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Local neighbourhood effect on hospitalisation expenditure in India

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Abstract

How do social forces influence an individual's attitude towards healthcare? We address this question by analysing the effect of neighbourhoods on individuals' hospitalisation expenditure in India. Using data on 8,269 neighbourhoods and employing a two-stage least absolute deviation estimation method, the results suggest that (1) hospitalisation expenditure of the median individual increases by 0.9 percent with a one percent increase in hospitalisation expenditure of neighbours, while it falls by roughly 0.6 percent with one standard deviation increase in the dispersion of hospitalisation expenditure of neighbours; and (2) disposable income elasticity of hospitalization expenditure is nearly 0.2, suggesting hospitalisation is a necessity. Policy interventions such as improved affordability of hospitalisation-related services may significantly benefit equitable healthcare in the country.

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1. Introduction

Connectedness between individuals in a community for healthcare may have solemn implications for social and human capital by way of reducing healthcare inequality and increasing healthy life expectancy, respectively (Derose and Varda, 2009). The mechanism for this connectedness is a flow of information, transmitted through demonstration, emotional support or normative behavior (Kawachi et al., 2008; Becker and Murphy, 2009; Abrams and Hogg, 1990), which accrues linking identity to individuals. However, linking with the community may require a considerable cost such as an outlay to maintain desired social status (Abrams and Hogg, 1990). This paper evaluates these opportunity gains and costs by investigating the relationship between an individual's hospitalisation expenditure with that of her local neighbourhood (henceforth, neighbourhood).

The existing literature finds neighbourhoods as important in explaining various socio-economic outcomes such as labour market outcomes (Montgomery, 1991), insurance (De Weerdt and Dercon, 2006) and health outcomes (Geruso and Spears, 2018). However, the role of neighbourhoods as a propellent to equitable healthcare access has largely been untouched. In order to address this aspect, we employ data from the 71st round of the National Sample Survey (NSS) on "Key Indicators of Social Consumption in India: Health". Using a two-stage least absolute deviation (2SLAD) regression, the results suggest that the average neighbourhood effect is a significant determinant of an individual's hospitalisation expenditure. Moreover, for some groups in rural as well as urban India, economic mobility aspirations spawn a binding trade-off between social linking costs and benefits.

From a public policy standpoint, the results suggest that interventions focusing on communities are more likely to improve equitable hospitalisation-related healthcare in the country. While a comprehensive debate exists on need for policy intervention in healthcare, the role of an external influence – as neighbourhood – is largely missing in these debates.

2. Attributing Neighbourhood Effect and Hospitalisation Expenditure

2.1. Neighbourhood Effect

In line with the strands in the literature, we conceptualise neighbourhood effect as transmitting through social demonstration, emotional support or normative behavior (Kawachi et al., 2008; Becker and Murphy, 2009; Abrams and Hogg, 1990). As such, a neighbourhood can influence an individual's decision through both, explicit and implicit information sharing (i.e., directly conveyed or inferred or both) that is cheaper, specific and verifiable, and offers a reference for an individual to make decisions. However, an individual linking with her neighbourhood also incurs a cost to maintain desired social status or identity.

This paper coherently includes both explicit and implicit information sharing with neighbours, and the trade-off between benefits and cost of linking with the neighbourhood, as the basic premise for the current setup is 'behaviour is determined by behaviour in a neighbourhood'. This implies that the trade-off between benefits and cost of linking with the neighbourhood may dynamically change based on the location (i.e., a given a state of information) and mobility (i.e., entry of new or exit of existing information) in the neighbourhood (Jackson and Rogers 2007; Newman 2010; König 2017). For example, an individual's reference to spend for a provision may be other individuals spend on that provision in the neighbourhood. Any change in the neighbourhood organisation, either as availability of new information or exit of existing information, may also change the reference for her decision. In order to incorporate these possibilities in the current framework, we employ two metrics of the neighbourhood

distribution – neighbours' average spend on a provision and dispersion in neighbours spend on that provision.

2.2. Hospitalisation Expenditure

The emphasis on hospitalisation expenditure is for two reasons. First, hospitalisation expenditure, unlike expenditure on consultation fee, medicines and diagnostic tests, is more likely to be driven by individuals' choice, rather than being quasi-fixed. For instance, individuals, in general, lack requisite expertise in finding an alternative to a consultation, diagnostic or medicine in a locality. These corresponding expenditures, therefore, are mostly fixed in a locality. Second, hospitalisation expenditure is uniquely defined in comparison to the expenditure on package components or consultation that are varied across medical procedures.

3. Hospitalisation Care in India

Hospitalisation rate (excluding childbirth) in India is 3.5 percent for rural population and 4.4 percent for urban population (Table 1). Private hospitals account for the bulk of these cases, even though individuals end up paying over four times than for that in a public hospital and spend similar number of days hospitalised. This suggests that the quality of care is significantly higher in the private hospitals and people in rural parts often travel to the urban areas for hospitalisation care, where they are typically located. Importantly, individuals spend a sizable share of hospitalisation expenses out of their income/savings, which is nearly 68 percent and 75 percent for rural and urban population respectively. Thus, it is very likely that these individuals use all available information, including that from their neighbours, in making hospitalisation decisions.[1]

Table 1. Key Characteristics of Hospitalisation Care in India, 2014

Characteristics	Rural	Urban
Hospitalisation rate (excluding childbirth), percentage of population in a year	3.5	4.4
Percentage of hospitalised cases (excluding childbirth), public hospital	42	32
Percentage of hospitalised cases (excluding childbirth), private hospital	58	68
Average number of days as inpatient (excluding childbirth), public hospital	7	8
Average number of days as inpatient (excluding childbirth), private hospital	7	7
Average expenditure for treatment per hospitalisation (excluding childbirth), INR, public hospital	5,636	7,670
Average expenditure for treatment per hospitalisation (excluding childbirth), INR, private hospital	21,726	32,375
Percentage of households meeting hospitalisation expense with income/savings	67.8	74.9
Percentage of hospitalisation for childbirth, public hospitals	70	47.5
Percentage of hospitalisation for childbirth, private hospitals	30	52.5

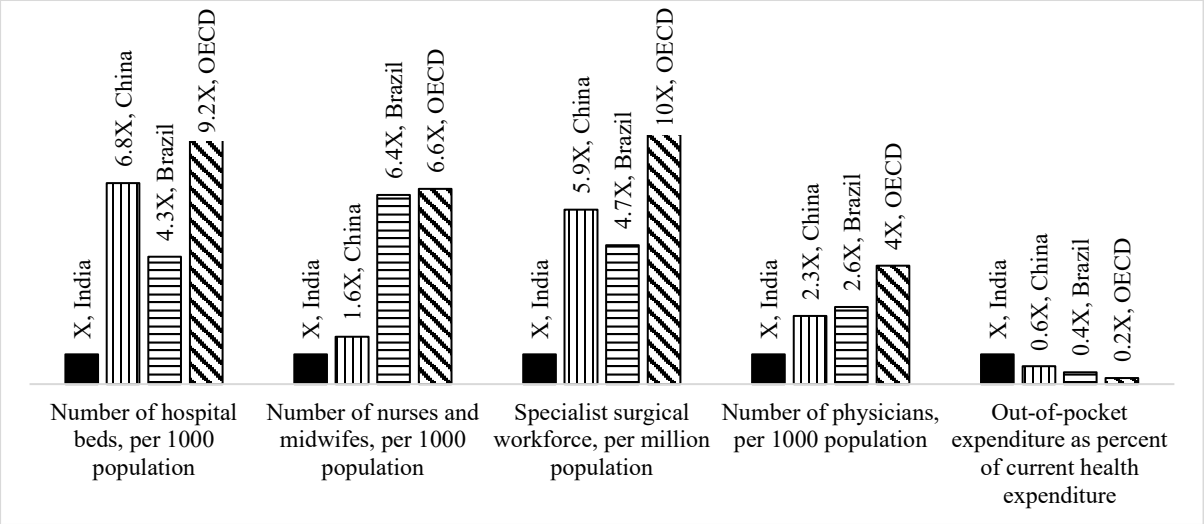
Source: 71st round of the NSS on 'Social Consumption: Health'

Figure 1 depicts some additional characteristics of hospitalisation care in India, relative to that in a reference group consisting of China, Brazil and the OECD countries. Hospitalisation care in India has a significant scope for catching up relative to these reference countries. It suggests

[1] Greater aversion to losses out of endowments (i.e., endowment effect) is a stylized behavioural phenomenon. See Kahneman et al. (1991) for a discussion.

that, on aggregate, hospitalisation is more likely to be an under-supplied service in the country, while individuals spend a proportionately larger share of income in availing these services. This strengthens the case for gathering all available information in making efficient hospitalisation decision.

Figure 1. Hospitalisation Care in India vis-à-vis China, Brazil and the OECD, 2014



Notes: Statistics for reference countries (China, Brazil and the OECD group) are depicted relative to that of India, which is the numeraire with value 'X'.

Source: World Health Organization's Global Health Workforce Statistics, OECD

Hospitalisation characteristics in India, as noted in Table 1 and Figure 1, also offer an important direction for assessing induced-demand effect from hospitals, a potential confounder in ascertaining the effect of neighbourhood on hospitalisation expenditure. That is, on aggregate, undersupply of hospitalisation services is more likely in India, which makes induced-demand from hospitals less probable ex ante. A deep-dive into the existing literature suggests a considerable spatial variation in induced-demand from hospitals, leading to both oversupply and undersupply of hospitalisation-related healthcare services depending on the geographical area (Burns, 2014; Bogg et al., 2016; Dahdah et al., 2018; Iles, 2018, 2019; Yaduvanshi et al., 2018; Bhatia et al., 2020). Typically, high-income individuals from urban areas are the targets for induced-demand from hospitals. Given this targeting approach and right-skewed income distribution in India, we do not expect induced-demand from hospitals to be binding on aggregate.[2]

4. Empirical Strategy

Two features of neighbourhoods are important in our empirical analysis (Jackson, 2008). First, behaviour is determined by behaviour in a neighbourhood, leading to a circularity of cause and effect. This imparts endogeneity in the system of behaviours. Second, within a neighbourhood, individuals typically have either very high or very low number of links (i.e., fat tails) and the underlying distribution reveals considerable skewness. These considerations prompt us to first log transform the (continuous) level variables and then perform a two-stage least absolute

[2]Induced-demand from hospitals is inherently latent and heterogenous, which makes its estimation and application beyond the scope of the current exercise. However, future research may focus on a complete assessment of induced-demand from hospitals under the current framework.

deviation (2SLAD) regression, which is an instrumental variable approach based on the LAD.[3] Specifically, we perform estimation for the 10th, 50th, and 90th percentiles. We also present the estimates based on two-stage least squares (2SLS) regression, which is based on OLS in both the stages, primarily because the tests for validity and exogeneity of the instruments are available only for the 2SLS. We use Wooldridge's (1995) robust score test for validity and exogeneity of the instruments.

The estimation of hospitalisation expenditure is based on the following specification:

$$HE_i = \alpha + \beta_1 Y_i + \beta_2 ANE_{-i} + \beta_3 DNE_{-i} + \sum_{j=1}^{n} \gamma_j X_{i,j} + \varepsilon_i \quad (1)$$

where i indicates an individual; HE is the natural logarithm of hospitalisation expenditure; α is intercept; Y is the natural logarithms of income; ANE is the mean of natural logarithms of neighbourhood hospitalisation expenditure and DNE is the dispersion in natural logarithms of neighbourhood hospitalisation expenditure – both computed after excluding the individual under investigation $(-i)$; β_1, β_2 and β_3 are coefficients of Y, ANE and DNE, respectively; $j = 1, \dots, n$ is the number of controls (X); γ is the coefficient associated with the controls; and ε is the error term. By construction, β_1 measures the income elasticity of hospitalisation expenditure. $\beta_1 < 1$ implies hospitalisation expenditure is a necessity, while $\beta_1 > 1$ implies hospitalisation expenditure is a luxury. The neighbourhood variables, ANE and DNE, are endogenous, and therefore we use 2SLAD regression for estimation.

5. Data and Variables

The main source of data for the empirical exercise, the 71st round of the NSS, consists of information on 334,377 individuals pan-India. 226,990 individuals in the survey do not report any hospitalisation expenditure, which we exclude from our analysis. For the remaining 107,387 individuals, 56,367 pertain to rural India and 51,020 pertain to urban India. Notably, the NSS sample represents national level heterogeneity and offers weights to ascertain that the survey aggregations proximate the population. The variables key variables for the estimation exercise are as follows:

- Hospitalisation expenditure: It is the natural logarithm of the ratio of total hospitalisation expenditure to the number of days in the hospital.
- Neighbourhood: A neighbourhood is census villages in rural India and Urban Frame Survey (UFS) blocks in urban India. Most economic and administrative activities in India are representative at these units, which implies individuals in these unit areas actively interact of for carrying out their day-to-day activities and exchange of information.
- Average neighbourhood hospitalisation expenditure (ANE): It is the mean of hospitalisation expenditure of neighbours, after excluding the individual under investigation. We expect it to have positive relationship with the hospitalisation expenditure of an individual, as a neighbourhood exerts a reflexive force.
- Dispersion in neighbourhood hospitalisation expenditure (DNE): It is the standard deviation (SD) of neighbours' hospitalisation expenditure, after excluding the individual

[3] LAD is a robust estimator relative to OLS-type estimators under fat tail conditions. See Cameron and Trivedi (2005), Haupt et. al (2014) and Maiti (2021) for a discussion.

under investigation. Its relationship with an individual's hospitalisation expenditure depends on relocation of the reference in the neighbourhood distribution.

- Monthly per-capita expenditure (MPCE): The NSS does not contain information on individuals' income, as it is often misreported. It rather contains information on the MPCE, which is the main pool for incurring any expenditure (i.e., disposable income). Natural logarithm of MPCE is taken for the empirical exercise. We expect a positive relationship between the MPCE and an individual's hospitalisation expenditure.
- Control variables: The control variables include availability of health insurance (dummy); having received healthcare treatment before (dummy); nature of treatment – allopathy or otherwise (dummy); type of hospital – private and otherwise (dummy); type of hospital ward – general and otherwise (dummy); household size (continuous); age (continuous); marital status (dummy); social group – general, scheduled caste, scheduled tribe and other backward class (three dummies); religion – Hinduism, Islam and Others (two dummies); occupation – regular, casual and self-employed (two dummies); educational level – up to primary, up to secondary, up to higher secondary, and graduation and above (three dummies); and dummies for the states.

Table 2. Summary statistics

	All India		Rural		Urban	
	Mean	Median	Mean	Median	Mean	Median
MPCE (INR '000)	23.94	12.76	21.16	11.60	27.02	14.40
Neighbourhoods in a district	16.52	13.00	14.20	12.00	19.08	14.00
Number of households in a neighbourhood	22.39	22.00	22.47	22.00	22.31	22.00
ANE	590.73	447.40	498.59	388.08	692.52	517.31
DNE	427.82	198.09	353.69	156.58	509.71	251.34

Notes: ANE is mean hospitalisation expenditure of the neighbours. DNE is dispersion in neighbourhood hospitalisation expenditure. MPCE is monthly per capita expenditure.

Source: 71st round of the NSS

Table 2 presents the summary statistics of key variables at three levels – all India, rural India and urban India. Two observations are noteworthy. First, on average, MPCE and ANE are higher in urban India than in rural India. However, DNE is higher in rural India than in urban India. Second, the key variables reveal considerable heterogeneity. Notably, they right-skewed, rendering 2SLAD as a suitable estimation choice.

6. Instrumental Variables

In constructing instruments for (average of and dispersion in) neighbourhood hospitalisation expenditure, we use information on drinking water sources and population density. The motivation for using these variables is as follows. First, about 30 percent of urban and 90 percent of rural Indian households depend completely on untreated surface or groundwater (World Bank, 2017), while almost 80 percent of the prevalent diseases in India are waterborne (Lok Sabha, 2018). These statistics imply that most water source provisions in India, whether sub-soil or surface sources, typically cater to a neighbourhood or few neighbourhoods in an area, and the nature of water-borne diseases in India has significant local similarity. Second, water is one of the first things offered to an individual visiting a neighbouring household. Its source, therefore, is a significant means of demonstration. Third, the number of hospitals, from supply side, is contingent on the size of population in an area represented by population density.

Table 3. Sources of Drinking Water, Percent

Drinking Water Sources	All India	Rural	Urban
Tap	52.31	39.07	66.94
Tube-well/hand pump	35.24	47.82	21.34
Pucca well	7.27	8.71	5.69
Bottled water	2.69	1.28	4.24
Tankers	0.74	0.59	0.92
Tank/pond	0.62	1.05	0.14
River/canal	0.27	0.48	0.03
Others	0.87	1.00	0.71
All sources	100.00	100.00	100.00

Source: 71st round of the NSS

The 71st round of the NSS contains information on eight alternative drinking water sources (Table 2). We rank these sources from eight to one in decreasing order based on their degree of safety and take their modal value and the deviation from the mode for each neighbourhood as the instruments for average and spread in hospitalisation expenditure of the neighbourhood. We compute the deviation from the mode (M) as follows:[4]

$$M = \left(\sum_{i=1}^{K}(f_m - f_i)\right) \Big/ N(K-1) = (Kf_m - N)/N(K-1) \qquad (2)$$

where f_m is the modal frequency, f_i is the frequency of the i^{th} group (source of water), K is the number of categories and N is the size of the neighbourhood.

In using population density as the instrument, we use information on district-level population density from the 2011 Census. Subsequently, we divide these densities by the square root of the number of neighbourhoods in each district for comparability across neighbourhoods.

7. Empirical Results

Table 4 presents the results on the determinants of individuals' hospitalisation expenditure.[5] Wooldridge's robust score test ascertains that ANE and DNE are endogenous and the instruments are valid.

ANE turns out to be significant in explaining individuals' hospitalisation expenditure with a positive coefficient across all sets of estimates. For the median individuals, hospitalisation expenditure increases by 0.9 percent with a one percent increase in hospitalisation expenditure of the neighbours. It suggests that societal information and normative conformity between individuals in a neighbourhood are key mechanisms for incurring hospitalisation expenditure. Therefore, hospitalisation-related healthcare measures, targeting even a few individuals, are likely to bring a sizable benefit through community transmission. Such a linking mechanism is especially relevant for public policy in ensuring equitable healthcare, as identification of all potential beneficiaries is intensively resource-draining (Muralidharan et al., 2016).

[4] See Freemen (1965) for a discussion on the deviation from the mode.

[5] Estimates for control variables are omitted to save space. They can be furnished on request.

Interestingly, the effect of ANE on hospitalisation expenditure is consistently larger for rural India than urban India. This difference can be attributed to relatively closer interaction of individuals in rural neighbourhoods than in urban neighbourhoods, mainly because of more informal nature of economic activities in rural India.

Table 4. 2SLAD Regression Results on Hospitalisation Expenditure

	2SLAD: 10th percentile			2SLAD: 50th percentile		
	All India	Rural	Urban	All India	Rural	Urban
ANE	0.862***	1.216***	0.534***	0.900***	0.872***	0.695***
	(16.545)	(15.360)	(14.707)	(18.793)	(6.344)	(10.929)
DNE	-1.194***	-1.370***	-0.114	-0.585***	-0.354	-0.579***
	(4.337)	(5.009)	(0.480)	(4.028)	(1.450)	(8.154)
MPCE	0.193***	0.123***	0.250***	0.212***	0.213***	0.260***
	(18.304)	(8.057)	(31.448)	(27.058)	(10.403)	(24.745)
	2SLAD: 90th percentile			2SLS		
	All India	Rural	Urban	All India	Rural	Urban
ANE	0.695***	0.759***	0.499***	0.629***	0.609***	0.559***
	(9.663)	(5.964)	(6.124)	(26.199)	(10.436)	(15.943)
DNE	-0.007	-0.339	0.117	0.237	0.443	-0.197
	(0.075)	(1.710)	(1.851)	(0.977)	(1.831)	(1.092)
MPCE	0.316***	0.287***	0.360***	0.256***	0.250***	0.287***
	(24.166)	(11.768)	(27.622)	(46.795)	(21.114)	(24.349)
Exogeneity test (P-value)				0.000	0.030	0.002
Instrument validity test (P-value)				0.763	0.136	0.127
Controls	availability of health insurance, having received treatment before, nature of treatment, type of hospital, type of hospital ward, household size, age, marital status, social group, religion, occupation, educational level and states dummies					

Notes: ANE is mean hospitalisation expenditure of the neighbours. DNE is SD of hospitalisation expenditure of the neighbours. MPCE is monthly per capita expenditure. Estimations are done with robust standard errors. Absolute t-statistics are in the parentheses. Test for exogeneity is based on the null that endogenous regressors in the model are in fact exogenous. Test for instrument validity is based on the null that instruments in the model are valid. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Source: 71st round of the NSS

The results for DNE suggest that hospitalisation expenditure of the median individual falls by roughly 0.6 percent with one standard deviation increase in the dispersion of hospitalisation expenditure of the neighbours. However, The coefficients associated with DNE do not show a consistent pattern across samples. They are significant for the lower (10th) percentile in rural India and the middle (50th) percentile in urban India, both with a negative sign. The coefficients at the all-India level are driven by these significant estimates. This is plausible because, as highlighted by Rama et al. (2015), for rural individuals at the lower percentile and urban individuals at the middle percentile, an increase in income/savings help them escape poverty and enable their upward economic mobility, respectively. A motivation as dire as these is bereft at the other income percentiles. From an equitable healthcare perspective, these results suggest that increasing social dispersion helps lower-class rural and the middle-class urban individuals in allocating expenditures to suit their economic mobility aspirations, while remaining socially linked.

The coefficients associated with MPCE (i.e., elasticity of hospitalisation expenditure with respect to MPCE) are positive and significant across all sets of estimates. At median, the estimated elasticity value is 0.212, while they are consistently lower than one. This implies that expenditure on hospitalisation is a necessity, not a luxury. Therefore, government intervention in hospitalisation-related healthcare is likely to increase efficacy and coverage of hospitalisation-related outcomes. Additionally, the elasticities are consistently higher for urban India and the upper percentiles than rural India and the lower percentiles, respectively. This is plausibly because hospitalisation-related healthcare has higher stake (opportunity cost) for individuals in urban areas and at upper percentile, respectively. At the same time, it implies a stronger need for government intervention in rural areas than in urban areas.

8. Conclusion

This paper focuses on investigating the influence of neighbourhood on individuals' hospitalisation expenditure. The key issue in the investigation pertains to trade-off between linking advantages and costs for individuals with their neighbourhood. Using a 2SLAD regression method, the results offer three key observations. First, average neighbourhood effect is an important determinant of hospitalisation expenditure accrual. This effect is consistently larger for rural India than urban India, suggesting that rural individuals are more dependent on their neighbours for hospitalisation-related decision making than urban individuals. Second, an increase in dispersion of neighbourhood hospitalisation expenditure shifts an individual's hospitalisation expenditure downwards at low income levels in rural India and middle income levels in urban India. This implies that the urge for upward economic mobility dominates the linking advantages with the neighbourhood. Third, the income elasticity of hospitalisation expenditure is consistently lower than one and thus hospitalisation is a necessity, not a luxury. Therefore, policies that relate to investments in social capital as making hospitalisation-related healthcare services more affordable are likely to bestow equitable hospitalisation-related healthcare outcomes.

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