (such as formal and informal education).

Serneels, 2008). The score of the respondent to each dimension provides a refined measure of individual cognitive abilities.

In addition to these usual dimensions of individual endowments, our study draws from the discipline of social psychology in the two following ways to establish indicators of personality traits: (*i*) we use the Long Big Five Inventory, which is a taxonomy that refers to five dimensions commonly used to describe human personality traits: openness to experience, conscientiousness, extraversion, agreeableness and emotional stability. Practically, a set of 42 questions (seven for each dimension) has been asked to the respondent in order to capture the five personality traits[4]. (*ii*) We implement an alternative and gender-specific personality traits factor analysis. The universality of the big Five Factor Model (FFM) has indeed been questioned in several economic and anthropological studies. Laajaj et al. (2019) show that their validity outside of western, educated, industrialised, rich, and democratic (WEIRD) population is limited because of a risk of misinterpreting the Big-Five survey. Moreover, by testing the FFM among forager-farmers in the Bolivian Amazon, Gurven et al. (2012) show that the FFM is not universal. They do not find strong support for the FFM but find consistency among factors relating to prosociality and industriousness. They argue that further research is needed on how lower rank-personality traits assemble into higher-order personality traits. Following the intuition of these studies, we implement our own factor analysis of the 42 questions on male and female subsamples separately. From this analysis we extract the first five factors, then proceed to a promax rotation and analyse the content of each factor (see Appendix 8). We implement checks of internal factor validity using the Cronbach alpha measure. We then compare the results of approaches (*i*) and (*ii*).

2.2.3 Estimating the determinants of income mobility and occupational transitions

Our econometric strategy to analyse income mobility consists in using the two aforementioned income mobility variables (i.e. absolute income mobility and relative income mobility) as dependent variables. The independent variables of interest are the cognitive skills Cog_var (i.e. Raven score, numeracy and literacy) and the personality traits $Perso\_var$. $Control\_var$ represents a vector of socio-demographic characteristics.

$$Income\_Mobility = \beta_0 + \beta_1 Cog\_var + \beta_2 Perso\_var + \beta_3 Control\_var \qquad \text{[Eq. 1]}$$

[4] In the analysis, we first correct personality items for acquiescence bias, i.e. the tendency to answer more in one direction (agree or disagree) over the other and then aggregate and standardize the traits. The acquiescence score for the sample is 2.84, meaning that given the 5 option Likert scale we have in the questionnaire, slight acquiescence is present in the sample, with individuals more likely to disagree with a statement than to agree. Cronbach's α, a measure of internal consistency of a construct, are mostly at or above the desirable value of 0.7. The value of α per trait in ascending order are: 0.60 (agreeableness), 0.61 (extraversion), 0.77 (emotional stability), 0.78 (openness to experience), and 0.85 (conscientiousness).

To analyse occupational transitions, our dependent variables are transitions to non-agricultural jobs and transitions from casual to regular jobs. Our aim being to analyse the determinants of transitions into non-agricultural and regular jobs, we create ordinal dependent variables which consider the opposite transition (i.e. transitions into non-agricultural jobs and casual jobs respectively) as the first-rank outcome, no transitions (i.e. stayers) as the second-rank outcome and the transitions of interest (i.e. transitions into non-agricultural and regular jobs respectively) as the third-rank outcome.

$$Occupational\_Transitions = \beta_0 + \beta_1 Cog\_var + \beta_2 Perso\_var + \beta_3 Control\_var \qquad \text{[Eq. 2]}$$

The estimation of Equation 1 by Ordinary Least Squares (OLS) and Equation 2 by an ordered probit model is likely to yield biased estimates.

First, all variables of interest (Cog_var and $Perso\_var$) were only collected during the second wave of data collection, meaning that they could either represent a determinant or a result of labour market mobility. To overcome this issue, following the literature that considers that personality traits do not change after the age of 25 (Cobb-Clark and Schurer, 2012), which has also been shown in surveys (Cobb-Clark and Tan, 2011), we restrict our sample to individuals older than 30 years old. This restriction also allows us to make the assumption that numeracy and literacy are unlikely to change between the two waves. Several studies in psychology and the cognitive sciences (Cattell, 1987; Salthouse, 2004; Schaie, 2005) have shown that human capital skills (numeracy, literacy, general intelligence) are believed to rise during childhood and teenage years and remain relatively stable throughout adulthood. The variables of interest (Cog_var and $Perso\_var$) are measured at the same point in time (2016-17), after schooling has been completed and the worker has entered the labour market. If some of our control variables (2010) influenced the degree to which other individuals developed, OLS estimates for returns to education or skills will be biased downwards, potentially underestimating the true effect. To illustrate, if cognitive ability is increased through education, by including controls for cognitive skills (literacy and numeracy) as well as educational attainment, our estimates for returns to cognitive skills would be the true partial effect. Cognitive skills and personality traits have been shown to be malleable by the educational system but also to be predictors of educational attainment (Heckman et al., 2006). Additionally, measurement error in both cognitive and personality traits is likely, although we show (footnote 4) that our measures of personality traits are of a rather good quality. Hence, our estimates should still be interpreted as lower bounds.

Second, our analysis faces sample selection issues. Because of the nature of our dependent variables ($Income\_Mobility$ and $Occupational\_Transitions$), the sample is restricted to those who declared a non-zero and non-missing income and those who had an occupation in both years. We therefore do not account for entry and exit in paid employment by only considering variation of income for those who are in paid employment in both waves of the survey. To overcome this sample selection issue, we use a Heckman model to estimate the determinants of income mobility and a Heckman ordered probit model to estimate the determinants of occupational transitions. The household dependency ratios in both years, defined as the number of active occupied individuals divided by the total number of household members, are used as exclusion restriction variables (Equation 3), allowing to compute an Inverse Mill's Ratio to correct for selection in our equations of interest (Equations 4 and 5). To ensure unbiased significance results, we report bootstrapped standard errors with 500 replications. Note that, by including cognitive skills and personality traits in the models we can control for a large amount of otherwise unobserved worker heterogeneity.

$$Employment = \beta_0 + \beta_1 Control + \beta_2 ER + \mu \quad \text{[Eq. 3]}$$

$$Income\_Mobility = \beta_0 + \beta_1 Cog\_var + \beta_2 Perso\_var + \beta_3 Control + IMR + \varepsilon \quad \text{[Eq. 4]}$$

$$Occupational\_Transitions = \beta_0 + \beta_1 Cog\_var + \beta_2 Perso\_var + \beta_3 Control + IMR + \varepsilon \quad \text{[Eq. 5]}$$

3. Descriptive evidence of labour market mobility

3.1. Labour market evolution in terms of occupations

The labour market structure in our study area has experienced multiple changes in the six-year gap between the two waves. Table 2 shows the distribution of the main occupation in 2010 and 2016-17. First, as elsewhere in Tamil Nadu and more generally in India, agricultural employment has declined drastically, especially for agricultural casual labourers whose share in total employment dropped from one-third in 2010 to one-fifth in 2016-17. Second, employment out of agriculture has simultaneously rose sharply for regular non-qualified workers; and declined for casual workers. These evolutions suggest a trend of regularisation of non-agricultural employment explained by the rapid development of the service sector in rural Tamil areas over the last decade. We can also note that the Mahatma Gandhi National Rural Employment Guarantee Act[5] (hereafter NREGA) scheme, which is a national employment programme aimed at alleviating rural poverty has become the main occupation for 11 percent of the occupied active population in 2016-17.

Two transition matrices are presented in Appendix 2 (whole sample and by gender) and 3 (by caste group). They show transition dynamics of respondents' main occupation between 2010 and 2016-17. The first striking feature is the substantial level of mobility. The figures in the diagonal line show the

[5] The NREGA scheme, implemented in 2005, aims to enhance livelihood security in rural areas by providing at least hundred days of wage employment per year to the poorest households. It mainly consists of labor-intensive and low-skilled tasks (like creating infrastructure for water harvesting, flood control, etc.) and in our study area the average yearly annual income is INR 4,500 per household (around USD 61).

share of stayers in each occupation. They indicate that except for self-employment, individuals are very likely to change their main occupation over the two periods. A closer look into the specific occupation transitions shows a shift out of agriculture. If one-third of individuals who were cultivators in 2010 are still engaged in this occupation in 2016-17, almost half of them shifted out of agriculture, mostly as non-qualified regular workers. People who were already engaged in non-agricultural activities have also experienced important occupational mobility. This is especially the case for casual labourers who are as likely to shift to casual agricultural work as becoming regular workers in non-agricultural jobs. We finally observe an important downgrading dynamic for qualified workers (only 15 percent of them in 2010 are still in such occupations in 2016-17).

Table 2. Labour market evolution between 2010 and 2016

	2010	**2016-17**
Labour market structure (Occupied Active Population aged of 15+)	*n=943*	*n=985*
Main occupation type (%)		
Cultivators	12.5	14.5
Agri. Casual Workers	33.8	21.4
Non-Agri. Casual Workers	20.7	13
Non-Agri. Regular Non-Qualified Workers	7.4	19.1
Non-Agri. Regular Qualified Workers	6	7.8
Self-Employment	12.7	13.2
Public Employment Scheme (NREGA)	6.8	11

Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data.

The transition matrices also provide insights on the 'regularisation' of employment. Are classified as casual labour: agricultural and non-agricultural casual jobs, and NREGA employment. Regular work thus encompasses the other occupations: qualified and non-qualified, cultivators[6] and self-employed[7]. We find a relative continuity in occupation type over time. Casual workers in 2010 are more likely to stay in this occupation type in 2016-17, the same goes for regular workers. However, a special attention given to labour dynamics by gender and caste indicates substantially different patterns.

Appendix 2 presents the transition matrices for men and women separately and illustrates the strong gender segmentation on the labour market. While men are more likely to exit agricultural jobs – only one-third of the casual agricultural labourers are still in this occupation in 2016 –, almost half of women engaged in agricultural casual occupations remained in such precarious activities. We can note that regular occupations are restricted to men, especially the qualified ones. It is also noteworthy that NREGA has become an important employment option, especially for former agricultural female workers who are facing a scarcity of job opportunities in the village and strong entry barriers in other

[6] Due to severe lacks of rain and irrigation facilities, subsistence farming has almost disappeared in our study area. The share of panel households holding land has decreased from 54 percent in 2010 to 30 percent in 2016-17. Farmers are no longer very small producers, and their activities are therefore considered as regular.
[7] Most of self-employment activities in our sample (such as grocery shop, rickshaw driver, potter, etc.) imply employment in a regular basis and are thus considered as regular activities.

labour markets segments, mostly located outside of the villages. Finally, if we observe a significant shift out of precarious activities for men (half of them who were casual workers in 2010 became regular workers in 2016-17), women seem to experience an opposite trend with a 'de-regularisation' of employment for almost half of them. Hence, gender inequalities in terms of employment opportunities are still substantial and the important development of the service sector in semi-rural areas seems to mostly benefit men (Himanshu, 2011).

In terms of caste affiliation (Appendix 3), distinctive trends can be observed. Shifting out of casual employment appears to be the privilege of upper castes. While more than 60 percent of Dalits engaged in casual work in 2010 are still casual workers in 2016-17, only 5 percent of upper castes have experienced the same transition. Conversely, in the regular segment of the labour market, inequality of opportunity reinforces segmentation of labour across castes and has reproduced caste segmentation. 80 percent of upper castes engaged in qualified non-agricultural regular work in 2010 were still doing regular activities in 2016-17. This excludes the few Dalits who were engaged in such regular qualified occupations and who all downgraded to non-qualified jobs or casual employment. Upper castes, who are often more educated and benefiting from better social and economic capital are more likely to (find and) stay in regular jobs.

3.2. Dynamics of income mobility

Looking at income mobility reveals additional information on how the labour market evolution has reinforced caste and gender inequalities in terms of income. Table 3 shows that overall, average annual income rose by 5,000 rupees (around USD 75 in 2016) over the six-year period, but this average amount masks strong heterogeneity. The first striking feature is that disadvantaged groups (i.e. women and Dalits) have on average lost around 700 rupees (USD 10.5) between 2010 and 2016-17. Conversely, men and non-Dalits seem to have benefited from the labour market evolution and we observe a significant rise in annual income for these social groups (up to USD 247 for upper castes).

In terms of relative income mobility, we observe overall little variation, indicating that despite important occupational mobility, the earnings gap is not dramatically changing over time. Upper castes, and to a lesser extent middle castes, have experienced not only a significant increase in their earnings but also an upward mobility in the income distribution[8]. In brief, we do not observe significant changes at the bottom of the distribution, where Dalits and women are over-represented, but the earnings gap is increasing between the middle and the upper tail of the distribution. In addition to a disadvantaged initial position in the income distribution, Dalits appear to experience important

[8] Appendix 4 presents the kernel density plots of relative income mobility distributions by caste and gender.

barriers to income mobility as they have experienced overall a higher downward mobility than an upward mobility in terms of relative income.

Table 3. Absolute and relative income mobility by gender and caste group

Absolute income	Obs	Mean change in annual income (INR)	Std. Dev.	Median change in annual income (INR)
Whole Sample	422	5037.1	35932.5	-495.6
Men	261	8626	42941.2	2240.3
Women	161	-781	18596.8	-2553.2
Dalit	232	-738.6	27128	-2462.4
Middle Castes	157	10663.4	42722.5	1132
Upper Castes	61	18874.8	46707.5	12773.5
Relative income	**Obs**	**Mean mobility in the distribution (in percentiles)**	**Std. Dev.**	**Median mobility in distribution (in percentiles)**
Whole Sample	422	0.6	31.2	0
Men	261	-0.2	32	0
Women	161	1.8	30	1
Dalit	232	-2.1	29.5	-2
Middle Castes	157	3.2	33.1	3
Upper Castes	61	7.1	32.7	10

Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data
Note: Nominal values of 2016 deflated using World Bank Measure of Consumer Price Index[9]

4. Estimating the determinants of labour market mobility

4.1. Income mobility – general and caste-wise results

This section presents the results stemming from Heckman estimations reported in regression tables of Appendices 6 and 7.[10] The dependent variables are absolute income mobility (difference in log incomes between both waves) and relative income mobility (rank change in percentiles between both waves). The variables of interest are the Big-Five personality traits and cognitive skills variables: numeracy score, literacy dummy and Raven CPM score. The general results (Appendix 6) show that cognitive skills are not determinants of income gain in absolute or relative terms. However, three of the Big-Five personality traits have positive and significant coefficients. Openness to experience, extraversion and emotional stability are determinants of positive income change (i.e. income increase)

[9] See CPI: https://data.worldbank.org/indicator/fp.cpi.totl
[10] Appendix 5 presents the descriptive statistics of the variables used in the econometric estimations.

in both absolute and relative terms, meaning that they are associated to increases in absolute income and increases in the relative income rank of individuals between both waves.

The fact that the cognitive skills variables are not significant imply that when other variables are held constant, a higher Raven score, literacy or numeracy levels are not associated with income mobility. Note that when we implement regressions without the Big-Five personality traits (results available upon request) we find no significant effect of the cognitive skills variables on absolute income mobility and a 10 percent level significant effect of the Raven score on relative income mobility. Since this coefficient does not remain significant in the estimations shown in Appendix 6, we can suppose that the Big-Five personality traits variables probably capture part of the effect of cognitive skills on relative income mobility.

The results of the Heckman estimations by caste group are presented in Appendix 7[11]. They show that openness to experience is a determinant of relative income change (the coefficient is positive and significant) for all caste groups. Emotional stability is positively related to absolute and relative income mobility for all caste groups. Two personality traits allow income mobility for Dalits, but in both cases the result is only significant at the 10 percent level. First, openness to experience is positively and significantly related to absolute income change for Dalits. Second, agreeableness is positively and significantly related to relative income change for the same group. Interactions show that upper castes have a smaller chance of income mobility (both absolute and relative) for the same level of emotional stability compared to middle castes, suggesting that this trait is factor contributing to the reshuffling of the socio-economic hierarchy among the non-Dalits.

4.2. Income mobility – gender results

In this section we present the results of our estimations by male and female subsamples (Appendix 9). To further explore the determinants of income mobility, we also implement our own factor analysis of the 42 personality questions by sex subsamples, from which we derive five male factors and five female factors. The procedure and results of the factor analyses are available in Appendix 8 and the results of Heckman estimations with gendered factors are presented in Appendix 9. Note that the internal validity of the gendered factors were measured using the Cronbach alpha and show higher internal validity of the gender-specific factors than the FFM factors[12].

[11] Note that to have sufficient observations in the regressions, we have disaggregated the sample in two groups: Dalits and Non-Dalits (including both middle castes and higher castes). However, to capture the specific effect of our variables of interest on the income mobility of higher castes, we have included belonging to an upper caste as an interactive variable in the Non-Dalit estimations (see columns 3 and 6).

[12] Cronbach alphas for both FFM factors and gender-specific factors are presented at Appendix A8.3.

The results using the FFM factors show that for men, openness to experience, conscientiousness, extraversion and emotional stability are determinants of absolute income mobility and relative income mobility. For women, emotional stability is the only determinant of absolute income mobility and relative income mobility. The cognitive skills are never significant for men. For women, literacy is positively related to absolute income mobility.

Looking at gendered personality traits provides a more in-depth understanding of the determinants of women's income mobility. Indeed, factors 1, 2 and 3 are significant for both absolute and relative income mobility. These factors respectively refer to (1) traits that indicate emotional stability (i.e. not changing moods easily, not being nervous and not being easily upset) combined with conscientiousness traits, also indicating some form of stability (e.g. not easily distracted, working hard) and one extraversion trait (i.e. talkative); (2) traits of openness to experience (i.e. like to talk, new ideas, curious, inventive) and emotional stability (does not feel depressed and does not worry a lot); (3) a combination of traits from all five factors (see Appendix 8). If we look at the gendered subsamples for men, only the first factor is significant. This factor combines conscientiousness and emotional stability items, which is consistent with FFM results. These observations illustrate the on-going debate on the universality of the Big-Five Inventory and, in our case study, it appears to be male-oriented as it hardly captures women's personality traits.

4.3. Occupational transitions

In this section, we present the results of Heckman ordered probit estimations of transitions to non-agricultural jobs and transition to regular jobs[13]. The results are presented in Appendices 11 and 12. In order to conduct the analysis, the outcome variables (i.e. transitions to non-agriculture and transitions to regular jobs) are interpreted as ordinal with three levels:

1. Reverse transition
2. No transition
3. Transition of interest (respectively entry into non-agriculture jobs and into regular jobs)

The results show that openness to experience and emotional stability are determinants of transitions to non-agricultural jobs and only emotional stability is a determinant of transition to regular jobs. The caste subsample estimations show that emotional stability is significant for Dalit groups for both types of transitions, and significant for Non-Dalit group only for transitions out of agriculture. In terms of gender the results show that, for women, exiting agriculture requires openness to experience and emotional stability whereas, for men, it only requires emotional stability.

[13] Descriptive statistics of Agriculture/Non-agriculture and Casual/Regular transition dynamics are presented in Appendix 10.

4.4. Complementary analyses

In order to further understand the dynamics of labour market mobility in our sample, we also conducted a complementary analysis of determinants of entry into the labour market by implementing a multinomial logit regression of the multinomial variable indicating either exit from the labour market, working in both waves, not working in both waves or entry in the labour market.[14] The results are shown in Appendix 13 and indicate that if cognitive skills are not significant for income or occupational mobility - except for literacy in the case of women, these skills are determinants of entry into the labour market. Compared to those who have not entered the labour market (base category), the Raven score positively influences the probability of entering the labour market. Two cognitive skills also positively influence this probability: openness to experience and conscientiousness.

We also investigated whether measures of interpersonal networks (potential and actual ties of workers[15]) could constitute transmission mechanisms between personality traits, cognitive skills and labour market outcomes. In order to do so, we implemented OLS regressions of the potential and actual workers' ties, as well as of the overall size of their social networks (measured as the sum of potential and actual ties, both formal and informal). The results presented in Appendix 14 show that emotional stability and numeracy are strongly and positively related to the potential ties of the social network, whereas the literacy score is negatively related to it (at the 10 percent level). This analysis, although only preliminary, confirms previous findings in South Asia (Hilger et al., 2018) and suggests that social ties are potentially transmission mechanisms through which cognitive skills and personality traits have an effect on labour market outcomes.

5. Discussion

Using a unique panel dataset allowing to study the role of cognitive and personality traits on labour market outcomes in rural India, we have identified to what extent individual differences could overcome social inequalities on the labour market. Given the rigid structures of the Indian society and its strong labour market inequalities, identifying the dynamics and determinants of social mobility, through earnings and occupational transitions, can inform more suitable public policies oriented

[14] This setup allows us to include more individuals in our regression. The total number of individuals in each category are: 32 who weren't active in any waves, 50 who entered the labour market, 30 who exited the labour market and 886 who were active in both waves. Note that this regression only includes individual who had non-missing data for all of the independent variables in the regression.

[15] These are both formal and informal interactions that gather all sorts of social connections that an individual may have made. These data on interactions were collected using a 'name generator' which was included as part of the individual NEEMSIS survey. The *actual* ties refer to links an individual has explicitly made (borrowed or lent money to others, recommended somebody - or received a recommendation - for a loan or for a job, or received help with a loan. The *potential* ties consist of all connections that an individual could use if the need occurred for the same purposes.

towards the most disadvantaged groups, namely women and Dalits. Our analysis of intra-generational mobility uses measures of cognitive and psychological differences that are scarcely used in the case of developing countries and deepen the understanding of the dynamics of income and occupational mobility in a rural area of Tamil Nadu. This analysis highlights the existence of a plurality of mechanisms reinforcing caste and gender inequalities. In doing so, we aim at articulating disjoint disciplinary approaches: on the one hand, behavioural economics; on the other hand, sociological and anthropological structuralist approaches. While the former fields, which include recent and fruitful advances in psychology economics, have provided new evidence that cognitive and socio-emotional skills are likely to have direct and indirect impacts on individual choices and outcomes in the labour markets, these approaches are too often disconnected from the analysis of social structures in which individuals are embedded. The second strand recognises that individuals cannot be considered outside of the social relations that make up the collective structure (Polanyi, 1944). Labour markets appear there as a place of negotiation and social interaction, where complex forms of power and domination are encompassed in relations of rivalry, exclusion, and cooperation. While both approaches are often presented as incompatible, they appear to have numerous points of convergence. Most behaviourists pay attention to the role of social norms and interactions, but overlook their inherent nature, while many structuralists emphasise structural origin of cognition and emotion, but disregard the extent to which they shape individual preferences and choices. The starting point of this paper was to recognise that both views are meaningful and need to be articulated, and our results illustrates the complementarity of both approaches in applied social sciences.

Our results show that, in terms of gender, men have experienced a regularisation of labour and an exit out of agriculture in rural Tamil Nadu, whereas women have experienced opposite trends. This contrasting evolution can be explained by the transformation of the labour market structure in the region. Over the past three decades, men progressively moved from agriculture towards construction work or employment in the growing service sector (Djurfeldt et al., 2008). Women have replaced men in the fields and then specialised in agricultural casual jobs (Patnaik et al., 2018). The *jobless growth* in India over the past decades, characterized by the informalization of the economy, has also maintained non-agricultural female activity in small production units with low productivity, thus favouring the persistence of precarious jobs (Himanshu, 2011). Improvements in education, first for young male individuals, have accentuated this gender distortion by orienting male employment towards industry and service sectors in nearby cities where regular jobs are more prevalent and also better paid. Women, for whom cultural specificities such as seclusion, limit access to employment and education, are still very dependent to employment within the village, where opportunities are scarce, mostly agriculture-oriented, low-paid and on a daily basis.

Regarding caste segmentation, we similarly observe a reinforcement of inequalities. The transition out of agriculture and out of casual employment seems to be a prerogative of the upper castes, already largely over-represented in such occupations. Middle caste workers are slowly moving into regular activities, but this trend remains fragile. The situation of Dalits is even more tenuous. Despite improvements in educational attainment and affirmative action policies, Dalits in our study area are still struggling to access public employment and other forms of socially valuable occupations. Moreover, the modest advances in terms of labour accessibility, for the few overcoming this social discrimination, hardly translate into earning gains.

Upward occupational and upward income mobility are strongly related, and it is no surprise to observe similar patterns regarding earnings gains over the six-year period of our surveys. Upper castes have benefited from the labour market transformations and their initial better endowments in terms of economic, social and cultural capital translate into a higher upward income and occupational mobility.

This paper also provides important contributions in terms of individual cognitive and psychological determinants of labour market mobility. An interesting finding is that, all things being equal, cognitive skills appear to play a limited role in income mobility, while personality traits seems to be significantly associated with income mobility. Unlike empirical evidence found in the economic literature on developing countries (e.g. Serneels, 2008; Lee and Newhouse, 2012[16]), neither numeracy, nor the Raven score which is a proxy for fluid intelligence are significantly related to relative or absolute income mobility. However, we do observe a significant effect of literacy on absolute income mobility for women. This result confirms previous findings for South Asia which use cognitive skills to observe gender wage differences in the non-agricultural sector (Nordman et al., 2019), and illustrates how access to education for women, in a context where a large share of women is illiterate, can enhance job opportunities out of the agricultural sector. The growing sector service in nearby small cities indeed requires literacy skills and only women having an educational background can access such occupations. As discussed earlier, the labour market is still strongly segmented along gender, but it is clear that the dynamics of women's empowerment can only emerge in a context where gender gaps in educational attainment stop preventing women from entering non-agricultural regular jobs (Guérin et al, 2020). This is especially true for Dalit women, since upper caste women are more likely to be involved in self-employed occupations, requiring a certain level of economic and social capital that lower castes rarely meet.

Our results also emphasize the crucial role of emotional stability for income mobility of Dalits and Non-Dalits. As shown in the literature (Almlund et al., 2011; Díaz et al., 2012), emotional stability is usually one of the personality traits having the most significant effect on labour market outcomes. Indeed, it doesn't come as a surprise that this type of trait would be beneficial in an area like rural Tamil Nadu, where workers are prone to socioeconomic shocks. We also observed that agreeableness

[16] Lee and Newhouse (2012) for instance, find that higher cognitive ability is associated with measures of better job quality.

is significantly correlated to relative income mobility for Dalits, but not to absolute income mobility. One possible explanation for this interesting pattern lies in the labour market structure and the strong hierarchical organisation of the Tamil rural society. As described in section 3, Dalits are more likely to be involved in casual occupations where relationships with the employer (oftentimes from higher castes) are crucial for job continuity. Having this personality trait does not allow absolute gains in income, but still appear to be essential to create and maintain efficient employment relationships. Social networks in the Indian society are well-known to influence job access and social mobility (Nandi, 2010; Beaman and Magruder, 2012), and the recommendation system remains an important feature of the labour market (Vijayabaskar and Kalaiyarasan, 2014; Hilger and Nordman, 2020). We also observe that, for men, openness to experience, emotional stability, conscientiousness and extraversion are significantly correlated to relative and absolute income mobility. In other words, in a highly competitive and narrow labour market, those being pro-active, enthusiastic and curious are more likely to be integrated into networks facilitating a better job accessibility, enabling to move up in the income distribution. Openness to experience, extraversion, and emotional stability are also known to increase access to broader and more diverse social networks (Wu et al., 2008; Pollet et al., 2011). Here, we assume and partly verify (with our network data) that social ties may constitute a transmission channel in the relationship between some dimensions of cognition and labour mobility.

In line with the results on income mobility, the occupational transitions analysis shows that emotional stability is one of the main determinants of mobility into better quality jobs. We also find that, for women, openness to experience is an important determinant of exiting agricultural jobs, suggesting that this type of mobility requires being able to take risks and to challenge highly constraining social norms such as seclusion. None of the cognitive skills variable allows individuals to enter better quality jobs which points towards the value of 'soft skills' in enabling access to better jobs.

Finally, our study provides suggestive evidence that in an effort to be universal, the FFM may blur the complexity of psychological traits of specific groups, leading to unclear evidence concerning their effects on labour mobility. Indeed, the universality of the Big-Five may not be appropriate in a context of a rigid society where the role of men and women are strongly compartmentalized and socially constructed. We attempt to provide an alternative personality taxonomy suited to the rural Indian context by identifying new gender-specific factors. These factors provide interesting results for women and have a higher internal validity than the FFM (as suggested by higher Cronbach alphas presented in Appendix 8.3). These results are in line with previous studies (for instance Laajaj et al., 2019) and suggest that more research is needed on the relevance of FFM factors for analysing the personality of non-WEIRD populations, especially with a gender dimension.

6. Conclusion

This study, using an original approach combining behaviourist and structuralist views, explores to what extent individual skills and personality traits facilitate labour market mobility of disadvantaged groups in the presence of constraining social structures. Based on a rural India case study, our results show that personality traits are important determinants of labour market mobility but also emphasize a strong rigidity of the socioeconomic structure of the Indian labour market in terms of gender and caste, and its relative stillness over time. While for women, literacy, emotional stability and openness to new experience appear to allow income gains, these benefits are limited by the labour market structure, maintaining them in low-skilled and casual occupations. For Dalits, emotional stability and agreeableness seem to play an important role in relative income mobility. These interesting findings highlight the segmented nature of the Indian labour market, which is still strongly organised by diverse forms of domination. As shown in previous research, the caste system adapts and rearranges (Harriss-White, 2003), mitigating the impact of any type of structural change to equalise livelihoods of individuals. Our paper calls for further research to understand how personality traits are acquired and shaped and how they can be leveraged to allow disadvantaged groups to access better jobs and higher incomes. Our results also call for further exploration of the nature and the variety of socioeconomic barriers facing disadvantaged groups in rural India. Indeed, even if individuals would have the required personality traits enabling an upward mobility pattern, it might not be sufficient to transcend caste and gender labour segregation because of other factors such as wage discrimination and nepotism.

References

Acosta, Pablo A., Noël Muller N., and Miguel Sarzosa. 2015. Beyond Qualifications. Returns to Cognitive and Socio-Emotional Skills in Colombia. *Policy Research Working Paper* 7430, World Bank.

Almlund, Mathilde, Angela L. Duckworth, James Heckman, and Tim Kautz. 2011. Personality Psychology and Economics. In *Handbook of the Economics of Education Volume 4*, eds. Eric A. Hanushek, Stephen J. Machin and Ludger Woessmann, 183–282. North Holland.

Azam, Mehtabul. 2016. Household Income Mobility in India 1993-2011. *IZA Discussion Paper Series 10308*.

Beaman, Lori, and Jeremy Magruder. 2012. Who Gets the Job Referral? Evidence from a Social Networks Experiment. *American Economic Review* 102 (7): 3574–93.

Béteille, André. 1991. The Reproduction of Inequality: Occupation, Caste and Family. *Contributions to Indian Sociology* 25 (1): 3–28.

Bramoullé, Yann, and Gilles Saint-Paul. 2010. Social Networks and Labor Market Transitions. *Labour Economics* 17 (1): 188–195.

Burkhauser, Richard V., Brian Nolan, and Kenneth A. Couch. 2012. Intragenerational Inequality and Intertemporal Mobility. In *The Oxford Handbook of Economic Inequality*, eds. Brian Nolan, Wiemer Salverda, and Timothy M. Smeeding, 523–46. Oxford University Press.

Carswell, Grace, and Geert De Neve. 2018. Towards a Political Economy of Skill Under Liberalisation: The Case of the Tiruppur Garment Cluster in South India. In *Industrial Labor on the Margins of Capitalism: Precarity, Class, and the Neoliberal Subject Volume 4*, eds. Chris Hann, and Jonathan Parry. 309–35. Berghahn Books.

Cattell, Raymond B. 1987. *Intelligence: Its Structure, Growth, and Action*. New York: Elsevier Science.

Cobb-Clark, Deborah A., and Stefanie Schurer. 2012. The Stability of Big-Five Personality Traits. *Economics Letters,* 115 (1): 11–15.

Cobb-Clark, Deborah A., and Michelle Tan M. 2011. Non-cognitive skills, occupational attainment, and relative wages. *Labour Economics* 18 (1): 1–13.

Deshpande, Ashwini. 2000. Does Caste Still Define Disparity? A Look at Inequality in Kerala, India. *American Economic Review* 90 (2): 322–25.

Díaz, Juan J., Omar Arias, and David V. Tudela. 2012. Does Perseverance Pay as Much as Being Smart?: The Returns to Cognitive and Non-cognitive Skills in urban Peru. *mimeo*. *The World Bank*, Washington DC.

Djurfeldt, Goran, Venkatesh Athreya, N. Jayakumar, Staffan Lindberg, A. Rajagopal, and R. Vidyasagar. 2008. Agrarian Change and Social Mobility in Tamil Nadu. *Economic and Political Weekly* 43 (45): 50–61.

Goldin, Claudia. 2014. A Pollution Theory of Discrimination: Male and Female Differences in Occupations and Earnings. In *Human Capital in History: The American Record*, eds. Leah Platt Boustan, Carola Frydman, and Robert A. Margo, 313–48. Chicago, IL: University of Chicago Press.

Granovetter, Mark. 1985. Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology* 91 (3): 481–510.

Guérin, Isabelle, Govindan Venkatasubramanian, and Sébastien Michiels. 2015. Labour in Contemporary South India. In *Indian Capitalism in Development*, eds. Barbara Harriss-White and Judith Heyer. Abingdon, Routledge.

Guérin, Isabelle, Sébastien Michiels, Christophe J. Nordman, Elena Reboul, and Govindan Venkatasubramanian. 2020. There Has Been No Silent Revolution: A Decade of Empowerment for Women in Rural Tamil Nadu. In *Advances in Women's Empowerment: Critical Insights from Asia, Africa and Latin America*, eds. Araceli O. Díaz and Marta B. Ochman, 183–200. Emerald Publishing.

Gurven, Michael, Christopher von Rueden, Maxim Massenkoff, Hillard Kaplan, and Marino Lero Vie. 2012. How Universal Is the Big Five? Testing the Five-Factor Model of Personality Variation Among Forager–Farmers in the Bolivian Amazon. *Journal of Personality and Social Psychology* 104 (2): 354–70.

Harriss-White, Barbara. 2003. *India working: Essays on society and economy*. Cambridge University Press.

Heckman, James J., Jora Stixrud, and Sergio Urzua. 2006. The Effects of Cognitive and Non-Cognitive Abilities on Labor Market Outcomes and Social Behavior. *Journal of Labor Economics* 24 (3): 411–482.

Hilger, Anne, Christophe J. Nordman, and Leopold Sarr. 2018. Cognitive and Non-Cognitive Skills, Hiring Channels, and Wages in Bangladesh. *IZA Discussion Paper Series 11578*.

Hilger, Anne, and Christophe J. Nordman. 2020. The Determinants of Trust: Evidence from Rural South India. *IZA Discussion Paper Series 13150*.

Himanshu. 2011. Employment Trends in India: A Re-examination. *Economic and Political Weekly* 46 (37).

Jäntti, Markus, and Stephen P. Jenkins. 2015. Income Mobility. In *Handbook of Income Distribution Volume 2*, eds. Anthony B. Atkinson and François Bourguignon, 807–935. Elsevier B.V.

Laajaj, Rachid, Karen Macours, Daniel A. Pinzon Hernandez, Omar Arias, Samuel D. Gosling, Jeff Potter, Marta Rubio-Codina, and Renos Vakis. 2019. Challenges to capture the big five personality traits in non-WEIRD Populations. *Science Advances* 5 (7).

Lee, Jean N., and David Newhouse. 2012. Cognitive Skills and Youth Labor Market Outcomes. Background Paper for the World Development Report 2012. The World Bank.

Long, Jason, and Joseph Ferrie. 2013. Intergenerational Occupational Mobility in Great Britain and the United States since 1850. *The American Economic Review* 103 (4): 1109–37.

Motiram, Sripad, and Ashish Singh. 2012. How Close Does the Apple Fall to the Tree? Some Evidence on Intergenerational Occupational Mobility from India. WIDER Working Paper 2012/101.

Nandi, Tushar. 2010. Social networks and employment in India. *Economics Bulletin* 30 (4): 2769–78.

Nordman, Christophe J., Isabelle Guérin, Arnaud Natal, Sébastien Michiels, and Govindan Venkatasubramanian. 2019. *NEEMSIS Survey Report: A Full Statistical Picture of the Household and Individual Data*. IRD-IFP, French Institute of Pondicherry – IFP, Institut de

Recherche pour le Développement – IRD. https://f-origin.hypotheses.org/wp-content/blogs.dir/3627/files/2020/04/NEEMSIS-Survey-Report-2019_Statistical-Tables.pdf

Nordman, Christophe J., Isabelle Guérin, Govindan Venkatasubramanian, Sébastien Michiels, Youna Lanos, Santosh Kumar, Antony Raj, and Anne Hilger. 2017. *NEEMSIS Survey Manual* Technical Report. IRD-IFP, French Institute of Pondicherry - IFP, Institut de Recherche pour le Développement – IRD. https://neemsis.hypotheses.org/files/2018/05/NEEMSIS_manual_final.pdf

Nordman, Christophe J., Leopold R. Sarr, and Smriti Sharma. 2019. Skills, Personality Traits, and Gender Wage Gaps: Evidence from Bangladesh. *Oxford Economic Papers* 71 (3): 687–708.

Papola, T. S., and K. P. Kannan. 2017. Towards an India wage report. ILO Working Papers n°994971390602676, International Labour Organization.

Patnaik, Itishree, Kuntala Lahiri-Dutt, Stewart Lockie, and Bill Pritchard. 2018. The feminization of agriculture or the feminization of agrarian distress? Tracking the trajectory of women in agriculture in India. *Journal of the Asia Pacific Economy* 2 (1): 138–155.

Polanyi, Karl. 1944. *The Great Transformation.* Boston, Beacon Press.

Pollet, Thomas V., Sam G. Roberts, and Robin I. Dunbar. 2011. Extraverts have Larger Social Network Layers: But do not Feel Emotionally Closer to Individuals at any Layer. *Journal of Individual Differences* 32 (3): 161–9.

Rama, Martin, Tara Béteille, Yue Li, Pradeep K. Mitra, and John L. Newman. 2014. *Addressing Inequality in South Asia*. South Asia Development Matters. World Bank.

Salthouse, Timothy A. 2004. What and When of Cognitive Aging. Current Directions. *Psychological Science* 13 (4): 140–4.

Sarkar, Sudipa, Soham Sahoo, and Stephan Klasen. 2019. Employment Transitions of Women in India: A Panel Analysis. *World Development* 115: 291–309.

Schaie, K. Warner. 2005. What Can We Learn From Longitudinal Studies of Adult Development?. *Research in Human Development* 2 (3): 133–58.

Serneels, Pieter. 2008. Human capital revisited: The role of experience and education when controlling for performance and cognitive skills. *Labour Economics* 15 (6): 1143–61.

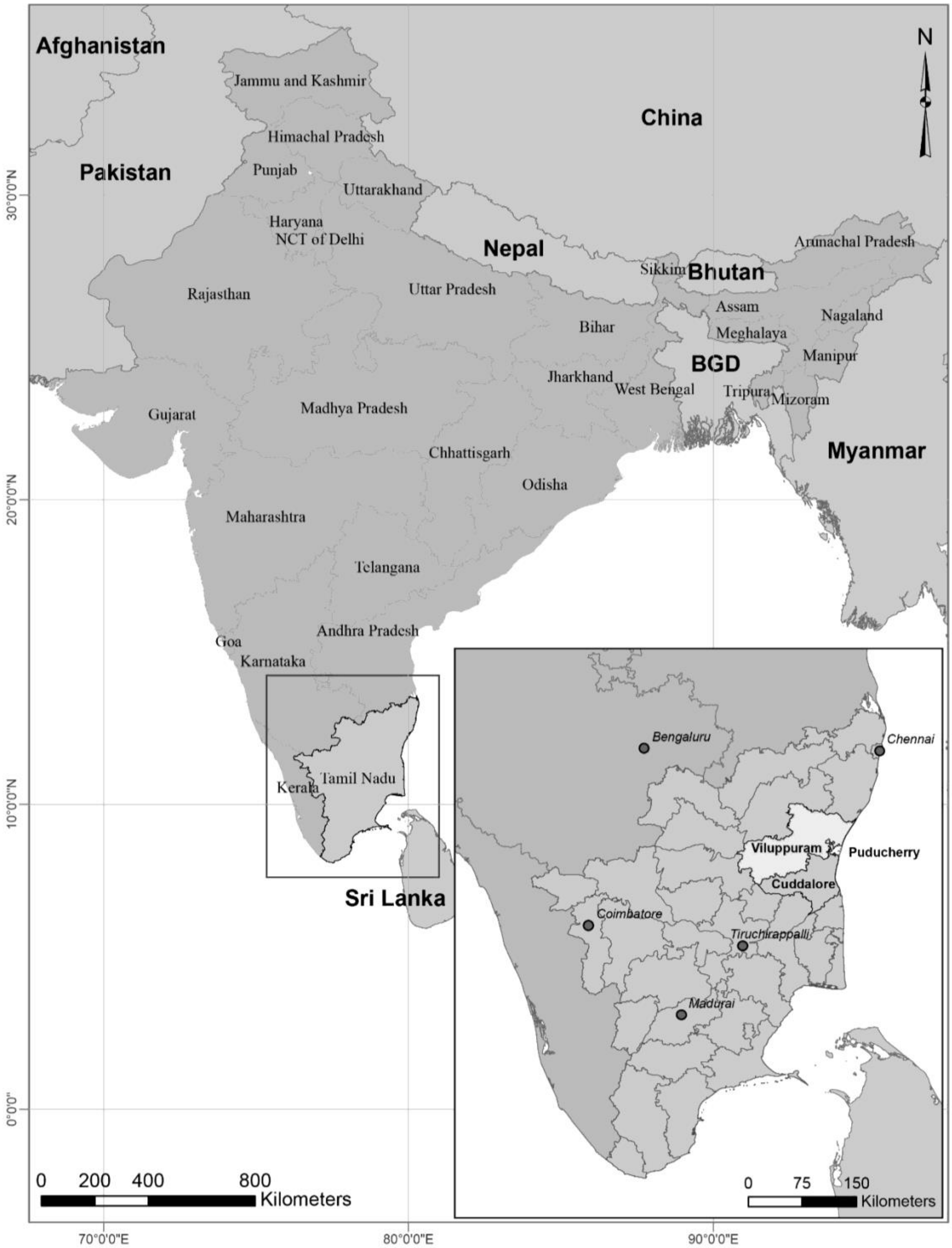
Sundari, S. 2020. Structural Changes and Quality of Women's Labour in India. *Indian Journal of Labour Economics* 63 (3): 689–717.

Vijayabaskar, M. 2010. Saving Agricultural Labour from Agriculture: SEZs and Politics of Silence in Tamil Nadu, *Economic and Political Weekly* 45 (6): 36–43.

Vijayabaskar, M., and A Kalaiyarasan. 2014. Caste as Social Capital. The Tiruppur Story. *Economic and Political Weekly* 49 (10): 34–38.

Methodological and statistical Appendix (online publication)

Appendix 1. Map of the study area



Source: Authors

Appendix 2. Transition matrix for main occupation (by gender)

Main occupation 2010 (ALL)	Main occupation 2016-17 Cultivator	Agri. Casual Worker	Non-Agri. Casual Workers	Non-Agri. Regular Non-Qualified Worker	Non-Agri. Regular Qualified Worker	Self-Employment	Public Employment Scheme (NREGA)	Total
Cultivator	**29.7**	14.1	10.9	28.1	3.1	7.8	6.2	100
Agri. Casual Worker	14.9	**41.1**	8.3	13.7	0.6	7.7	13.7	100
Non-Agri. Casual Worker	17.7	24	**27.1**	20.8	0	5.2	5.2	100
Non-Agri. Regular Non-Qualified Worker	10.5	5.3	15.8	**42.1**	5.3	15.8	5.3	100
Non-Agri. Regular Qualified Worker	15.4	15.4	7.7	23.1	**15.4**	15.4	7.7	100
Self-Employment	4.9	9.8	6.6	14.7	0	**59**	4.9	100
Public Employment Scheme (NREGA)	12.9	22.6	12.9	6.4	0	19.3	**25.8**	100
Total	15.9	25.9	13.	18.4	1.3	15.5	10	100
Main occupation 2010 (Male)								
Cultivator	**28.8**	15.2	11.9	30.5	3.4	8.5	1.7	100
Agri. Casual Worker	18.6	**32.2**	13.6	20.3	1.7	10.2	3.4	100
Non-Agri. Casual Worker	23.1	21.5	**26.1**	21.5	0	6.1	1.5	100
Non-Agri. Regular Non-Qualified Worker	11.1	0	16.7	**44.4**	5.6	16.7	5.6	100
Non-Agri. Regular Qualified Worker	18.2	9.1	9.1	27.3	**18.2**	18.2	0	100
Self-Employment	5.6	11.1	7.4	14.8	0	**57.4**	3.7	100
Public Employment Scheme (NREGA)	0	0	0	0	0	0	**0**	100
Total	18.8	18.4	15	23.7	2.3	19.2	2.6	100
Main occupation 2010 (Female)								
Cultivator	**40**	0	0	0	0	0	60	100
Agri. Casual Worker	12.8	**45.9**	5.5	10.1	0	6.4	19.3	100
Non-Agri. Casual Worker	6.4	29	**29**	19.3	0	3.2	12.9	100
Non-Agri. Regular Non-Qualified Worker	0	100	0	**0**	0	0	0	100
Non-Agri. Regular Qualified Worker	0	50	0	0	**0**	0	50	100
Self-Employment	0	0	0	14.3	0	**71.4**	14.3	100
Public Employment Scheme (NREGA)	12.9	22.6	12.9	6.4	0	19.3	**25.8**	100
Total	11.8	36.6	10.2	10.7	0	10.2	20.4	100

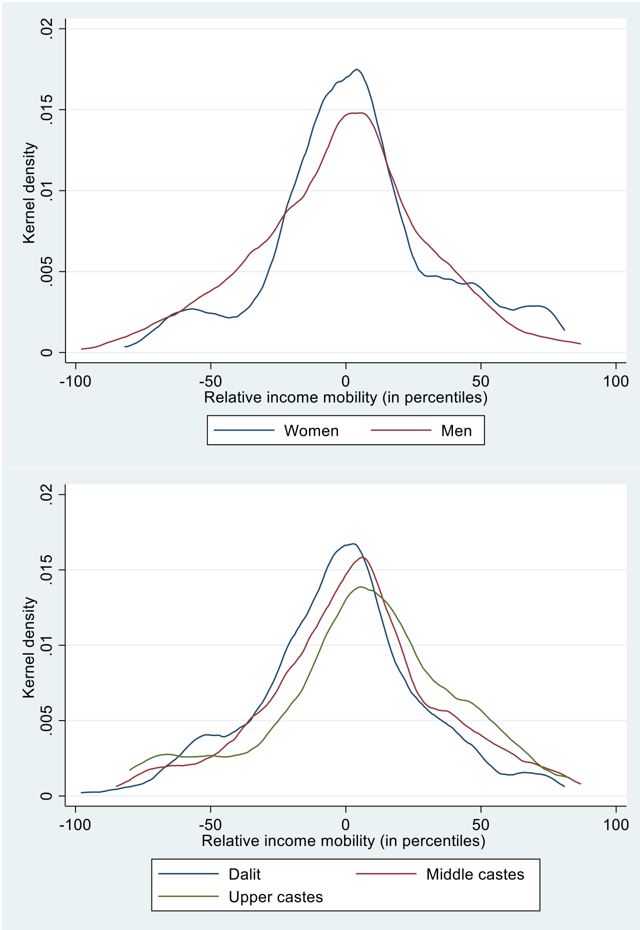
Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data

Appendix 3. Transition matrix for main occupation (by caste)

Main occupation 2010 (Dalit)	Main occupation 2016-17							
	Cultivator	Agri. Casual Worker	Non-Agri. Casual Workers	Non-Agri. Regular Non-Qualified Worker	Non-Agri. Regular Qualified Worker	Self-Employment	Public Employment Scheme (NREGA)	Total
Cultivator	**20**	30	10	30	0	5	5	100
Agri. Casual Worker	7.1	**49.1**	7.1	13.4	0.9	5.4	17	100
Non-Agri. Casual Worker	8.2	27.9	**37.7**	18	0	3.3	4.9	100
Non-Agri. Regular Non-Qualified Worker	0	25	25	**25**	0	0	25	100
Non-Agri. Regular Qualified Worker	0	33.3	16.7	33.3	**0**	16.7	0	100
Self-Employment	4.3	26.1	4.3	21.7	0	**39.1**	4.3	100
Public Employment Scheme (NREGA)	16.7	33.3	16.7	0	0	0	**33.3**	100
Total	8.4	38.2	16	16.8	0.42	8	12.2	100
Main occupation 2010 (Middle caste)								
Cultivator	**30.6**	8.3	11.1	27.8	5.6	11.1	5.6	100
Agri. Casual Worker	32.7	**26.9**	11.5	15.4	0	5.8	7.7	100
Non-Agri. Casual Worker	36.4	18.2	**9.1**	21.2	0	9.1	6.1	100
Non-Agri. Regular Non-Qualified Worker	14.3	0	14.3	**42.9**	7.1	21.4	0	100
Non-Agri. Regular Qualified Worker	40	0	0	0	**20**	20	20	100
Self-Employment	5.6	0	16.7	5.6	0	**61.1**	11.1	100
Public Employment Scheme (NREGA)	6.7	20	13.3	13.3	0	20	**26.7**	100
Total	26.6	15	11.6	19.6	2.3	16.2	8.7	100
Main occupation 2010 (upper caste)								
Cultivator	**50**	0	12.5	25	0	0	12.5	100
Agri. Casual Worker	0	**0**	0	0	0	100	0	100
Non-Agri. Casual Worker	0	0	**0**	100	0	0	0	100
Non-Agri. Regular Non-Qualified Worker	0	0	0	**100**	0	0	0	100
Non-Agri. Regular Qualified Worker	0	0	0	50	**50**	0	0	100
Self-Employment	5	0	0	15	0	**80**	0	100
Public Employment Scheme (NREGA)	25	0	0	0	0	75	**0**	100
Total	14.6	0	2.4	21.9	2.4	56.1	2.4	100

Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data

Appendix 4. Kernel density of relative income mobility (in percentiles) by gender and caste



Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data

Appendix 5. Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
Openness	0.19	0.47	-0.94	1.42
Conscientiousness	-0.12	0.29	-1.12	0.82
Extraversion	-0.19	0.34	-1.10	0.95
Agreeableness	0.12	0.31	-1.16	1.01
Emotional Stability	0.05	0.43	-1.53	1.37
Raven Score	11.96	8.13	0	36
Literacy	0.46	0.50	0	1
Numeracy score	1.50	1.23	0	4
Education level (base below primary)				
Below Primary	0.50	0.50	0	1
Completed Primary	0.23	0.42	0	1
Completed Middle School	0.14	0.35	0	1
Completed High School	0.09	0.29	0	1
Completed Higher Secondary School	0.03	0.17	0	1
Bachelors	0.01	0.10	0	1
Age	40.46	8.85	22	69
Age Squared	1714.85	738.83	484	4761
Female	0.38	0.49	0	1
Caste Group				
Dalit	0.56	0.50	0	1
Middle Caste	0.37	0.48	0	1
Upper Caste	0.08	0.27	0	1
Relationship to head				
Head	0.58	0.49	0	1
Wife	0.33	0.47	0	1
Son	0.08	0.27	0	1
Other	0.02	0.13	0	1
Casual worker	0.64	0.48	0	1
Agricultural worker	0.51	0.50	0	1
Log income in 2010	9.89	0.82	8.01	11.88
Log income of the rest of the household	10.88	0.59	8.41	12.30
Villages				
GOV	0.06	0.24	0	1
KAR	0.09	0.29	0	1
KOR	0.11	0.31	0	1
KUV	0.12	0.32	0	1
MAN	0.11	0.32	0	1
MANAM	0.09	0.29	0	1
NAT	0.10	0.30	0	1
ORA	0.09	0.29	0	1
SEM	0.10	0.30	0	1

Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data

Appendix 6. Determinants of income mobility - Heckman estimation results

	Absolute Income Change - Whole sample	Relative Income Change - Whole sample
Big-Five Personality Traits		
Openness	0.469**	13.557***
	(0.191)	(4.130)
Conscientiousness	0.213	8.122
	(0.262)	(5.848)
Extraversion	0.381**	9.899**
	(0.176)	(4.072)
Agreeableness	0.030	2.607
	(0.228)	(5.042)
Emotional Stability	0.899***	22.736***
	(0.177)	(4.017)
Cognitive skills		
Raven Score	0.003	0.220
	(0.008)	(0.173)
Literacy	0.211	3.640
	(0.224)	(4.834)
Numeracy score	0.010	-0.885
	(0.063)	(1.410)
Log income (2010)	-0.900***	-30.242***
	(0.092)	(1.945)
Agricultural job	-0.095	2.240
	(0.100)	(2.479)
Casual job	-0.165	-3.532
	(0.135)	(3.020)
Education level (base below primary)		
Completed Primary	0.092	4.864
	(0.197)	(4.441)
Completed Middle School	-0.091	3.550
	(0.240)	(4.924)
Completed High School	-0.250	-0.875
	(0.278)	(6.534)
Completed Higher Secondary School	-0.138	-0.951
	(0.400)	(9.888)
Bachelors	0.330	8.368
	(0.819)	(18.522)
Age	0.051	1.769
	(0.053)	(1.292)
Squared age	-0.001	-0.028*
	(0.001)	(0.016)
Female	-1.179***	-24.383***
	(0.268)	(5.938)
Caste (base: Dalit)		
Middle Caste	0.068	1.591
	(0.121)	(2.868)
Upper Caste	0.406	10.016
	(0.419)	(10.364)
Household income without respondent's	-0.064	-1.583

	(0.111)	(2.380)
Relationship to head (base: head)		
Wife	-0.031	-2.146
	(0.304)	(7.037)
Son	-0.211	-2.845
	(0.420)	(10.321)
Other	-1.027	-30.891*
	(0.681)	(16.280)
Villages		
GOV	-0.292	-6.018
	(0.443)	(11.127)
KAR	-0.018	-0.245
	(0.217)	(5.703)
KOR	-0.074	-2.315
	(0.189)	(4.499)
KUV	0.233	9.028*
	(0.196)	(4.623)
MAN	0.089	5.519
	(0.195)	(4.675)
MANAM	-0.252	-3.856
	(0.227)	(5.308)
NAT	-0.122	-1.736
	(0.220)	(4.808)
ORA	-0.073	-1.499
	(0.211)	(4.867)
SEM	-0.267	-4.361
	(0.212)	(5.418)
Lambda (selection correction)	0.528	13.083*
	(0.326)	(7.545)
Constant	9.183***	289.835***
	(1.643)	(39.447)
Exclusion restriction from selection equation		
Dependence ratio (2010)	-6.294***	-6.294***
	(0.392)	(0.392)
Dependence ratio (2016)	1.309***	1.309***
	(0.344)	(0.344)
Observations	422	422

Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data.

Note: Bootstrapped standard errors (500 replications) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.The coefficients presented here are obtained from Heckman estimations with the household dependency ratios of 2010 and 2016 as exclusion restrictions.

Appendix 7. Determinants of income mobility by caste - Heckman estimation results (Full table)

	Absolute Income Change			Relative Income Change		
	Dalit	**Non-Dalit**	**Non-Dalit (with Upper caste interaction)**	**Dalit**	**Non-Dalit**	**Non-Dalit (with Upper caste interaction)**
Big-Five Personality Traits						
Openness	0.460*	0.487	0.582	15.312***	13.459*	17.247**
	(0.264)	(0.325)	(0.387)	(5.348)	(7.842)	(8.636)
Conscientiousness	0.177	0.364	0.671	7.520	12.073	21.522*
	(0.386)	(0.395)	(0.517)	(8.792)	(9.773)	(11.565)
Extraversion	0.317	0.420	0.551	9.940	6.478	9.519
	(0.251)	(0.296)	(0.379)	(6.045)	(7.881)	(9.047)
Agreeableness	0.223	-0.260	-0.310	10.711*	-8.519	-7.766
	(0.288)	(0.353)	(0.458)	(6.267)	(9.322)	(11.062)
Emotional Stability	0.751***	0.994***	1.340***	19.326***	26.563***	35.553***
	(0.230)	(0.293)	(0.335)	(5.487)	(6.748)	(7.276)
Cognitive skills						
Raven Score	-0.001	0.004	-0.011	0.019	0.342	-0.009
	(0.013)	(0.011)	(0.013)	(0.264)	(0.313)	(0.346)
Literacy	0.283	0.340	0.520	7.302	4.385	8.763
	(0.300)	(0.282)	(0.324)	(7.483)	(6.571)	(7.248)
Numeracy score	-0.023	0.079	0.131	-1.112	-0.331	0.954
	(0.084)	(0.100)	(0.117)	(2.023)	(2.529)	(2.851)
Interaction terms						
Openness # Upper Caste			-1.048			-29.328
			(0.990)			(26.449)
Conscientiousness # Upper Caste			-1.453			-49.486
			(1.602)			(40.415)
Extraversion # Upper Caste			-0.377			-2.134
			(1.079)			(27.496)
Agreeableness # Upper Caste			-0.041			-12.845
			(1.427)			(40.514)
Emotional Stability # Upper Caste			-2.170***			-53.303**
			(0.837)			(22.309)
Raven Score # Upper Caste			0.005			-0.090
			(0.036)			(0.971)

Literacy # Upper Caste			-0.473			-14.320
			(0.591)			(16.232)
Numeracy # Upper Caste			-0.258			-7.636
			(0.269)			(6.408)
Log income (2010)	-0.871***	-0.986***	-1.014***	-28.528***	-32.383***	-33.366***
	(0.139)	(0.146)	(0.160)	(3.065)	(3.621)	(4.265)
Casual job	-0.166	-0.206	-0.154	-2.918	-4.425	-3.210
	(0.182)	(0.210)	(0.232)	(4.816)	(5.155)	(5.238)
Agricultural job	-0.296**	0.147	0.085	-1.450	6.537	5.403
	(0.133)	(0.178)	(0.175)	(3.257)	(4.096)	(4.052)
Education level (base below primary)						
Completed Primary	0.069	-0.070	-0.187	2.281	5.791	2.617
	(0.247)	(0.299)	(0.312)	(5.954)	(7.034)	(7.355)
Completed Middle School	-0.324	-0.136	-0.239	-4.628	6.216	3.713
	(0.342)	(0.329)	(0.353)	(7.438)	(7.594)	(8.079)
Completed High School	-0.208	-0.550	-0.605	-1.487	-5.362	-5.730
	(0.392)	(0.399)	(0.441)	(8.100)	(10.208)	(11.554)
Completed Higher Secondary School	-0.186	-0.678	-0.635	-4.927	-7.849	-7.614
	(0.559)	(0.742)	(0.654)	(14.715)	(16.580)	(15.838)
Bachelors		0.314	0.485		10.971	16.846
		(0.767)	(0.951)		(19.358)	(24.610)
Age	-0.006	0.095	0.105	0.324	2.796	3.238
	(0.063)	(0.098)	(0.103)	(1.370)	(2.338)	(2.461)
Squared age	-0.000	-0.001	-0.002	-0.008	-0.040	-0.048
	(0.001)	(0.001)	(0.001)	(0.016)	(0.029)	(0.031)
Female	-0.743*	-1.818***	-1.778***	-15.247**	-40.462***	-39.630***
	(0.397)	(0.449)	(0.472)	(7.584)	(9.281)	(11.589)
Household income without respondent's	-0.084	-0.181	-0.201	-2.982	-3.492	-4.703
	(0.156)	(0.198)	(0.238)	(3.539)	(5.240)	(5.854)
Relationship to head (base: head)						
Wife	-0.087	0.189	-0.196	-2.308	4.833	-7.564
	(0.367)	(0.618)	(0.721)	(7.556)	(14.794)	(16.988)
Son	0.402	-0.155	-0.604	7.498	-0.446	-14.530
	(0.782)	(0.650)	(0.699)	(17.127)	(14.614)	(15.284)
Other	-0.730	-0.745	-1.980	-31.723*	-21.131	-54.680

	(0.802)	(1.366)	(1.521)	(17.134)	(31.194)	(38.765)
Villages						
GOV		-0.181	-0.717		-0.406	-19.335
		(0.389)	(0.742)		(10.394)	(16.866)
KAR	-0.143	-0.019	-0.033	-7.585	5.080	3.693
	(0.297)	(0.402)	(0.447)	(6.209)	(9.346)	(9.933)
KOR	0.120	-0.360	-0.179	0.149	-6.876	-2.426
	(0.282)	(0.342)	(0.349)	(6.287)	(8.669)	(8.602)
KUV	0.563**	-0.062	-0.045	15.921**	4.879	4.875
	(0.273)	(0.294)	(0.291)	(6.263)	(7.297)	(7.527)
MAN	0.034	0.248	0.329	3.506	10.554	12.002
	(0.258)	(0.316)	(0.364)	(6.000)	(8.211)	(8.403)
MANAM	-0.009	-0.262	-0.320	-0.532	-0.179	-2.153
	(0.272)	(0.460)	(0.492)	(6.165)	(11.201)	(11.699)
NAT	-0.018	-0.120	-0.074	-0.397	-1.003	-0.797
	(0.272)	(0.402)	(0.457)	(5.800)	(10.171)	(10.753)
ORA	0.260	-0.533	-0.518	2.984	-6.539	-6.520
	(0.252)	(0.396)	(0.467)	(5.820)	(9.108)	(10.317)
SEM	-0.202	0.050	-0.049	-4.465	5.748	2.852
	(0.299)	(0.346)	(0.408)	(6.810)	(9.581)	(10.250)
Lambda (selection correction)	-0.033	0.670	1.043*	5.859	14.354	26.836**
	(0.425)	(0.475)	(0.556)	(8.939)	(11.526)	(12.549)
Constant						
Exclusion restriction from selection equation						
Dependence ratio (2010)	2.158***	1.462**	1.462***	2.158***	1.462**	1.462**
	(0.613)	(0.574)	(0.553)	(0.597)	(0.575)	(0.570)
Dependence ratio (2016)	1.110***	-0.207	-0.207	1.110***	-0.207	-0.207
	(0.429)	(0.379)	(0.399)	(0.427)	(0.385)	(0.400)
Observations	232	190	190	232	190	190

Source: Authors' computations of RUME (2010) and NEEMSIS (2016-2017) data.

Note: Bootstrapped standard errors (500 replications) in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The coefficients presented here are obtained from Heckman estimations with the household dependency ratios of 2010 and 2016 as exclusion restrictions.

Appendix 8. Gender specific personality factors

Big-Five Personality Traits Long Inventory Description

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

Source: NEEMSIS (2016-2017)*;* Authors' computations.

A8.1. Female personality factors

Main factors analysis results

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.6985	3.42903	0.22	0.22
Factor2	4.26947	2.00943	0.122	0.3419
Factor3	2.26004	0.49535	0.0646	0.4065
Factor4	1.76469	0.28499	0.0504	0.4569
Factor5	1.4797	0.15804	0.0423	0.4992
Factor6	1.32166	0.13334	0.0378	0.537
Factor7	1.18832	0.11485	0.034	0.5709
Factor8	1.07347	0.09397	0.0307	0.6016
Factor9	0.9795	0.06804	0.028	0.6296
Factor10	0.91146	0.04505	0.026	0.6556

Note: LR test: independent vs. saturated: chi2(595) = 4017.58 Prob>chi2 = 0.0000

Personality traits variables associated with the 5 main female factors

Factors	F1F	F2F	F3F	F4F	F5F
changemood	**0.8151***	0.4113*	-0.2514*	-0.1429	-0.3845*
easilydistracted	**0.7494***	*0.5501**	-0.2757*	-0.0700	-0.3503*
helpfulwithothers	**0.6920***	0.0070	-0.2824*	0.0402	0.0315
talkative	**0.6501***	-0.0006	-0.0522	0.2854*	-0.4135*
appointmentontime	**-0.6436***	-0.4708*	-0.0180	-0.0906	0.1108
putoffduties	**0.6394***	*0.5158**	-0.2655*	-0.1218	-0.5841*
makeplans	-0.5842*	-0.4935*	0.3598*	-0.2650*	0.4532*
nervous	0.5759*	*0.5690**	-0.2171*	-0.1422	-0.1217
repetitivetasks	-0.5735*	-0.2511*	-0.1500	-0.2945*	0.1399
completeduties	-0.5278*	-0.2465*	-0.2355*	-0.3960*	0.0455
workhard	-0.5278*	-0.3154*	0.0626	-0.1062	0.0581
easilyupset	0.3611*	**0.7831***	-0.3473*	-0.2747*	-0.1290
managestress	-0.3539*	-0.1275	0.3198*	0.3783*	0.2333*
shywithpeople	0.3305*	0.4971*	-0.2772*	-0.2652*	0.1277
staycalm	-0.3172*	0.2389*	0.0504	0.1490	0.4931*
inventive	-0.3169*	*-0.5319**	0.5476*	0.1117	0.2427*
rudetoother	0.2882*	0.1705*	-0.0210	-0.1574*	**-0.6647***
enthusiastic	-0.2819*	-0.4186*	0.2850*	-0.1388	0.3988*
feeldepressed	0.2612*	**0.7518***	-0.0613	-0.0250	-0.2320*
enjoypeople	-0.2441*	0.0288	0.0651	-0.1001	0.2271*
worryalot	0.2403*	**0.8077***	-0.3761*	-0.1012	-0.1584*
curious	-0.2273*	-0.4101*	**0.7014***	0.1977*	0.3739*
liketothink	-0.2233*	-0.3278*	0.4010*	**0.6068***	0.1062
forgiveother	0.2003*	0.1487	**-0.7792***	-0.2567*	0.0532
organized	-0.1853*	*-0.5403**	0.4176*	-0.0249	0.2501*
talktomanypeople	0.1479	0.0082	0.2686*	**0.7041***	-0.0440
workwithother	-0.1462	-0.0604	-0.1052	-0.1144	0.0876
understandotherfeeling	0.1277	0.2358*	0.1265	0.0421	-0.5603*
newideas	-0.0874	-0.4241*	**0.6116***	0.2387*	0.0633
interestedbyart	-0.0726	-0.1715*	0.2162*	0.0729	0.0552
activeimagination	-0.0360	-0.3143*	0.3939*	0.5177*	0.0029
sharefeelings	-0.0266	-0.2182*	0.2016*	**0.6294***	0.3109*
trustingofother	0.0253	0.1548*	-0.2964*	-0.2306*	0.0294

expressingthoughts	0.0186	-0.1064	0.0881	**0.6789***	0.0671
toleratefaults	0.0062	0.2903*	**-0.6882***	-0.2169*	0.1288

Source: Authors' computations

Personality traits associated with female factors

Factors	**Significant items**					
Factor F1F	changemood *(ES)*	easilydistracted *(Co)*	helpfulwithothers *(Ag)*	talkative *(Ex)*	appointmentontime *(Co)*	putoffduties *(Co)*
Factor F2F	worryalot *(ES)*	easilyupset *(ES)*	feeldepressed *(ES)*			
Factor F3F	forgiveother *(Ag)*	curious *(Op)*	toleratefaults *(Ag)*	newideas *(Op)*		
Factor F4F	talktomanypeople *(Ex)*	expressingthoughts *(Ex)*	sharefeelings *(Ex)*	liketothink *(Op)*		
Factor F5F	rudetoother *(Ag)*					

Source: Authors.

Note: Personality traits associated to variables are given in brackets (ES: Emotional Stability; Ag: Agreeableness; Co: Conscientiousness; Ex: Extraversion; Op: Openness).

A8.2. Male personality factors

Main factors analysis results

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	7.43684	3.42355	0.2125	0.2125
Factor2	4.01329	1.65715	0.1147	0.3271
Factor3	2.35614	0.55632	0.0673	0.3945
Factor4	1.79982	0.2952	0.0514	0.4459
Factor5	1.50462	0.04203	0.043	0.4889
Factor6	1.46259	0.34358	0.0418	0.5307
Factor7	1.11901	0.03595	0.032	0.5626
Factor8	1.08306	0.09541	0.0309	0.5936
Factor9	0.98765	0.06556	0.0282	0.6218
Factor10	0.9221	0.08189	0.0263	0.6481

Note: LR test: independent vs. saturated: chi2(595) = 5230.20 Prob>chi2 = 0.0000

Personality traits variables associated with the 5 main male factors

Factors	F1M	F2M	F3M	F4M	F5M
easilydistracted	**0.7923***	-0.3804*	-0.1219	0.1029	-0.1544*
nervous	**0.7915***	-0.2326*	-0.2253*	-0.1060	-0.0576
changemood	**0.7840***	-0.4365*	-0.1566*	0.0182	-0.2680*
putoffduties	**0.6553***	**-0.6001***	-0.1618*	0.0418	-0.1590*
feeldepressed	**0.6446***	-0.2213*	-0.2509*	-0.0473	0.2311*
easilyupset	**0.6170***	-0.2474*	-0.2465*	-0.3066*	0.1722*
worryalot	0.5971*	-0.2002*	-0.2945*	-0.2372*	0.1090
makeplans	-0.5921*	0.5657*	0.0189	-0.2372*	0.2115*
appointmentontime	-0.5891*	0.4736*	-0.1700*	-0.4273*	0.1215
enthusiastic	-0.5567*	0.4448*	0.1005	-0.0999	0.1684*
completeduties	-0.5128*	0.3708*	-0.2306*	*-0.5077**	-0.0194
repetitivetasks	-0.5063*	0.2654*	-0.2936*	-0.2580*	-0.0470
organized	-0.4415*	0.4189*	-0.0553	-0.1836*	0.1949*
helpfulwithothers	0.4308*	-0.3399*	0.0595	0.1039	-0.4196*
shywithpeople	0.4296*	-0.1090	-0.2824*	-0.3340*	-0.1652*
workwithother	-0.4265*	0.3675*	-0.4469*	-0.0587	0.0875
workhard	-0.4190*	**0.7014***	-0.2116*	-0.1386*	0.0543
talkative	0.3939*	-0.3299*	0.0253	*0.5310**	-0.0691
inventive	-0.3894*	0.2160*	0.5842*	0.1531*	0.2249*
enjoypeople	-0.3623*	0.0851	-0.0560	0.1808*	-0.0079
rudetoother	0.3416*	**-0.7723***	-0.1500*	-0.0339	-0.1954*
understandotherfeeling	0.3200*	-0.3809*	0.2103*	0.2485*	0.4434*
liketothink	-0.2488*	-0.1633*	0.5582*	0.2948*	0.3402*
activeimagination	-0.2477*	0.0777	**0.6835***	0.3211*	0.1403*
curious	-0.2410*	0.1340*	**0.7267***	0.2321*	0.2439*
newideas	-0.2152*	0.0954	**0.6979***	0.0872	0.1348*
managestress	-0.2112*	0.1467*	-0.0126	0.1384*	0.1485*
forgiveother	0.1448*	-0.2049*	-0.2393*	-0.1306	**-0.7274***
sharefeelings	-0.1031	0.2741*	0.3359*	*0.5435**	0.1682*
expressingthoughts	-0.0883	0.0625	0.3969*	**0.6418***	0.0333
staycalm	-0.0782	0.0228	0.0286	0.0642	-0.0237
interestedbyart	-0.0688	-0.0417	0.5203*	0.1840*	0.2032*
talktomanypeople	-0.0493	-0.1125	0.1046	**0.7090***	0.1580*
trustingofother	-0.0388	0.1372*	-0.1305	-0.0947	-0.0812
toleratefaults	-0.0226	-0.0305	-0.2894*	-0.1030	**-0.7013***

Source: Authors' computations

Personality traits associated with male factors

Factors	Significant items					
Factor F1F	easilydistracted *(Co)*	nervous *(ES)*	changemood *(ES)*	putoffduties *(Co)*	feeldepressed *(ES)*	easilyupset *(ES)*
Factor F2F	rudetoother *(Ag)*	workhard *(Co)*	putoffduties *(Co)*			
Factor F3F	curious *(Op)*	newideas *(Op)*	activeimagination *(Op)*			
Factor F4F	talktomanypeople *(Ex)*	expressingthoughts *(Ex)*				
Factor F5F	forgiveother *(Ag)*	toleratefaults *(Ag)*				

Note: Personality traits associated to variables are given in brackets (ES: Emotional Stability; Ag: Agreeableness; Co: Conscientiousness; Ex: Extraversion; Op: Openness).

A8.3. Comparison of factors: Cronbach Alphas for FFM and gender-specific factors

	FFM Factors		Gender Specific Factors	
Factors	Cronbach Alpha FFM Female	Cronbach Alpha FFM Male	Cronbach Alpha Factors Female	Cronbach Alpha Factors Male
Factor 1	0.696	0.727	0.881	0.877
Factor 2	0.814	0.799	0.832	0.712
Factor 3	0.546	0.598	0.797	0.753
Factor 4	0.463	0.374	0.729	0.659
Factor 5	0.744	0.724	0.588	0.659

Source: Authors' computations

Appendix 9. Determinants of income mobility by gender - Heckman estimation results

	Absolute Income Change - Men	Relative Income Change - Men	Absolute Income Change - Men	Relative Income Change - Men	Absolute Income Change - Women	Relative Income Change - Women	Absolute Income Change - Women	Relative Income Change - Women
Big-Five Personality Traits								
Openness	0.440**	14.145***			0.421	10.766		
	(0.213)	(5.454)			(0.338)	(7.387)		
Conscientiousness	0.552*	16.949**			-0.292	-4.904		
	(0.323)	(8.281)			(0.458)	(8.869)		
Extraversion	0.450**	13.705**			0.050	0.084		
	(0.226)	(5.460)			(0.360)	(7.493)		
Agreeableness	0.219	4.981			-0.409	-4.565		
	(0.309)	(7.472)			(0.397)	(8.251)		
Emotional Stability	0.813***	22.109***			0.851***	20.616***		
	(0.215)	(5.186)			(0.307)	(6.248)		
Male factors								
FM1			0.173*	4.916**				
			(0.088)	(2.340)				
FM2			-0.038	-1.733				
			(0.083)	(2.175)				
FM3			0.019	1.241				
			(0.100)	(2.459)				
FM4			0.094	2.681				
			(0.076)	(1.755)				
FM5			0.101	2.867				
			(0.078)	(1.859)				
Female factors								
FF1							0.238**	4.968*
							(0.114)	(2.868)
FF2							0.255**	6.606**
							(0.124)	(2.780)
FF3							0.254*	5.361*
							(0.143)	(3.146)
FF4							0.066	1.314

							(0.113)	(2.297)
FF5							0.101	1.913
							(0.120)	(2.536)
Cognitive skills								
Raven Score	-0.001	0.137	0.001	0.150	0.000	0.039	-0.016	-0.266
	(0.009)	(0.246)	(0.010)	(0.267)	(0.017)	(0.310)	(0.017)	(0.342)
Literacy	-0.072	-1.225	-0.107	-2.110	0.635*	12.436	0.726**	13.819
	(0.270)	(6.550)	(0.292)	(6.588)	(0.353)	(7.924)	(0.366)	(8.553)
Numeracy score	0.064	0.686	0.090	0.594	0.052	0.409	-0.037	-1.493
	(0.075)	(1.838)	(0.078)	(1.993)	(0.139)	(3.153)	(0.147)	(3.536)
Log income (2010)	-1.145***	-38.015***	-1.098***	-36.250***	-0.633***	-22.900***	-0.654***	-24.062***
	(0.139)	(3.549)	(0.158)	(3.738)	(0.139)	(3.722)	(0.175)	(3.754)
Agricultural job	-0.064	1.203	-0.125	-0.494	-0.252	0.877	-0.304	-0.449
	(0.127)	(3.116)	(0.134)	(3.637)	(0.187)	(4.752)	(0.211)	(5.177)
Casual job	-0.325**	-7.049**	-0.282**	-5.305	0.709**	14.017	0.812*	15.700*
	(0.131)	(3.216)	(0.138)	(3.513)	(0.358)	(8.560)	(0.432)	(8.801)
Education level (base below primary)								
Completed Primary	0.222	7.349	0.195	8.088	-0.061	0.472	0.055	3.839
	(0.258)	(6.871)	(0.270)	(6.499)	(0.307)	(7.510)	(0.331)	(7.083)
Completed Middle School	0.247	10.130	0.218	10.847	-0.674	-7.747	-0.359	-1.323
	(0.282)	(7.776)	(0.302)	(7.302)	(0.442)	(9.971)	(0.471)	(10.359)
Completed High School	-0.006	4.920	-0.044	5.219	-0.489	-9.045	-0.247	-4.307
	(0.323)	(9.112)	(0.362)	(9.224)	(0.494)	(10.443)	(0.571)	(11.736)
Completed Higher Secondary School	0.095	3.021	0.030	2.629				
	(0.427)	(11.251)	(0.447)	(11.128)				
Bachelors	0.626	14.810	0.446	9.723				
	(0.752)	(21.000)	(0.817)	(19.743)				
Age	-0.026	0.468	-0.043	0.133	0.190*	4.430**	0.184	4.299*
	(0.070)	(1.619)	(0.076)	(1.818)	(0.098)	(1.945)	(0.116)	(2.211)
Squared age	-0.000	-0.014	0.000	-0.008	-0.003**	-0.060**	-0.003*	-0.058**
	(0.001)	(0.020)	(0.001)	(0.022)	(0.001)	(0.025)	(0.002)	(0.029)
Caste (base: Dalit)								
Middle Caste	0.329**	7.915**	0.300*	6.820*	-0.202	-3.109	-0.183	-2.610

	(0.152)	(3.788)	(0.160)	(3.854)	(0.252)	(5.683)	(0.288)	(5.839)
Upper Caste	0.695	17.790	0.594	16.452	0.806	27.227	1.746	49.640**
	(0.450)	(12.095)	(0.556)	(13.398)	(1.037)	(22.729)	(1.161)	(24.568)
Household income without respondent's	0.046	1.116	0.038	-0.127	-0.178	-3.555	-0.254	-5.426
	(0.177)	(4.254)	(0.208)	(4.312)	(0.173)	(3.689)	(0.215)	(4.494)
Relationship to head (base: head)								
Wife					-0.114	-0.924	-0.026	0.564
					(0.331)	(6.936)	(0.358)	(7.365)
Son	-0.470	-11.165	-0.396	-12.344				
	(0.554)	(13.456)	(0.605)	(14.669)				
Other	-1.492	-39.582	-1.442	-43.162	-1.157	-26.098	-1.109	-25.361
	(0.979)	(24.954)	(1.073)	(29.283)	(0.801)	(17.591)	(0.969)	(20.770)
Villages								
GOV	-0.448	-9.411	-0.391	-7.885	-0.404	-26.755	-1.537	-52.437**
	(0.494)	(13.149)	(0.586)	(14.323)	(1.029)	(21.019)	(1.011)	(21.143)
KAR	0.008	-0.525	-0.092	-3.266	-0.341	-6.216	-0.265	-4.768
	(0.242)	(7.131)	(0.272)	(7.419)	(0.372)	(8.498)	(0.471)	(10.060)
KOR	-0.336	-7.375	-0.395	-9.336	0.008	-1.029	0.095	0.687
	(0.302)	(7.158)	(0.303)	(7.959)	(0.287)	(6.625)	(0.301)	(6.189)
KUV	0.111	7.582	-0.093	1.778	0.523	15.112*	0.294	10.977
	(0.240)	(6.067)	(0.242)	(5.706)	(0.342)	(8.609)	(0.378)	(9.513)
MAN	0.314	10.658*	0.259	8.389	-0.283	-2.751	-0.246	-2.073
	(0.221)	(5.780)	(0.231)	(6.152)	(0.343)	(7.849)	(0.342)	(8.393)
MANAM	-0.219	-4.029	-0.352	-6.898	-0.373	-1.246	0.169	10.136
	(0.260)	(7.241)	(0.291)	(7.374)	(0.477)	(9.684)	(0.441)	(8.860)
NAT	-0.024	-0.037	0.060	1.657	-0.632*	-10.849	-0.682	-12.191
	(0.266)	(6.317)	(0.243)	(6.226)	(0.378)	(9.157)	(0.422)	(8.632)
ORA	0.077	3.066	-0.073	0.474	-0.586*	-11.660	-0.359	-6.666
	(0.259)	(6.743)	(0.290)	(7.681)	(0.355)	(8.405)	(0.463)	(9.836)
SEM	-0.149	-0.854	-0.288	-3.927	-0.641	-12.763	-0.611	-11.460
	(0.264)	(6.575)	(0.268)	(6.515)	(0.401)	(8.721)	(0.425)	(9.489)
Lambda (selection correction)	0.560	15.405	0.465	16.018	0.451	8.977	0.438	8.142
	(0.480)	(10.676)	(0.509)	(11.956)	(0.355)	(7.461)	(0.419)	(7.862)

Constant	12.150***	368.864***	12.064***	370.066***	3.827	158.151**	4.881	192.228***
	(2.453)	(58.278)	(2.416)	(59.976)	(2.805)	(62.549)	(3.210)	(64.299)
Exclusion restriction from selection equation								
Dependence ratio (2010)	0.296	0.296	0.137	0.137	2.906***	2.906***	2.766***	2.766***
	(0.561)	(0.569)	(0.531)	(0.544)	(0.521)	(0.508)	(0.549)	(0.570)
Dependence ratio (2016)	0.980**	0.980**	0.955**	0.955**	-0.419	-0.419	-0.420	-0.420
	(0.430)	(0.435)	(0.452)	(0.424)	(0.399)	(0.390)	(0.425)	(0.429)
Observations	261	261	261	261	161	161	161	161

Source: Authors' computation of RUME (2010) and NEEMSIS (2016-2017) data.
Note: Bootstrapped standard errors (500 replications) in parentheses. The coefficients presented here are obtained from Heckman estimations with the household dependency ratios of 2010 and 2016 as exclusion restrictions.

Appendix 10. Summary statistics of Agriculture/Non-agriculture and Casual/Regular transitions

	Whole sample	Men	Women	Dalit	Middle	Upper
Agriculture/non-agriculture transitions						
Transitions to agriculture	14.60	17.67	10.22	15.55	16.18	2.44
No transition (agriculture)	32.96	22.18	48.39	39.08	29.48	12.20
No transition (non-agriculture)	31.42	37.97	22.04	28.15	28.90	60.98
Transition to non-agriculture	21.02	22.18	19.35	17.23	25.43	24.39
Casual/Regular transitions						
Transition to casual	9.95	13.41	4.35	9.91	10.83	6.06
No transition (casual)	42.42	23.37	73.29	58.19	28.03	0
No transition (regular)	25.83	39.46	3.73	12.93	33.12	81.82
Transition to regular	21.80	23.75	23.68	18.97	28.03	12.12

Source: Authors' computation of RUME (2010) and NEEMSIS (2016-2017) data

Appendix 11. Transitions to non-agricultural jobs – Heckman ordered probit estimation results

	Transition to Non-Agricultural Jobs - Heckman Ordered Probit Estimates						
	Whole sample	Dalit	Non-Dalit	Men	Women	Men	Women
Big-Five Personality Traits							
Openness	0.927**	1.150	0.870	0.622	1.778*		
	(0.433)	(0.744)	(0.902)	(0.570)	(1.072)		
Conscientiousness	0.161	0.234	0.158	-0.393	1.178		
	(0.582)	(1.015)	(1.028)	(0.848)	(1.229)		
Extraversion	0.350	0.704	0.052	0.228	0.864		
	(0.405)	(0.661)	(0.733)	(0.573)	(0.948)		
Agreeableness	0.137	0.759	-0.410	-0.248	0.721		
	(0.475)	(0.804)	(0.912)	(0.670)	(1.301)		
Emotional Stability	1.396***	1.414**	1.546**	1.101**	2.250**		
	(0.402)	(0.700)	(0.736)	(0.541)	(0.969)		
Male factors							
FM1						0.422*	
						(0.245)	
FM2						-0.173	
						(0.271)	
FM3						0.531**	
						(0.240)	
FM4						0.352	
						(0.231)	
FM5						0.016	
						(0.204)	
Female factors							
FF1							0.534
							(0.532)
FF2							0.467
							(0.468)
FF3							0.424
							(0.554)
FF4							0.040
							(0.407)
FF5							0.119
							(0.371)
Cognitive skills							
Raven Score	-0.004	0.008	-0.012	-0.006	0.023	-0.028	0.020

	(0.017)	(0.032)	(0.026)	(0.022)	(0.048)	(0.025)	(0.055)
Literacy	0.406	0.207	0.654	-0.036	1.591	-0.040	1.422
	(0.384)	(0.782)	(0.609)	(0.564)	(1.226)	(0.577)	(1.435)
Numeracy score	-0.062	-0.017	-0.156	-0.101	0.081	-0.132	-0.079
	(0.159)	(0.250)	(0.257)	(0.194)	(0.376)	(0.206)	(0.474)
Log income (2010)	-0.889***	-1.229***	-0.600	-0.638*	-1.615***	-0.519	-1.538*
	(0.212)	(0.365)	(0.403)	(0.350)	(0.614)	(0.418)	(0.848)
Education level (base below primary)							
Completed Primary	-0.101	0.234	-0.377	0.134	-0.631	0.081	-0.374
	(0.364)	(0.641)	(0.640)	(0.649)	(0.903)	(0.701)	(1.116)
Completed Middle School	0.947*	0.332	1.312	1.183	-0.720	1.184	-0.181
	(0.497)	(0.868)	(0.814)	(0.815)	(1.356)	(0.859)	(1.554)
Completed High School	0.460	0.184	0.560	0.937	-1.026	0.893	-0.830
	(0.608)	(1.051)	(0.936)	(0.869)	(1.424)	(0.926)	(1.604)
Completed Higher Secondary School	0.493	2.288	-0.323	0.962		1.194	
	(0.725)	(3.071)	(1.007)	(0.840)		(0.883)	
Bachelors	0.384		0.569	0.994		1.842	
	(5.361)		(5.848)	(4.771)		(4.627)	
Age	0.154	-0.006	0.058	-0.025	0.447	-0.020	0.393
	(0.127)	(0.181)	(0.232)	(0.211)	(0.328)	(0.240)	(0.438)
Squared age	-0.002	-0.001	-0.001	0.000	-0.007	0.000	-0.006
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.006)
Female	-0.105	0.299	-1.001				
	(0.653)	(1.182)	(1.390)				
Caste (base: Dalit)							
Middle Caste	0.141				-0.703	-0.035	-0.729
	(0.270)				(0.977)	(0.401)	(1.046)
Upper Caste	0.373				-5.473	0.535	-5.483
	(0.681)				(5.929)	(0.952)	(6.828)
Household income without respondent's	-0.113	-0.118	-0.278	0.013	-0.675	-0.176	-0.836
	(0.215)	(0.327)	(0.453)	(0.370)	(0.558)	(0.364)	(0.729)
Relationship to head (base: head)							
Wife	-0.780	-1.619	0.927		-1.518		-1.176
	(0.714)	(1.140)	(1.729)		(1.534)		(1.639)

Son	-1.450	-2.267	-0.691	-0.192		-0.174	
	(1.213)	(2.007)	(1.534)	(1.784)		(1.885)	
Other	-1.871	-4.036	0.550	0.416	-5.081	0.684	-3.894
	(1.723)	(4.001)	(3.106)	(2.246)	(3.814)	(2.490)	(4.267)
Villages							
GOV	0.058		-0.099	-0.605	4.560	-0.109	5.112
	(0.849)		(1.276)	(1.111)	(9.755)	(1.265)	(10.976)
KAR	-1.497***	-1.398	-1.913*	-1.431*	-1.895	-1.277	-0.821
	(0.570)	(1.070)	(1.099)	(0.851)	(2.012)	(0.871)	(2.149)
KOR	-0.771	-1.436*	-0.775	-1.058	-0.753	-1.155	-0.703
	(0.483)	(0.739)	(0.916)	(0.843)	(0.985)	(0.884)	(1.238)
KUV	-0.050	0.229	-0.765	-0.010	-1.272	-0.635	-1.705
	(0.489)	(0.706)	(0.969)	(0.713)	(1.329)	(0.825)	(1.910)
MAN	-0.473	-0.761	-0.632	-0.180	-1.736	-0.419	-1.798
	(0.480)	(0.816)	(0.930)	(0.763)	(1.571)	(0.801)	(1.584)
MANAM	-0.641	-0.499	-1.018	-0.819	-0.716	-0.820	-0.020
	(0.529)	(0.805)	(1.232)	(0.749)	(1.538)	(0.833)	(2.220)
NAT	-1.176**	-1.326	-1.543	-0.956	-2.999*	-0.730	-3.198*
	(0.556)	(0.858)	(1.118)	(0.800)	(1.598)	(0.929)	(1.911)
ORA	-0.556	-0.951	-0.501	-0.171	-2.840**	0.726	-2.182
	(0.556)	(0.923)	(1.085)	(0.880)	(1.336)	(0.960)	(1.594)
SEM	-1.698***	-1.594*	-1.572	-1.539**	-3.103*	-1.445*	-2.750
	(0.574)	(0.892)	(1.048)	(0.770)	(1.675)	(0.859)	(1.888)
Lambda (selection correction)	0.525	0.697	0.286	-0.650	2.193*	-0.699	2.123
	(0.680)	(0.999)	(0.995)	(1.372)	(1.311)	(1.502)	(1.541)
Ologit Cuts							
Cut1	-10.165**	-18.040***	-10.350	-9.671	-19.962*	-11.148	-21.725
	(3.948)	(6.206)	(7.089)	(6.272)	(10.429)	(7.213)	(14.148)
Cut2	-6.449*	-13.863**	-6.657	-6.422	-14.093	-7.546	-15.874
	(3.902)	(6.084)	(6.967)	(6.246)	(9.813)	(7.123)	(13.424)
Observations	452	238	214	266	186	266	186

Source: Authors' computation of RUME (2010) and NEEMSIS (2016-2017) data.
Note: Bootstrapped standard errors (500 replications) in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The coefficients presented here are obtained from Heckman ordered probit estimations with the household dependency ratios of 2010 and 2016 as exclusion restrictions.

Appendix 12. Transitions to regular jobs – Heckman ordered probit estimation results

	Transition to Regular Jobs - Heckman Ordered Probit Estimates						
	Whole sample	Dalit	Non-Dalit	Men	Women	Men	Women
Big-Five Personality Traits							
Openness	0.418	0.797	0.396	-0.004	1.473		
	(0.433)	(0.682)	(0.869)	(0.624)	(1.043)		
Conscientiousness	0.313	0.613	0.868	0.342	0.309		
	(0.630)	(1.030)	(0.982)	(0.857)	(1.477)		
Extraversion	0.322	0.771	0.473	0.002	1.144		
	(0.430)	(0.843)	(0.738)	(0.574)	(1.087)		
Agreeableness	0.203	0.385	0.487	0.095	0.678		
	(0.509)	(0.769)	(0.962)	(0.687)	(1.266)		
Emotional Stability	0.972**	1.691***	0.459	0.695	1.740		
	(0.384)	(0.648)	(0.677)	(0.531)	(1.058)		
Male factors							
FM1						0.588**	
						(0.237)	
FM2						0.166	
						(0.193)	
FM3						0.084	
						(0.232)	
FM4						0.054	
						(0.208)	
FM5						-0.033	
						(0.198)	
Female factors							
FF1							0.836*
							(0.487)
FF2							0.205
							(0.481)
FF3							0.575
							(0.573)
FF4							0.402
							(0.369)
FF5							0.111
							(0.308)
Cognitive skills							
Raven Score	0.022	0.031	0.002	0.023	0.058	0.012	0.057
	(0.016)	(0.030)	(0.026)	(0.020)	(0.051)	(0.022)	(0.060)
Literacy	0.209	0.927	-0.068	0.067	0.031	0.061	-0.546
	(0.447)	(0.869)	(0.694)	(0.629)	(1.204)	(0.642)	(1.394)
Numeracy score	0.094	-0.286	0.355	-0.022	0.677	0.003	0.600
	(0.152)	(0.287)	(0.257)	(0.198)	(0.459)	(0.188)	(0.484)
Log income (2010)	-0.676***	-0.869***	-0.675*	-0.820**	-0.681	-0.850**	-0.764
	(0.193)	(0.326)	(0.375)	(0.352)	(0.522)	(0.388)	(0.591)
Education level (base below primary)							
Completed Primary	-0.152	-0.780	0.292	-0.155	-0.477	-0.115	-0.101
	(0.430)	(0.770)	(0.798)	(0.738)	(1.025)	(0.761)	(1.024)
Completed Middle School	-0.518	-0.734	-0.099	-0.388	-1.877	-0.326	-1.151
	(0.505)	(0.960)	(0.858)	(0.863)	(1.395)	(0.846)	(1.360)
Completed High School	-0.769	-0.882	-0.608	-0.196	-3.182	-0.272	-2.707
	(0.633)	(1.178)	(1.004)	(0.817)	(2.091)	(0.887)	(2.085)
Completed Higher Secondary School	-0.600	0.722	-1.951	-0.141		-0.143	
	(0.713)	(1.704)	(1.397)	(0.909)		(0.889)	

Bachelors	0.204		0.806	0.551		0.920	
	(3.099)		(3.324)	(2.894)		(3.316)	
Age	0.127	0.197	0.075	-0.022	0.178	0.006	0.009
	(0.131)	(0.187)	(0.252)	(0.219)	(0.384)	(0.216)	(0.394)
Squared age	-0.002	-0.003	-0.002	-0.000	-0.003	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.003)	(0.005)
Female	-0.054	0.233	-1.582				
	(0.707)	(1.395)	(1.390)				
Caste (base: Dalit)							
Middle Caste	0.391			0.417	0.297	0.540	0.450
	(0.276)			(0.376)	(0.844)	(0.410)	(0.882)
Upper Caste	-0.277		-1.142	-0.365	-0.108	-0.247	0.584
	(0.741)		(0.902)	(0.884)	(7.641)	(1.009)	(6.390)
Household income without respondent’s	0.166	0.419	-0.438	0.215	0.181	0.270	0.137
	(0.226)	(0.378)	(0.504)	(0.390)	(0.558)	(0.417)	(0.619)
Relationship to head (base: head)							
Wife	-0.219	-0.761	-0.259		-0.054		0.058
	(0.730)	(1.280)	(1.845)		(1.770)		(1.796)
Son	-0.802	-1.229	-2.820*	0.185		-0.106	
	(1.178)	(2.791)	(1.558)	(1.817)		(1.746)	
Other	-0.728	-3.026	-2.752	-0.053	-0.544	-0.080	0.090
	(1.905)	(2.537)	(4.951)	(2.263)	(4.565)	(2.061)	(4.533)
Villages							
GOV	0.604		0.119	0.276	1.795	0.557	2.050
	(0.940)		(1.290)	(1.154)	(10.724)	(1.256)	(10.146)
KAR	-0.724	-0.812	-1.077	-0.375	-1.411	-0.447	-1.269
	(0.568)	(0.882)	(1.097)	(0.871)	(2.012)	(0.896)	(1.717)
KOR	-0.066	0.031	-0.296	0.176	-0.140	0.372	0.238
	(0.497)	(0.805)	(1.029)	(0.829)	(0.963)	(0.810)	(1.022)
KUV	0.433	0.910	-0.187	0.255	0.707	0.010	0.179
	(0.560)	(1.034)	(1.005)	(0.902)	(1.297)	(0.904)	(1.535)
MAN	-0.542	-0.842	-0.122	-0.717	-0.520	-0.732	-0.652
	(0.591)	(0.873)	(1.089)	(0.980)	(1.950)	(0.873)	(1.380)
MANAM	-1.070*	-1.347	-1.352	-1.245	-0.400	-1.352	-0.368
	(0.608)	(0.927)	(1.014)	(0.855)	(1.682)	(0.869)	(2.043)
NAT	0.843	0.682	1.212	0.618	1.002	0.712	0.994
	(0.514)	(0.882)	(1.103)	(0.838)	(1.562)	(0.828)	(1.629)
ORA	-0.218	-0.413	-0.179	0.206	-1.593	0.344	-0.882
	(0.524)	(0.890)	(0.982)	(0.854)	(1.291)	(0.854)	(1.561)
SEM	-0.336	-1.160	0.340	0.066	-1.349	0.280	-0.971
	(0.597)	(0.963)	(1.083)	(0.929)	(1.443)	(1.016)	(1.543)
Lambda (selection correction)	0.508	1.203	2.159**	-0.415	0.905	-0.256	0.736
	(0.695)	(1.233)	(1.004)	(1.310)	(1.152)	(1.217)	(1.180)
Ologit Cuts							
Cut1	-5.297	-3.930	-13.758*	-9.257	-5.017	-8.614	-9.269
	(3.734)	(6.439)	(7.934)	(6.602)	(9.437)	(6.424)	(10.672)
Cut2	-1.427	0.517	-9.840	-5.745	0.626	-5.146	-3.630
	(3.722)	(6.354)	(7.887)	(6.542)	(9.851)	(6.371)	(10.887)
Observations	452	238	214	266	186	266	186

Source: Authors’ computation of RUME (2010) and NEEMSIS (2016-2017) data.

Note: Bootstrapped standard errors (500 replications) in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The coefficients presented here are obtained from Heckman ordered probit estimations with the household dependency ratios of 2010 and 2016 as exclusion restrictions.

Appendix 13. Determinants of entry into the labour market

	Change of occupational status			
	No entry (base category)	Entry	Exit	Active in both waves
Big-Five Personality Traits				
Openness		3.148**	2.287	2.968**
		(1.487)	(1.612)	(1.352)
Conscientiousness		4.133**	3.376	3.661*
		(2.100)	(2.259)	(1.953)
Extraversion		1.807	2.734*	1.248
		(1.566)	(1.660)	(1.477)
Agreeableness		1.851	0.211	2.407
		(1.708)	(1.871)	(1.576)
Emotional Stability		0.406	0.417	0.768
		(1.266)	(1.349)	(1.185)
Cognitive skills				
Raven Score		0.105*	0.129**	0.042
		(0.055)	(0.059)	(0.050)
Literacy		-2.050	-2.918	-0.667
		(1.546)	(1.888)	(1.465)
Numeracy score		0.555	-0.232	0.097
		(0.623)	(0.675)	(0.599)
Education level (base below primary)				
Completed Primary		-1.811	-1.871	-2.027
		(1.349)	(1.503)	(1.273)
Completed Middle School		-5.329***	-1.570	-5.601***
		(1.778)	(2.084)	(1.657)
Completed High School		-4.163*	0.188	-3.263
		(2.188)	(2.510)	(2.076)
Completed Higher Secondary School		-15.986***	-8.874**	-16.370***
		(4.286)	(4.518)	(4.279)
Bachelors		-22.975	-17.078	-24.424
		(735.255)	(735.257)	(735.255)
Age		-0.483	-0.489	-0.156
		(0.367)	(0.380)	(0.348)
Squared age		0.002	0.003	-0.001
		(0.004)	(0.004)	(0.004)
Female		-18.153	-15.573	-20.374
		(6,863.094)	(6,863.094)	(6,863.094)
Caste (base: Dalit)				
Middle caste		-1.150	-1.257	-2.188**
		(1.166)	(1.225)	(1.107)
Upper caste		-0.129	2.435	-1.309
		(1.622)	(1.968)	(1.508)
Relationship to head (base: head)				
Wife		-16.687	-18.740	-18.629
		(6,882.823)	(6,882.823)	(6,882.822)
Son		0.129	-0.726	-2.577
		(2,244.992)	(2,244.992)	(2,244.992)
Other		-21.048	-45.313	-24.255
		(6,882.823)	(24,632.619)	(6,882.823)
Villages				
GOV		-2.792	-4.693*	-4.017*
		(2.511)	(2.760)	(2.280)
KAR		3.520*	1.457	0.948

		(1.827)	(1.942)	(1.681)
KOR		-16.662	-19.608	0.170
		(4,171.256)	(4,343.236)	(1.688)
KUV		19.427	18.299	17.610
		(3,416.270)	(3,416.270)	(3,416.270)
MAN		27.938	26.969	26.894
		(2,362.732)	(2,362.732)	(2,362.732)
MANAM		-2.306	-21.892	-4.649***
		(1.837)	(4,848.459)	(1.631)
NAT		6.962***	-14.356	5.876**
		(2.500)	(3,981.602)	(2.405)
ORA		0.290	0.111	-0.862
		(1.730)	(1.743)	(1.514)
SEM		-0.247	-2.782*	-2.818**
		(1.452)	(1.654)	(1.236)
Constant		53.893	53.009	55.859
		(1,104.232)	(1,104.237)	(1,104.230)
Observations	32	50	30	886

Source: Authors' computation of RUME (2010) and NEEMSIS (2016-2017) data.
Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The coefficients presented here are obtained from a multinomial logistic estimation.

Appendix 14. OLS determinants of interpersonal networks (workers' potential and actual ties)

	Actual ties	Potential ties	Total ties
Big-Five Personality Traits			
Openness	-0.535*	-0.724	-1.259
	(0.317)	(0.650)	(0.776)
Conscientiousness	-0.123	-0.197	-0.320
	(0.443)	(0.909)	(1.087)
Extraversion	0.053	0.639	0.692
	(0.311)	(0.638)	(0.762)
Agreeableness	-0.704*	-0.779	-1.483
	(0.375)	(0.769)	(0.919)
Emotional Stability	-0.095	1.148**	1.053
	(0.268)	(0.551)	(0.658)
Cognitive skills			
Raven Score	-0.002	-0.035	-0.037
	(0.012)	(0.025)	(0.030)
Literacy	0.062	-1.083*	-1.021
	(0.300)	(0.615)	(0.736)
Numeracy score	-0.017	0.563***	0.546**
	(0.103)	(0.211)	(0.252)
Education level (base below primary)			
Completed Primary	0.230	0.583	0.812
	(0.275)	(0.564)	(0.674)
Completed Middle School	0.099	0.761	0.860
	(0.352)	(0.723)	(0.864)
Completed High School	-0.533	-0.004	-0.537
	(0.397)	(0.813)	(0.972)
Completed Higher Secondary School	0.975*	2.279*	3.254**
	(0.582)	(1.194)	(1.427)
Bachelors	-0.448	2.927	2.479
	(0.953)	(1.955)	(2.336)
Age	0.102	0.469**	0.571**
	(0.105)	(0.215)	(0.257)
Squared age	-0.001	-0.004**	-0.005*
	(0.001)	(0.002)	(0.003)
Female	-0.188	-0.822	-1.011
	(0.421)	(0.863)	(1.031)
Caste (base: Dalit)			
Middle Caste	0.107	-0.067	0.040
	(0.179)	(0.366)	(0.438)
Upper Caste	0.844***	2.875***	3.719***
	(0.325)	(0.666)	(0.796)
Household income without respondent's	-0.341**	0.249	-0.092
	(0.150)	(0.307)	(0.367)
Relationship to head (base: head)			
Wife	-1.184***	0.417	-0.768
	(0.424)	(0.870)	(1.040)
Son	-0.221	-0.038	-0.259
	(0.359)	(0.737)	(0.880)
Other	-0.685	1.375	0.690

	(0.671)	(1.376)	(1.644)
Constant	3.075	-7.322	-4.247
	(3.037)	(6.229)	(7.445)
Observations	439	439	439
R-squared	0.241	0.176	0.238

Source: Authors' computation NEEMSIS (2016-2017) data.
Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.