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Does social capital increase healthcare financing's projection? Results from the rural household of Uttar Pradesh, India

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ABSTRACT

In the absence of adequate social security, out-of-pocket health expenditure compels households to adopt coping strategies, such as utilizing savings, selling assets, or acquiring external financial support (EFS) by borrowing with interest. Households' probability of acquiring EFS and its amount (intensity) depends on its social capital – the nature of social relationships and resources embedded within social networks. This study examines the effect of social capital on the probability and intensity of EFS during health events in Uttar Pradesh (UP), India. The analysis used data from a cross-sectional survey of 6218 households, reporting 3066 healthcare events, from two districts of UP. Household heads (HH) reported demographic, socioeconomic, and health-related information, including EFS, for each household member. Self-reported data from Shortened and Adapted Social Capital Assessment Tool in India (SASCAT-I) was used to generate four unique social capital measures (organizational participation, social support, trust, and social cohesion) at HH and community-level, using multilevel confirmatory factor analysis. After descriptive analysis, two-part mixed-effect models were implemented to estimate the probability and intensity of EFS as a function of social capital measures, where multilevel mixed-effects probit regression was used as the first-part and multilevel mixed-effects linear model with log link and gamma distribution as the second-part. Controlling for all covariates, the probability of acquiring EFS significantly increased ($p = 0.04$) with higher social support of the HH and significantly decreased ($p = 0.02$) with higher community social cohesion. Conditional to receiving any EFS, higher social trust of the HH resulted in higher intensity of EFS ($p = 0.09$). Social support and trust may enable households to cope up with financial stress. However, controlling for the other dimensions of social capital, high cohesiveness with the community might restrict a household's access to external resources demonstrating the unintended effect of social capital exerted by formal or informal social control.

1. Introduction

In seven decades since independence, the Indian health sector has made significant progress in improving access and availability of health services, infrastructure, human resources, and availability of vaccines and medicines (Patel et al., 2015). At a broader contextual level, income has risen, millions have been lifted out of poverty, the country is urbanizing rapidly, and the population is aging (Desai et al., 2010). While continuing to grapple with the prevention and control of communicable diseases, staggered reduction of maternal and child mortality, and the burden of non-communicable illnesses and substance abuse (Al Kibria, Swasey, Hasan, Sharmeen, & Day, 2019; Hasan, Cohen, et al., 2020; Zodpey & Farooqui, 2018), the Indian health sector is facing a growing challenge of rising healthcare expenditure (Sangar, Dutt, & Thakur, 2019). At the national level, 59% of the total healthcare expenditure is financed by households' out-of-pocket contributions (National Health Accounts Technical Secretariat National Health Systems Resource Centre & Ministry of Health and Family Welfare, 2019). The burden of

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healthcare expenditure is surprisingly high for the rural region of northern India – more specifically in Uttar Pradesh. The latest Sample Survey (2019) reported that a household in Uttar Pradesh spends around International.$ [Int.$][1] 1264 for each hospital stay episode and Int.$ 41 per non-hospitalization events (1 Int.$ = 20.65 Indian Rupee, TheWorld Bank, 2017).

High out-of-pocket payment while seeking healthcare often leads to financial catastrophe (World Health Organization, 2017). An analysis of the 75th round of the National Sample Survey reported four out of five (81%) household of India faces catastrophic expenditure (10% of household's total consumption expenditure) and 40% households fall into poverty when paying for healthcare (Yadav, Menon, & John, 2021). The impact of catastrophic health expenditure reduces healthcare utilization, leading to a pervasive cycle of ill health and poverty (Russell, Fox-Rushby, & Arhin, 1995).

The high burden of healthcare costs results from the absence of an effective formal financial risk-sharing mechanism. At the national level, only 14% of the rural and 19% of the urban population are covered by any health insurance in India (National Sample Survey Office, 2019). Moreover, in Uttar Pradesh, only 6.1% of the households have at least one member insured by any health insurance package (International Institute for Population Sciences & ICF, 2017). Thus, the financial burden of healthcare has to be coped with using various informal risk-sharing mechanisms, such as using the savings, selling or mortgaging assets, borrowing, or reducing consumption expenditures (Quintussi, Van de Poel, Panda, & Rutten, 2015). According to the most recent estimates, household income and savings together are the most significant sources for healthcare payment (80% and 84% for rural and urban areas accordingly). In comparison, around 17% of the rural and 12% of the urban households use external financial support (EFS) – such as borrowed money or contribution/gift/help from friends and family – to pay for the cost of hospitalization (National Sample Survey Office, 2019).

Relying on one's associational network for this type of informal borrowing and gift-giving largely depends on social capital (Kanbur et al., 2000). Bourdieu (1986) and Lin (2001) defined social capital mainly focusing on the economic value of the expected return for one's investment in the social relationships. According to them, social capital is defined as the characteristics of social relationships and the actual or potential resources embedded within the social network of a person that can be accessed and utilized in the time of need (Bourdieu, 1986; Lin, 2001).

Social capital is often used as an alternative form of social insurance for "*tapping resources*" from neighbors, friends, and social groups to cushion the shocks of healthcare costs (Ravallion, 2016; Townsend, 1995; World Bank, 2014). Acquiring EFS as borrowed money or a gift from friends and relatives to pay for healthcare is identified as an *"Idiosyncratic Risk Sharing"* (Dercon, 2002). However, there are limitations to this type of risk-sharing strategy. The type, frequency, and severity of the disease can drastically change the coping strategies (Morduch, 1999). Moreover, socioeconomic status and health-related behaviors also affect the ability of the household to implement these informal risk-sharing strategies, such as drawing on social support from the community. De Weerdt (2004) reported that poor households often struggle to mitigate financial stress because of fewer social contacts or limited resources within their networks. Nevertheless, these coping strategies may have far-reaching consequences in the future as they continue the *"inequity and patronage lined with the risk sharing agreement"* (Fafchamps, 2003).

Previous literature anecdotally reported social capital as a coping strategy to mitigate the financial stress of healthcare (Fang, Shia, & Ma, 2012; Hoque, Dasgupta, Naznin, & Al Mamun, 2015; Nguyen et al., 2012; Quintussi et al., 2015). According to Chou (2006), there are three possible ways a household can use social capital as an economic tool: (a) using the information from the social network to obtain instrumental support (Valente, Hoffman, Ritt-Olson, Lichtman, & Johnson, 2003), (b) being cohesive with social groups to acquire social support (Kawachi et al., 2013), and (c) transforming the credit of social capital into human capital (Bourdieu, 1986). However, to date, no study has quantitatively explored if the stock of social capital within a household has any empirical association with the probability of acquiring EFS and its intensity (amount of EFS acquired).

Addressing this gap in evidence, this is the first study that had explored the first two mechanisms whereby being a part of social groups or deeply embedding yourself with the social norms could allow you to access financial resources within the social networks. This study aims to statistically examine the association between household head's social capital and the probability and intensity of acquiring EFS while paying for healthcare, using two-part mixed-effects models in a sample from rural Uttar Pradesh, India.

2. Methods

2.1. Conceptualizing social capital and healthcare payment using two-part mixed-effects models

Fig. 1 presented our framework, which conceptualized how social capital – along with other social determinants – influences the acquisition of EFS for healthcare expenditure during the care-seeking event using a conceptual framework (Fig. 1). During a healthcare-seeking event for its member, a household engages with the health system embedded within the community. A household has to finance for the care-seeking events – if any expenditure is incurred – via a wide range of strategies such as using their saving, selling or mortgaging assets, or borrowing (Quintussi et al., 2015; Russell, 2001). Without the presence of a robust social safety net, a household with overwhelming financial stress may try to draw supports from its community as financial gifts or borrowed credit (Dhanaraj, 2016). However, the stress-buffering effect of EFS largely depends on two critical elements – (a) the probability of acquiring any EFS and (b) the amount of EFS acquired (its intensity) if any EFS was received.

This phenomenon splits up the analytical sample into two groups – (1) receivers vs. non-receivers of EFS – presenting a binary distribution, and (2) who received any amount of EFS – presenting a continuous distribution. The nature of the relationship between covariates (such as social capital) and EFS will be considerably different for these two underlying analytical samples (Sauzet, Razum, Widera, & Brzoska, 2019). Furthermore, while exploring this relationship, the statistical analysis must account for the hierarchical nature of the data (health-seeking events nested in individuals nested in households nested in communities) using multilevel regression models (Hasan, Dean, et al., 2020; Rice & Jones, 1997). Thus, our study had implemented two-part mixed-effects models by fitting the binary and continuous components of EFS separately as a function of the covariates (Aitchison, 1955; J.; Zhao et al., 2020; T.; Zhao et al., 2016).

2.1.1. Part 1 – selection equation: multilevel mixed-effects probit regression

The first part, the selection equation, of the two-part mixed-effect model considers a binomial distribution – whether any EFS was received ($y > 0$) for paying for a healthcare event or not ($y = 0$) – and implements a mixed-effects probit regression to estimate the probability of acquiring any EFS. Let us consider M number of household members, each of whom had multiple healthcare events for which EFS can be acquired. These events can be influenced by a set of fixed effects x_{ij} and random

[1] AIC = Akaike information criterion; CI = Confidence intervals; EFS = External financial support; ICC = Intraclass correlation coefficient; Int.$ = International.$; MCFA = Multilevel confirmatory factor analysis; LL = Log-Likelihood; PPP = Purchasing power parity; SASCAT-I = Shortened and adapted social capital assessment tool in India; SD = Standard deviation; VIF = Variance inflation factor.

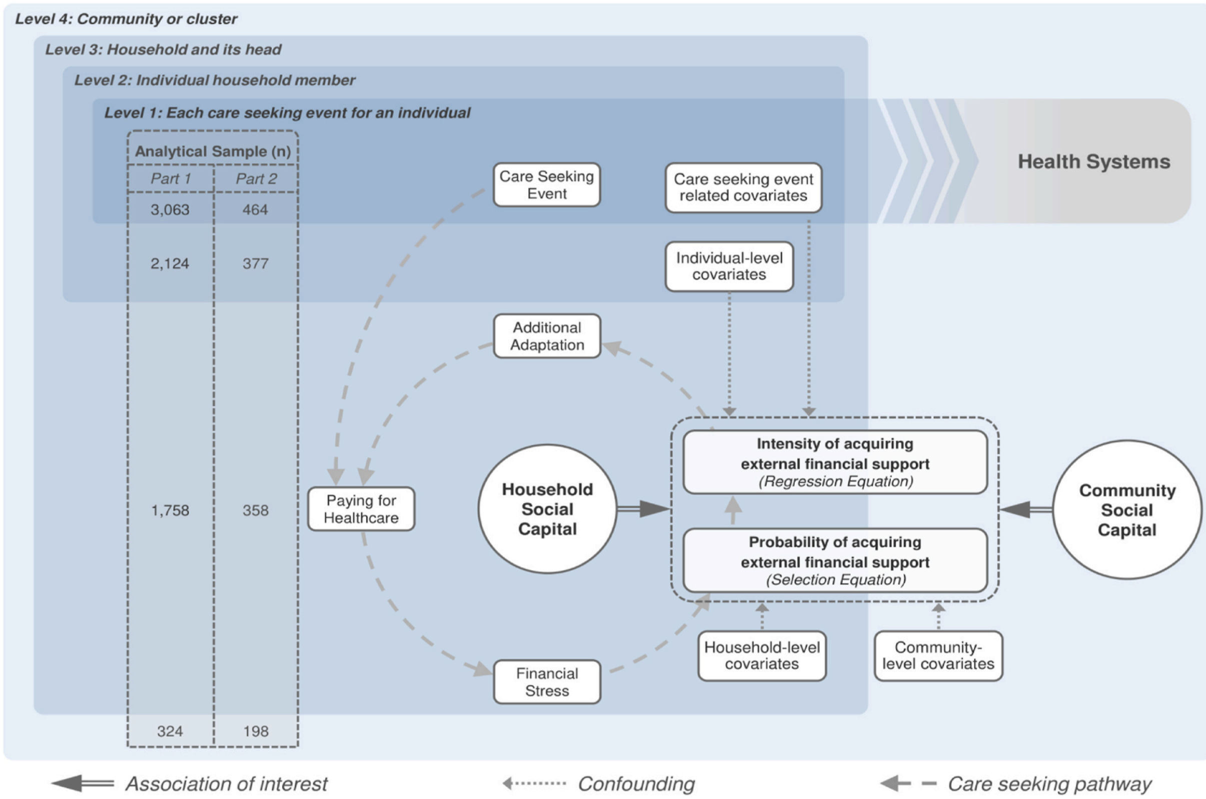

Fig. 1. Conceptual framework to explore the role of social capital as a determinant of DPT3 immunization among 12-59-month-old children in UP, India.

effects u_{ij}. The probability function of acquiring EFS can be defined as:

$$Pr(y_{ij} > 0 | x_{ij}, u_j) = H(x_{ij}\beta_{p1} + u_j) \quad (1)$$

Here, $j = 1, \ldots, M$ individuals, with the j individual having $i = 1, \ldots, n_j$ healthcare-seeking events. The outcome (y_{ij}) is a binary response, where $y_{ij} > 0$ if any EFS is acquired and $y_{ij} = 0$ otherwise, x_{ij} is the $1 \times p$ row vector of fixed effects, and β_{p1} are their associated regression coefficients for the Part 1 model. Considering no random slope, u_j is the random intercept for each individual, which follows a multivariate normal distribution with the mean of 0 and a variance of σ^2_u. Lastly, $H(\bullet)$ presented a standard normal cumulative distribution function. For the probit regression, this function estimates the probability of ($y_{ij} > 0$). While equation (1) presents a simplified two-level model, the mixed-effects probit regression can be extended into three or four levels with nested random intercepts for households and communities as higher-level clusters.

2.1.2. Part 2 – regression equation: multilevel mixed-effects linear model with log link and gamma distribution

Conditional to any EFS acquired ($y_{ij} > 0$), the intensity of EFS can be fitted with a multilevel mixed-effects linear model. This is called the “regression equation”. If we consider n number of healthcare-seeking events, for which EFS is received, are clustered within each of M individuals, the estimated intensity of EFS can be defined as:

$$g\{E(y_{ij} | y_{ij} > 0, x_{ij}, v_j)\} = x_{ij}\beta_{p2} + v_j, \; y_{ij} \sim F \quad (2)$$

Here, $j = 1, \ldots, M$ individuals, with the j individual having $i = 1, \ldots, n_j$ healthcare-seeking events with $y_{ij} > 0$. Also, $y_{ij}|y_{ij} > 0$ is the $n \times 1$ vector for the EFS intensity reported by the household, which takes the form of the F distribution. The model also includes the $1 \times p$ row vector of x_{ij} covariates as fixed effects, for each of them, β_{p2} are the associated regression coefficients for the Part 2 model. Without considering any random slopes, v_j indicates the random intercept for each individual having a multivariate normal distribution with the mean of 0 and a variance of σ^2_v. Here, $g(\bullet)$ is identified as an invertible link function. Specific distribution (F) and link function (g) must be specified for the linear mixed-effect model during the estimation process. Much like healthcare expenditure data, the positive values of EFS tends to be right-skewed (O’Donnell, van Doorslaer, Wagstaff, & Lindelow, 2007). In this case, log link and gamma distribution perform exceptionally well (Malehi, Pourmotahari, & Angali, 2015), and equation (2) can be re-specified as:

$$ln(y_{ij} | y_{ij} > 0, x_{ij}, v_j) = \beta_0 + x_{ij}\beta_{p2} + v_j + \varepsilon_{ij}, \; y_{ij} \sim Gamma \quad (3)$$

$$E(y_{ij} | y_{ij} > 0, x_{ij}) = exp^{x_{ij}\beta_{p2}} \quad (4)$$

The $\beta_0 + x_{ij}\beta_{p2}$ presents the overall regression line for all individuals, v_j indicates the random intercept, representing the variability of each individual from the mean, and ε_{ij} is the normally distributed random error. Due to the natural log transformation of $y_{ij}|y_{ij} > 0$ response, β_0 and β_{p2} estimates need to be exponentiated for interpretation. This retransformation changes the β_0 as the geometric mean of EFS of all individuals and β_{p2} as the multiplicative coefficient (rate ratio) in reference to the β_0. If the data present additional higher levels of clustering, this two-level model can be naturally extended into three or four levels by including additional random intercepts.

2.2. Study design and analytical sample

The analytical sample of this study came from a cross-sectional household survey conducted in six census blocks of two rural districts of Uttar Pradesh, India. The survey was conducted from June to August 2017 in 6218 randomly selected households from 346 rural communities (averaging 17–18 households per cluster). The ethical approval for the survey was obtained from the Institutional Review Board Office of the author’s institute and locally from the Center for Media Studies, New Delhi, India.

After receiving oral informed consent, trained data collectors interviewed the household heads (≥18 years) using a multi-topic structured questionnaire. Each household head reported a wide range of information, including demographic information, socioeconomic and consumption data of the household, and the social capital of the household head. The respondents also provided detailed information on the illness, care-seeking events, healthcare expenditure, the source, and the amount for healthcare payment strategies for each household member within the last six months of the survey.

The unit of analysis of this study was "healthcare-seeking events" of the individual household members. The analytical sample consisted of 3066 healthcare events sought by 2127 members of 1761 households within 324 communities. The response rate was 99%, with only three observations missing the age of the respondents. The effective sample size for Part 1 (selection equation) was 3063 healthcare events from 2124 members living in 1758 households nested within 324 communities. And the effective sample size for the Part 2 (regression equation) was 464 healthcare events – for which any EFS was received – from 377 members living in 358 households nested within 198 communities (Fig. 1).

2.3. Outcome variable

The response variable of the study was the total amount of money (in Indian Rupees) the household has acquired as EFS. Household heads separately reported the amount of EFS acquired as help/gift and borrowed money for each healthcare-seeking event within the last six months preceding the survey. We considered the cumulative amount from the two sources as the EFS values. In this analysis, the selection equation considered a binary EFS indicator using the zero vs. non-zero EFS values as the outcome, and for the regression equation, the outcome was the positive values of EFS (see supplement 1 in Additional File 1). For ease of interpretation, EFS values were converted into Int.$ using the 2017 Purchasing Power Parity (PPP) conversion factor for India (The World Bank, 2017).

2.4. Explanatory variables

2.4.1. Household head and community social capital measure

The measure of social capital of the household heads and the communities were the primary explanatory variables of this study. During the survey, each household head responded to the Shortened and Adapted Social Capital Assessment Tool in India (SASCAT-I) (Hasan et al., 2019), where they reported their community participation (2 questions), collective action (2 questions), social support (3 questions), social cohesion (3 questions), and trust (3 questions). These responses were categorized into 12 categorical indicators and used as the input for a multilevel confirmatory factor analytical model (MCFA), considering each household head as level one (n = 6218) and community as level two (n = 346) (Heck & Thomas, 2015).

Four unique latent constructs of social capital emerged from the MCFA – both at the household and community level – classified as organizational participation, social support, trust, and social cohesion. Standardized factor scores were obtained from the MCFA model as the composite measure for the social capital constructs and included in the analysis (see supplement 2 and 3 in Additional File 1 for details).

2.5. Other covariates

The association between the social capital and acquisition of EFS and its intensity could be confounded by several factors, such as the attributes of each healthcare event – the type of illness, type of healthcare providers, and the frequency of healthcare-seeking episodes by an individual within the six months preceding the survey. Similarly, characteristics of the individual household members for whom healthcare was sought (e.g., age, gender, education, disability, etc.), traits of the household heads (gender, education, occupation, etc.), and features of the household itself (religion, caste, wealth, financial stability, monthly health expenditure, etc.) can influence the relationship between social capital measures and EFS.

As each household is embedded within the community, the community's organization, its environment, and the socio-cultural factors would also affect the ability of a household head to draw in EFS (Nyswander, 1956). Thus, considering the hierarchical nature of the data and the confounding effect of the social determinants from various levels of the community, a wide range of covariates were included in the analysis (Table 1).

2.6. Analytical strategy for implementing the two-part mixed-effects model

Before implementing the regression models, we performed descriptive analysis and explored the Intraclass Correlation Coefficient (ICC) of EFS for the underlying two sub-samples. This is particularly necessary to understand the proportion of the overall variance of EFS explained by the members, household, and community-level, which informed the number of random intercepts needed to be included in the regression models (Rice & Jones, 1997).

The ICC for the analytical sample of Part 1 (selection equation, n = 3063) indicated 45%, 38%, and 10% of the total variance of the binary EFS outcome was attributed to individual members (level 2, n = 2124), household (level 3, n = 1758) and community (level 4, n = 324), respectively. Thus, we implemented four-level mixed-effect probit models as Part 1 of the two-part model. We did not observe a similar pattern of ICC for the EFS intensity in the analytical sample of Part 2 (regression equation, n = 464). Only 18 out of 358 households (5%) – which had acquired EFS – had more than one member for whom the EFS was acquired. Including individual members as a separate random intercept in the mixed-effect model would not provide any additional benefit. Thus, we implemented three-level mixed-effect models with log link and gamma distribution as Part 2, where 72% and 5% of the total variance of EFS intensity was attributed to the households (level 2, n = 358) and community (level 3, n = 198).

To understand the explanatory power of the covariates, first, bivariate regression models were implemented. Covariates with a p-value ≤ 0.2 in the bivariate regressions were included in the multiple regression model (Maldonado & Greenland, 1993). Before developing the multivariate models, the multicollinearity of the eligible covariates was assessed using the variance inflation factor (VIF). Next, we separately implemented the adjusted regression models with the appropriate number of random intercepts (identified from the ICC values) with no random slopes.

For estimating the adjusted effect of social capital measures, we have implemented six alternative specifications of Part 1 and 2 regression models, starting with a null model with no covariate (Model 1) and incrementally including fixed effects associated with social capital (Model 2), healthcare events (Model 3), household members (Model 4), households and its heads (Model 5), and the community (Model 6). For the ease of interpretation of the final model (Model 6), we calculated the marginal effects of the estimated coefficients of the multilevel mixed-effects probit model, which indicated the marginal probability of acquiring EFS as a function of the covariates. For the multilevel mixed-effects linear model, we exponentiated the estimated coefficients, which represented the ratio of the acquired EFS amount in reference to the baseline (constant or β_0) as a function of the covariates.

To assess the overall significance of the categorical variables, Wald tests were used after each regression. The goodness of fit of all adjusted models was evaluated using Log-Likelihood (LL) and Akaike information criterion (AIC). In addition, to assess the robustness of our final model, sensitivity analysis was conducted considering only borrowed money, and gifted money as the outcome variable, separately, instead of the cumulative EFS value.

Table 1
Covariates included in the two-part mixed-effects models according to the level of analysis.

Variables	Type	Description
Level 1 covariates: Characteristics of the care-seeking events		
Cause of health-seeking	Categorical	Health condition for which care has been sought
Sequence of health visits	Categorical	A dummy variable indicating the first, second, or the third episode of the healthcare-seeking event for a household member in the last six months
Healthcare provider	Categorical	Type of providers from whom healthcare was sought after
Level 2 covariates: Characteristics of the individual household members for whom healthcare was sought		
Gender	Binary	Gender of an individual household member
Age categories	Categorical	Age of the household member as a category
Relationship with household head	Categorical	Relationship of the household member with the household head
Education	Categorical	Educational attainment of the household member
Employment status	Binary	Employment status of the household member
Disability	Binary	Presence of any disability of the household member
Level 3 covariates: Characteristics of the household heads and the household		
Gender	Binary	Gender of the household head
Age categories	Categorical	Age categories of the household heads
Education	Categorical	Educational attainment of the household head
Occupation	Categorical	Occupation of the household heads
Freedom of decision making	Binary	Perceived level of freedom of decision making of the household heads
Household head's social capital measures	Continuous	Four standardized factor scores of household head's social capital constructs derived from the MCFA measured by Adapted Social Capital Assessment Tool-India (SASCAT-I)
Religion	Binary	Religion of the household
Caste	Categorical	Social caste of the household
Caste concordance	Binary	An indicator which reflects if the household caste was the same as the dominant caste of the community
Wealth	Categorical	Asset index was developed by principal component analysis using 27 household asset-related binary variables. The standardized score of the first component was used to create five asset quintile groups, where Quintile 1 was assigned to the least wealthy household, and Quintile 5 was assigned to the wealthiest household
Financial stability	Categorical	Response of the household heads to the question *"In the last* 12 months*, how has your financial situation changed overall?"*
Household member number	Continuous	Number of members living in the household for the last six months
Monthly health expenditure	Continuous	Reported total monthly healthcare expenditure converted into the International.$ using Purchasing Power Parity (PPP) 2017 of India*. This is considered as the proxy of the severity of illness.
Level 4 covariates: Characteristics of the community		
Census block	Categorical	The administrative boundary which serves as the enumeration block of the census in each district
Community wealth	Continuous	Standardized average scores of the first component of principal component analysis from the households of each cluster
Community reciprocity	Continuous	The community-level average response of household heads of two questions: (1) "Do you think people in your village generally are willing to help each other out?" and (2) "Do you think if you help someone in your village, they will help you in return when you need it?" (response: Yes = 2, Sometime = 1, No = 0)
Community social capital	Continuous	Community-level standardized factor scores of four social capital constructs derived from the MCFA

Note: * = 1 International Doller = 20.648 Rupee (https://data.worldbank.org/indicator/PA.NUS.PPP?locations=IN).

3. Results

Overall, for 15.13% (n = 464) of healthcare-seeking events, the household heads received some amount of EFS within the last six months preceding the survey. Conditional on any EFS received, a household acquired an average of Int.$ 386.10 (range Int.$ 0.05–4794.65) as EFS, which indicated the data was skewed to the right, and application of log link is an appropriate decision (see supplement 4 in Additional File 1). Table 2 presents the descriptive statistics of the care-seeking events (n = 3066) and any care-seeking for which EFS was acquired (n = 464). Fig. 2 shows the distribution of the 12 social capital indicators reported by 1761 household heads disaggregated by the respondents who reported not acquiring (n = 1403) vs. acquiring some EFS (n = 358). A statistically significant difference ($p < 0.05$) was observed for their collective action, emotional support, informational support, trust in strangers, and sense of belonging.

The effect estimates of social capital measures were robust and stable across all alternative specification models with different sets of covariates (Fig. 3) (see supplement 5, 7, and 8 in Additional File 1 for more details). Moreover, the sensitivity analysis indicated that the final model estimates were valid. The models developed using borrowed and gifted money as separate outcome variables also presented a similar pattern of association with social capital measures (see supplement 9 and 10 in Additional File 1). Table 3 presents the adjusted marginal probability of acquiring EFS estimated using four-level mixed-effect probit model (Part 1: Selection Equation) and adjusted exponentiated estimates (or rate ratio) of the intensity of EFS estimated using from three-level mixed-effect linear models with log link and gamma distribution (Part 2: Regression Equation) from Model 6.

After adjusting for all fixed and random effects in the model, the probability of acquiring EFS during a health-seeking event significantly increased with a higher level of social support of the household head. In contrast, the intensity of EFS did not have any association with the household head's social support (Table 3). Within the same community, comparing two household heads with the difference of one standard deviation (SD) of social support, the household head with higher social support had a 2% higher probability of acquiring EFS (marginal probability = 0.02; 95% Confidence Intervals [CI] = 0.001, 0.03; p = 0.04), compared to a household head with the lower social support. On the other hand, the probability of acquiring EFS significantly decreased (p = 0.02) with increasing community-level social cohesion, while the intensity of EFS did not have any significant association (p = 0.49) with the community's cohesiveness. The result suggested, between two communities that differed by 1 SD of social cohesion, a household head living in the community with higher social cohesion had a 3% lower probability of acquiring EFS (marginal probability = −0.03; 95% CI = −0.06, −0.01; p = 0.02), compared to a household head from a community with lower social cohesion.

None of the social capital measures presented any significant association with the intensity of EFS (at the level of $p < 0.05$). However, considering a significance level of $p < 0.10$, the intensity of EFS – conditional on any EFS received – increased with a higher level of trust of the household head. Household heads living in the same community, who acquired at least Int.$ 1 as EFS during a care-seeking event for any

Table 2
Characteristics of study participants and their associated healthcare events in two rural districts of Uttar Pradesh, India.

	All care-seeking events (n = 3066)		Care seeking events for which external financial support received (n = 464)		
	N	*Col%*	*N*	*Col%*	
Characteristics of Healthcare Event					
Cause of health-seeking					
Pregnancy or delivery	201	6.56	52	11.21	
Acute Illness	1331	43.41	188	40.52	
Chronic illness	726	23.68	106	22.84	
Accident or injury	213	6.95	56	12.07	
Others	595	19.41	62	13.36	
Sequence of health visits					
First	2191	71.46	365	78.66	
Second	580	18.92	75	16.16	
Third	295	9.62	24	5.17	
Healthcare provider					
Public	641	20.91	105	22.63	
Private	2005	65.39	333	71.77	
Informal	420	13.70	26	5.60	
			Mean	*Min*	*Max*
Acquired financial support (Int.$)*			386.1	0.05	4794.65
Member's Characteristics					
Gender					
Male	1411	46.02	201	43.32	
Female	1655	53.98	263	56.68	
Age categories					
0–15 years	773	25.21	98	21.12	
16–49 years	1581	51.57	260	56.03	
50 yeas or above	709	23.12	106	22.84	
Relationship with household head					
Self	820	26.74	120	25.86	
Spouse	830	27.07	139	29.96	
Child/Parents	1140	37.18	175	37.72	
Others	276	9.00	30	6.47	
Education					
No Education	1037	33.82	155	33.41	
Up to primary	823	26.84	146	31.47	
Up to secondary	581	18.95	88	18.97	
Above secondary	242	7.89	34	7.33	
Child	383	12.49	41	8.84	
Employment					
Unemployed	2113	68.92	332	71.55	
Employed	953	31.08	132	28.45	
Disability					
No	2929	95.53	431	92.89	
Yes	137	4.47	33	7.11	
Household Head's Characteristics					
Gender					
Male	2674	87.21	399	85.99	
Female	392	12.79	65	14.01	
Age Categories					
Less than 30 years	646	21.07	129	27.80	
31–40	859	28.02	118	25.43	
41–50	663	21.62	93	20.04	
51–60	536	17.48	84	18.10	
61 and above	362	11.81	40	8.62	
Education					
No Education	924	30.14	157	33.84	
Up to primary	835	27.23	136	29.31	
Up to secondary	951	31.02	137	29.53	
Above secondary	356	11.61	34	7.33	
Occupation					
Agriculture	1539	50.20	197	42.46	
Wage laborer	769	25.08	149	32.11	
Self-employed & Salaried	345	11.25	44	9.48	
Unemployed	413	13.47	74	15.95	
Freedom of decision making					
Low	284	9.26	56	12.07	
High	2782	90.74	408	87.93	
Household's Characteristics					
Religion					
Hindu	2678	87.35	410	88.36	
Muslim and Others	388	12.65	54	11.64	
Caste					
General	618	20.16	87	18.75	
ST/SC	1291	42.11	193	41.59	

(*continued on next page*)

Table 2 (*continued*)

	All care-seeking events (n = 3066)			Care seeking events for which external financial support received (n = 464)		
	N	*Col%*		*N*	*Col%*	
OBC and Others	1157	37.74		184	39.66	
Caste concordance[b]						
No	1173	38.26		188	40.52	
Yes	1893	61.74		276	59.48	
Wealth						
Poorest	511	16.67		91	19.61	
Poorer	570	18.59		104	22.41	
Medium	633	20.65		90	19.40	
Richer	630	20.55		93	20.04	
Richest	722	23.55		86	18.53	
Financial stability						
Worsen	966	31.51		227	48.92	
Stable	1716	55.97		200	43.10	
Improved	384	12.52		37	7.97	
	Mean	*Min*	*Max*	*Mean*	*Min*	*Max*
Household member number (Count)	5.36	1	18	5.23	1	17
Monthly health expenditure (Int.$)*				434.99	0.05	22297.56
Community's Characteristics						
Census block						
Behadar	722	23.55		86	18.53	
Kachhauna	303	9.88		43	9.27	
Kothwan	525	17.12		83	17.89	
Kasmanda	379	12.36		55	11.85	
Machhrehta	488	15.92		104	22.41	
Sidhauli	649	21.17		93	20.04	
	Mean	*Min*	*Max*	*Mean*	*Min*	*Max*
Community wealth[c]	0.09	−2.00	3.63	−0.01	−2.00	3.63
Community reciprocity	0.87	0.00	2.29	0.87	0.00	2.29

Note: a = Social capital scores were measured as the standardized factor score generated by multilevel confirmatory factor analysis of social capital indicators of Shortened Adapted Social Capital Assessment Tool in India (SASCAT-I) b = Caste concordance: Household caste is the same as the caste of the majority of the population in the community.
c = Community wealth is measured by the average of the individual household wealth index generated by PCA.
* International.$ is calculated using Purchasing Power Parity (PPP) 2017 of India: 1 International Doller = 20.648 Rupee (https://data.worldbank.org/indicator/PA.NUS.PPP?locations=IN).

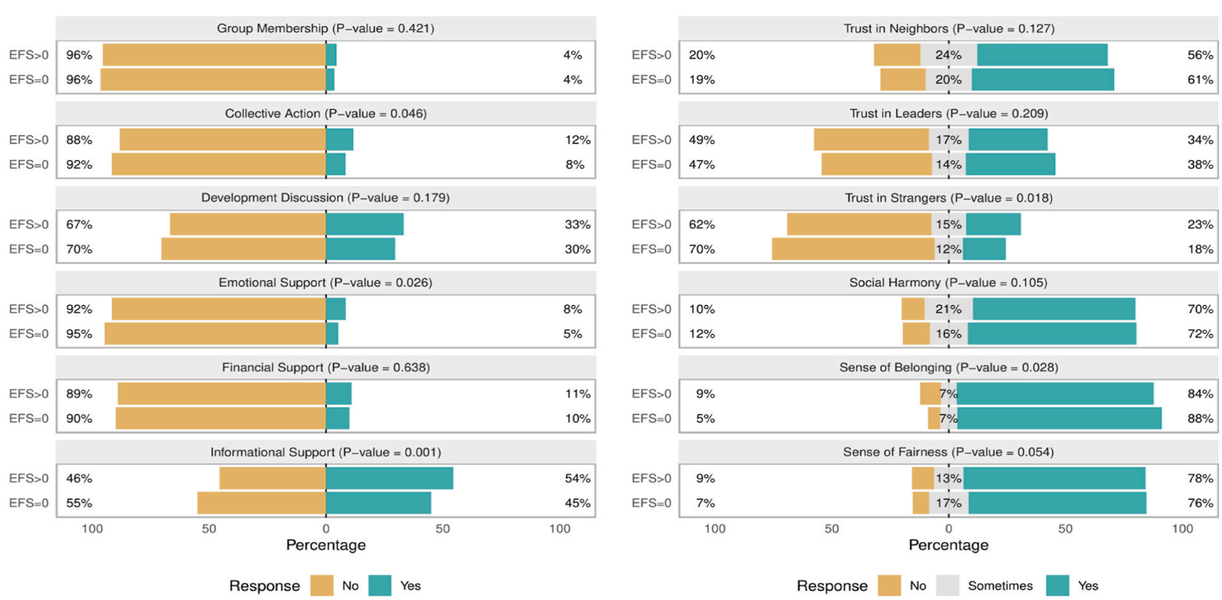

Fig. 2. Distribution of social capital indicators of household heads (n = 1749) and mothers (n = 1779) of 12–59-month-old children in UP, India.

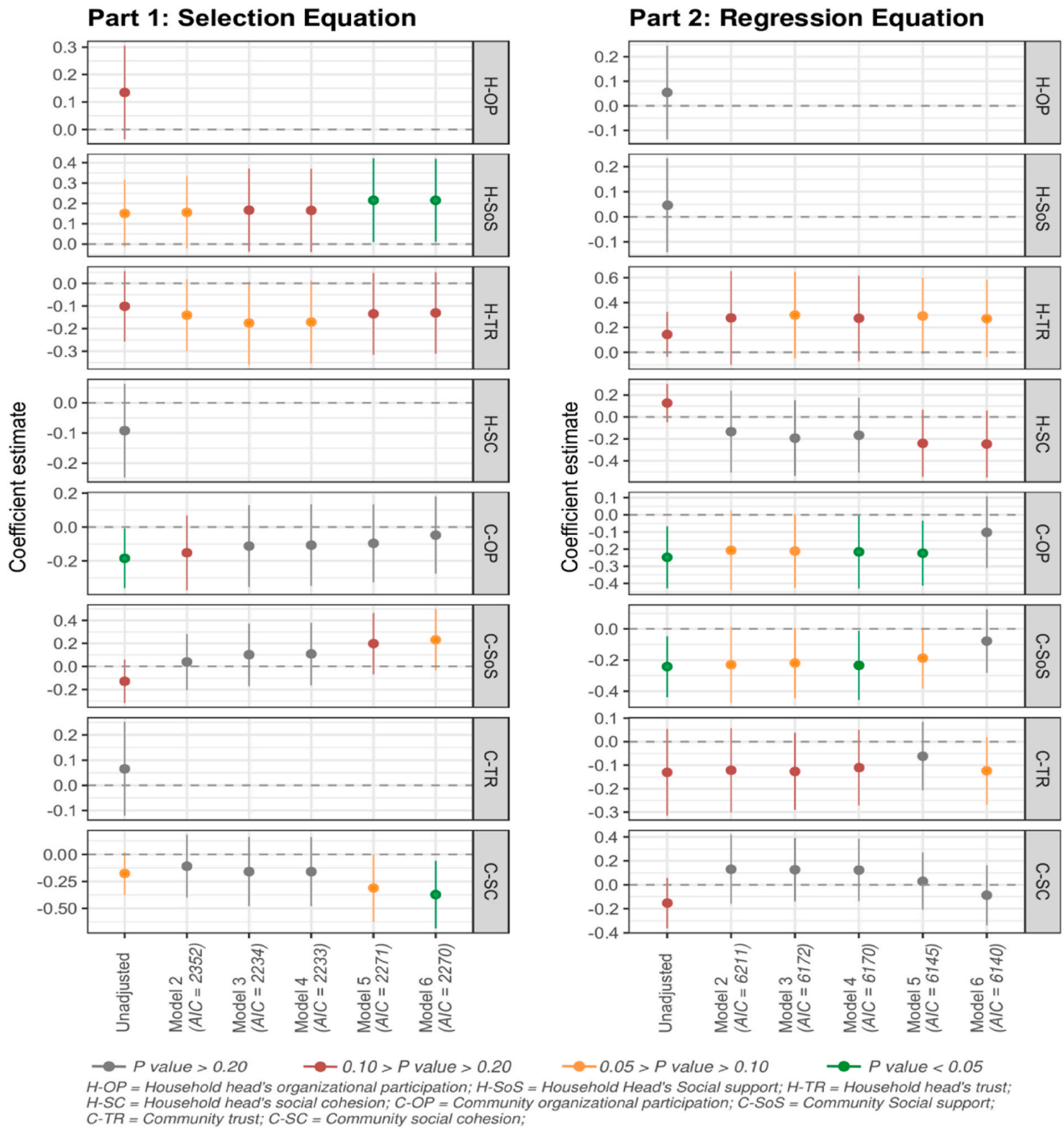

Fig. 3. Effect estimates of the social capital measures derived from four-level mixed-effect probit model (Part 1: selection equation) and three-level mixed-effects linear model with log link and gamma distribution (Part 2: regression equation) in rural Uttar Pradesh, India.

household member, was able to acquire a higher amount of EFS as a factor of 1.31 (95% CI = 0.96, 1.79, p = 0.09) with every 1 SD increase of their level of trust, after adjusting all fixed and random effects in the model.

4. Discussion

4.1. Discussion of the result

We found that for around 15% of healthcare-seeking events, EFS was acquired to pay for healthcare expenditures in Uttar Pradesh, a finding similar to the latest national estimate. According to the National Sample Survey (2019), around 16.8% of rural households of India financed hospitalization events either by borrowing or acquiring financial contributions from friends or relatives. The role of social capital in acquiring EFS was very much nuanced. We found that social capital constructs were both negatively (i.e., social cohesion) and positively (i.e., social support, trust) associated with EFS. Social capital also appeared to be a contextual feature of the community. Several studies also identified the contextual nature of social capital by reporting its influence on self-rated health (Mohnen, Groenewegen, Völker, & Flap, 2011), care-seeking behavior (Hasan, Dean, et al., 2020; Story, 2014), and mental health (De Silva, Huttly, Harpham, & Kenward, 2007).

The first set of results was rather intuitive, indicating a higher likelihood of a household head acquiring any EFS for a health event if he/she had higher social support. Bourdieusian perspective of social capital theorized that actual or potential neighborhood resources could support the health and wellbeing of an individual or community, “either in the absence of or in conjunction with, their own economic and cultural capital” (Carpiano, 2008). Our study – along with several previous

Table 3
Multivariate fixed and random-effect estimates derived from Model 6 of four-level mixed-effect probit model (Part 1: selection equation) and three-level mixed-effects linear model with log link and gamma distribution (Part 2: regression equation) in rural Uttar Pradesh, India.

	Four-level mixed-effect probit model (Part 1: selection equation)				Three-level mixed-effect linear model with log link and gamma distribution (Part 2: regression equation)			
	Adjusted Marginal Probability		[95% CI]	P Value	Adjusted Rate Ratio		[95% CI]	P Value
Fixed Effects								
Household head's social capital[a]								
H-SoS	0.02	*	[0.001, 0.03]	0.04	*Not included in adjusted model*[e]			
H-TR	−0.01		[-0.03, 0.004]	0.20	1.31	#	[0.96, 1.79]	0.09
H-SC	*Not included in adjusted model*[e]				0.78	#	[0.58, 1.06]	0.11
Community social capital[a]								
C-OP	−0.004		[-0.02, 0.02]	0.69	0.90		[0.73, 1.11]	0.34
C-SoS	0.02	#	[-0.002, 0.04]	0.09	0.93		[0.75, 1.13]	0.45
C-TR	*Not included in adjusted model*[e]				0.90	#	[0.78, 1.04]	0.14
C-SC	−0.03	*	[-0.06, −0.01]	0.02	0.92		[0.71, 1.18]	0.49
Characteristics of Healthcare Event								
Cause of health-seeking (Ref: Acute Illness)								
Pregnancy or delivery	0.08	*	[0.02, 0.15]	0.00	1.18		[0.71, 1.96]	0.00
Chronic illness	0.02	#	[-0.01, 0.06]		0.88		[0.61, 1.28]	
Accident or injury	0.08	**	[0.02, 0.15]		1.30		[0.83, 2.04]	
Others	−0.04	*	[-0.07, −0.01]		0.45	***	[0.29, 0.69]	
Sequence of health visits (Ref: First)								
Second	−0.03	**	[-0.06, −0.01]	0.00	0.65	*	[0.47, 0.91]	0.02
Third	−0.05	***	[-0.08, −0.02]		0.61	#	[0.35, 1.05]	
Healthcare provider (Ref: Public)								
Private	0.04	**	[0.01, 0.07]	0.00	0.94		[0.67, 1.32]	0.00
Informal	−0.07	**	[-0.10, −0.03]		0.25	***	[0.12, 0.49]	
Member's Characteristics								
Patient's age categories (Ref: 0–15 years)								
16–49 years	0.03	#	[-0.001, 0.07]	0.12	1.77	*	[1.10, 2.84]	0.06
50 yeas or above	0.05	#	[-0.001, 0.10]		1.59	#	[0.94, 2.68]	
Relationship with household head (Ref: Self)								
Spouse	*Not included in adjusted model*[e]				1.07		[0.73, 1.57]	0.92
Child/Parents					1.17		[0.75, 1.83]	
Others					1.12		[0.59, 2.13]	
Employment (Ref: Unemployed)								
Employed	−0.03	#	[-0.06, 0.004]	0.11	*Not included in adjusted model*[e]			
Disability (Ref: No)								
Yes	0.07	#	[-0.01, 0.14]	0.06	*Not included in adjusted model*[e]			
Household Head's Characteristics								
Age categories (Ref: less than 30 years)								
31-40	−0.04	#	[-0.09, 0.003]	0.03	*Not included in adjusted model*[e]			
41-50	−0.06	*	[-0.10, −0.01]					
51-60	−0.03		[-0.09, 0.02]					
61 and above	−0.09	**	[-0.15, −0.04]					
Education (Ref: No Education)								
Up to primary	−0.002		[-0.04, 0.04]	0.19	*Not included in adjusted model*[e]			
Up to secondary	−0.01		[-0.05, 0.03]					
Above secondary	−0.06	*	[-0.11, −0.01]					
Household head's occupation (Ref: Agriculture)								
Wage laborer	0.03		[-0.01, 0.07]	0.33	*Not included in adjusted model*[e]			
Self-employed & Salaried	0.02		[-0.03, 0.07]					
Unemployed	0.03		[-0.02, 0.08]					
Freedom of decision making (Ref; Low)								
High	−0.03		[-0.08, 0.02]	0.22	1.06		[0.69, 1.62]	0.80
Household's Characteristics								
Household caste (Ref: General)								
ST/SC	*Not included in adjusted model*[e]				0.82		[0.55, 1.23]	0.58
OBC and Others					0.82		[0.54, 1.23]	
Caste concordance[b] (Ref: No)								
Yes	*Not included in adjusted model*[e]				0.86		[0.64, 1.16]	0.32
Household wealth (Ref: Poorest)								
Poorer	0.02		[-0.03, 0.07]	0.51	1.46	#	[0.96, 2.24]	0.35
Medium	−0.001		[-0.05, 0.05]		1.34		[0.85, 2.11]	
Richer	−0.01		[-0.06, 0.04]		1.51	#	[0.94, 2.41]	
Richest	−0.02		[-0.07, 0.02]		1.55	#	[0.93, 2.59]	
Financial stability of the household (Ref: Worsen)								
Stable	−0.10	***	[-0.13, −0.06]	0.00	*Not included in adjusted model*[e]			
Improved	−0.15	***	[-0.20, −0.11]					
Household member number (Count)	*Not included in adjusted model*[e]				1.02		[0.95, 1.10]	0.57
Monthly health expenditure (per Int.$100)[c]	0.006	***	[0.004, 0.007]	0.00	1.04	***	[1.02, 1.06]	0.00
Community's Characteristics								
Census block (Ref: Behadar)								
Kachhauna	0.03		[-0.02, 0.09]	0.10	1.83	#	[1.00, 3.33]	0.40

(*continued on next page*)

Table 3 (*continued*)

	Four-level mixed-effect probit model (Part 1: selection equation)				Three-level mixed-effect linear model with log link and gamma distribution (Part 2: regression equation)			
	Adjusted Marginal Probability		[95% CI]	P Value	Adjusted Rate Ratio		[95% CI]	P Value
Kothwan	0.04	#	[-0.01, 0.09]		1.25		[0.76, 2.07]	
Kasmanda	0.01		[-0.03, 0.06]		1.27		[0.73, 2.21]	
Machhrehta	0.08	**	[0.03, 0.13]		1.12		[0.68, 1.83]	
Sidhauli	0.02		[-0.02, 0.07]		1.04		[0.65, 1.68]	
Community wealth[d]	*Not included in adjusted model*[e]				0.98		[0.83, 1.15]	0.77
Community reciprocity	*Not included in adjusted model*[e]				0.65	*	[0.44, 0.95]	0.03
Random Effects								
Level 4: Community variance	0.18							
Level 4: ICC	0.03							
Level 3: Household variance	2.48				~0.001			
Level 3: ICC	0.35				~0.001			
Level 2: Household members variance	2.26				0.57			
Level 2: ICC	0.47				0.69			
Fit Statistics								
Log-likelihood (LL)	−1041				−3032			
Akaike information criterion (AIC)	2170				6140			
Observations	**3063**				**464**			

Note: The adjusted regressions include data from 3063 health events of 2124 individual household members from 1758 households within 324 communities or sampling clusters, *** = $p < 0.001$, ** = $p < 0.01$, * = $p < 0.05$, # = $p < 0.20$.
a = Social capital scores were measured as the standardized factor score generated by multi-level confirmatory factor analysis of social capital indicators of Shortened Adapted Social Capital Assessment Tool in India (SASCAT-I).
b = Caste concordance: Household caste is the same as the caste of the majority of the population in the community.
c = Int.$ is calculated using Purchasing Power Parity (PPP) 2017 of India: 1 Int..$ = 20.648 Rup (https://data.worldbank.org/indicator/PA.NUS.PPP?locations=IN).
d = Community wealth is measured by the average of the individual household wealth index generated by PCA.
H-SoS = Household head's social support, H-TR = Household head's trust, H-SC = Household head's social cohesion.
C-OP = Community organizational participation, C-SoS = Community social support, C-TR = Community trust.
C-SC = Community social cohesion.
e = Variable was not included in the adjusted model as it did not present a significant association in the unadjusted model. Please, see the supplement 5 in the Additional File 1 for more information.

investigations (Domínguez & Watkins, 2003; Hoque et al., 2015; Nguyen et al., 2012; Quintussi et al., 2015) – support the theory that households can draw upon the resources embedded within their social connections to cope with the financial burden of healthcare.

Still, there are limitations to EFS as a type of informal health insurance. The social, cultural, and political fabric of the community can drastically change the effectiveness of using EFS as a risk-sharing strategy (Morduch, 1999). Our results showed that living in a highly cohesive community reduced the probability of receiving EFS. Such a negative impact is postulated as the "dark side" of social capital by Alejandro Portes (2014). Within a highly cohesive community, over-reliance on social capital could exert a coercive effect, especially during financial stress (Lakon, Godette, & Hipp, 2008). Though household heads may readily avail EFS if their social network includes individuals or groups with power and authority, a tightly-knit community can impose informal social control, which results in the social exclusion of those who deviate from the norm (e.g., those with chronic or disabling health conditions) (Portes, 1998).

Thus, households facing impoverishment due to high healthcare expenditure may not be able to mitigate their financial stress while living in a community with stronger social cohesion, as they have been ostracized, leading to fewer social contacts (De Weerdt, 2004). Being closely-knitted members of a cohesive but impoverished neighborhood, such as a rural community of Uttar Pradesh, individuals often face excessive demands to share their limited resources supporting other members (Villalonga-Olives & Kawachi, 2017), leading to a strategic share of resources based on their social position and network.

An alternative explanation is postulated by Kondo and Shirai (2013). While investigating the role of social cohesion on the microfinance program, they have found that highly cohesive communities with limited financial resources support themselves by non-financial means or by developing informal financial support systems. Such informal arrangement can be leveraged when rural households receive consultation or medications as a credited service without immediate point-of-care payments, for which payments are made later (Kruk, Goldmann, & Galea, 2009; Morduch, 1999). Information on such credited service was not collected during the survey, which can potentially underestimate the probability and intensity of EFS within the sample.

We did not observe any association between the trust of a household head and the probability of acquiring EFS. According to Carpiano (2008), on its own, trust may not be sufficient to achieve a specific aim – such as acquiring EFS for healthcare expenditure – by a person or group, but the critical determinant is the stock of resources that can be accessed using social networks (Carpiano, 2008). Glanville and Story (2018) suggested that trust can strengthen norms of reciprocity and enable collective action to benefit the wellbeing of the community. Specifically, their findings suggested that trust activates resources within one's social network to support better health (Glanville & Story, 2018). Supporting their hypothesis, we found that if the stock of resources was accessed, the trust might have played a role in tapping more significant amounts of resources (Anderson & Mellor, 2008), which was observed in the positive association between individualized trust and the intensity of EFS (at the level of $p < 0.10$). Although other economic concepts such as "altruism" (Michalski, 2003) or "warm glow" – the selfish pleasure or emotional reward of performing a selfless act (Andreoni, 1989) – may explain cooperative behavior such as transaction of EFS, within the scope of this study, we were not able to explore these concepts.

4.2. Strengths and limitations

This study broke new ground in the economic sociology research on social capital by implementing two-part mixed-effects models within a multilevel semi-continuous data structure. Implementation of this advanced econometric model allowed us to explore the relationship between social capital and the probability of acquiring EFS and the intensity of EFS, simultaneously, to understand the contextual nature of social capital in the rural communities of Uttar Pradesh, India. Using a validated social capital assessment tool (Hasan et al., 2019) and implementing the MCFA model to develop social capital measures – devoid of any measurement error (Heck & Thomas, 2015) – further strengthen our study. Furthermore, including a wide range of confounders in the analysis using a comprehensive conceptual framework made our analysis robust.

We also acknowledge a few limitations of the study. Due to the limitation of the data collection process, we could not include the severity of the illness associated with the health-seeking events, which could influence the healthcare expenditure vis-a-vis the amount of EFS acquired. We have included each household's total monthly health expenditure as a proxy variable to account for this confounding factor. The study collected data on the current level of the household head's social capital, while the health-seeking event could be sought up to six months preceding the date of the survey. However, we assume that the social capital of the household heads may not drastically change within the last six months (Claridge, 2018).

While it would be ideal for estimating the effect of social capital by modeling the financial gifts and borrowed money as separate outcomes in the regressions, we aggregated these two sources of EFS for retaining the adequate sample size for analysis. The sensitivity analysis has supported the validity of this decision by demonstrating the stability of the effect estimates of the social capital measures across the different outcome variables (see supplement 9 and 10 in Additional File 1). And lastly, we cannot make any causal inference because of the study's cross-sectional design.

5. Conclusion

This paper concludes that external financing sources are a significant contributor to healthcare payment in rural northern India. Social support plays a pivotal role while households of Uttar Pradesh acquired EFS to cope with the financial stress of healthcare costs. The individualized social trust of the household head also acts as a catalyst for acquiring more EFS, only if the household heads can access external financing first. Furthermore, being highly cohesive with the community may limit household heads from accessing external financial resources. These results provide critical insights into how social relationships were leveraged – almost like a transactional good (Kawachi & Subramanian, 2018) – within India's rural community, where social relationships are heavily influenced by gender, religion, caste, and class hierarchies (Goli, Maurya, & Sharma, 2015; Kowal & Afshar, 2015; Srivatsan, 2015).

However, to appropriately contextualized our result, we have also carried out a follow-up qualitative study by exploring the role of social capital as a coping strategy for healthcare payment among a subsample of the study participants. The result of that study will provide further insights into the lived experience of rural households when drawing on community resources for healthcare payment and how social capital affects their attitude, perceived social norm, self-efficacy, and agency when they rely on such an informal system.

Currently, less than 20% of the population of India is covered by any health insurance. It is not surprising that households still bear 59% of the total healthcare cost (National Health Accounts Technical Secretariat National Health Systems Resource Centre & Ministry of Health and Family Welfare, 2019) and continue to rely upon pervasive coping strategies. Therefore, the government of India must not undermine the strength of the communal society and the resources embedded in social networks in rural India (Serra, 1999). In this regard, using the resources within the community can bridge the gap between the ability to pay and utilization of healthcare (Donfouet & Mahieu, 2012) and break the insidious cycle of poverty and ill-health (Russell et al., 1995). India has a long history of developing and implementing grassroots-level programs (such as community-based health insurance), which are tailor-made according to the community's need and best suited for rural India's unique social and cultural milieu (Bhageerathy, Nair, & Bhaskaran, 2017; Ranson, 2003). Mainstreaming such initiatives and developing a clear pathway to integrate them within formal health insurance structures should be considered a practical step forward. Moreover, future research should explore the value of social capital as a resource for paying for healthcare to understand the interplay among healthcare financing, social support, and community cohesiveness. The findings of such a study will be immensely valuable as India strives to expand its social safety nets for its 1.36 billion population.

Authors contribution

The study was conceptualized by MZH and KDR with the support of SG. MZH supervised the household survey and the data collection process along with the supportive supervision of AA. MZH led data management and performed all statistical analyses. WTS, DMB, KDR, AA, and SG contributed to interpreting the result of the study. The first draft of the manuscript was developed by MZH under the supervision of KDR, DMB, and WTS. All authors contributed to the manuscript revision process, and they read and approved the final version before the submission.

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Declaration of competing interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2021.100901.

Ethical approval

Ethical approval for the study was received from the Institutional Review Board Office of Johns Hopkins Bloomberg School of Public Health, Maryland, USA (IRB No: 00007469) and locally from the Center for Media Studies, New Delhi, India (IRB No: IRB00006230).

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