WORKING PAPER 255/2024

WORK ACTIVITY STATUS OF MALE YOUTH IN INDIA: ROLE OF SOCIAL NETWORKS

Ronak Maheshwari
Brinda Viswanathan

MSE
Mentoring Excellence

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

January 2024

Work Activity Status of Male Youth in India: Role of Social Networks

Ronak Maheshwari
Research Scholar, Madras School of Economics, Chennai-600 025 (India)
phd21ronak@mse.ac.in
(Corresponding Author)

and

Brinda Viswanathan
Professor, Madras School of Economics, Gandhi Mandapam Road, Chennai
brinda@mse.ac.in

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

January 2024

WORKING PAPER 255/2024

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

January 2024

Phone: 2230 0304/2230 0307/2235 2157
Fax: 2235 4847/2235 2155
Email : info@mse.ac.in
Website: www.mse.ac.in

Price : Rs. 35

Work Activity Status of Male Youth in India: Role of Social Networks

Ronak Maheshwari and Brinda Viswanathan

Abstract

The Right to Education Act of 2010 makes education a fundamental right for children aged six to fourteen years. Between 18 and 21 years, the activities of young adults diverge into pursuing further education or entering the labor force, or Not in Educational Employment and Training (NEET). Very few studies analyze the factors involved in these three choices and in particular, how the role of family and non-family networks varies across these activity statuses of youth in India after controlling for other covariates. This study attempts to fill this gap based on an empirical analysis of boys aged 18-21 years from the IHDS data for 2005-06 and 2011-12. The results from the discrete choice multinomial logit model show that, after controlling for socio-economic status, the primary source of household income, and parents' education, both family and non-family networks increase the odds of enrolling in higher education or training compared to NEET while non-family networks favor workforce participation compared to NEET. The results further highlight that in addition to the number of ties the types of ties have a greater influence on the work-activity-related decisions of the youth.

Keywords: *Higher Education; Labor Force Participation; NEET; Social Networks; Youth Labor*

JEL Codes: *I23, J24, J64, N30, P36*

Acknowledgement

The authors would also like to thank Dr. Neelanjan Sen and Dr. S. Subash for their valuable comments during this study. Earlier versions of this study were presented by the first author in the first Ph.D. Seminar Series (May 2023) at Madras School of Economics, Chennai; Doctoral Colloquium on Economics and Development Studies (August 23-25, 2023), at MIDS, Chennai; 22nd IASSI Annual Conference (2-4 November 2023) at CESS, Hyderabad *and the Fourth International Conference on Issues in Economic Theory* and *Policy (27* and *28 December 2023) at Presidency University, Kolkata. The authors would like to thank the participants of all these seminars for providing useful suggestions and contributing towards improving the quality of discussions in this study. The authors are solely responsible for any errors that remain.*

Ronak Maheshwari
Brinda Viswanathan

INTRODUCTION

The Sustainable Development Goals, 2030, in its fourth goal, requires nations across the world to ensure quality education and inclusive learning opportunities. Similarly, Goal 8 seeks to ensure productive and decent employment for all. In the backdrop of these two sustainable development goals, an important aspect is that school education is a fundamental right (and hence compulsory) in about 145 countries in the world from ages six to fourteen years. After this, the activity status of the young adults up to the age of 21 diverges and categorized into pursuing further education or taking up employment or not in employment, education, or training (or NEET, henceforth).

Access to quality education leading to quality employment is the primary goal of the nations by the age of 21 years and large gaps exist within and between nations in attaining this goal. The key problem of employment of the youth has prevailed over time. In the past three decades, the youth unemployment rate has remained significantly higher than the total unemployment rate globally the youth unemployment rate in the world has increased from 10 percent in 1991 to around 15 percent in 2021 (World Bank, 2023). In India, the youth unemployment rate (12.9 percent on usual status in 2020-21) (MoSPI, 2021) is significantly higher than the global youth unemployment rate and the national total unemployment rate at about 25 percent in recent years.

School-to-work transition, referred to as the switch or shift from education to work, plays an important role in employment for the youth as it addresses the gaps between young and adult workers (Pastore, 2018). It involves three stakeholders i.e., the graduating youth, the educational institution, and the employers. Starting with the youth graduating from the educational institution as education is believed to enhance earnings, this relationship between education and earnings was formalized into an economic model by Becker (1964). Indicating investment in education as a form of capital, Schultz (1961) coined the term human capital. Subsequently, human capital accumulation became a key determinant of economic growth in the endogenous growth models of Mankiw *et. al.* (1992); and Romer (1992 and 1994). Additionally, the social networks literature points out that education has a contagion effect. When it is passed on, it brings about necessary changes in the world around us because an educated person potentially influences others to get educated (Calvo-Armengol et. al, 2007). The challenges of school-to-work transition and ultimately to youth unemployment begin with challenges associated to the linkage between education and employment.

In India, the school-to-work transition has focused on the challenges faced in the absorption into the labor market after graduating (Bisht and Pattanaik, 2020) or women facing lower returns to Vocational Education and Training, or educational mismatch (Sharma and Sharma, 2017). This study focuses on the primary stakeholder, i.e., the graduating youth. Upon completion of high school, youth is faced with the choice of pursuing either higher education or joining the labor force. As labeled by ILO (2015), those who are unable to join either, comprise the discouraged labor force or Not in Employment Education and Training (NEET). As the economic outcome is often embedded in social relations (Jackson, 2007), social network theory offers to explain how social relations and social networks (such as caste or race-based networks, peer networks, etc.) impact labor market outcomes (Calvo-Armengol and Jackson, 2005) and determine educational outcomes (Calvo-Armengol *et. al.*, 2009). Shortcomings on the part of any one of the three stakeholders can lead to inefficient transitions to work (Rosenbaum *et. al.*, 1990)[1]. These shortcomings may arise due to improper information flow between the stakeholders. Improper information flow between educational institutions and employers often prevents interdependence and

[1] Most of the summary here is based on Rosenbaum, et.al., 1990, who draws from the studies of Williamson, 1975; Stinchcombe, 1985; Granovetter, 1986; Useem, 1986 and Zucker, 1986.

restricts/constraints/or acts as a barrier to school-to-work transition. Educational achievement is often seen as a signal of the job seeker’s true talent endowment and reducing the information asymmetry gap in the labor market (Spence, 1978; Checchi, 2006). However, it may be possible that the assumption of signaling theory that information can be trusted does not necessarily hold true. Network theory provides ways in which meaning and trust can be assigned to the information available in the labor market. These methods go beyond the market and consider social interactions. Trust in signals can be enhanced through social interactions and social norms that attach credibility to information exchange. Therefore, institutional linkages facilitate efficiency and strengthen the transition between educational achievement and jobs.

Few Indian studies have looked at the role of social networks and social relations on the labor market and educational outcomes. However, most of these studies focus only on the role of social networks either on educational decisions i.e., the role of family networks in decisions related to stream choice (Ravindranath and Viswanathan, 2021), or on employment through the role of caste-based networks in future job prospects (Munshi and Rosenzweig, 2001). The present study focuses on the role of such networks and their influence on the decision to work, pursue higher education, or NEET after completing high school. This study is based on the observed work activity status of male youth in India, in the 18-21 year age group for the year 2011-12 from the India Human Development Survey (IHDS-II)(Desai et. al, 2018) on the role of social network after controlling for individual, parental, household and regional factors. In order to avoid endogeneity that social networks may have been fostered in order to seek certain outcomes, the social network data at the household level from the previous wave of the panel survey in 2004-05 ((IHDS-I (Desai and Vanneman, 2018) is used.

The next section of the paper reviews the relevant studies that describe how networks function and how they impact important economic outcomes, especially education and employment. Theis is followed by the section describing the data, variables and the econometric methodology employed to study and then the section on results discusses the findings on how the role of social networks differ in the decisions regarding choosing an activity to pursue after high school. The paper concludes by highlighting the limitations of the present study, and the possible ways to improve upon them.

REVIEW OF LITERATURE

The earliest study in the field of economics that incorporated social networks to explain economic phenomena was based on the labor market. Rees (1966) has mostly discussed the possible networks that may exist in the labor market.

Regarding incorporating social structure into economic analysis, a significant contribution has come from sociologists. One of the interesting contributions in this direction is the strength of weak ties (SWT), hypothesized by Granovetter (1973). A tie refers to a link between two agents and a collection of such ties makes a network. He defines the strength of a tie as a probable linear function of the amount of time, emotional intensity, and intimacy. The main argument presented is that analysis of the processes in interpersonal networks can provide an effective bridge between micro and macro-level processes. Small-scale interactions among networks can be translated into large-scale outcomes. However, it is not just weak ties that facilitate status attainment. Social positions of contacts play an important role in determining how far weak ties can go. This is further complemented by the personal characteristics of the individual such as educational and family characteristics (Lin *et. al.*, 1981). It is not how many people you know that matters. What matters is who you know (Jackson, 2019).

In addition to personal characteristics and the status of the contacts, the decisions that we make regarding pursuing higher education, joining the labor force, etc., are also influenced by our peers

(Calvo-Armengol *et. al.*, 2009). Social networks in addition to influencing behavior can also be mediums for the relay of information. The information aspect has also been discussed in Granovetter (1973) where weak ties turn out to be mediums through which information is relayed more frequently. Labor markets are networked and all job-related information is conveyed through this network. The quality of such information depends on the type of nodes or individuals in the network. Better employment status of an individual's contacts leads to the relay of better information. In addition to this, the initial conditions of a network also play a key role in the relay of information (Calvo-Armengol and Jackson, 2003). In a network with worse initial conditions such as low education, marginalized communities, etc., the expected future stream of income is generally low. If there is no bridge between networks with better and worse-off conditions, there will be a higher dropout rate among the worse-off networks. This also explains the inequality in labor markets faced by marginalized communities.

In the Indian context, this can point toward how community-based or caste-based networks can limit future career paths (Munshi and Rosenzweig, 2001). Partitioning a community into cliques can strictly limit community organizations. In addition to this, it lays importance on the inevitable role that educational attainment (initial conditions argument) can play in deciding a network one ends up being a part of, and future employment/career opportunities (see Rosenbaum et. al, 1990 for a survey of literature linking bridging education and employment from various perspectives). Therefore, it is important to emphasize weak ties as well. Focus only on strong ties confines the analysis only to small, well-defined groups (Granovetter, 1973).

Very few studies in the Indian context have tried explaining career (jobs and education) choices by incorporating the role of networks. These studies have confined themselves mostly to strong ties. For example, the role of family networks in influencing gender parity in higher education (Ravindranath and Viswanathan, 2021) and the role of caste networks in determining career choices (Munshi and Rosenzweig, 2006). Munshi and Rosenzweig (2006) have tried to explain that male working-class networks at the caste level confine themselves to traditional jobs which have lower returns. On the contrary, many female workers of the same caste did not participate in the labor market. Consequently, they have very few networks to confine them to traditional work. Therefore, they have been seen as taking full advantage of the better opportunities available which are beyond the caste networks.

Another major finding is the declining role of caste networks in case one has English education. They have emphasized that those with English knowledge do not rely on caste networks and end up forming a caste in themselves. This is true in the sense that English knowledge leads to higher returns, with the ones having fluent knowledge having been found to receive half as large the returns to a graduate degree (Azam *et. al.*, 2013). Thus, English knowledge can be seen as denting the caste networks. This again strengthens the case for weak ties as claimed by Granovetter(1973). Ravindranath and Viswanathan (2021) have found a significant relationship between social networks and gender differences in the case of stream enrolment. They have observed female students having lower odds of enrolling in non-arts streams compared to males. However, the odds increase in case they have access to social networks, particularly if the connections are women.

Both these studies have highlighted the role and importance of social network influences among the youth in making choices related to higher education (Ravindranath and Viswanathan, 2021) and employment (Munshi and Rosenzweig, 2006). However, those in NEET remain unseen from the social network lens. Additionally, no study in the Indian context analyzes the influence of social networks on the observed outcome (or the choice made) between joining the workforce, pursuing higher education, or choosing to be in NEET among the 18-21-year-olds who have completed secondary schooling. Given these gaps in the existing literature in economics, this study tries to specifically examine the influence of both the number of social ties and the nature (own, family, and other) of such ties in making career-related choices i.e., enrolment in higher education, or employed or not in education, or in employment/training abbreviated as NEET (Not in Employment, Education or Training).

METHODOLOGY AND DATA

Empirical Model for Activity Status

The empirical model for economic activity is based on the multinomial logit model (MNL) with the three mutually exclusive activity statuses education, labor force, and NEET as reported by the 18-21-year-old men in 2011-12. Multinomial logit models are used for modeling occupational choice (Schmidt and Strauss, 1975; Viswanathan, 2020; Abraham and Shrivastava, 2022).

Since the dependent variable is a categorical variable with three categories, the study employs a multinomial logit model to understand the role of social networks in determining the choice of activity of the youth. Thus, we estimate the following multinomial logit model where the ith individual chooses from one of the three (j) activities. The probability of each activity is stated in equations 1(a) and (b) below:

$$Prob(y = j) = \frac{e^{\beta_j x_{ij}}}{1+\sum_{j=1}^{2} e^{\beta_j x_{ij}}} \quad \text{for j=1,2} \tag{1a}$$

and

$$Prob(y = 0) = \frac{1}{1+\sum_{j=1}^{2} e^{\beta_j x_{ij}}} \tag{1b}$$

We can estimate the log odds ratio from the following equation:

$$ln\Omega_{m|b}(\mathbf{x}) = \beta_{1(m|b)}\text{SN\_Num}_i + \beta_{2(m|b)}\text{SN\_type}_i + \mathbf{Z}\boldsymbol{\gamma}_{\boldsymbol{m|b}} + \varepsilon_i \tag{2}$$

for m=1 or 2 and where, $\Omega = \frac{\Pr(y=m)}{\Pr(y=b)}$

b =base outcome (here NEET) and m=1 for education and m=2 for labor force

SN_Num = No. of ties

SN_Type=Types of ties

$\boldsymbol{\beta}_i$= Vector of associated coefficients

Z = Vector of Control Variables;

$\boldsymbol{\gamma}$ = Vector of associated coefficient

Equation (2) mentions the two variables of interest (*SN_Num and SN_Type*) different from the set of control variables **Z** and **X** is the set of vectors combining both sets of regressor variables. This study further estimates the Relative Risk Ratio (RRR) which measures the effect of one regressor x_k when it increases by a small positive value δ as a ratio of the odds before and after the increase in x_k. That is, for an additional δ increase in x_k, the odds of outcome m compared to another outcome n (usually the omitted/benchmark category, or NEET in this study) is expected to change by the factor given in the right-hand side of the equation (3) below.

$$\frac{\Omega_{m|n}(\mathbf{x}, x_k+\delta)}{\Omega_{m|n}(\mathbf{x}, x_k)} = e^{\beta_{k,m|n}\delta} \qquad (3)$$

Independence of Irrelevant Alternatives (IIA) Assumption

While interpreting the MNL using RRR, we compare the odds of the *m^th^* category with the benchmark or base category. Therefore, the comparison is independent of any other available outcome alternative. This is referred to as the Independence of Irrelevant Alternatives (IIA) assumption. It follows from the assumption of independent and homoscedastic error terms in the multinomial logit model (Greene, 2008). In our model, taking NEET as the benchmark category, the odds of choosing to pursue higher education compared to the odds of being NEET is estimated independent of whether choosing to join the labor market is an available alternative. Since the available alternatives are dissimilar in our analysis, there is little reason for the assumption to be violated. However, this can prove to be a limitation in cases where the alternatives are similar and lead to a violation of the IIA assumption (Long, 1997). This limitation is overcome by the Multinomial Probit Model (MNP) which assumes joint normally distributed error terms. Therefore, we have compared the marginal effects of MNL and MNP below.

Marginal Effects

Marginal effects show the change in the probability of an outcome due to a small change in an independent variable, holding the other variables constant or at their means or specific values. Equation (4a) below shows the marginal effects for a continuous independent variable i.e., a change in the probability of an outcome due to a small (infinitesimal) change in the independent variable.

$$\frac{\partial Pr(y=m|\mathbf{x})}{\partial x} = Pr(y=m|\mathbf{x})[\beta_{km} - \sum_{j=1}^{3} \beta_{kj} \Pr(y=j|\mathbf{x})] \quad (4a)$$

The marginal effects can also be considered for a discrete change Δx_k in x_k with the starting value as x_S and ending value as x_E in equation (4b) below.

$$\frac{\Delta Pr(y=m|\mathbf{x})}{\Delta x_k} = Pr(y=m|\mathbf{x}, x_k = x_E) - Pr(y=m|\mathbf{x}, x_k = x_s) \quad (4b)$$

Data

This study makes use of the two waves of the household panel dataset Indian Human Development Survey (or IHDS). The IHDS dataset is a nationally representative, multi-topic survey covering topics such as education, employment, and social networks (Desai and Vanneman, 2017). The first wave i.e., IHDS-I in 2004-05 (Desai *et. al.*, 2018) has been utilized for social network variables as a result of both data quality and endogeneity. Current social networks may be potentially influencing the current work activity status while the current networks may be a result of the current work activity status[2]. The analysis is confined to male youth in the 18-21 age group in IHDS-II (Desai *et. al.*, 2018). The female youth is not included in the analysis because of attrition, as a significant proportion of young women get married and their household may not be tracked from the first to the second wave. The challenges for modeling the choices for women is then complex due to the following two reasons. The daughter in a household in the first wave may not be tracked in the same household in the 2nd wave if she marries and settles elsewhere. Similarly, a daughter-in-law could join the family between the 1st and the 2nd wave.

Activity Status Variables

The dependent variable is *activity status* with three (unordered) categories i.e. education, labor force and NEET. Education refers to those who are pursuing education (enrolled in a college or vocational education or training) while labor force refers to all those who report being in the labor force and includes individuals who are either employed or actively searching for jobs. The benchmark category is NEET which includes individuals neither enrolled in higher education, vocational education, or training nor employed or looking for jobs and referred as the discouraged labor force. The activity status variable has been detailed in Table 1.

Social Network Variables

The IHDS dataset is the only nationally representative dataset that has survey questions and responses on what may be loosely defined as social networks of individuals and household members along with youth activity status[3]. Both rounds of IHDS provide information about an individual's

[2] Arun *et. al.* (2016) while studying the role of social networks on consumption expenditure in India use the number of social networks and other recreational facilities in a village as an instrument for the number of social networks affiliated to a household.

[3] Though the data set is more than a decade old, it is used here to understand the role of social networks based on a pan-India survey of households and individuals that is nationally representative and also allows us to control for a rich set of covariates associated with youth activity status.

social networks, which can be further categorized into acquaintance and membership networks. Acquaintance networks are household-level variables where network-related questions have been asked to the head of the household. These include if the household is acquainted with someone in certain professions i.e., medical, education, and political. For acquaintance networks, IHDS-I asks the respondents if they have acquaintance with someone in the medical profession, the education profession, or any profession related to politics. These acquaintances if present are further categorized into: belonging to the same household, different household but the same family, or outside the family. Further, information on whether the acquaintance belongs to the same caste, gender, or religion is also collected. All this enables formation of a wider categorization of networks that aligns with the literature on how social networks are defined.

Another set of social network variables is affiliation or membership networks. These are individual-level variables that provide information on whether an individual is affiliated with an organization. The organizations in the IHDS dataset include *mahila mandal* (women's groups), youth/sports clubs, employee unions, co-operatives, NGOs, caste organizations, religious groups, social groups, lions/rotary clubs, self-help groups, festival groups.

For our analysis, we utilize the social network variables provided in the dataset by dividing them into two categories i.e., number of ties and the types of ties. As mentioned earlier, a tie refers to a link between two agents and several ties collectively comprise a network. The two variables are described as follows:

(1) **Number of ties**: The number of ties is a count variable that counts the number of connections an individual has (Arun et. al, 2015). If the household head is acquainted with someone, other members of the household are also assumed to be acquainted with them through the household head. Therefore, the

household head's acquaintance with someone is also taken as the individual under study being linked to them.

As far as membership networks are concerned, an individual being affiliated with an organization is treated as one tie or link as the individual will be connected to at least one member in the organization. Therefore, the total number of ties includes the number of acquaintances of the individual through the household head and the number of organizations one is affiliated with. The way it affects the work activity decision will depend on the nature of the network one has access to. Since this variable combines both acquaintance and affiliation networks, we may expect it to strongly influence the decision to pursue higher education or to join the labor market over being in the NEET. This can be expected only if the ties in such networks are more with those people who can bring in better information related to job opportunities or that related to higher education (Calvo-Armengol and Jackson, 2009).

(2) **Types of ties**: This variable is based exclusively on acquaintance networks. It is based on Granovetter's concept of strong and weak ties (Granovetter, 1973). Ties comprising family networks can be viewed as strong ties as per its definition where a higher level of intimacy is categorized as leading to strong ties. Since family ties include those in the same household as well, we assume a higher level of intimacy among the family ties. The non-family ties can be called weak ties as the individuals are connected to them through the household head. For example, a doctor who is a friend of the grandparents or parents. We have defined it as a categorical variable comprising three mutually exclusive categories:

(a) All ties: It includes all individuals who have ties *both in and outside their families* to people in the given professions.

(b) Non-family ties: Includes only those individuals who have acquaintances in the given professions but outside families *only*.

(c) None: Includes individuals who do not have any acquaintances with people in the above-mentioned professions.

Other control variables to account for the socioeconomic status of individuals, parents' education, and regional differences are used from IHDS II. Socioeconomic status has been accounted for by using asset quintiles and primary sources of income in the analysis where the former represents household wealth. The rationale behind the inclusion of these variables is that wealthier households and households with higher family incomes may be able to afford better education for the children in the household. Historical disadvantage also plays a key role in the work activity decisions of households and therefore caste has also been accounted for, which Calvo-Armengol and Jackson (2004) describe as initial conditions.

RESULTS AND DISCUSSION

Summary statistics of the variables used in the analysis are presented in Table 2. The average number of ties an individual has in the dataset is below 1 (including no ties) and the median value is four. Table 3 shows the distribution of individuals in each activity across asset quintiles. The proportion of those who enroll in education increases as we go up the quintile. However, those who chose to work are less among the higher quintiles. The proportion of those in the labor force keeps decreasing as we move from the first to the fifth quintile. In the case of those who are NEET, the proportion slightly increases from the first to the third quintile but decreases from the fourth to the fifth. However, the difference in absolute values is not much in the case of NEET. This shows that those who are well off are more inclined towards pursuing higher education compared to those who are not so wealthy.

Table 1: Summary of the dependent variable

Work Activity status	Definition	Count	Percent
Education	Those enrolled in higher education after high school.	1,805	32.68
Labor Force	Employed in either part-time or full-time work or searching for jobs.	3,238	58.62
NEET	Neither enrolled in education or vocational training nor employed or actively searching for jobs.	481	8.7
Total		5524	100

Source: Author's estimation based on IHDS-II (2011/12) data.

Table 2: Summary Statistics of Covariates used in Estimation

Variable	Count	Mean$	Std. Dev.	Min.	Max
Types of Ties @					
None	2443	0.442	0.497	0	1
All Networks	979	0.177	0.382	0	1
Non-family	2102	0.381	0.486	0	1
Number of ties @	5524	4.071	2.07	0	15
Asset Quintiles #					
1	848	0.154	0.361	0	1
2	1043	0.189	0.391	0	1
3	1141	0.207	0.405	0	1
4	1168	0.211	0.408	0	1
5	1324	0.24	0.427	0	1
Primary Source of Income#					
Agriculture and Allied	1591	0.288	0.453	0	1
Ag Labr	603	0.109	0.312	0	1
Non Ag Labr	1285	0.233	0.423	0	1
Artisans	98	0.018	0.132	0	1
Business	799	0.145	0.352	0	1
Salaried	1018	0.184	0.388	0	1
Others	130	0.024	0.152	0	1
Religion#					
Hindu	4315	0.781	0.414	0	1
Muslim	827	0.150	0.357	0	1
Christian	127	0.023	0.150	0	1
Sikh	167	0.030	0.171	0	1
Others	88	0.016	0.125	0	1
Caste#					
Brahmin	221	0.04	0.196	0	1
Forward/General	1264	0.229	0.42	0	1
OBC	2310	0.418	0.493	0	1
Scheduled Castes	1198	0.217	0.412	0	1
Scheduled Tribes	447	0.081	0.273	0	1
Others	84	0.015	0.122	0	1
Father's Education#					
Till Primary	2853	0.516	0.5	0	1

Variable	Count	Mean$	Std. Dev.	Min.	Max
Till Secondary	2025	0.367	0.482	0	1
Higher sec. and Above	646	0.117	0.321	0	1
Mother's Education#					
Till Primary	4063	0.736	0.441	0	1
Till Secondary	1214	0.22	0.414	0	1
Higher sec. and Above	247	0.045	0.207	0	1

Source: Author's estimation based on IHDS-I (2004/05) and II (2011/12) data;

Note: (1) @Variables from IHDS-I (2004-05); (2) #Variables from IHDS-II (2011-12); (3) $For binary discrete variables, the mean is the share of the respective category.

Table 3: Distribution of activity chosen by individuals across various quintiles.

Column1	Quin 1	Quin 2	Quin 3	Quin 4	Quin 5	Total
	(percent)	(percent)	(percent)	(percent)	(percent)	(percent)
Education	106	196	300	420	783	1,805
	(12.5)	(18.79)	(26.29)	(35.96)	(59.14)	(32.68)
Labor Force	668	772	735	625	438	3,238
	(78.77)	(74.02)	(64.42)	(53.51)	(33.08)	(58.62)
NEET	74	75	106	123	103	481
	(8.726)	(7.191)	(9.29)	(10.53)	(7.779)	(8.71)
Total	848	1043	1141	1168	1324	5524

Source: Author's estimation based on II (2011/12) data;

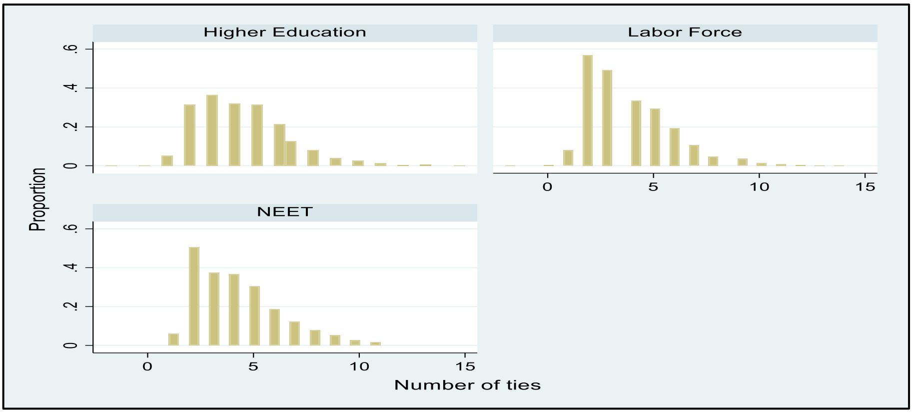
Note: (1) Asset quintiles are based on an index based on individuals' ownership of durable goods;

(2) The numbers are the sample observations and the values in brackets are the estimated proportion accounting for sampling weights;

(3) Each asset quintile is not 20 percent as the quintiles are based on all India data while here we are considering only those households with 18–21-year-olds.

Figure 1 plots the proportion of individuals having various numbers of ties. The maximum number of ties possible is fifteen. It is observed that the proportion of individuals in education, whether they have one tie or five, is approximately the same i.e., about 0.4. The average and median number of ties are four and three respectively. The proportion associated with these numbers is highest in the case of education i.e., 0.4. In other words, people opting for higher education are better networked compared to those in the labor force. However, this association between choosing higher education and social networks could also be associated with parental education. An econometric model will allow us to control for other variables and to find the effect of social networks on the choice of activity status of the male youth[4]. The statistical significance of the association between social networks and activity status can be examined from the results of the multinomial logit model (Table 4). The table with a full set of covariates is presented in the Appendix (Table A1).

Figure 1: Proportion of ties across activity status



Source: Author's own calculations

Across all the models in the table, we compare the odds of enrolling in education versus NEET and joining the labor force versus NEET based on (2) above. The key regressors are the number of ties (*SN_ties*) and types of ties (*SN_type*).

[4] If there is a potential endogeneity in the social network formation or the type of ties, then the model estimates could be biased and inconsistent and will be examined in further extension to this study.

Choice between Higher Education and NEET

We discuss the results from the Multinomial Logit model (equation 1a and 1b) and the interpretations are made using the Relative Risk Ratio (equation 3). While comparing the odds of enrolling in higher education versus being in NEET, it can be seen that the number of ties variable is not statistically significant meaning that the number of ties is not significantly associated with the work activity decision. All ties and non-family ties are statistically significant implying that the way networks are being formed plays a role in the individual's activity-related decisions. The RRR for the former ranges between 1.4 (Model 1) to 2.05 (Model 3) and that of the latter lie in the range 1.28 (Model 3) to 1.5 (Model 1). This shows that both these variables increase the odds of choosing higher education while comparing the decision to pursue higher education or NEET.

Table 4: Results from the Multinomial Logit Model with Relat*ive* R*isk* Ratio

Dependent variable: activity status	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Model 1		Model 2		Model 3		Model 4		Model 5	
	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)
Social Networks										
Number of ties (#)	1.004	0.903***	0.990	0.902***	0.983	0.903***	0.987	0.910***	0.985	0.923***
	(0.0287)	(0.0247)	(0.0283)	(0.0249)	(0.0282)	(0.0248)	(0.0288)	(0.0249)	(0.0288)	(0.0255)
Family and Non-family ties v/s no ties (#)	2.057***	0.895	1.574***	1.050	1.423**	0.997	1.462**	0.939	1.727***	0.985
	(0.326)	(0.139)	(0.260)	(0.170)	(0.234)	(0.159)	(0.238)	(0.147)	(0.279)	(0.154)
Non-family v/s no ties (#)	1.504***	1.261*	1.334**	1.289**	1.281*	1.269*	1.309**	1.266*	1.402**	1.282**
	(0.199)	(0.156)	(0.178)	(0.161)	(0.173)	(0.160)	(0.176)	(0.158)	(0.187)	(0.160)
Other Control Variables (*)	**Religion +Residence (Urban/Rural)**		**Religion+ Caste+ Primary Source of Income+ HH Asset Quintiles+ Residence (Urban/Rural)**		**Religion+Primary Source of Income+ Residence (Urban/Rural) + Father's Education**		**Religion+ Residence (Urban/Rural) +Father's Education**		**Religion+ Residence (Urban/Rural) +Mother's Education**	
Constant	3.125***	9.583***	2.215**	18.22***	2.176***	21.09***	1.696***	14.16***	2.230***	13.65***
	(0.371)	(1.072)	(0.760)	(6.083)	(0.397)	(3.485)	(0.255)	(1.896)	(0.297)	(1.686)
Observations	5,524	5,524	5,524	5,524	5,524	5,524	5,524	5,524	5,524	5,524

Source: Author's own estimates from IHDS panel data

Note: (1) *Variables from IHDS-I (2004-05);
(2) #Variables from IHDS-II (2011-12);
(3) Robust standard errors in parentheses;
(4) *** p<0.01, ** p<0.05, * p<0.10.

In Model 1, the RRR for *All Ties* is 2.05 meaning that if an individual has at least one tie with any individual from the medical, educational, or political professions, which is within the family, the odds that s/he will choose to pursue higher education increase by a factor of 2.05. If the ties with people in these professions exist only outside the family, then the odds of enrolling in higher education increase by a factor of 1.50 as compared to being in NEET. In addition to the key variables, we have accounted for the residence of the individual i.e., if they reside in a rural or urban setting and religion. The coefficient corresponding to Urban v/s Rural shows that residing in an urban area increases the odds of enrolling in higher education as compared to NEET by a factor of approximately 1.7. Therefore, residing in an urban setting is more favorable to enrolment in education as compared to being in the discouraged labor force. We see the same result for urban dwellers across the models. The coefficient for Urban v/s Rural reduces slightly as we include more controls suggesting the relative importance of the additional control variables. The influence of these control variables is discussed below.

However, Model 1 does not take into consideration other factors that, in addition to an individual's networks, could potentially impact the decisions related to work activity status. To account for all such factors, in Model 2 we have introduced household wealth status through asset quintiles and caste categories. The lowermost quintile (Quintile 1) is the benchmark category. The RRR coefficient increases as we go up the quintiles. RRR corresponding Quintile 2 suggests higher odds of enrolling in higher education as compared to being in the discouraged labor force by a factor of 1.7. As we move up the quintiles the RRR also increases. For instance, quintile 5 has the highest RRR which means that individuals belonging to the wealthiest households increase the odds of educational enrolment by a factor of approximately 3.7. Although the caste categories are not individually statistically significant, it can be seen that the odds associated with our key independent variables are reduced upon the inclusion of the caste variable. The inclusion of the father's education (Model 3 and Model 4) seems to have a higher influence on the work-activity-related decisions of the youth. The magnitude of the odds ratio also increases with the father's education level. The higher the father's education (as compared to no education), the higher the odds that the individual will pursue higher education. This may have implications for acquaintance-related networks as well. In conclusion, we may say that if the network comprises at least one family tie, the odds favoring the decision to pursue higher education as compared to being in NEET are higher as compared to when the networks don't have family ties at all (or just have non-family ties).

The argument is quite analogous to the one provided by Calvo-Armengol and Jackson (2009), although in the context of labor markets. They have shown that in a network where there are agents with longer unemployment spells, there would be a higher conditional expectation that an agent's contacts will be unemployed. This in turn leads to a lower probability of obtaining information about jobs through the social network. Coming to our case, the ties that individuals form through their household heads are with people in professions that require them to pursue higher education before choosing to work. Therefore, we can expect a higher probability of higher education-related information to pass through the social network.

Choice between Labor Force Participation and NEET

Next, we compare the odds that an individual chooses to be in the labor force versus NEET (odd numbered columns). We find that the number of ties works against youth being in the labor force. For instance, in Model 3, with an increase in the number of ties, the odds of joining the labor force decrease by a factor of 0.903 as compared to being in NEET. It is the non-family ties that increase the odds of participation in the labor force rather than being in NEET. Referring to the same model, we see that having non-family ties with people in the medical, educational, and politically related professions, the odds of joining the labor force increase by a factor of approximately 1.3. The odds for the same are comparable across models. The explanation for this lies in the relay of job-related information through social networks in the labor market and the resulting inequality in the labor market (Calvo-Armengol and Jackson, 2003). Continuing in the labor force or dropping out of it will depend on the costs associated with networks as also observed by Lin *et. al.* (1981). Since non-family ties are mostly with people who have good employment status i.e., teachers and doctors, the relayed information will be of better quality. This could also be due to the reasoning provided by Granovetter (1973) that weaker ties (as we have assumed the nature of non-family ties to be) provide access to a wider range of information while strong ties confine one to small-well-defined groups.

However, if we analyze the number of ties, then it is largely based on an individual's direct links and membership networks. Being a member of certain social groups requires a significant time spent in those groups creating a higher probability of being in NEET. Since most individuals joining the labor force belong to the lowermost asset quintile, the information relayed in that case does not seem to favor either joining the labor market or pursuing higher education and thereby higher dropout rates leading them into the NEET category.

Results from Marginal Effects

Figure 2a: Marginal effects from Multinomial Logit Model

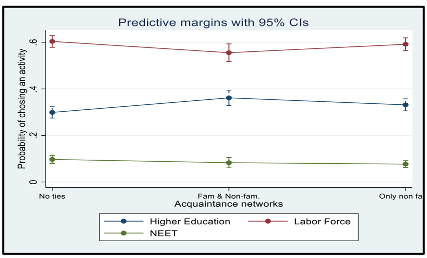
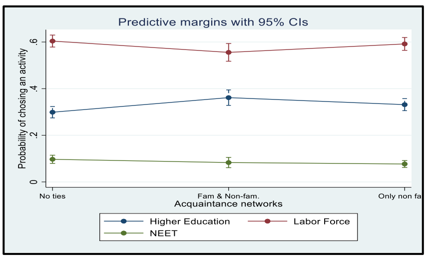


Figure 2b: Marginal effects from Multinomial Probit Model



Focusing on the social network variables, i.e., the number of ties and the type of ties, we see that in both the models an additional network tie the probability of choosing higher education increases while that of being in the labor force decreases. The estimates of average marginal effects for both MNL and MNP models are in Table A2 in Appendix A. In the case of types of ties, we compare the effects of having a combination of family and non-family ties with having no ties and just non-family ties with having no ties. Having a combination of family and non-family ties increases the probability of choosing to pursue higher education by around 6 percentage points while it decreases the probability of choosing to be in the labor force by 4 percentage points, approximately. Moving to the case of just non-family ties, compared to no ties, having just non-family ties increases the probability of pursuing higher education by approximately 3 percentage points while it decreases the probability of being in the labor force by 1 percentage point. The marginal effects are the same for both MNL and MNP (See Figures 2a and 2b). The multinomial probit model assumes a correlation between the error terms. However, the MNP estimated over here is estimated using the *mprobit* command in the STATA 17 statistical software package which does not assume a correlation between the errors. Therefore, it is the probit counterpart of the multinomial logit model estimated using STATA (*mlogit* command) and hence assumes IIA (Long and Freese, 2006).

CONCLUSION

When it comes to labor market outcomes, among other factors such as family characteristics, regional characteristics, etc., education is also a key determinant. The key career-related decisions that one has to take include whether to pursue higher education or to join the labor force. However, what drives individuals to make these decisions also depends partly on whom they observe, interact and are influenced by.

This study for the first time in the Indian context analyses the role of social networks in the decision to choose between, *post school education*, or *employment*, or *NEET* by Indian males aged 18-21 years in 2011-12. The results from this study reveals that both family and non-family networks play a crucial role in determining the activity status of an individual. Thus, certain career-related decisions are influenced by the people around us, or the people we observe and those whom we interact with. The results show that it is the types of ties, rin addition to the number of ties that is significantly associated with these decisions. This is in line with the conclusions put forward by Lin *et. al.* (1981) where the social position of the contacts determined an individual's ultimate position. Similarly, Jackson (2019) argues that if one has a friend who has a network of a vast network of people and another friend who has access to a network of people who are not well networked, the chances of relaying information, rumor, influence, etc. will be higher in the former case as that friend is better positioned in the society. Lin *et. al.* (1981) and Jackson (2019) both argue the same point in different ways.

Limitations and Further Scope

Social network data poses the challenge of social structures being endogenous and related to various characteristics of the agents involved [5]. While networks can influence economic outcomes, the formation of such networks can also be driven by the same economic phenomenon. In this study, the network variables are taken to be predetermined based on the previous wave, about seven years prior when these 18–21-year-olds would be in early school. Thus potential endogeneity in social networks is addressed but in a limited manner and a more rigorous approach could be attempted similar to Iyengar (2011), Arun *et. al.* (2016), and Bose *et. al.* (2021) using the IV method.

Further, individual level heterogeneity could have been better modeled to account for such omitted variables, which could be correlated with network variables and also the choice of the activity status. The gap of seven years between the two panels of IHDS seems long for the type of outcome variables modeled here and posed challenges in not being

[5] See Jackson (2008) for a discussion on endogeneity and other challenges to empirical analysis involving social network data.

able to exploit the panel nature of the data more effectively. We hope to address this in future extensions of the analysis by considering individual-level controls such as high school grades and English knowledge proficiency (an important requisite for the job market) as in Azam *et. al.*, (2013).

The data on social networks is limited in the wide range of possible networks and is further constrained for the available network type in terms of the information being discrete (takes the value 1 if a household is acquainted with someone, and 0 otherwise) rather than the dyadic form that network structures are expected to be. Various conceptual and empirical literature shows that knowing network structures can elicit a whole lot of information such as highlighting who an important contact is in a network, how information flows through the networks, who in an individual's network influences their decisions, and so on. One possible extension could be to (loosely) categorize the existing acquaintance-based social network variables into strong ties and weak ties, based on Granovetter (1973). For example, any acquaintance belonging to the same family or caste can be treated as strong ties, while those outside the family or caste can be treated as weak ties. The categorization can be used to study the impact of strong and weak ties on the choice of activity of the male youth.

Overall, given the data and other limitations, the results from this study have some interesting findings regarding the role of social networks in individual decisions.

REFERENCES

Agrawal, T., and A. Agrawal (2017). "Vocational Education and Training in India: A Labour Market Perspective", *Journal of Vocational Education and Training*, *69* (2), 246-265.

Andersen, T. M. and H. Vetter (1995). "Equilibrium Youth Unemployment", *Journal of Economics*, *61*(1), 1-10.

Azam, M., A. Chin and N. Prakash (2013). "The Returns to English-Language Skills in India", *Economic Development and Cultural Change*, *61*(2), 335-367.

Becker, G. S., K. M. Murphy, and R. Tamura (1990), "Human Capital, Fertility, and Economic Growth", *Journal of Political Economy*, *98*(5, Part 2), S12-S37. 13.

Bisht, N., and F. Pattanaik (2021), "Exploring the Magnitude of Inclusion of Indian Youth In the World of Work Based On Choices of Educational Attainment", *Journal of Economics and Development*, *23*(2), 128-143.

Bisht, N., and F. Pattanaik (2021), "How Inclusive Is "Inclusive Development" In India? Challenges and Prospects of Indian Youth Labour Market", *International Business Education Journal*, *14* (1), 17-33.

Bloch, F., M. O. Jackson, and P. Tebaldi (2023), "Centrality Measures In Networks", *Social Choice and Welfare*, 1-41.

Boorman, S. A. (1975), "A Combinatorial Optimization Model For Transmission of Job Information Through Contact Networks", *The Bell Journal of Economics*, 216-249.

Calvo-Armengol, A., and M. O. Jackson (2004), "The Effects of Social Networks On Employment and Inequality", *American Economic Review*, 94(3), 426-454.

Calvó-Armengol, A., E. Patacchini, and Y. Zenou, (2009), "Peer Effects and Social Networks In Education, *The Review Of Economic Studies*, *76*(4), 1239-1267.

Checchi, D. (2006). "The Economics of Education: Human Capital, Family Background, and Inequality, *Cambridge University Press*.

Desai, Sonalde, Reeve Vanneman, and National Council of Applied Economic Research, New Delhi. India Human Development Survey (IHDS), 2005. Inter-university Consortium for Political and Social Research [distributor], 2018-08-08. https://doi.org/10.3886/ICPSR22626.v12

Desai, Sonalde, Reeve Vanneman and National Council of Applied Economic Research. India Human Development Survey-II (IHDS-II), 2011-12. Inter-university Consortium for Political and Social Research [distributor], 2018-08-08. https://doi.org/10.3886/ICPSR36151.v6

Granovetter, M. S. (1973), "The Strength of Weak Ties", *American Journal of Sociology*, *78*(6), 1360-1380.

Granovetter, M. (2018), "Economic Action and Social Structure: The Problem of Embeddedness", *The Sociology of Economic Life* (pp. 22-45). Routledge.

Hanushek, E. A. (2012), "Dual Education: Europe's Secret Recipe?", In *CESifo Forum* (Vol. 13, No. 3, pp. 29-34), München: Ifo Institut-Leibniz-Institut Für Wirtschaftsforschung An Der Universität München.

Jackson, M. O. (2007), "The Study of Social Networks In Economics", *The Missing Links: Formation and Decay of Economic Networks*, *76*, 210-225.

Jackson, M. O. (2008), *Social and Economic Networks* (Vol. 3). Princeton: Princeton University Press.

Jackson, M. O. (2019). *The Human Network: How Your Social Position Determines Your Power, Beliefs, and Behaviors*. Vintage.

Lin, N., W. M. Ensel, and J. C. Vaughn (1981), "Social Resources and Strength of Ties: Structural Factors In Occupational Status Attainment", *American Sociological Review*, 393-405.

Lindbeck, A., and D.J. Snower (2001), "Insiders Versus Outsiders", *Journal of Economic Perspectives*, *15*(1), 165-188.

Long, J. S., and J. Freese (2006), *Regression Models For Categorical Dependent Variables Using Stata* (Vol. 7), Stata Press.

Maitra, P., and A. Sharma (2009, November), "Parents and Children: Education Across Generations In India", In *5th Annual Conference On Economic Growth and Development, ISI Delhi, Delhi*.

Mamgain, R. P., and S. Tiwari (2016), "Youth In India: Challenges of Employment and Inclusion", *Journal of Social and Economic Development*, *18*(1), 85-100.

Mankiw, N. G., D. Romer, and D.N. Weil (1992), "A Contribution to the Empirics of Economic Growth", *The Quarterly Journal of Economics*, *107*(2), 407-437.

Mehrotra, S., A. Gandhi, and B.K. Sahoo (2013), "Estimating India's Skill Gap: On A Realistic Basis For 2022", *Economic and Political Weekly*, 102-111.

Montgomery, J. D. (1991), "Social Networks and Labor-Market Outcomes: Toward An Economic Analysis", *The American Economic Review*, *81*(5), 1408-1418.

Montgomery, J. D. (1992), "Job Search and Network Composition: Implications of the Strength-of-Weak-Ties Hypothesis", *American Sociological Review*, 586-596.

MoSPI, Government of India. (2022). *Annual Report: PLFS, 2020–2021.* Ministry of Statistics and Programme Implementation.

Munshi, K., and M. Rosenzweig (2006), "Traditional Institutions Meet the Modern World: Caste, Gender, and Schooling Choice In A Globalizing Economy", *American Economic Review*, *96*(4), 1225-1252.

Pastore, F. (2018), "Why Is Youth Unemployment So High and Different Across Countries?", *IZA World of Labor*, 14.

Ravi, Shamika; Neelanjana Gupta, & Puneeth Nagaraj (2019), "Reviving Higher Education in India," Brookings India Research Paper No. 112019-01

Ravindranath, K., and B. Viswanathan (2021), "Gender Parity in Higher Education Enrolment: Role of Family Networks".

Rees, A. (1966), "Information Networks In Labor Markets", *The American Economic Review*, *56*(1/2), 559-566.

Romer, P. M. (1988), "Capital Accumulation In the Theory of Long-Run Growth (No. 123)", University of Rochester-Center For Economic Research (RCER).

Romer, P. M. (1994), "The Origins of Endogenous Growth", *Journal Of Economic Perspectives*, *8* (1), 3-22.

Rosenbaum, J., E. Kariya, R. Settersten, and T. Maier (1990), "Market and Network Theories of the Transition From High School to Work: Their Application to Industrialized Societies", *Annual Review of Sociology*, 263-299.

Schultz, T. W. (1961), "Investment In Human Capital", *The American Economic Review*, *51*(1), 1-17.

Scott Long, J. (1997), "Regression Models For Categorical and Limited Dependent Variables", *Advanced Quantitative Techniques In the Social Sciences*, *7*.

Sharma, S. and P. Sharma (2017), "Educational Mismatch and Its Impact On Earnings: Evidence From Indian Labour Market", *International Journal of Social Economics*.

Singh, A., and P. Jaykumar (2019), "On the Road to Consensus: Key Soft Skills Required For Youth Employment In the Service Sector", *Worldwide Hospitality and Tourism Themes*.

Spence, M. (1978), "Job Market Signaling", In *Uncertainty In Economics* (Pp. 281-306). Academic Press.

Stinchcombe, A. L. (1985), "Contracts As Hierarchical Documents. A. Stinchcombe And C. Heimer, Eds. Organization Theory and Project Management.

Useem, E. L. (1986), "Low Tech Education In A High-Tech World: Corporations and Classrooms In the New Information Society", The Free Press.

Venkatanarayana, M., and S. Mahendra Dev (2012), "Youth Employment and Unemployment In India", http://igidr.ac.in/pdf/publication/WP-2011-009.pdf

Vincent, A., and D. Rajasekhar (2021), "Who Participates In Vocational Education and Training In India? An Analysis of Socio-Economic Determinants", *Journal of Vocational Education and Training*, 1-20.

World Bank (2020). Available at https://data.worldbank.org/

Witenstein, M. A., and R. Iyengar (2021), "A Bottom-Up Approach to Improve Women's Access to Technical and Vocational Education and Training In India: Examining A Non-Formal Education Upskilling Programme", *International Review of Education*, *67*(4), 475-48.

Appendix

Table A1: Results from the Multinomial Logit Model with Relative Risk Ratio (RRR)

Dependent variable: activity status	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Model 1		Model 2		Model 3		Model 4		Model 5	
Base category: NEET	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)	RRR Coeff. (Higher Ed.)	RRR Coeff. (Lab. Force)
Social Networks# and Religion (base: Hindus)* and Caste (base: Brahmin)* and Primary Income Source (base: Agri and Allied)*										
Number of ties	1.004	0.903***	0.990	0.902***	0.983	0.903***	0.987	0.910***	0.985	0.923***
	(0.0287)	(0.0247)	(0.0283)	(0.0249)	(0.0282)	(0.0248)	(0.0288)	(0.0249)	(0.0288)	(0.0255)
All ties v/s no ties	2.057***	0.895	1.574***	1.050	1.423**	0.997	1.462**	0.939	1.727***	0.985
	(0.326)	(0.139)	(0.260)	(0.170)	(0.234)	(0.159)	(0.238)	(0.147)	(0.279)	(0.154)
Non-family v/s no ties	1.504***	1.261*	1.334**	1.289**	1.281*	1.269*	1.309**	1.266*	1.402**	1.282**
	(0.199)	(0.156)	(0.178)	(0.161)	(0.173)	(0.160)	(0.176)	(0.158)	(0.187)	(0.160)
Muslims	0.452***	0.850	0.486***	0.897	0.556***	0.826	0.540***	0.826	0.497***	0.803*
	(0.0635)	(0.109)	(0.0746)	(0.127)	(0.0789)	(0.107)	(0.0764)	(0.106)	(0.0705)	(0.103)
Christians	0.834	0.477**	0.757	0.535**	0.847	0.539**	0.834	0.490**	0.692	0.547**
	(0.239)	(0.141)	(0.226)	(0.166)	(0.248)	(0.164)	(0.241)	(0.145)	(0.203)	(0.163)
Sikhs	1.094	1.019	0.743	1.270	1.027	1.045	0.992	1.015	0.902	1.152
	(0.359)	(0.318)	(0.250)	(0.401)	(0.345)	(0.322)	(0.332)	(0.316)	(0.302)	(0.364)
Buddhists, Jain, etc.	1.421	0.782	1.562	0.701	1.434	0.805	1.479	0.769	1.357	0.854
	(0.588)	(0.330)	(0.679)	(0.306)	(0.613)	(0.345)	(0.628)	(0.325)	(0.569)	(0.362)
General (except Brahmin)			0.887	0.898						
			(0.262)	(0.272)						
OBC			0.759	1.042						
			(0.216)	(0.304)						
SC			0.732	1.223						
			(0.220)	(0.373)						
ST v/s			0.648	1.264						

Brahmins			(0.226)	(0.432)						
Others v/s Brahmins			0.804	1.246						
			(0.410)	(0.605)						
Agri. Labor			0.890	0.616**	0.911	0.655**				
			(0.186)	(0.116)	(0.189)	(0.122)				
NonAg Labr			0.637***	0.508***	0.622***	0.540***				
			(0.110)	(0.0796)	(0.105)	(0.0826)				
Artisans			0.725	0.830	0.686	0.865				
			(0.306)	(0.330)	(0.291)	(0.344)				
Business			0.748	0.677**	0.743	0.661**				
			(0.149)	(0.126)	(0.147)	(0.122)				
Salaried			0.872	0.359***	0.779	0.351***				
			(0.155)	(0.0627)	(0.140)	(0.0617)				
Others			0.747	0.304***	0.684	0.290***				
			(0.235)	(0.0976)	(0.217)	(0.0924)				
Asset Quintiles (base First quintile)*										
Quintile 2			1.744***	1.235						
			(0.360)	(0.216)						
Quintile 3			1.735***	0.926						
			(0.338)	(0.153)						
Quintile 4			1.909***	0.820						
			(0.384)	(0.144)						
Quintile 5			3.702***	0.765						
			(0.796)	(0.148)						
Urban v/s Rural*	1.704***	0.445***	1.356**	0.652***	1.516***	0.603***	1.364***	0.467***	1.359***	0.519***
	(0.186)	(0.0472)	(0.179)	(0.0828)	(0.193)	(0.0730)	(0.154)	(0.0505)	(0.157)	(0.0580)
Father's Education* (base: no education)										
1-4 years v/					0.941	0.773	0.967	0.792		
					(0.171)	(0.122)	(0.175)	(0.124)		
Uptil primary					1.281	0.933	1.313	0.952		
					(0.263)	(0.174)	(0.266)	(0.174)		

Class 6-9					1.904***	0.759**	1.941***	0.768**		
					(0.283)	(0.103)	(0.282)	(0.102)		
Secondary and					3.104***	0.826	3.196***	0.780		
11					(0.598)	(0.155)	(0.586)	(0.139)		
Highr					3.135***	0.755	3.236***	0.670		
Secondary					(0.795)	(0.192)	(0.794)	(0.165)		
Grad. And					7.080***	0.873	7.389***	0.766		
above					(2.161)	(0.278)	(2.194)	(0.238)		
Mother's Education* (base: no education)										
1-4 years									1.208	0.700**
									(0.229)	(0.125)
Uptil primary									1.462**	0.674**
									(0.274)	(0.122)
Class 6-9									1.547***	0.522***
									(0.226)	(0.0749)
Secondary and									2.095***	0.360***
11									(0.421)	(0.0767)
Highr									5.203***	0.574
Secondary									(2.209)	(0.267)
Grad. And									4.190***	0.556
above									(1.843)	(0.268)
Constant	3.125***	9.583***	2.215**	18.22***	2.176***	21.09***	1.696***	14.16***	2.230***	13.65***
	(0.371)	(1.072)	(0.760)	(6.083)	(0.397)	(3.485)	(0.255)	(1.896)	(0.297)	(1.686)
Observations	5,524	5,524	5,524	5,524	5,524	5,524	5,524	5,524	5,524	5,524
Note: Robust S. E. in parentheses (*** p<0.01, ** p<0.05, * p<0.1); #: Variables from IHDS-I (2004-05);*: Variables from IHDS-II (2011-12)										

Table A2: Marginal Effects from Multinomial Logit and Multinomial Probit Models.

	Marginal Effects from MNL			Marginal Effects from MNP		
Outcomes	**Higher Education**	**Labor Force**	**NEET**	**Higher Education**	**Labor Force**	**NEET**
Number of Ties	0.00889*	-0.0123**	0.00345	0.00854*	-0.0117*	0.00345
	(0.00427)	(0.00470)	(0.00292)	(0.00431)	(0.00467)	(0.00292)
All ties (base=None)	0.0625**	-0.0486*	-0.0139	0.0641**	-0.0512*	-0.0139
	(0.0222)	(0.0247)	(0.0151)	(0.0225)	(0.0248)	(0.0151)
Only non-Family ties	0.0325	-0.0124	-0.0201	0.0318	-0.0127	-0.0201
	(0.0195)	(0.0208)	(0.0125)	(0.0197)	(0.0209)	(0.0125)
Muslim	-0.111***	0.0791***	0.0323*	-0.113***	0.0775***	0.0323*
	(0.0166)	(0.0194)	(0.0139)	(0.0167)	(0.0196)	(0.0139)
Christian	-0.0402	0.00403	0.0362	-0.0468	0.0102	0.0362
	(0.0413)	(0.0514)	(0.0347)	(0.0418)	(0.0511)	(0.0347)
Sikh	-0.0159	-0.0174	0.0332	-0.0159	-0.0172	0.0332
	(0.0463)	(0.0533)	(0.0457)	(0.0484)	(0.0538)	(0.0457)
Others	0.121*	-0.0867	-0.0346	0.123*	-0.0880	-0.0346
	(0.0590)	(0.0596)	(0.0201)	(0.0590)	(0.0592)	(0.0201)
Urban (base=Rural)	0.132***	-0.142***	0.00991	0.132***	-0.142***	0.00991
	(0.0195)	(0.0208)	(0.0127)	(0.0195)	(0.0207)	(0.0127)
Quintile 2	0.0501	-0.0237	-0.0264	0.0457	-0.0193	-0.0264
	(0.0289)	(0.0308)	(0.0183)	(0.0278)	(0.0300)	(0.0183)
Quintile 3	0.0998***	-0.107***	0.00689	0.0966***	-0.102**	0.00689
	(0.0292)	(0.0317)	(0.0202)	(0.0284)	(0.0312)	(0.0202)
Quintile 4	0.132***	-0.140***	0.00758	0.126***	-0.134***	0.00758
	(4.33)	(-4.14)	(0.32)	(0.0299)	(0.0330)	(0.0235)
Quintile 5	0.328***	-0.307***	-0.0212	0.323***	-0.302***	-0.0212
	(0.0340)	(0.0362)	(0.0236)	(0.1982)	(0.0353)	(0.0235)
Agricultural Labor base= Agri.& allied)	-0.0196	-0.00911	0.0287	-0.0220	-0.00625	0.0287
	(0.0294)	(0.0302)	(0.0195)	(0.0287)	(0.0301)	(0.0195)
Non Agri Labor	-0.0233	-0.0165	0.0398**	-0.0227	-0.0158	0.0398**
	(0.0240)	(0.0254)	(0.0144)	(0.0240)	(0.0255)	(0.0144)
Artisans	-0.0867*	0.0821	0.00456	-0.0887*	0.0863	0.00456
	(0.0414)	(0.0480)	(0.0267)	(0.0413)	(0.0480)	(0.0267)
Business	-0.0162	-0.00973	0.0259	-0.0132	-0.0115	0.0259
	(0.0259)	(0.0279)	(0.0161)	(0.0259)	(0.0279)	(0.0161)
Salaried	0.114***	-0.155***	0.0409*	0.117***	-0.157***	0.0409*
	(0.0278)	(0.0294)	(0.0168)	(0.0279)	(0.0291)	(0.0168)
Others	0.119*	-0.163**	0.0440	0.124*	-0.163**	0.0440
	(0.0501)	(0.0525)	(0.0315)	(0.0508)	(0.0522)	(0.0315)
Central (Base =north)	-0.0101	0.0460	-0.0360*	-0.0149	0.0495	-0.0360*
	(0.0220)	(0.0265)	(0.0182)	(0.0222)	(0.0262)	(0.0182)
West	0.0813***	-0.0681**	-0.0132	0.0771***	-0.0667**	-0.0132
	(0.0219)	(0.0260)	(0.0175)	(0.0223)	(0.0257)	(0.0175)

South	0.141***	-0.139***	-0.00201	0.138***	-0.138***	-0.00201
	(0.0251)	(0.0288)	(0.0190)	(0.0255)	(0.0287)	(0.0190)
East	0.0648*	-0.0825**	0.0176	0.0585*	-0.0781*	0.0176
	(0.0283)	(0.0320)	(0.0226)	(0.0280)	(0.0314)	(0.0226)
Northeast	0.0622	-0.178***	0.116**	0.0604	-0.178***	0.116**
	(0.0432)	(0.0495)	(0.0401)	(0.0435)	(0.0496)	(0.0401)
Observations	**5524**	**5524**	**5524**	**5524**	**5524**	**5524**

Source: Author's own estimates using IHDS data.

Note: Robust Standard errors in parentheses * p<0.05** p<0.01 *** p<0.001

MSE Monographs

* Monograph 34/2015
  Farm Production Diversity, Household Dietary Diversity and Women's BMI: A Study of Rural Indian Farm Households
  Brinda Viswanathan

* Monograph 35/2016
  Valuation of Coastal and Marine Ecosystem Services in India: Macro Assessment
  K. S. Kavi Kumar, Lavanya Ravikanth Anneboina, Ramachandra Bhatta, P. Naren, Megha Nath, Abhijit Sharan, Pranab Mukhopadhyay, Santadas Ghosh, Vanessa da Costa and Sulochana Pednekar

* Monograph 36/2017
  Underlying Drivers of India's Potential Growth
  C.Rangarajan and D.K. Srivastava

* Monograph 37/2018
  India: The Need for Good Macro Policies *(4th Dr. Raja J. Chelliah Memorial Lecture)*
  Ashok K. Lahiri

* Monograph 38/2018
  Finances of Tamil Nadu Government
  K R Shanmugam

* Monograph 39/2018
  Growth Dynamics of Tamil Nadu Economy
  K R Shanmugam

* Monograph 40/2018
  Goods and Services Tax: Revenue Implications and RNR for Tamil Nadu
  D.K. Srivastava, K.R. Shanmugam

* Monograph 41/2018
  Medium Term Macro Econometric Model of the Indian Economy
  D.K. Srivastava, K.R. Shanmugam

* Monograph 42/2018
  A Macro-Econometric Model of the Indian Economy Based on Quarterly Data
  D.K. Srivastava

* Monograph 43/2019
  The Evolving GST
  Indira Rajaraman

MSE Working Papers

Recent Issues

* Working Paper 246/2023
  Role of State in Food and Nutrition security: A case of Telangana
  Gummadi Sridevi, Amalendu Jyotishi, Matta Srinivas & Balaji
* Working Paper 247/2023
  The Impact of Monetary and Fiscal Stimulus on Stock Returns During the COVID-19 Pandemic
  Chinmaya Behera, Badri Narayan Rath & Pramod Kumar Mishra
* Working Paper 248/2023
  Deflecting Economic Sanctions: Do Trade and Political Alliances Matter?
  Devasmita Jena, Akash & Prachi Gupta
* Working Paper 249/2023
  The Lausanne School of Economics
  S. Pridiksha & T. Archana
* Working Paper 250/2023
  Determinants of Efficiency of Commercial Banks in India after Global Crises
  K. Ravirajan & K. R. Shanmugam
* Working Paper 251/2023
  Determinants of Non-Performing Assets of Commercial Banks in India
  K. Ravirajan & K. R. Shanmugam
* Working Paper 252/2023
  The Effect of Technology on Financial Performance of Indian Banks
  K. Ravirajan & K. R. Shanmugam
* Working Paper 253/2023
  Public Debt and External Debt Sustainability among BRICS Countries
  Magulsha George & K. R. Shanmugam
* Working Paper 254/2023
  Efficiency of Commercial Banks in India after Global Financial Crisis
  K. Ravirajan & K. R. Shanmugam

---

* Working papers are downloadable from MSE website http://www.mse.ac.in

$ Restricted circulation