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Coal Mining and Access to Livelihood Capitals: Mines and Non-mines Affected Villages in Jharkhand (India)

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Abstract

This study aims to evaluate the situation of livelihood capital utilisation, its major determinant and rising inequality in its utilisation during economic transformation. It uses primary data of 416 sample households from predefined compared groups (viz. mines exposed versus non-exposed villages) which was collected under the cross-sectional research designed by a structured questionnaire. The principal component analysis, bivariate, logistic regression, iv-probit 2sls regression and concentration index (CI) are used to achieve the study objectives. The odds ratio shows that mines affected villages were less likely to utilise natural capital. Although it had a significantly higher likelihood to utilise social, physical, economic capitals compare with their counterparts. Besides, the odds of human capital does not show any utilisation differences between both residential settings. However, in the context of aggregate utilisation of ACI, there is a significantly higher likelihood for mines affected villages. The study applied iv-probit 2sls regression and found that mines generated income had significant influences over ACI. The CI coefficient shows that in mines affected villages social capital equally utilise by across all income class than other capitals. In a nutshell, finite nature of coal-generated income has no sustainability; hence, it shows an inverse association with livelihood sustainability.

Keywords: Natural capital, economic capital, social capital, physical capital, human capital, coal mining, sustainability

I. Introduction

Mining activity translates minerals into different forms of capital that contribute to a nation's output. In the contemporary world with the rising demand for energy resources, along with favourable mining policy, coal mining sector transformed into an investment hub. Moreover, in the absence of a suitable alternative source of energy, the role of coal becomes crucial to fulfil energy requirement for heavy industries and other developmental projects and hence, its extraction becomes inevitable (Sherbinin et al., 2008).

On the one hand, installation of coal mining industries creates a range of positive effects not only at the national level but also on proximate population by providing direct or indirect benefits such as the creation of high earning jobs, roads, schools, water facilities, hospitals, etc (Hota & Behera, 2016; Mishra, 2009). Nevertheless, on the opposite hand, several researchers criticising coal mining led developmental theory of economic growth. They argued that benefits and related costs of mining are unfairly distributed not only at a local level but also at the national level (Emel & Huber, 2008). However, mainly proximate population to mines bears the cost of mining because mining cannot be done without unduly interfering and damaging the local environment.

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Consequently, widespread degradation of the ecosystem (e.g. fresh air and water, timber and non-timber forest products, a decline in the water table, etc.) has been eroding and transforming the traditional means of livelihood of the proximate population in a mining-based economy. In this economic transformation, a significant share of coal mining-related benefits was grabbed by the local elite, and the unaffected population resides away from the mining area. Nevertheless, arises effects from mining are attributed to various personal as well as household capabilities such as social background, resource ownership, access to economic and political power, education, etc (Mishra & Pujari, 2008; Hendryx & Ahern, 2009; Mishra & Reddy, 2010; Arifwidodo & Perera, 2011; Hota & Behera, 2016).

The availability of capabilities affects the wellbeing of any person and household by either direct or indirect ways. The example of direct capabilities is, land, access to forest resources, earning, asset ownership, etc., whereas indirect capabilities are social status, better education, better health, etc. It implicitly influences the wellbeing of the individual and household altogether. Both perspectives make an integrated approach to the economic and social development of the household (Sen, 1997).

Chambers and Conway (1991) in their classical paper mention that *"… capabilities, assets (store, resources, claims and access), and activities are required for a means of living"* (p. 6). These qualities or capabilities are categorised as different dimensions of livelihood capitals (namely, natural, social, human, physical and economic). Further, *"… livelihood is sustainable when it can cope with and recover from stresses and shocks and maintain or enhance its capabilities and assets, and provide sustainable livelihood opportunities for the next generation; which contributes net benefits to other livelihoods at the local and global levels and in the short and long terms"* (p. 6).

India holds the fifth most significant coal reserves and is third-largest coal producer country in the world. Further, at the national level, Jharkhand ranks first for coal endowment and second for its production followed by Chhattisgarh. The State Government has continuously diverted its forest land to increase coal production[1]. The proximate villages to the coal mines consider the mining as a shock which destroys or modifies their survival capabilities. The present study tries to examine the utilisation level, and pattern of different livelihood capitals, its major determinants and role of disposable income reap from coal to improve the household capabilities to utilise a high level of capitals. It also attempts to examine the emerging inequality in capital utilisation levels during economic structural changes.

II. Methodology

Setting and location

The study was conducted in Baghmara block of Dhanbad district (known as 'the coal capital of India') of Jharkhand, India. It is the only block of the district where approximately half (33 out of 71) of the panchayats have a coal-bearing capacity and having a coal mine which is mainly operated by Bharat Coking Coal Limited (BCCL). This geographical variation/clustering in the location of mines within the block provided us with an opportunity to conduct a cross-sectional comparative study. Also, the demographic and socio-economic characteristics of this block show that out of the total population of 334,309, as many as 33.4 per cent of people live in the urban areas (Census of India, 2011). The majority of its population is composed of Hindus (87.5%), followed by Muslims (10.6). The caste composition of this block shows that 26 per cent of the population belongs to the Scheduled Castes (SCs) and Scheduled Tribes (STs). The working-age (15-60) of the population is nearly 39.5 per cent, while the rest is the dependent population in the age groups 0-14 and 60+ years.

[1] https://coal.nic.in/sites/upload_files/coal/files/curentnotices/30-08-2018.pdf

Sample group

The targeted population for this study consisted of households from mines affected and non-mines affected villages. The sampled households were selected by using a multistage sampling technique in the first stage, whereby we obtained a list of 34 villages which were affected by the mining activity of BCCL from initiation year of mining to till the year 2015. After that, we have matched the list of villages with the village-level information from the Census of India (2011) to know the present status of the villages. The matching exercise revealed that only 20 out of 34 villages at present exist, the remaining villages either vanished or transformed from villages to towns. The existing villages were then categorised according to the mining activity as opencast mining (5), underground mining activity (12) and discontinued mining (3). For the study convenient, we selected opencast and underground mines affected villages. From them, we chose two villages each (that is, four mines affected villages) by using the Probability Proportional to Size (PPS) sampling technique.

As this is a comparative study, we selected four non-mines affected villages based on two criteria: firstly, the villages should be located at least 5 km (aerial distance) away from the coal mines, and secondly, they should have approximately the same proportion of SCs population corresponding to the selected mines affected villages.

After the selection of eight villages, 52 households were selected for interviews from each village. The interview was conducted with the help of systematic random sampling (that is, the total number of the households in the village divided by the total number of the desired household sample) from the sampling frame of the village. In this way, the study collected complete data from 416 households (see Table 1). This sample size was decided to fulfil/ fix the desired quota of the sample because of two reasons: firstly, this study not only deals with the estimation of prevalence rate, and secondly, while pre-testing the interview schedule of this study, it was observed that the prefixed sample size is sufficient to achieve the objectives in the context of time and money constraint.

Ethical clearance

The study was approved by the Students Research Ethics Committee (SREC) of the International Institute for Population Sciences (IIPS), Mumbai. The Committee examined the methodological, technical and ethical soundness of the study. Also, before conducting the interviews, we obtained the prior consent of the participants and assured them of confidentiality.

Table 1: Hierarchical flow chart for sample selection

Selection	Study area	Criteria/rationale
State	Jharkhand	State affected profoundly by coal mining activities in the country
District	Dhanbad	Known as the coal capital of India due to the highest production of coal
Block	Baghmara	Nearly one-half panchayats of the block have the coal-bearing capacity
Village	Four mining-affected villages	Two affected villages each from the underground and opencast mining categories
	Four non-mining affected villages	Selected corresponding to mining-affected villages based on the criteria of distance from coal mines and the proportion of SCs population
Household	52 HHs/village	Systematic random sampling based on a sampling frame
Total sample size 416		

Data collection

The concurrent mixed-method approach of data collection was used for data collection. The fieldwork for the study was carried out from September 2014 to February 2015 by the first author. It was assumed that the data collection strategy comprehensively assesses the research questions. For the collection of quantitative data related to the utilisation of livelihood capitals, we formulated a standard indicator with the motivation of a sustainable livelihood (SL) framework given by Department for International Development (DFID). The asset-based data collection is considered as more reliable in this context, Sahn and Devid (2003) argued that it uses simple questions or direct observation by the interviewer consequently, it suffers less from recall biases. The related close-ended questions were first formulated in English and later translated to Hindi.

The survey instrument was pre-tested with 30 sample households to check the suitability of the tool for necessary modifications. After the survey, all the questionnaires were reviewed for accuracy, consistency and completeness and where necessary, additional field visits were made to clarify data entries to improve data quality. The data was entered in the CS-Pro 6.2 (The Census and Survey Processing System) database which has been developed by the U.S. Census Bureau and ICF Macro, and the data analysis was done on Stata 13.1.

For the collection of qualitative information on different issues, we did key informant interviews (KIIs) with the stakeholders (i.e., BCCL officers, a local administrative officer, NGO workers, political leaders, school teachers and Rozgar Sevaks). In-depth interviews (IDIs) were conducted with Gram Sabha presidents of each mine-affected village to know the village-level problems. Besides, four focused group discussions (FGDs) were done with a pre-existing 5 to 8-member groups of people of heterogeneous ages for better interaction in the mining-affected villages using a pre-structured interview schedule. All the standard guidelines of FGDs were followed. The collected qualitative information was coded and analysed with the help of the Atlas.ti 5.0 software.

Methods

The study has analysed the data in seven steps. First, it constructed the livelihood indices based on DFID approach with suitable modification according to the study needs. However, this framework does not attempt to provide an exact representation of reality. It provides little insight into the livelihood endeavours of poor peoples for poverty reduction. Specifically, the SL approach believes that during livelihood endeavour people require a range of assets to achieve positive livelihood outcomes. These assets were broadly categorised into five types of livelihood capitals, (namely, natural capital, social capital, economic capital, physical capital and human capital). Together in equal proportion, these capitals work to yield several types of livelihood outcomes that people need.

The Principal Component Analysis (PCA) has been used to make different livelihood capital indices. Basically, it is a dimension-reduction tool that can be used to reduce a broad set of variables to a small set that still contains most of the information in the large set. Before applying PCA for making indices, we converted all the categorical variables into binary form. After the preliminary works, PCA has been applied to the selected variables and eigenvectors, derived from the component matrix that has been used as weights for summary statistics and factor score of the variables used in the computation. The predicted value of the composite index has divided into two parts based on the mean value, i.e., 1) lower than the mean value, and 2) more than and equal to mean value. We have not divided the index value into more than two parts because of the small sample size as it might lead to lower cell frequencies in further analysis. We also checked the reliability of the index with the help of Cronbach alpha (**α**) value.

Secondly, the Cronbach alpha (**α**) test has been used to estimate the reliability of the indices. The obtained value for **α** usually indicates the percentage of reliable variance and internal consistency. If the α value lower than 0.5 consider as low reliable, whereas when the α value has more than and equal to 0.5 consider being reliable and acceptable. Further, α value lies between 0.5 and 0.7 consider as moderate reliable, 0.7 and 0.9 as highly reliable and greater than 0.9 excellently reliable (Hinton et al., 2014; Schmitt, 1996; Sijtsma, 2009).

Economic Capital Index (ECI)

This index is created with the help of variables like per capita yearly household income (that is, 0=less than thirty thousand and 1=more than and equal to thirty thousand) and household's ownership of insurance coverage. The α value for the index is about 0.66.

Natural Capital Index (NCI)

This index is created with the help of variables like access to farmland, selling of forest products, and household use of forest products. The α value for the index is about 0.52.

Physical Capital Index (PCI)

This is an index created with the help of given information on 26 durable household items like pucca house structure, four or more rooms, LPG connection, kitchen facility, latrine facility, etc. The α value for the index is about 0.89.

Social Capital Index (SCI)

This is a composite index created with the help of variables like easy access to a member of legislative assembly (MLA), participation in socio-political gatherings and membership of a socio/ political organisation. The α value for the index is about 0.55.

Human Capital Index (HCI)

This is a composite index created with the help of variables like schooling of the head of a household (that is, 0=less than 10 years of schooling and 1=10 or more years of schooling), any member of a household has at least 10 or more years of schooling and vocational education training of the head of a household (that is, 0=no training & 1=ITI or other). The α value for the index is about 0.58.

All-Capital Index (ACI)

Empirically, it is proved that access to livelihood capital affects the status of household differently, but the study of holistic development of household by capitals effectively only is done with its aggregated effect. Hence, in this order composite index of livelihood capital has been created with the help of used information in different livelihood capitals, namely, physical capital, economic capital, human capital, social capital and natural capital. The α value for this index is about 0.90.

Thirdly, bivariate analyses have been carried out to assess the level of utilisation of different livelihood capital in both types of villages. Fourthly, the tri-variate analysis has been conducted to see the utilisation pattern of all capitals. Fifthly, the binary logistic regressions have been carried out to identify the main determinants of different livelihood capital utilisation. Sixthly, the instrumental variable probit two-stage least square (IV-probit 2sls)-regression has been used along with 'Wald test' of the exogeneity to see the effect of income on the utilisation of high ACI. This method is used to see the income endogeneity caused by unobservable shocks led by coal mining generated income which affects its utilisation level by households. As an instrument, the study used the two village-level variables of distance (in km.) such as distance to the 1) primary health care centre and 2) primary school. Both the distance indicators symbolise the development status of the village (Balanay et al., 2014; Khandker et al., 2009). Seventhly, the concentration index has been calculated to see the emerging inequality in the course of economic transformation.

III. Results

Utilisation level of different livelihood capitals

Table 2 shows the utilisation levels of livelihood capitals. Households from mines affected villages were utilised 21 per cent less NCI compared with their counterparts. However, in the context of rest of other capitals utilisation, households from mines affected villages were 15 per cent more SCI, 16 per cent more PCI, 2 per cent more HCI and 8 per cent more ECI than their counterparts. Moreover, ACI shows that households from mines affected villages utilised 13 per cent more capital than those from non-mines affected villages.

Table 2: Percentage utilisation of high level of livelihood capitals by households in Dhanbad, 2015

High capital index	Non-mines affected villages	Mines affected villages	All villages
NCI	52.4	33.2	42.8
SCI	38.9	53.4	46.2
PCI	35.1	51.4	43.3
HCI	40.9	39.4	40.1
ECI	29.3	37.5	33.4
ACI	37.0	50.0	43.5
Total (N)	(208)	(208)	(416)

Note: Low level + High level=100%, Higher the value means higher the utilisation level and vice versa.
NCI: Natural capital index; SCI: Social capital index; PCI: Physical capital index; HCI: Human capital index; ECI: Economic capital index, ACI: All capital index.

Utilisation pattern of ACI

Table 3 shows the higher utilisation of ACI by households from both types of villages. It was found that joint and nuclear households from mines affected villages utilised 17 and 11 per cent respectively more capital than their counterparts. In general joint households utilised it almost one and half times more than nuclear family size households. Its utilisation also follows the caste hierarchy in general. Forward castes utilised it more, followed by OBCs and SCs and STs in both types of villages. Further, SC, ST and OBC households from mines affected villages were utilised ACI 8 per cent and 20 per cent respectively more than their counterparts. Years of schooling influence capital utilisation and similarly those household heads who had 10 or more years of schooling utilised ACI more than illiterate and less schooled household heads.

Further, between both types of villages, households from mines affected villages utilised it almost 22 per cent more than those of non-mines affected villages. Age of household head is a significant predictor of capital utilisation. With the increase in age of household head, the utilisation level of capital also increases. Households from mines affected villages utilised more capital than non-mines affected villages according to age. According to the principal occupation of household utilisation level of capital varies. Households having no earner and regular salaried households from mines affected villages utilise more capital compared with their counterparts. The utilisation of capital increases with house-type kaccha to pucca: the households from mine-affected villages were more affected compared with their counterparts. With the size of farmland holding, the utilisation of capital by household increased. In the non-mines affected villages, the highest farmland holder utilises more capital than his counterpart.

Table 3: Percentage of households utilise a high level of ACI by background characteristics, Dhanbad, 2015

Background characteristics	Non-mines affected villages	Mines affected villages	All villages
Family type			
Joint	53.85	70.91	62.62
Nuclear	31.41	42.48	36.89
Caste			
SCs/STs	30.70	38.57	33.70
OBCs	31.15	51.55	43.67
Forward castes (general)	69.70	65.85	67.57
Years of schooling of the head of household			
Illiterate	17.74	23.21	20.34
Less than 10 years	25.35	44.44	36.02
More than 10 years	64.00	82.26	72.26
Age of household head			
21-35years	17.78	40	26.67
36-55years	39.45	47.06	43.13
More than 55 years	48.15	57.89	53.85
The principal occupation of household			
No earner	11.76	47.37	30.56
Regular salaried job	70.21	80.95	76.36
Self-employed	66.67	64.29	65.08
Wage labour & agriculture	22.76	20.24	21.74
Type of household			
Kuccha	12.50	26.67	19.83
Semi-pucca	22.00	40.54	29.89
Pucca	57.84	65.77	61.97
Farmland size			
No land	28.57	44.25	38.64
Less than 2 acres	31.9	50.88	38.15
More than 2 acres	75.86	65.79	70.15
Total (N)	(208)	(208)	(416)

Note: Low level + High level=100%, Higher the value means higher the utilisation level and vice versa.

Comparison of the odds ratio of adjusted and unadjusted logistic regression for different livelihood capitals

Table 4 comprises the result of two different types of binary logistic regression models, i.e., adjusted and unadjusted. By these logit models, the study tries to understand the utilisation of different livelihood capitals in both residential settings. The unadjusted logistic regression has carried out with a single predictor variable, whereas adjusted regression models have been performed with several controlled background characteristics. Both table mainly show changes in the odds ratio of utilisation of different livelihood capitals in unadjusted to the adjusted regression models. It uses the different indices (such as NCI, SCI, HCI, ECI, PCI and ACI) as dependent variables, that is equal to one if villages get high capital access and zero otherwise.

The unadjusted regression model shows that mines affected villages were positively associated with utilisation of high level of livelihood capitals, namely, SCI, ECI, PCI and ACI. In contrast, in the adjusted model, utilisation was positively associated with only SCI, PCI and ACI. Besides, odds ratio shows that households from mines affected villages significantly 55 per cent less utilise NCI in both the regression models. It proves that the availability of NCI was considerably low in mines affected villages. The utilisation of SCI in households of mines affected village significantly increases by 1.7 times (in the unadjusted model) to 1.9 times (in the adjusted model). It signifies the role of other confounding factors which enhance the utilisation capability of

SCI by households of mines affected villages. The utilisation of HCI in mines affected villages did not show a significant effect, whereas its utilisation shows a reduction from unadjusted to adjusted regression models. It indicates that mines affected villages lag from their counterparts in terms of HCI formation. The ECI was significantly 1.4 times more likely to be associated with mines affected villages in the unadjusted model, but in the adjusted model, it not only becomes insignificant but also reduces by 11 percentage points. The odds ratio of PCI in the unadjusted model refers that mines affected villages were significantly 1.7 times more likely to utilise it, and it further increased significantly to 2.3 times after adjusting other confounding factors. The odds ratio of ACI shows in the mines affected villages utilisation of high capital was significantly 1.7 times more in the unadjusted model and further increased significantly up to 2.1 times after adjusting other confounding factors than its counterpart.

Table 4: Odds ratio of different livelihood capital utilisation by a household in mines affected and not affected villages in Dhanbad, 2015

Capitals	Unadjusted		Adjusted	
	Odds ratio	[95% C I]	Odds ratio	[95% C I]
NCI	0.451***	[0.270 0.602]	0.452**	[0.247 0.827]
SCI	1.794***	[1.215 2.649]	1.964**	[1.048 3.678]
HCI	0.942	[0.636 1.393]	0.771	[0.430 1.383]
ECI	1.446*	[0.959 2.178]	0.891	[0.489 1.624]
PCI	1.788***	[1.321 2.904]	2.392**	[1.128 5.074]
ACI	1.719***	[1.150 2.515]	2.127*	[0.976 4.639]

Notes: P-value *p<.1, **p<.05, ***p<.01. All adjusted logit models were controlled with several confounding variables *(refer appendix table 1-6)* according to their dependent variable.

Qualitative insights

For the diminishing utilisation of natural capital by mines affected village, one of the Gram Sabha Presidents (56-year-old male) stated,

> *"Earlier this place was known as a 'rice-bowl', but after initiation of coal mining in this area life of people has drastically changed. BCCL is now becoming a key player in reshaping the physiography of the area according to their need. It digs the land anywhere, and it creates a big mountain of debris. It changes the flow of rivers for its mines' safety, also discharges mine water into it. Sometimes BCCL also makes an artificial river to pump out collected water in the mines. In this whole process of land use, a huge amount of vegetation has been lost."*

In the context of social capital formation, one of the respondents (50-year-old male school teacher) stated,

> *"Here all the people have to face many problems on a day to day basis because of BCCL's activities. Whenever its activities created problems, people protested against it collectively."*

In the context of the diminished human capital utilisation, one respondent (50-year-old male school teacher) discussed the education scenario and stated,

> *"After the opening of mines in the area, stealing of coal has become an everyday phenomenon. Children and youth are heavily involved in this type of activity to earn easy money, and once they are habituated with it, they ignore their education and further involvement in harmful activities like gambling and drinking."*

The other informant (44-year-old male) discussed the health services and stated,

> *"We get some medical assistance from state government hospitals only. They do not provide ambulance service, and it always suffers from a shortage of medicines. Usually, doctors do not come on time; therefore, sometimes we have to spend several hours in waiting."*

In the context of diminished economic capital utilisation, one Gram Sabha President (70-year-old male) informed,

> *"Job against land compensation is a very messy issue which cannot be addressed by BCCL or government properly. One job against two acres of land and no job but only cash compensation against less land has destroyed the harmony of the family because whoever gets more share of benefit tries to separate from the joint family structure."*

Another Gram Sabha President (50-year-old male) remarked,

> *"Out-sourced companies often avoid employing local people for work because they do not want any problem or threat from the labour union. Moreover, for getting a job in these companies, you have to have a high-level recommendation."*

Results of IV-probit 2SLS regression

The likelihood of ACI utilisation increases from unadjusted to adjusted logistic regression. This increment possible caused by income endogeneity. In this context, Table 5 exhibits the evidence associated with the income effects on utilisation of high ACI. The positive income (exp.β= 29.1) effects on ACI implies that income has a capability to bring opportunities that tend to enhance the capability of a household to utilise higher ACI. Besides, the OBCs and forward caste groups show significantly [exp.β= 2.2 and exp.β= 1.8 times respectively] more chance to utilise high ACI. The household size, such as four-five-members and six or more members were significantly [exp.β= 3.2 and exp.β= 8.4 times respectively] more likely to utilise high ACI. More than two or more earners in a household are significantly [exp.β= 0.48] less likely to utilise the high ACI. Exponential coefficients (β) shows that more than 35-year-old head of household, the occupation of the head of household and villages affected by mining activity has not only become insignificant but also their utilisation level of high ACI reduces considerably. Moreover, utilisation likelihood of high ACI has significantly reduced by 9 percentage point for mines affected village.

At the bottom of the Table, the result of 'Wald test' of the exogeneity for instrumented variables are mentioned which rejects the null hypothesis of no endogeneity. Moreover, the test statistic is significant, which shows the availability of sufficient information in the sample to reject the null hypothesis, and so this probit regression is appropriate to explain it.

Results of concentration index (CI)

Previous studies have indicated that with economic transformation of the area, inequality has been emerging in the utilisation of the different livelihood capitals. Hence, we attempted to assess the magnitude of inequality through the concentration index in the utilisation of different livelihood capitals (Table 6). The concentration index has been constructed for both types of villages to illustrate absolute and relative inequality. Results indicate that in general natural capital was mainly used by poor households and rest other capitals mainly by better-off households. Specifically, in the mines affected villages, natural capital is significantly (CI -0.27, ***p<.01) utilised by poor households. Affluent households significantly utilised physical, human and economic capitals. In the case of social capital, its index value is only 0.02 and insignificant, which means that due to mining effect, social class barriers in mines affected villages have been broken, and now it is equally utilised by all social classes.

IV. Discussion

This study contributes six main findings to the livelihood capital utilisation and its sustainability in the proximate villages to mines. First, coal mining significantly affects the household's natural capital utilisation capabilities by more than half. Secondly, coal mining and social capital show inverse relationship and hence mines affected villages have significantly 1.9 times more likely to utilise social capital ability compared with its counterpart. Thirdly, there was no significant difference between both mines affected and not affected villages in the utilisation of human capital. Fourth, households from mines affected village utilise economic capital significantly 1.4 times more than their counterparts. Nevertheless, after adjustment with the other predictor factors, its utilisation not only becomes insignificant but also reduced by 11 per cent. Fifth, households from mines affected villages utilise 1.7 times more physical capital than their counterparts, and even after controlling other confounding factors, the likelihood of their utilisation has increased up to 2.3 times. Sixth, the findings of IV regression confirm the positive disposable income effect on the utilisation of high ACI.

Table 5: IV-Probit 2SLS regression of the probability for ACI utilisation in Dhanbad, 2015

Background characteristics	Coef. (β)	[95% C I]
Income	3.371***	[0.971 5.770]
Mining status of the villages		
Non-mines affected villages®		
Mines affected villages	-0.089	[-0.519 0.341]
Age of the household head		
25-35 Years®		
36-55 Years	-0.481	[-1.351 0.389]
More than 55 years	-0.579	[-1.775 0.618]
Caste		
SCs/STs®		
OBCs	0.808**	[0.118 1.497]
Forward castes (generals)	0.596*	[-0.043 1.235]
Size of the household		
1-3 Members®		
4-5 Members	1.189**	[0.076 2.303]
6 or more members	2.129***	[0.597 3.662]
Earners		
Less than two earners®		
Two or more earners	-0.739**	[-1.469 -0.010]
Constant	-34.131***	[-57.695 -10.567]
Wald test of exogeneity	3.77*	

Note: P-value *p<.1, **p<.05, ***p<.01
Predictor variable 'Occupation of the household head' also controlled for this regression model.

Table 6: Concentration index by livelihood capitals and villages status in Dhanbad, 2015

Index	Mines affected villages		Non-mines affected villages	
	CI	SE	CI	SE
NCI	-0.27***	0.06	-0.18***	0.04
PCI	0.30***	0.03	0.34***	0.05
SCI	0.02	0.04	0.17**	0.05
HCI	0.18***	0.05	0.12***	0.05
ECI	0.48***	0.04	0.53***	0.05
ACI	0.34***	0.03	0.36***	0.05

Note: P-value *p<.1, **p<.05, ***p<.01.

Forest regions are mineral-rich, but due to mining activity, extensive deforestation has occurred in the past, and it continues. Hence, the forest-dependent population is severely affected by mining by losing its traditional means of livelihood. Mining dismantles the agricultural system and gathering of forest products for livelihood (Hota & Behera, 2016; Mishra & Reddy, 2010; Mishra & Pujari, 2008; Papworth et al., 2017). This deprivation from their traditional means of livelihood makes people interdependent, and they develop a strong community feel and increasing the utilisation of social capital. It is evident that if any community protest against a socio-political issue increases the community bondage too (Malone, 2008). Our results confirm that those household heads attending social gatherings are significantly 1.7 times more likely to utilise social capital. Several previous studies proved that the association between poverty and social capital utilisation is strong (Sun et al., 2009).

In terms of human capital formation or enrichment, there was no significant difference between mines affected and not affected villages. This finding is entirely contrary to the mining industry’s claims that under CSR activity, they usually organise medical camps and hospital facility, education and technical training to the proximate population. However, the reluctant efforts of mining industry towards human capital formation in mines affected villages directly affects their economic performance. Consequently, their households can only utilise the only low level of economic capital hence, unemployment, low wages, unskilled work, lack of entrepreneurship, etc., are normal (Betz et al., 2015; Douglas & Walker, 2017; Narula et al., 2017). However, there is the disparity in the HCI and ECI utilisation, forward castes followed by OBCs and SCs/STs. This finding is consistent with a previous study which stated that usually education and earning opportunity follow caste hierarchy and are mainly concentrated around forward castes (Dershem & Gzirishvili, 1998). Coal mining has a consistently inverse association with measures linked to population growth and entrepreneurship, and thereby future economic growth.

Households from mines affected villages utilise a higher level of physical capital compared with their counterpart households. This finding is consistent with previous studies which stated that due to structural transformation, not only mining industries develop physical infrastructure in proximate villages but also people use different physical assets in their homes (Mishra, 2009). Factors such as higher age of household head, a higher number of household members, 10 or more years of schooling of household head, media exposure of the household head, more than two acres of farmland holdings and households having high expenditure have three times higher chance to utilise PCI.

The study has found that households of mines affected villages significantly use all types of capital (ACI). There is a positive income effect on the utilisation of high ACI. The disposable income generated by coal mining can bring opportunities in its vicinity, and enhances the utilisation level of high capital of the households. However, after controlling income effect, utilisation of high capital in mines affected villages not only becomes insignificant but also reduces. This finding indicates that after the closing of mines, there will be a significant decline in the local economy in earning opportunity. Previous studies have also found indications of a resource bane in the mining regions and its depressing effect on proximate population (Betz et al., 2015; Boyce & Herbert Emery, 2011; Douglas & Walker, 2017).

Conclusion

Based on the current study, we draw some conclusions. ACI shows the aggregated positive effect on its higher utilisation by households from mines affected villages. Nevertheless, after the adjustment of income endogeneity from the households, higher utilisation of ACI by mines affected villages becomes not only insignificant but also becomes negative. Hence, the adjusted net effect on the utilisation of ACI disapproves of the linear relation between coal mines and livelihood capital for human wellbeing in Dhanbad.

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Appendix Tables

Appendix Table 1: The determinant of NCI utilisation by households in the mines affected and not affected villages, Dhanbad, 2015

	Odds Ratio	[95% C I]
Mining status of the villages		
Non-mines affected villages®		
Mines affected villages	0.452**	[0.247 0.827]
Sex		
Male®		
Female	2.744**	[1.055 7.134]
Age		
25-35 years®		
36-55 years	2.081**	[1.058 4.093]
More than 55 years	1.593	[0.690 3.680]
Caste		
SCs/STs®		
OBCs	1.311	[0.736 2.333]
Forward castes (general)	0.477*	[0.220 1.034]
Year of schooling		
No formal schooling®		
Less than 10 years of schooling	0.535**	[0.290 0.989]
10 or more years of schooling	0.532*	[0.254 1.117]
Media exposure		
No exposure®		
Any newspaper/TV	0.557*	[0.310 1.001]
Participation in socio-political gathering		
No®		
Yes	1.763*	[0.971 3.203]
Occupation of the household head		
No occupation®		
Regular salaried	1.253	[0.494 3.179]
Self-employed	0.398*	[0.136 1.165]
Wage labour & agriculture	1.534	[0.677 3.471]
Farmland size		
No land®		
Less than 2 acres	5.841***	[3.190 10.695]
More than 2 acres	7.744***	[3.557 16.860]
Monthly per capita expenditure		
Low®		
Middle	0.960	[0.517 1.785]
High	0.248***	[0.114 0.539]
Log-likelihood	-205.486	

Note: P-value *p<.1, **p<.05, ***p<.01; ®= Reference category; Predictor variables such as household size, number of household earner, BPL/ AAY, type of household and debt status of the household also controlled for this model of logistic regression.

Appendix Table 2: The determinant of SCI utilisation by households in the mines affected and not affected villages, Dhanbad, 2015

	Odds Ratio	[95% C I]	
Mining status of the villages			
Non-mines affected villages®			
Mines affected villages	1.964**	[1.048	3.678]
Media exposure			
No exposure®			
Any newspaper/TV	2.967***	[1.460	6.031]
Participation in a social gathering			
No®			
Yes	1.728*	[0.944	3.165]
BPL/AAY			
No®			
Yes	27.261***	[13.218	56.220]
Monthly per capita expenditure			
Low®			
Middle	1.985*	[0.969	4.069]
High	2.983***	[1.310	6.794]
Debt status of household			
No®			
Yes	1.590*	[0.959	2.638]
Log-likelihood	-199.105		

Note: P-value *p<.1, **p<.05, ***p<.01; ®= Reference category; Predictor variables such as sex, age, household size, caste, years of schooling, occupation of the head of household, number of household earners, farmland size status of the household are controlled for this model of logistic regression.; Abbreviations- Below Poverty Line (BPL), Antyodaya Anna Yojna (AAY).

Appendix Table 3: The determinant of HCI utilisation by households in the mines affected and not affected villages, Dhanbad, 2015

	Odds Ratio	[95% C I]	
Mining status of the villages			
Non-mines affected villages®			
Mines affected villages	0.771	[0.430	1.383]
Sex			
Male			
Female	0.179***	[0.052	0.617]
Caste			
SCs/STs®			
OBCs	2.230***	[1.278	3.891]
Forward castes (general)	2.635***	[1.304	5.326]
Media exposure			
No exposure®			
Any newspaper/TV	1.936**	[1.067	3.512]
Participation in the social gathering			
No®			
Yes	0.537**	[0.310	0.931]
Occupation of the household head			
No occupation®			
Regular salaried	2.437*	[0.984	6.033]
Self employed	1.896	[0.757	4.751]
Wage labourers & agriculture	0.807	[0.353	1.846]
Size of the household			
1-3 members®			
4-5 members	2.264**	[1.085	4.724]
6 or more members	2.242**	[1.013	4.960]
BPL/AAY			
No			
Yes	0.561**	[0.322	0.977]
Farmland size			
No land®			
Less than 2 acres	1.870**	[1.073	3.259]
More than 2 acres	2.327**	[1.157	4.678]
Log-likelihood	-215.637		

Note: P-value *p<.1, **p<.05, ***p<.01; ®= Reference category; Predictor variables such as age, number of household earner, farmland size, MPCE, and debt status of the household are controlled for this model of logistic regression. Abbreviations- Below Poverty Line (BPL), Antyodaya Anna Yojna (AAY).

Appendix Table 4: The determinant of ECI utilisation by households in the mines affected and not affected villages, Dhanbad., 2015

	Odds Ratio	[95% C I]	
Mining status of the villages			
Non-mines affected villages®			
Mines affected villages	0.891	[0.489	1.624]
Age of the household head			
25-35 years®			
36-55 years	1.650	[0.761	3.581]
More than 55 years	2.251*	[0.879	5.769]
Year of schooling of the household head			
No formal schooling®			
Less than 10 years of schooling	2.158**	[1.018	4.575]
10 or more years of schooling	2.749**	[1.190	6.351]
Media exposure			
No exposure®			
Any newspaper/TV media	7.627***	[3.887	14.967]
Size of the household			
1-3 members®			
4-5 members	0.480*	[0.229	1.006]
6 or more members	0.599	[0.260	1.380]
BPL/AAY			
No®			
Yes	0.268***	[0.119	0.608]
Occupation of the household head			
No occupation®			
Regular salaried	2.326*	[0.882	6.130]
Self employed	2.369*	[0.863	6.501]
Wage labourers & agriculture	0.632	[0.246	1.621]
Number of household earners			
Less than two earners®			
Two or more earners	2.197**	[1.137	4.246]
Log-likelihood	-180.233		

Note: P-value *p<.1, **p<.05, ***p<.01; ®= Reference category; Predictor variables such as sex, caste, access to Member of the Legislative Assembly (MLA), farmland holding, debt status of the household are controlled for this model of logistic regression. Abbreviations- Below Poverty Line (BPL), Antyodaya Anna Yojna (AAY).

Appendix Table 5: The determinant of PCI utilisation by households in the mines affected and not affected villages, Dhanbad, 2015

	Odds Ratio	[95% C I]	
Mining status of the villages			
Non-mines affected villages®			
Mines affected villages	2.392**	[1.128	5.074]
Size of the household			
1-3 members®			
4-5 members	1.386	[0.607	3.162]
6 or more members	3.590***	[1.386	9.304]
Year of schooling of the household head			
No formal schooling®			
Less than 10 years of schooling	1.332	[0.605	2.931]
10 or more years of schooling	3.269**	[1.315	8.126]
Media exposure			
No exposure®			
Any newspaper/TV	6.321***	[3.016	13.249]
Age of the household head			
25-35 years®			
36-55 years	2.159*	[0.917	5.083]
More than 55 years	3.784**	[1.299	11.027]
BPL/AAY			
No®			
Yes	0.207***	[0.101	0.423]
Farmland size			
No land®			
Less than 2 acres	1.443	[0.718	2.902]
More than 2 acres	3.814***	[1.523	9.553]
Monthly per capita expenditure			
Low®			
Middle	1.005	[0.458	2.208]
High	4.736***	[1.947	11.521]
Debt status of household			
No®			
Yes	0.481**	[0.256	0.904]
Log-likelihood	-149.107		

Note: P-value *p<.1, **p<.05, ***p<.01; ®= Reference category; Predictor variables such as sex, caste, participation in a social gathering, the occupation of the head of households, and the number of household earners are controlled for this model of logistic regression. Abbreviations- Below Poverty Line (BPL), Antyodaya Anna Yojna (AAY).

Appendix table 6: The determinant of ACI utilisation by households in the mines affected and not affected villages, Dhanbad, 2015

	Odds Ratio	[95% C I]	
Mining status of the villages			
Non-mines affected villages®			
Mines affected villages	2.127*	[0.976	4.639]
Age of the household head			
25-35 years®			
36-55 years	1.748	[0.727	4.204]
More than 55 years	3.281**	[1.083	9.945]
Years of schooling of the household head			
No formal schooling®			
Less than 10 years of schooling	1.176	[0.516	2.681]
10 or more years of schooling	5.610***	[2.152	14.623]
Media exposure			
No exposure®			
Any newspaper/TV media	7.387***	[3.441	15.856]
Size of the household			
1-3 members®			
4-5 members	1.386	[0.591	3.251]
6 or more members	3.426**	[1.282	9.157]
BPL/AAY			
No®			
Yes	0.259***	[0.125	0.538]
Farmland size			
No land®			
Less than 2 acres	1.796	[0.872	3.699]
More than 2 acres	4.007***	[1.556	10.320]
Monthly per capita expenditure			
Low®			
Middle	1.593	[0.707	3.591]
High	8.825***	[3.522	22.117]
Log-likelihood	-140.725		

Note: P-value *p<.1, **p<.05, ***p<.01; ®= Reference category; Predictor variables such as sex, caste, participation in a social gathering, the occupation of the head of households, number of household earners and debt status of the household are controlled for this model of logistic regression. Abbreviations- Below Poverty Line (BPL), Antyodaya Anna Yojna (AAY).