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Legal Status and Deprivation in India's Urban Slums:

An Analysis of Two Decades of National Sample Survey Data

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Abstract

In India, 52–98 million people live in urban slums, and 59% of slums are “non-notified” or lack legal recognition by the government. In this paper, we use data on 2,901 slums from four waves of the National Sample Survey (NSS) spanning almost 20 years to test the hypothesis that non-notified status is associated with greater deprivation in access to basic services, thereby increasing vulnerability to poor health outcomes. To quantify deprivation for each slum, we construct a basic services deprivation score (BSDS), which includes variables that affect health, such as access to piped water, latrines, solid waste disposal, schools, and health centers. In a regression analysis, we find a robust association between non-notified status and greater deprivation after controlling for other variables. Our analysis reveals a progressive reduction in deprivation the longer a slum has been notified. In addition, data from the 2012 NSS show that, despite suffering from greater deprivation, non-notified slums were much less likely to receive financial aid from government slum improvement schemes. Our findings suggest that legally recognizing non-notified slums and targeting government aid to these settlements may be crucial for improving health outcomes and diminishing urban disparities.

Keywords: slums, legal status, notified, deprivation, basic services, health, water, sanitation, India

1 Introduction

The Government of India and the United Nations define slums in part by lack of access to basic services, especially water and sanitation infrastructure (Ministry of Housing and Urban Poverty Alleviation 2010; UN-HABITAT 2002). In India, 52–98 million people live in urban slums (Census of India 2013; Millennium Development Goals Database 2014). India's slum population has substantially poorer health outcomes compared with its non-slum urban population (Agarwal 2011; Gupta et al. 2009).

India's slum population is by no means homogenous. Variability exists in the severity of deprivation among different slums, which may result in differences in health outcomes for different settlements within the same city (Agarwal and Taneja 2005; Osrin et al. 2011; Subbaraman et al. 2012). One source of this variability is a legal divide between notified slums, which the government recognizes, and non-notified slums, which lack legal recognition. About 59% of Indian slum settlements are non-notified, while 37% of slum households are non-notified because these slums have smaller average population sizes (National Sample Survey Organization 2013).

In some states, notified status confers basic security of tenure, such as the right to rehabilitation in the event of displacement for development projects (Murthy 2012). In addition, notification is often required to access city services, such as water supply, sanitation infrastructure, and electricity, which may contribute to differences in health outcomes between slums (Subbaraman et al. 2012). To our knowledge, no studies have evaluated the relationship between legal status and access to services using nationally representative data. This relationship may be confounded by characteristics other than legal status that may cause deprivation, such as state government policies, the type of land on which a slum is located, or a slum's population size.

To investigate the contribution of legal status to deprivation in access to services, we analyze data from India's National Sample Survey (NSS), which collects information on socioeconomic, industrial, agricultural, and housing indicators. The NSS collected cross-sectional data on slums in India in four survey waves spanning nearly 20 years. The NSS is the only national-level survey that routinely collects information on the legal status of slums, providing a unique opportunity to evaluate the relationship between legal status and deprivation over time. Other surveys, such as the Census of India, have been criticized for undercounting non-notified slums (Ministry of Housing and Urban Poverty Alleviation 2010).

In this paper, we first discuss trends in slum notification and access to basic services over two decades. Second, we describe deprivation in India's slums over time by combining indicators for access to services into a composite basic services deprivation score (BSDS). Third, we identify risk factors for deprivation using a multilevel regression model to test the hypothesis that legal status is independently associated with deprivation. Finally, we identify factors associated with slums receiving government financial aid to understand whether resources for slum improvement are being targeted to the communities most in need.

2 Methods

(i) Data Sources and Descriptive Statistics

We use the 49^{th} (1993), 58^{th} (2002), 65^{th} (2008—2009), and 69^{th} (2012) NSS rounds, which provide nationally representative cross-sectional data on 2,901 slums across all survey rounds. One limitation of these surveys is that they capture information on entire slum settlements (rather than on individuals or households). The surveys therefore describe living conditions for the majority of residents in each slum and do not provide information on heterogeneity *within* each settlement.

To ensure we correctly interpreted the datasets, we first successfully replicated descriptive statistics contained in publicly available reports on these NSS waves, with the exception of select statistics from the 1993 report (National Sample Survey Organization 1997; 2003; 2010; 2013). We estimated 40 more slums (a 0.04% difference) and 147,472 more slum households (a 2% difference) at a national level than were reported in the 1993 report. These minor inconsistencies may be due to differences between the publicly available NSS data and those used to create the report or to small rounding errors in the survey weights.

For most descriptive statistics and the regression models, we restricted our analyses to 10 states with at least 10 observations (i.e., 10 slums) in each survey year, since this minimum number facilitates better estimates of state-level effects. The states included in the analysis are Andhra Pradesh, Bihar, Delhi, Gujarat, Karnataka, Madhya Pradesh, Maharashtra, Orissa, Tamil Nadu, and West Bengal. This restriction results in a sample of 2,411 slums across all survey years. Further restriction to slums with no missing information for variables in the analyses results in a final sample of 2,390 slums for the 10 states.

We generated descriptive statistics by using survey weights to estimate the total number of slums in the 10 states. We then estimated the percent of slums with different types of legal status and that lack access to key basic services, stratified by survey year, to gain insights into trends over time.

(ii) Basic Services Deprivation Score

The outcome in regression analysis 1 is a 12-item index of “deprivation” called the Basic Services Deprivation Score (BSDS). The item weights in Table 1 allow us to calculate a value for each slum ranging from 0 to 14. We convert this value into a BSDS ranging from 0 to 100 by dividing by the range and multiplying by 100. A higher score indicates greater deprivation.

Table 1: National Sample Survey Items Used to Construct the Basic Services Deprivation Score

National Sample Survey item	Description	Weight
Source of drinking water	Tap	0
	Tubewell or handpump	1
	Well or other (tank, river, etc.)	2
Latrine facilities	Septic, flush, or pour flush	0
	Service or pit latrine	1
	Other (public latrine with or without payment required)	1
	No latrine	2
Sewer infrastructure	Underground sewer system	0
	No underground sewer	2
Solid waste disposal	Collection by the municipality or panchayat	0
	No arrangement or collection by residents	1
Drainage	Underground or covered	0
	Open high-quality drainage	0.5
	Open low-quality or no drainage	1
Electricity access	Household use with or without street lights	0
	Street lights only	0.5
	No electricity	1
Quality of road within the slum	Motorable or cartable	0
	Non-motorable or non-cartable	1
Road within slum gets waterlogged in the monsoon	No	0
	Yes	1
Quality of approach road to the slum	Motorable or cartable	0
	Non-motorable or non-cartable	0.5
Approach road gets waterlogged in the monsoon	No	0
	Yes	0.5
Distance to nearest government primary school	<1 km	0
	≥1 km	1
Distance to nearest health center	<1 km	0
	≥1 km	1

For some items, responses have been collapsed into single categories (e.g., “public latrines with payment” and “public latrines without payment”).

Our rationale for the BSDS partly derives from Amartya Sen’s definition of poverty as “capability deprivation” (Sen 1999). Each BSDS item represents a service that people “have reason to value” because it enhances human capabilities. These services require government intervention to support infrastructure or service delivery (in the case of waterlogging, the items serve as surrogate indicators of the quality of sewer and drainage infrastructure). Absence of any of these services may result in deprivation by adversely affecting quality of life. For example, a study found that deprivation faced by households in a Mumbai slum—measured using a "slum adversity index" that includes many BSDS items—is strongly associated with psychological distress (Subbaraman et al. 2014).

All BSDS items are also strongly associated with physical health. We weight water and sanitation items more heavily in the BSDS because these have the strongest relationship with health outcomes, such as infant mortality and child nutrition levels (Bartram and Cairncross 2010). Diarrheal illness is strongly associated with water and sanitation access, and diarrhea is one of the top causes of morbidity and mortality for children under five years of age who live in slums (Choudhary and Jayaswal 1989; Gladstone et al. 2008). Transitioning from an unimproved water supply to a high-quality piped supply leads to an average reduction in diarrheal illness of 80%, while access to sanitation infrastructure leads to an average reduction of 70% (Wolf et al. 2014).

We weight other BSDS items less heavily because their association with health outcomes is not as robust; however, deprivation with regard to any of the items can cause poor health. Lack of solid waste collection increases risk of diarrhea, dengue, and leptospirosis (Hagan et al. 2016; Hayes et al. 2003). Lack of government provision of electricity may lead slum residents to create poorly wired connections, increasing the risk of electrocution and fires (Subbaraman et al. 2012). Greater distance of slums from health facilities is associated with lower immunization rates (Ghei et al. 2010). Greater distance from schools can adversely affect mothers' educational attainment, which is associated with adverse child health outcomes (Agarwal and Srivastava 2009).

We explore whether the results are robust to model specification and BSDS scoring methodology by constructing the following alternative models, which are presented in the Appendix: (1) a model in which legal status is represented as a dichotomous variable (i.e., “notified” or “non-notified) rather than as a continuous variable (i.e., number of years notified); (2) a model in which factor analysis using a polychoric correlation matrix is used to weight the different variables in the BSDS; (3) a model in which the BSDS is constructed using scoring weights derived from a regression model of items correlated with infant mortality identified through a separate analysis of the National Family Health Survey-3 (NFHS-3) (IIPS and Macro International 2007); and (4) a model in which the “state” variable is included as a fixed effect (as compared to the multilevel model in the primary analysis, in which slums are nested within states).

Factor analysis is used to either reduce a large number of variables (into a score, for example), or detect the structure and relationship between variables in order to classify them. We use factor analysis to reduce the 12 characteristics of slums described in Table 5 into a BSDS, employing a polychoric correlation matrix procedure because all variables are dichotomous. We transform the resulting index into a final BSDS ranging between 0 and 100 by subtracting each value by the minimum, dividing by the range, and multiplying by 100.

To use scoring weights derived from the NFHS-3, we first identified all variables in the NFHS-3 births that are equivalent to an NSS survey item in Table 1. These variables were source of drinking water, type of toilet facility, and sewer access. We recoded these NFHS-3 variables to be as consistent with the response options for the matching NSS variables as possible. To obtain the weights for each response item for each of the variables, we estimate a regression model of infant mortality on each item, restricting the sample to only include children in slums in the NFHS-3 dataset. The regression model standard errors are clustered at the household level because there can be more than one child under 5 years of age in a household. The coefficients from this regression serve as the BSDS weights, which we applied to and summed across the matching variables in the NSS, resulting in a BSDS for each slum. As with the factor analysis, this value was transformed into a final BSDS ranging from 0 to 100 by subtracting each score by the minimum, dividing by the range, and multiplying by 100. Since this (NFHS-3) version of the BSDS score contains fewer variables than the other scoring options, its variation is smaller than the other scoring methodologies'.

(iii) Regression Analysis 1—Predictors of Deprivation in Access to Basic Services

The BSDS is the outcome (dependent variable) in this analysis. The independent variable of interest is legal status, represented as the number of years a slum has been notified (a continuous variable), with 0 years indicating that the slum is non-notified. In an additional regression analysis that is not included in this paper, we alternatively represented legal status as a dichotomous variable (notified vs. non-notified) and found qualitatively similar results (findings available upon request).

Other independent variables include (1) the number of households in the slum (per every 100 household increase); (2) ownership of the land the slum is on (e.g., local government, central government, or private); (3) the slum's location within the city (i.e., fringe or central); (4) type of area around the slum (i.e., residential, commercial, or industrial); and (5) whether the slum has a community association. We control for the survey year as a fixed effect in the model. We include quadratic (squared) terms for "years notified" and for "number of households in the slum," as quadratic terms for these variables were significant at the 5% level.

India is a federal country with different policies at the national, state, and local levels. To understand the influence of state policies (i.e., the "state effect"), we built a multilevel model because NSS data are reported in a hierarchical fashion, with slums "nested" within states. Differences in slum deprivation across states are represented by cluster-level intercepts in the model. Multilevel analysis also allows estimation of the proportion of variation in the BSDS that is accounted for by clustering of slums within states (i.e., intra-class correlation).

We also evaluated how much of the variation in the BSDS is accounted for by legal status and other variables. Using a generalized version of Cohen's F^2 effect size measure, we assess changes in the adjusted R^2 for the full model when each independent variable is excluded. To understand the proportion of variation attributable to the state variable, we compare the multilevel model to one without the state random effect.

(iv) Regression Analysis 2—Predictors of Receiving Financial Support through a Slum Improvement Scheme

Using 2012 NSS data from 706 slums in the 10 largest states, we investigate whether financial support for slum improvement provided by the central government has been equitably distributed. The 2012 NSS asked whether each slum "benefited from the Jawaharlal Nehru National Urban Renewal Mission (JNNURM), the Rajiv Awas Yojana (RAY), or any other slum improvement scheme" (National Sample Survey Organization, 2013). The answer to this question ("yes" or "no") is the outcome (dependent variable) in the multilevel logistic regression model. This question was not asked in NSS surveys prior to 2012.

We include legal status as a dichotomous independent variable (i.e., "notified" or "non-notified"), because, unlike in regression analysis 1, we are trying to understand whether each slum's current legal status (rather than the length of time it has been notified) influences the odds of receiving financial support. We include the BSDS as an independent variable to understand whether severity of deprivation influences the odds of receiving support. We divide the BSDS into three categories: low (≤30), medium (31–60), and high (>60) deprivation. We also include the other covariates from regression analysis 1 in this model.

3 Results

(i) Trends in Slum Notification over Two Decades

The number of non-notified slums at the national level and in the 10 states with the largest slum populations decreased between 1993 and 2012; however, the percent of all slums that are non-notified declined from 1993 to 2002, but then plateaued and increased between 2008 and 2012. With regard to slum households, both the number and percent of non-notified households at the national level and in the 10 states decreased from 1993 to 2002, but then plateaued and increased between 2008 and 2012 (Table 2).

Table 2: Trends in Slum Notification for All States in India and for the 10 States with the Largest Slum Populations

Year	Category of slum	Slum settlements – All states		Slum households – All states		Slum settlements – 10 largest states		Slum households – 10 largest states	
		Sample[a] N	Estimated[b] N (%)[c]	Sample[a] N	Estimated[b] N (%)[c]	Sample[a] N	Estimated[b] N (%)[c]	Sample[a] N	Estimated[b] N (%)[c]
1993	Notified	194	20,805 (36.9)	38,823	2,798,718 (46.0)	154	18,423 (37.7)	24,070	2,309,319 (44.3)
	Non-notified	404	35,560 (64.1)	72,363	3,282,754 (54.0)	343	30,499 (62.3)	33,698	2,903,605 (55.7)
	All	598	56,364 (100)	67,533	6,081,472 (100)	497	48,932 (100)	57,768	5,212,924 (100)
2002	Notified	360	26,166 (50.6)	40,005	5,358,272 (65.1)	293	24,474 (52.9)	64,176	5,153,874 (66.1)
	Non-notified	332	25,522 (49.4)	126,113	2,871,472 (34.9)	265	21,805 (47.1)	35,749	2,648,505 (33.9)
	All	692	51,688 (100)	112,368	8,229,744 (100)	558	46,279 (100)	99,925	7,802,379 (100)
2008	Notified	365	24,781 (50.6)	126,113	7,030,004 (69.2)	309	22,852 (50.7)	87,317	5,554,564 (65.2)
	Non-notified	365	24,213 (49.4)	49,048	3,129,820 (30.8)	320	22,212 (49.3)	44,007	2,959,573 (34.8)
	All	730	48,994 (100)	175,161	10,159,824 (100)	629	45,064 (100)	131,324	8,514,137 (100)
2012	Notified	441	13,761 (41.1)	684,257	5,559,775 (63.1)	350	11,140 (38.9)	604,146	4,940,409 (62.2)
	Non-notified	440	19,749 (59.9)	259,353	3,249,239 (36.9)	356	17,495 (61.1)	216,530	3,006,599 (37.8)
	All	881	33,510 (100)	943,610	8,809,013 (100)	706	28,635 (100)	820,676	7,947,008 (100)
All years	Notified	1,360	85,514 (44.9)	911,443	20,746,769 (62.3)	1,106	76,889 (45.5)	779,709	1,795,8167 (60.9)
	Non-notified	1,541	105,043 (55.1)	387,229	12,533,284 (37.7)	1,284	92,011 (54.5)	329,984	11,518,282 (39.1)
	All	2,901	190,557 (100)	1,298,672	33,280,053 (100)	2,390	168,901 (100)	1,109,693	29,476,449 (100)

[a]"Sample" indicates the unweighted number of slums or slum households in the survey. For the 10 largest states, only observations with non-missing data for the independent and dependent variables are included.
[b]"Estimated" indicates the weighted number (the number of slums and households the sample represents).
[c]Represents the percent out of all estimated slums or estimated households in a given year.

(ii) Trends in Access to Basic Services over Two Decades

In the 10 states with the largest slum populations, most indicators show a decrease in the percent of slums experiencing lack of access to services from 1993 to 2012 (Table 3). The percent experiencing deprivation increased during this time period for only three indicators: lack of a motorable or cartable approach road, lack of a school within one kilometer, and lack of a health center within one kilometer.

Table 3: Trends in Access to Services by Legal Status in 10 States with the Largest Slum Populations in India

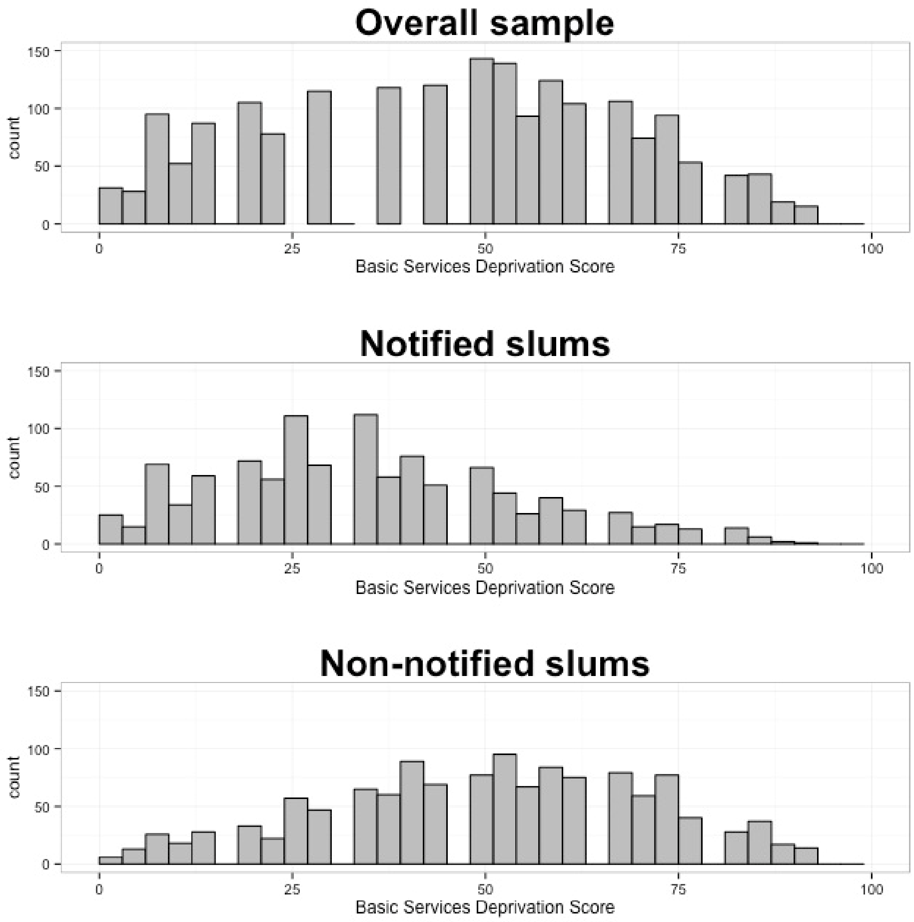
Service	Category of slum	1993	2002	2008–09	2012
		Estimated N (%)[a]	Estimated N (%)[a]	Estimated N (%)[a]	Estimated N (%)[a]
Lack of piped water	Notified	6,881 (37.3)	3,503 (14.3)	4,111 (18.0)	1,805 (16.2)
	Non-notified	9,216 (30.2)	5,762 (26.4)	4,518 (20.3)	5,873 (33.6)
	All	16,097 (32.9)	9,265 (20.0)	8,629 (19.1)	7,678 (26.8)
Lack of septic, flush, or pour flush toilet	Notified	11,357 (61.6)	8,026 (32.8)	7,324 (32.1)	3,090 (27.7)
	Non-notified	19,088 (62.6)	13,582 (62.3)	11,253 (50.7)	9,963(57.0)
	All	30,445 (62.2)	21,608 (46.7)	18,577 (41.2)	13,054 (45.6)
Lack of sewer infrastructure	Notified	14,572 (79.1)	16,925 (69.2)	14,835 (64.9)	5,995 (53.8)
	Non-notified	25,933 (85.0)	18,265 (83.8)	17,940 (80.8)	14,350 (82.0)
	All	40,506 (82.8)	35,190 (76.0)	32,775 (72.7)	20,345 (71.0)
Lack of solid waste disposal	Notified	4,764 (25.9)	4,714 (19.3)	5,164 (22.6)	1,981 (17.8)
	Non-notified	16,502 (54.1)	11,642 (53.4)	9,458 (42.6)	8,459 (48.4)
	All	21,265 (43.5)	16,356 (35.3)	14,621 (32.4)	10,441 (36.5)
Lack of underground or covered drainage	Notified	15,105 (82.0)	17,875 (73.0)	13,367 (58.5)	7,129 (64.0)
	Non-notified	27,052 (88.7)	18,632 (85.4)	16,603 (74.7)	13,603 (77.8)
	All	42,158 (86.2)	36,507 (78.9)	29,971 (66.5)	20,732 (72.4)
Slum faces waterlogging	Notified	5,638 (30.6)	5,783 (23.6)	7,545 (33.0)	3,988 (35.8)
	Non-notified	15,377 (50.4)	10,301 (47.2)	9,658 (43.5)	7,477 (42.7)
	All	21,015 (43.0)	16,084 (34.8)	17,202 (38.2)	11,465 (40.0)
Lack of electricity for household use	Notified	7,571 (41.1)	1,033 (4.2)	1,468 (6.4)	312 (2.8)
	Non-notified	10,268 (33.7)	3,792 (17.4)	4,209 (19.0)	3,233 (18.5)
	All	17,839 (36.5)	4,825 (10.4)	5,677 (12.6)	3,546 (12.4)
Lack of motorable or cartable roads within the slum	Notified	7,038 (38.2)	6,779 (27.7)	4,927 (21.6)	1,808 (16.2)
	Non-notified	18,508 (60.7)	12,760 (58.5)	8,944 (40.3)	7,184 (41.1)
	All	25,546 (52.2)	19,540 (42.2)	13,871 (30.8)	8,992 (31.4)
Lack of motorable or cartable approach road	Notified	1,325 (7.2)	4,097 (16.7)	5,485 (24.0)	1,897 (17.0)
	Non-notified	6,432 (21.1)	6,573 (30.1)	6,783 (30.5)	3,862 (22.1)
	All	7,748 (15.8)	10,670 (23.1)	12,268 (27.2)	5,759 (20.1)
No school within 1 km	Notified	837 (4.5)	1,709 (7.0)	2,540 (11.1)	937 (8.4)
	Non-notified	3,433 (11.3)	1,886 (8.6)	2,990 (13.5)	1,870 (10.7)
	All	4,270 (8.7)	3,595 (7.8)	5,530 (12.3)	2,807 (9.8)
No health center within 1 km	Notified	3,580 (19.4)	12,777 (52.2)	10,437 (45.7)	5,427 (48.7)
	Non-notified	13,176 (43.2)	11,187 (51.3)	12,576 (56.6)	9,089 (52.0)
	All	16,757 (34.3)	23,964 (51.8)	23,013 (51.1)	14,516 (50.7)

[a]Represents the estimated number and percent of slums lacking access to each service within each slum category (i.e., notified, non-notified, or all slums) for each survey year. For example, 6,881 notified slums in 1993 lacked access to piped water, which is 37.3% of all 18,423 notified slums in 1993.

However, these trends differ based on legal status, with notified slums experiencing greater reductions in deprivation for most indicators compared with non-notified slums (Table 3). For the services that are most vital for health—water, sewer, and toilet access—the percent of slums without access fell among notified slums, while the percent of slums without access grew worse (in the case of water) or essentially remained stable (for sewers and toilets) among non-notified slums. For other indicators (electricity, drainage, and a functional road within the slum), the percent without access declined for both notified and non-notified slums, but notified slums experienced considerably greater reductions in deprivation. In 2012, for every basic service assessed by the NSS, a greater proportion of non-notified slums lacked access as compared with notified slums (Table 3).

By providing a composite measure of deprivation, the BSDS allows for analysis of general trends in deprivation over time in the 10 states with the largest slum populations. Including data for slums across all survey rounds, Figure 1 shows that the BSDS has a relatively normal distribution. The distribution of scores is right-skewed for the sub-sample of notified slums and left-skewed for the sub-sample of non-notified slums, suggesting that, on average, notified slums have less deprivation in access to basic services than non-notified slums.

Figure 1: Histograms of the Distribution of the BSDS in the 10 States with the Largest Slum Populations



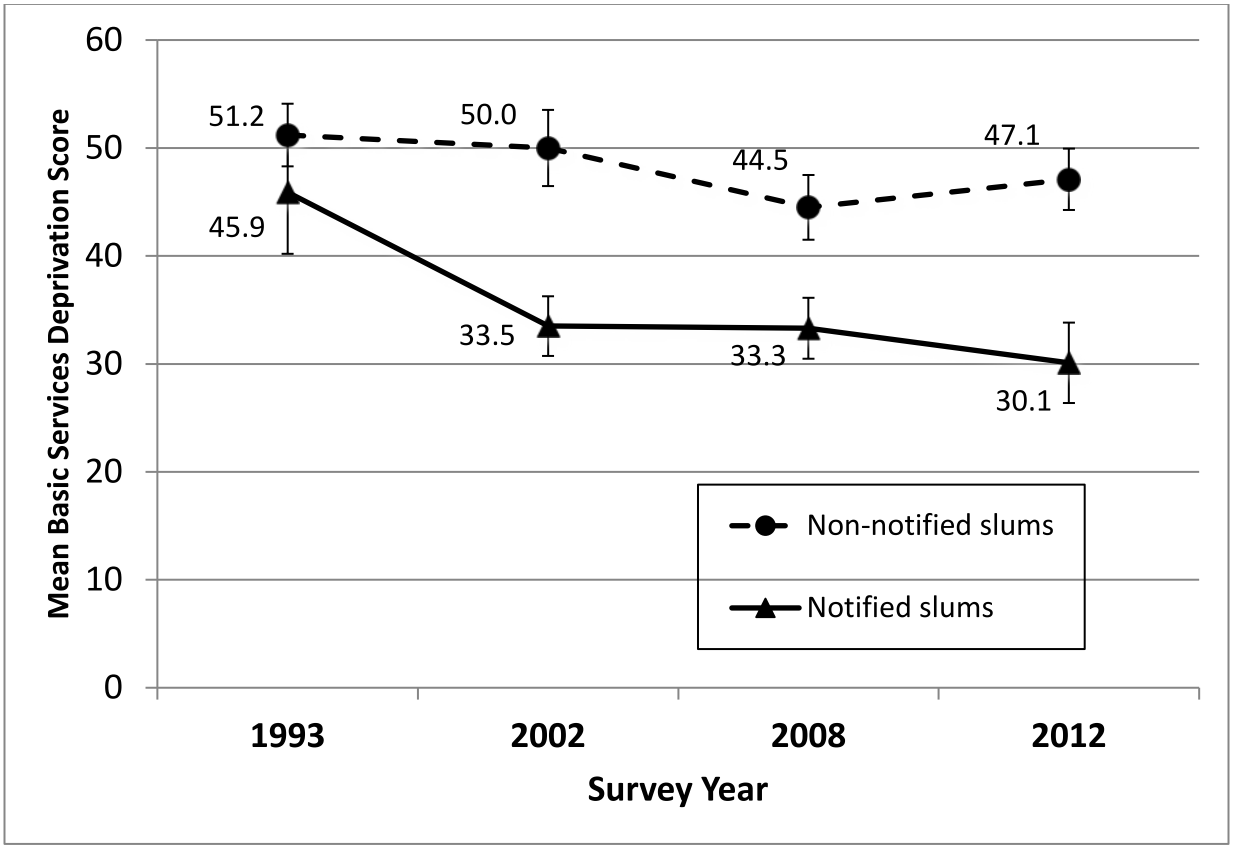
Evaluation of the average BSDS in different survey years reveals widening disparity in deprivation between notified and non-notified slums. In 1993, there was no significant difference between the mean BSDS for notified and non-notified slums (p=0.103) (Table 4). For notified slums, the mean BSDS declined 34% between 1993 and 2012 (p <0.001), whereas the mean BSDS for non-notified slums declined 8%, which is not statistically significant (p=0.146) (Figure 1). In other words, on average, disparity in deprivation between notified and non-notified slums has emerged and widened. For non-notified slums, deprivation in access to services has not declined meaningfully over two decades.

Table 4: Basic Services Deprivation Score (BSDS) in All Slums, Notified Slums, and Non-Notified Slums in 10 States in India with the Largest Slum Populations

Year	BSDS in All Slums (Sample *N*=2,390; Estimated *N*=168,901)	BSDS in Notified Slums (Sample *N*=1,106; Estimated *N*=76,889)	BSDS in Non-Notified Slums (Sample *N*=1,284; Estimated *N*=92,011)	p-value for the difference in mean BSDS between notified and non-notified slums
	Mean (SE)	Mean (SE)	Mean (SE)	
1993	49.2 (1.37)	45.9 (2.91)	51.2 (1.48)	0.103
2002	41.3 (1.21)	33.5 (1.41)	50.0 (1.80)	<0.001
2008	38.8 (1.07)	33.3 (1.44)	44.5 (1.53)	<0.001
2012	40.5 (1.89)	30.1 (1.90)	47.1 (1.45)	<0.001

SE=standard error.

Figure 2: Trends in the Basic Services Deprivation Score in 10 States with the Largest Slum Populations, 1993–2012



(iii) Predictors of Deprivation in Access to Basic Services

In the multilevel regression model, legal status (i.e., number of years of notification) has a substantial association with BSDS, even after controlling for covariates (Table 5). Every additional year of notification is associated with a 0.768 point decline in BSDS ($p<0.001$). A quadratic term for years notified is significant, suggesting a non-linear association in which the magnitude of decline in BSDS lessens with increasing years of notification. A scatterplot based on the regression model—with a fitted line estimating the predicted BSDS with increasing years of notification—illustrates this non-linear association (Figure 2). After controlling for covariates, the predicted BSDS is 50 for slums that have never been notified, 39 for slums notified for 10 years, 35 for slums notified for 20 years, and 24 for slums notified for 40 years. The most rapid decline in average BSDS occurs in the first decade after notification.

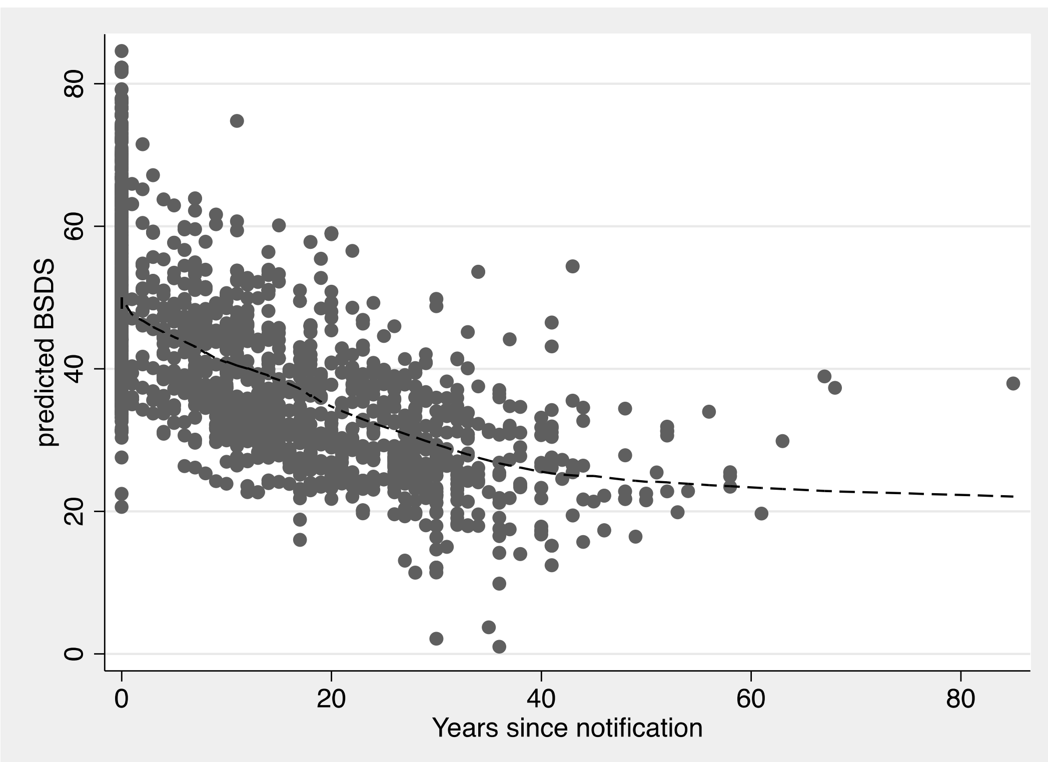
Table 5: Predictors of the Basic Services Deprivation Score (BSDS) in a Multilevel Regression Model Including Data from 10 States with the Largest Slum Populations

	Descriptive statistics Continuous variables: Mean (SE) Categorical variables: Estimated N (%)	**Multivariable findings** (Estimated *N*=168,901) β-coefficient (95%CI)	**p-value***
Years notified (*per each one-year increase in the time a slum has been notified*)	7.86 (0.33)	-0.768 (-0.914, -0.622)	<0.001
Years notified, quadratic term	203.39 (12.81)	0.009 (0.005, 0.013)	<0.001
Year of survey			
1993	48,923 (29.0)	-	-
2002	46,279 (27.4)	-5.448 (-7.621, -3.275)	<0.001
2008	45,064 (26.7)	-8.372 (-10.570, -6.175)	<0.001
2012	28,635 (17.0)	-5.654 (-7.870, -3.438)	<0.001
Number of households in the slum (*per each 100-household increase*)	1.84 (0.09)	-0.148 (-0.218, -0.079)	<0.001
Number of households in the slum, quadratic term	32.80 (6.05)	0.0002 (0.0001, 0.0003)	<0.001
Land type			
State or city government	66,737 (39.5)	-	-
Central government	8,155 (4.8)	6.785 (3.480, 10.089)	<0.001
Private	64,407 (38.1)	-3.182 (-4.880, -1.483)	<0.001
Other or not known	29,600 (17.5)	1.293 (-0.780, 3.366)	0.222
Slum location			
Central area	126,126 (74.7)	-	-
Fringe area	42,775 (25.3)	8.439 (6.816, 10.063)	<0.001
Area surrounding slum			
Residential	127,836 (75.7)	-	-
Commercial	8,355 (5.0)	0.076 (-3.299, 3.451)	0.965
Industrial	11,842 (7.0)	4.219 (1.252, 7.186)	0.005
Other, including more slum settlements	20,867 (12.4)	2.347 (0.365, 4.328)	0.020
Community association for slum improvement			
Yes	49,585 (29.4)	-	-
No	119,315 (70.6)	4.291 (2.622, 5.961)	<0.001

Constant	-	51.422 (45.641, 57.202)	<0.001
State random effects			
Andhra Pradesh	23,703 (14.0)	-5.027 (-6.367, -3.688)	<0.001
Bihar	7,322 (4.3)	16.844 (14.309, 19.379)	<0.001
Delhi	10,029 (5.9)	-6.997 (-9.274, -4.719)	<0.001
Gujarat	10,266 (6.1)	1.413 (-0.356, 3.182)	1.000
Karnataka	11,437 (6.8)	-5.227 (-7.092, -3.361)	<0.001
Madhya Pradesh	11,661(6.9)	2.725 (1.081, 4.369)	0.212
Maharashtra	52,045 (30.8)	-9.079 (-10.037, -8.122)	<0.001
Orissa	4,574 (2.7)	13.213 (10.817, 15.609)	<0.001
Tamil Nadu	13,022 (7.7)	0.484 (-1.148, 2.117)	1.000
West Bengal	24,841 (14.7)	-8.349 (-9.659, -7.039)	<0.001
Variance of the random intercept (p-value)		73.911 (<0.001)	
Variation in BSDS attributable to state (intra-class correlation)		19.43%	

*p-values for random effects are corrected for multiple comparisons (multiplied by the number of comparisons and capped at 1.00). Confidence intervals for random effects are corrected to allow readers to make multiple comparisons between states (Goldstein and Healy 1995)

Figure 3: Scatterplot and Fitted Line Estimating the Relationship between Years of Notification and the Basic Service Deprivation Score (BSDS) after Adjusting for Covariates in a Multilevel Regression Model.



The 2002, 2008, and 2012 survey years are associated with a significantly lower BSDS compared with 1993 (Table 5). Larger slum size (in households) is significantly associated with a lower

BSDS, and the quadratic term suggests a non-linear relationship in which the magnitude of decrease in BSDS declines as slum size increases. As compared with slums on city or state government land, slums on central government land have a significantly higher BSDS, and slums on private land have a lower average BSDS. Slums on the fringes of cities have a significantly higher BSDS on average than those in central areas. Having a community slum improvement association is significantly associated with a lower BSDS. In the multilevel model, Andhra Pradesh, Delhi, Karnataka, Maharashtra, and West Bengal have significantly lower BSDS on average, while Bihar and Orissa have significantly higher average BSDS.

Evaluating the model R^2 with and without each independent variable shows that legal status explains the largest percent of variance in the BSDS (9.3%). Other covariates explain a smaller proportion of the variance, including the state random effect (5.0%), slum location in a central or fringe area (4.4%), survey year (2.4%), land ownership (1.9%), presence or absence of a community association (1.0%), number of households (0.7%), and type of area surrounding the slum (0.5%).

Tables A1-A4 in the Appendix to this manuscript present the results of four alternative approaches to this analysis of the relationship between notification and deprivation in access to basic services. All four alternative approaches to the primary analysis result in similar findings. The regression results are qualitatively similar regardless of both the way the BSDS is constructed and the way legal status is defined (i.e., as a continuous or dichotomous variable).

In Table A1, legal status is represented as a dichotomous variable (i.e., "notified" or "non-notified" at time of the survey) in a multilevel model using the primary BSDS definition described in Table 1. The findings suggest that, on average, notified slums have a BSDS that is 10.5 points lower than non-notified slums. Findings for the other covariates are qualitatively similar, with the exception of slums in Madhya Pradesh having a significantly higher BSDS on average in this model.

Table A2 presents a multilevel model in which the BSDS is constructed using the same variables as in Table 1, but these variables are weighted using factor analysis. In this model, each year of notification is associated with an average 0.870 point decline in BSDS, and this relationship is non-linear. Findings for the other covariates are qualitatively similar to the findings in Table 5.

Table A3 presents a multilevel model in which the BSDS is constructed using a smaller number of variables that were identified and weighted based on a separate analysis of data from the NFHS-3. In this model, each year of notification is associated with an average 0.829 point decline in BSDS, and this relationship is non-linear. Findings for the other covariates are qualitatively similar to the findings in Table 5.

Table A4 presents a fixed effects model using the primary BSDS definition described in Table 1. In this model, each year of notification is associated with an average 0.763 point decline in BSDS, and this relationship is non-linear. Findings for most other covariates are qualitatively similar to the findings in Table 5; however, since this is not a multilevel model, states were compared to Bihar as a reference group. Slums in all states except Orissa have a significantly lower BSDS on average as compared to slums in Bihar.

(iv) Predictors of Receiving Financial Support for Slum Improvement

After controlling for covariates, the multilevel logistic regression model shows that non-notified slums have lower odds of receiving financial support from government schemes compared with notified slums ($p<0.001$) (Table 6). None of the covariates are significantly associated with receiving financial support. The BSDS is not significantly associated with receiving financial support, suggesting that funding has not been distributed based on the severity of a slum's deprivation. Slums in West Bengal had significantly higher odds of receiving financial support compared with slums in other states.

Table 6: Predictors of Receiving Financial Support from Government Slum Improvement Schemes in a Multilevel Logistic Regression Model Using Data from the 2012 NSS

Predictors	Multivariable findings (*N*=706, Estimated *N*=28,635) Odds ratio (CI)	p-value[a]
Notified		
Yes	-	
No	0.379 (0.246, 0.584)	<0.001
BSDS		
Low (≤30)	-	
Medium (31–60)	1.013 (0.671, 1.529)	0.951
High (>61)	0.723 (0.390, 1.341	0.304
Number of households in the slum		
<100	-	
101–300	0.933 (0.526,1.655)	0.814
301–800	1.251 (0.702, 2.228)	0.447
>801	0.854 (0.449, 1.622)	0.629
Land type		
Public local government	-	
Public central government	0.321 (0.088, 1.166)	0.084
Private	0.875 (0.584, 1.312)	0.519
Other or not known	0.941 (0.529, 1.674)	0.836
Slum location		
Central area	-	
Fringe area	1.019 (0.686, 1.515)	0.925
Type of area surrounding slum		
Residential	-	
Commercial	0.395 (0.129, 1.208)	0.103
Industrial	0.699 (0.270-1.811)	0.461

Other, including more slum settlements	1.145 (0.770-1.703)	0.505
Community association for slum improvement		
Yes	-	
No	0.709 (0.457-1.101)	0.125
Constant	0.791 (0.366, 1.710)	0.551
State random effects		
Andhra Pradesh	1.244 (0.956, 1.618)	1.000
Bihar	0.835 (0.516, 1.350)	1.000
Delhi[b]	-	-
Gujarat	1.131 (0.769, 1.665)	1.000
Karnataka	1.638 (1.177, 2.279)	0.380
Madhya Pradesh	0.995 (0.743, 1.332)	1.000
Maharashtra	0.786 (0.610, 1.014)	1.000
Orissa	0.752 (0.447, 1.264)	1.000
Tamil Nadu	0.621 (0.422, 0.912)	1.000
West Bengal	2.192 (1.638, 2.934)	0.002
Standard deviation of the random intercept	0.477 (0.232, 0.980)	-
Variation in receiving government funding attributable to state (intra-class correlation coefficient)	0.065	-

CI=confidence interval
[a]p-values for random effects are corrected for multiple comparisons (multiplied by the number of comparisons; capped at 1.00). Confidence intervals for the random effects are corrected to allow readers to make multiple comparisons between states (Goldstein and Healy 1995).
[b]Delhi slums did not report receiving any financial support in the 2012 NSS.

4 Discussion

(i) Legal Status and Deprivation in Slums

In this analysis of four waves of NSS data, we find that legal status has a strong influence on access to basic services in slums in India. Non-notified slums have lagged in access to every basic service provided by municipalities. The difference in average BSDS between notified and non-notified slums increased considerably over two decades, revealing widening disparities in deprivation. In fact, the average BSDS for non-notified slums remained statistically unchanged between 1993 and 2012, suggesting no reduction in the severity of deprivation faced by non-notified slums.

Of greatest concern is that disparities in access to services that are crucial for health increased the most. The percent of non-notified slums without piped water increased from 1993 to 2012, while the percent of notified slums without piped water declined. Similarly, the percent of non-notified slums without sewer infrastructure remained essentially unchanged, while the percent of notified slums without sewer infrastructure decreased substantially.

The multilevel regression analysis shows that the association between legal status and deprivation is significant even after controlling for other factors that could explain the severity of deprivation. The number of years a slum has been notified explains more of the variance in BSDS than any other factor. Most convincingly, we find a progressive non-linear reduction in deprivation the longer that a slum is notified, with benefits accruing most rapidly in the first decade after notification.

Providing legal recognition may therefore be a powerful intervention for improving access to basic services, thereby improving health outcomes in slums. Prior studies have focused on how legal recognition may motivate slum residents to improve the quality of their homes, due to lower threat of eviction (Field 2005; Gandelman 2010; Nakamura 2016). Our findings suggest that the benefits of legal recognition extend well beyond improvements in housing quality. By eliminating legal barriers to government provision of services, notification may serve as a gateway to accessing entitlements that are vital for life—including water, sanitation, electricity, schools, and health centers. Even if service delivery is suboptimal, notification confers basic rights and social recognition upon slum residents, empowering them to mobilize collectively to claim these entitlements (Appadurai 2001).

(ii) Barriers to Reducing Deprivation in Non-Notified Slums

Our analysis reveals two other concerning trends with implications for deprivation in India's slums. First, despite the strong association between notification and reduced deprivation, progress on notification seems to have stalled and reversed after 2008. Between 2008 and 2012, the number of non-notified slum households in India and the percent of all slum households that were non-notified increased. Why progress in notification has stalled is unclear, though some argue that neoliberal ideology has undermined the public's perception of slum residents as legitimate urban citizens (Bhan 2014). If this represents the start of a longer-term trend, reversal of progress in slum notification could slow the decline of deprivation in cities and increase inter-slum disparities (between notified and non-notified slums) and intra-urban disparities (between slum and non-slum populations).

A second barrier to reducing deprivation is that, despite greater average deprivation in non-notified slums, these slums were less likely to receive government financial aid. In addition, provision of government aid has no association with the severity of deprivation in a slum. While schemes like the JNNURM do not list legal status as a formal barrier to receiving support, in practice, non-notified status may serve as a hurdle that prevents these schemes from helping communities that need this aid the most.

(iii) Other Predictors of Deprivation in Slums

Our analysis highlights additional factors that influence deprivation. Slums on central government land (as compared with city or state land) experience greater deprivation. India's constitution designates certain areas in cities (including railways, airports, and seaports) as being under the legal jurisdiction of the central government. India's central government has no official policy for providing slums with legal recognition (Gangan 2010). Unlike city and state governments, which face democratic pressure to extend services to slums, the central government is not held accountable for the living conditions of slum residents through elections (Murthy 2012). Even when city governments are motivated to extend services to slums on central government land, they cannot do so without a "no objection certificate" from central government authorities. As a result, slums on central government land—despite having existed for decades in some cases—often suffer from severe deprivation (Juneja 2001; Subbaraman et al. 2012).

Another factor associated with lower average deprivation is having a community association. This finding affirms studies highlighting the role that slum dwellers' federations and similar organizations play in empowering communities to negotiate for services from local governments (Appadurai 2001; Patel et al. 2012).

Smaller slums, slums on city fringes, and slums in industrial areas suffer from greater deprivation. Slums on the city periphery or in industrial areas generally attract newer migrants, who may not be as politically empowered as longer established populations. Furthermore, slum residents are often relocated to peripheries of cities after episodes of home demolition, so the greater deprivation in these slums could partly reflect a "penalty" resulting from displacement.

(iv) Limitations of the Analysis

This observational study is not designed to determine whether the association between legal status and deprivation is causal. The NSS does not follow the same slums longitudinally, which would provide a better understanding of the temporal relationship between notification and deprivation. This association could be due to reverse causation. For example, slums with lower levels of deprivation could have greater collective efficacy to lobby for notified status. However, our finding that the average BSDS declines with increasing years of notification highlights a "dose-dependent" association that strengthens the likelihood of a causal relationship (Bradford Hill 1965). In addition, case studies highlight lack of security of tenure as a barrier to accessing services in slums, suggesting that a causal relationship is plausible (Murthy 2012; Subbaraman et al. 2012).

Confounding or mediating variables linked both with legal status and BSDS could also partly explain this association. For example, non-notified slums may be more likely to attract recent migrants who do not have the financial resources to afford a home in a notified slum. These individuals might have lower motivation to get access to basic services, fewer financial resources to pay for private connections to services, or lower collective efficacy to lobby officials to provide services.

Furthermore, the NSS data assume that all households within a slum have the same legal status. However, in some settings, households within a slum may be heterogeneous with regard to legal status. For example, in Mumbai, individual slum households may gain legal recognition and access to services based on whether the family was living in the home prior to a specified cut-off date (Bjorkman 2014). As a result, slums in Mumbai may have a mix of notified and non-notified households. The NSS collected community-level information, which limits our understanding of the influence of this household-level variability on deprivation.

We must therefore consider whether “ecological fallacy”—the misattribution of community-level associations to household-level relationships—affects the interpretation of our results. We believe that this bias is limited for a few reasons. First, legal recognition is designated at the community level in most settings. Second, in settings where legal status is heterogeneous within slums, the NSS probably correctly classified slums based on whether most households in that slum fit the designated legal category. Because many services require community-scale infrastructure development, if most households in a slum are non-notified, surrounding notified households are also likely to partly suffer from the “neighborhood-level” effects of deprivation (Lilford et al. 2016).

Finally, if heterogeneity in legal status exists within slums that the NSS did not capture, this biases our findings toward the null hypothesis that legal status has no association with the BSDS. In other words, the magnitude of this association could be greater than is reported in our analysis. Future large-scale surveys, such as the NSS and the National Family Health Survey, should include robust measures of legal status at the household level to better understand the relationship between legal status and deprivation for people living in slums.

5 Conclusions

Lack of legal recognition seems to be an intractable issue for slums in India and globally. Millions of urban citizens remain “off the map” from the standpoint of political and social recognition (Subbaraman et al. 2012). Many governments justify failing to extend basic services to slum residents using the concept of “opportunistic influx”—the idea that provision of services might encourage greater migration from rural areas, thereby paradoxically increasing urban deprivation. This argument is rooted in older academic theories that claim that providing jobs and improving living standards for the urban poor would accelerate urban unemployment and poverty through increased migration (Harris and Todaro 1970). However, these theories have fallen out of favor because they are supported by little empirical evidence. A substantial proportion of urban population growth occurs in situ and is not due to rural-urban migration. Moreover, extensive evidence suggests that provision of basic services enhances human capabilities and economic growth (Marx et al. 2013; Sen 1999). Despite the absence of evidence to support the theory of opportunistic influx, many government policies remain stuck in a state of inertia, leaving non-notified slums in a legal limbo, sometimes for decades (Marx et al. 2013).

Our study adds to a growing literature suggesting that lack of legal recognition perpetuates urban inequality in housing conditions, quality of life, and health outcomes (Nakamura 2016; Subbaraman et al. 2012, 2014). Providing legal recognition could be a powerful strategy for reducing deprivation and suffering by transforming slum residents into urban citizens with fundamental rights.

Where governments are unwilling to provide legal recognition, strategies for partial extension of services to slums without providing security of tenure may be one avenue around the policy trap. For example, a recent Bombay High Court ruling disentangled the right to water from land tenure by ordering Mumbai’s city corporation to provide basic access to water for non-notified slums (Subbaraman and Murthy 2015). Given the stalling of progress on slum notification in India, disentangling service delivery and security of tenure may provide an alternative strategy for reducing deprivation.

Finally, non-notified slums have been less likely to receive support from government schemes aimed at reducing urban disparities. Given that legal status is demonstrated to be a strong marker of deprivation, current government schemes for improving life in cities, such as the Smart Cities Mission and the Atal Mission for Rejuvenation and Urban Transformation (AMRUT), should target resources to non-notified slums. Alternatively, mapping the severity of deprivation in different slums—using evidence-based metrics that correlate with health outcomes—could help target financial support to communities most in need (Osrin et al. 2011). Increasing notification and better targeting of financial support may be key strategies for reducing deprivation, poor health outcomes, and suffering for people living in slums in India.

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Appendix

Table A1: Predictors of the Basic Services Deprivation Score (BSDS) in a Multilevel Regression Model Including Data from 10 States with the Largest Slum Populations – *Legal Status as a Dichotomous Variable*

	Multivariable findings (Estimated *N*=168,901) β-coefficient (95%CI)	**p-value***
Notified		
No	-	-
Yes	-10.546 (-12.092, -9.001)	<0.001
Year of survey		
1993	-	-
2002	-5.496, (-7.691, -3.301)	<0.001
2008	-8.810 (-11.020, -6.599)	<0.001
2012	-6.621 (-8.842, -4.401)	<0.001
Number of households in the slum (*per each 100-household increase*)	-0.172 (-0.242, -0.102)	<0.001
Number of households in the slum, quadratic term	0.0002 (0.0001,0 .0003)	<0.001
Land type		
State or city government	-	-
Central government	6.467 (3.129, 9.806)	<0.001
Private	-3.158 (-4.872, -1.444)	<0.001
Other or not known	1.198 (-0.896, 3.293)	0.262
Slum location		
Central area	-	-
Fringe area	8.850 (7.214, 10.486)	<0.001
Area surrounding slum		
Residential	-	-
Commercial	0.397 (-3.007, 3.800)	0.819
Industrial	4.689 (1.699, 7.679)	0.002
Other, including more slum settlements	2.146 (0.150, 4.142)	0.035
Community association for slum improvement		
Yes	-	-
No	4.058 (2.367, 5.750)	<0.001
Constant	52.384 (46.451, 58.317)	<0.001
State random effects		
Andhra Pradesh	-5.188 (-6.539, -3.836)	<0.001
Bihar	17.293 (14.734, 19.852)	<0.001
Delhi	-7.370 (-9.669, -5.071)	<0.001
Gujarat	1.495 (-0.291, 3.280)	1.000
Karnataka	-4.984 (-6.866, -3.101)	0.002
Madhya Pradesh	3.398 (1.739, 5.057)	0.044
Maharashtra	-9.560 (-10.526, -8.595)	<0.001
Orissa	13.413 (10.994, 15.832)	<0.001
Tamil Nadu	-0.139 (-1.786, 1.509)	1.000

West Bengal	-8.359 (-9.680, -7.037)	<0.001
Variance of the random intercept (p-value)	77.788 (31.367, 192.911)	<0.001
Variation in BSDS attributable to state (intra-class correlation)	19.96%	

*p-values for random effects are corrected for multiple comparisons (multiplied by the number of comparisons and capped at 1.00). Confidence intervals for random effects are corrected to allow readers to make multiple comparisons between states (Goldstein and Healy 1995).

Table A2: Predictors of the Basic Services Deprivation Score (BSDS) in a Multilevel Regression Model Including Data from 10 States with the Largest Slum Populations – *BSDS Constructed Using Factor Analysis*

	Multivariable findings (Estimated *N*=168,901) β-coefficient (95%CI)	**p-value***
Years notified (*per each one-year increase in the time a slum has been notified*)	-0.870 (-1.023, -.716)	<0.001
Years notified, quadratic term	0.010 (0.007, 0.0143)	<0.001
Year of survey		
1993	-	-
2002	-7.333 (-9.622, -5.043)	<0.001
2008	-10.826 (-13.142, -8.511)	<0.001
2012	-8.733 (-11.068, -6.399)	<0.001
Number of households in the slum (*per each 100-household increase*)	-0.1289 (-0.202, -0.056)	0.001
Number of households in the slum, quadratic term	0.0002 (0.00007, .0003)	0.001
Land type		
State or city government	-	-
Central government	7.305 (3.823, 10.788)	<0.001
Private	-3.489 (-5.279, -1.699)	<0.001
Other or not known	1.607 (-0.578, 3.792)	0.149
Slum location		
Central area	-	-
Fringe area	8.278 (6.567, 9.989)	<0.001
Area surrounding slum		
Residential	-	-
Commercial	0.124 (-3.432, 3.681)	0.945
Industrial	3.423 (0.297, 6.550)	0.032
Other, including more slum settlements	1.621 (-0.466, 3.709)	0.128
Community association for slum improvement		
Yes	-	-
No	4.707 (2.947, 6.466)	<0.001
Constant	51.833 (45.659, 58.006)	<0.001
State random effects		
Andhra Pradesh	-5.802 (-7.213, -4.390)	<0.001
Bihar	17.945 (15.271, 20.618)	<0.001
Delhi	-7.544 (-9.946, -5.143)	<0.001

Gujarat	2.462 (0.597, 4.328)	0.665
Karnataka	-4.484 (-6.451, -2.517)	0.015
Madhya Pradesh	2.300 (0.567, 4.032)	0.651
Maharashtra	-10.197 (-11.206, -9.188)	<0.001
Orissa	14.261 (11.735, 16.788)	<0.001
Tamil Nadu	-0.231 (-1.952, 1.491)	1.000
West Bengal	-8.710 (-10.091, -7.329)	<0.001
Variance of the random intercept (p-value)	84.676 (34.139, 210.024)	<0.001
Variation in BSDS attributable to state (intra-class correlation)	19.92%	

*p-values for random effects are corrected for multiple comparisons (multiplied by the number of comparisons and capped at 1.00). Confidence intervals for random effects are corrected to allow readers to make multiple comparisons between states (Goldstein and Healy 1995).

Table A3: Predictors of the Basic Services Deprivation Score (BSDS) in a Multilevel Regression Model Including Data from 10 States with the Largest Slum Populations – *BSDS Constructed and Weighted Based on an Analysis of the NFHS-3*

	Multivariable findings (Estimated *N*=168,901) β-coefficient (95%CI)	**p-value***
Years notified (*per each one-year increase in the time a slum has been notified*)	-0.829 (-1.059, -0.598)	<0.001
Years notified, quadratic term	0.009 (0.004, 0.015)	0.001
Year of survey		
1993	-	-
2002	-5.293 (-8.723, -1.864)	0.002
2008	-7.913 (-11.381, -4.445)	<0.001
2012	-4.569 (-8.066, -1.072)	0.010
Number of households in the slum (*per each 100-household increase*)	-.148593 (-0.258, -0.039)	0.008
Number of households in the slum, quadratic term	0.0002 (0.00002, .0003)	0.029
Land type		
State or city government	-	-
Central government	7.171 (1.956, 12.386)	0.007
Private	-5.165 (-7.845, -2.484)	<0.001
Other or not known	-0.325 (-3.596, 2.946)	0.846
Slum location		
Central area	-	-
Fringe area	10.047 (7.484, 12.609)	<0.001
Area surrounding slum		
Residential	-	-
Commercial	-0.981 (-6.308, 4.345)	0.718
Industrial	6.617 (1.935, 11.299)	0.006
Other, including more slum settlements	2.794 (-0.334, 5.921)	0.080
Community association for slum improvement		
Yes	-	-
No	3.822 (1.187, 6.458)	0.004

Constant	44.072 (35.912, 52.231)	<0.001
State random effects		
Andhra Pradesh	-7.685 (-9.795, -5.576)	<0.001
Bihar	23.509 (19.535, 27.483)	<0.001
Delhi	-8.950 (-12.526, -5.375)	0.005
Gujarat	0.686 (-2.097, 3.470)	1.000
Karnataka	-2.623 (-5.557, 0.310)	1.000
Madhya Pradesh	3.795 (1.208, 6.382)	0.414
Maharashtra	-14.872 (-16.382, -13.363)	<0.001
Orissa	18.510 (14.752, 22.269)	<0.001
Tamil Nadu	-3.920 (-6.490, -1.351)	0.340
West Bengal	-8.449 (-10.513, -6.385)	<0.001
Variance of the random intercept (p-value)	140.730 (<0.001)	
Variation in BSDS attributable to state (intra-class correlation)	15.56%	

*p-values for random effects are corrected for multiple comparisons (multiplied by the number of comparisons and capped at 1.00). Confidence intervals for random effects are corrected to allow readers to make multiple comparisons between states (Goldstein and Healy 1995).

Table A4: Predictors of the Basic Services Deprivation Score (BSDS) Including Data from 10 States with the Largest Slum Populations – *Fixed Effects Model*

	Multivariable findings (Estimated *N*=168,901) β-coefficient (95%CI)	**p-value***
Years notified (*per each one-year increase in the time a slum has been notified*)	-0.763 (-0.910, -0.617)	<0.001
Years notified, quadratic term	0.009 (0.005, 0.013)	<0.001
Year of survey		
1993	-	-
2002	-5.442 (-7.623, -3.261)	<0.001
2008	-8.369 (-10.574, -6.163)	<0.001
2012	-5.710 (-7.934, -3.485)	<0.001
Number of households in the slum (*per each 100-household increase*)	-0.147 (-0.217, -0.077)	<0.001
Number of households in the slum, quadratic term	0.0002 (.0001, 0.0003)	<0.001
Land type		
State or city government	-	-
Central government	6.652 (3.333, 9.970)	<0.001
Private	-3.172 (-4.878, -1.466)	<0.001
Other or not known	1.234 (-0.848, 3.316)	0.245
Slum location		
Central area	-	-
Fringe area	8.421 (6.791, 10.051)	<0.001
Area surrounding slum		
Residential	-	-
Commercial	0.106 (-3.281, 3.494)	0.951

Industrial	4.265 (1.287, 7.243)	0.005
Other, including more slum settlements	2.369 (0.381, 4.358)	0.020
Community association for slum improvement		
Yes	-	-
No	4.257 (2.581, 5.934)	<0.001
State fixed effects		
Andhra Pradesh	-22.814 (-27.088, -18.540)	<0.001
Bihar	-	-
Delhi	-24.984 (-30.080, -19.889)	<0.001
Gujarat	-16.253 (-20.834, -11.671)	<0.001
Karnataka	-23.074 (-27.737, -18.410)	<0.001
Madhya Pradesh	-14.919 (-19.374, -10.464)	<0.001
Maharashtra	-26.864 (-30.932, -22.797)	<0.001
Orissa	-3.903 (-8.995, 1.189)	0.133
Tamil Nadu	-17.197 (-21.622, -12.772)	<0.001
West Bengal	-26.153 (-30.356, -21.950)	<0.001
Constant	69.148 (64.736, 73.560)	<0.001