

Development Research at High Geographic Resolution: An Analysis of Night-Lights, Firms, and Poverty in India Using the SHRUG Open Data Platform

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Abstract

The SHRUG is an open data platform describing multidimensional socioeconomic development across 600,000 villages and towns in India. This paper presents three illustrative analyses only possible with high-resolution data. First, it confirms that nighttime lights are highly significant proxies for population, employment, per capita consumption, and electrification at very local levels. However, elasticities between night-lights and these variables are far lower in time series than in cross section, and vary widely across context and level of aggregation. Next, this study shows that the distribution of manufacturing employment across villages follows a power law: the majority of rural Indians have considerably less access to manufacturing employment than is suggested by aggregate data. Third, a poverty mapping exercise explores local heterogeneity in living standards and estimates the potential targeting improvement from allocating programs at the village—rather than at the district—level. The SHRUG can serve as a model for open high-resolution data in developing countries.

JEL classification: R11, C81, O12

Keywords: open data, big data, administrative data, nighttime lights, poverty, India

1. Introduction

Development and economic growth, insofar as they affect the living standards of individuals, are highly localized phenomena. Employment opportunities, schools, public goods, and welfare schemes are relevant to individuals primarily if they are accessible within a short distance. However, due to the nature of data

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Table 1. Geographic Variance Decomposition of SHRUG Variables

	State	District	
<i>Panel A. Share of variance in town-level outcomes explained by state, district</i>			
Consumption per capita	0.399	0.642	
Non-farm employment per capita	0.102	0.254	
Night-lights per capita	0.048	0.183	
Population density	0.162	0.304	
Average forest cover	0.491	0.756	
<i>Panel B. Share of variance in village-level outcomes explained by state, district, subdistrict</i>			
	State	District	Subdistrict
Consumption per capita	0.321	0.450	0.526
Non-farm employment per capita	0.021	0.044	0.075
Night-lights per capita	0.056	0.113	0.148
Population density	0.202	0.290	0.338
Average forest cover	0.456	0.633	0.723

Source: Authors' analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India (SHRUG).
Note: The table presents the spatial decomposition of the variance of a selection of variables in the SHRUG for urban municipalities (towns, Panel A) and rural municipalities (villages, Panel B). Stated values are the R^2 from regressions of each variable on a set of, respectively, state-, district-, and subdistrict-level fixed effects. As there is rarely more than one town per subdistrict, we stop at the district decomposition for urban areas. Consumption per capita is estimated based on economic variables in the Socioeconomic and Caste Census. Employment per capita is calculated by dividing 2013 Economic Census (EC13) non-farm employment by the total population from the 2011 Population Census. Night-lights per capita is calculated by dividing calibrated total light from 2013 by the 2011 Population Census population. Average forest cover is a 2014 measure derived from Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Continuous Fields (VCF). Population density is the 2001 total population divided by 2001 census land area.

available to researchers, analysis of development has largely occurred at an aggregate geographic scale. In India, much policy and research has been based on the National Sample Surveys, which have tracked socioeconomic change at the district level since independence. But a single Indian district is home to around 2 million people, often with vast variation in living standards. This variation is demonstrated in [table 1](#), which shows the share of variation in various development outcomes at different levels of geographic variation. In fact, 55 percent of variation in mean village per capita consumption and over 95 percent of variation in rural non-farm employment occurs below the district level. The National Sample Surveys often base district statistics on fewer than 100 households per district, missing much of this microgeographic variation.

The computerization of government administration and the proliferation of new data sources such as satellite imagery have provided researchers with the opportunity to study development at higher geographic resolution than ever before. However, it has been enormously costly and time consuming to discover, obtain, clean, and merge data sources that were not designed for social science research. When researchers do pay the fixed costs, it is often difficult for other research teams to make use of those data; despite recent efforts to make data availability a key part of the publication process, published data are rarely comprehensive or easily linked to other data sources. The high fixed costs of making use of new data are particularly harmful to researchers lacking the funding and time to make major investments in data assembly, such as many doctoral students and researchers in the very countries that development economics seeks to study.

This paper introduces the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India (SHRUG), a multidimensional socioeconomic data platform with high-geographic-resolution data on demography, non-farm employment structure, political outcomes, forest cover, night-lights, and administrative program operation, among other dimensions, for the universe of municipalities (towns and villages) and legislative constituencies in India from 1990 to 2018 (see [table 2](#)).¹ The SHRUG is an

1 Villages (rural, median population 832) and towns (urban, median population 14,684) are the lowest level for which the Population Census and many other datasets make data available. The lowest level of government in India is comprised of

Table 2. SHRUG Summary

Dataset	Years	Description	Units of observation
Population Census	1991, 2001, 2011	Demographic data, social groups, village & town amenities, including electrification, roads, post offices, markets, health centers, schools, land use, and water source	Village, town, constituency, district
Economic Census	1990, 1998, 2005, 2013	Employment and sector of all non-ag firms, including manufacturing and services, formal and informal, government and private firms	Village, town, constituency
Socioeconomic and Caste Census (SECC)	2012	Consumption estimates, poverty, agricultural labor share	Village, town
Election results	1980–2018	Candidate name/party/votes	Constituency/candidate
Politician assets/crime	2003–2018	Criminal charges, assets, liabilities, education for all politicians contesting a member of the legislative assembly seats	Constituency/candidate
Night-lights	1994–2013	Proxy for electrification and economic activity	Village, town, constituency
Forest cover	2000–2019	Percentage tree cover from Vegetation Continuous Fields	Village, town, constituency
Rural road construction	2000–2013	Administrative data from Pradhan Mantri Gram Sadak Yojana (PMGSY), including length, material, cost, and milestones	Village

open dataset but also an open data platform that is structured to facilitate and encourage sharing of readily linkable data between researchers in the future.

In this paper we present three analyses that shed light on the distribution of economic opportunity within highly localized regions, analyses that are only possible with high-resolution data like the SHRUG.

We begin by examining the effectiveness of nighttime lights as a measure of local development. Nighttime lights, as measured from outer space, have been widely used in recent years to examine patterns of development in places where local economic data are not available. Nighttime lights are particularly used in analyses of programs that have geographic variation more precise than what can be observed in aggregate data; the ability to observe an economic outcome in a $1 \text{ km} \times 1 \text{ km}$ cell is a key comparative advantage of night-lights. Given the lack of high-precision economic data in most developing countries, the assumption that night-lights have the same elasticities at both very high and very low levels of geographic aggregation with a range of outcome variables is largely untested.²

Our results confirm that night-lights are a highly statistically significant log-linear proxy for a range of development outcomes—population, employment, per capita consumption, and electrification—at a very narrow geographical level, even in specifications with regional fixed effects, in both the cross section and in the time series. However, there are two significant caveats. First, because night-lights have independent correlations with each of these outcomes, it is difficult to tell from night-lights alone which of these proxy variables are being measured. Researchers have used night-lights as a proxy for GDP growth, cross-sectional GDP, urban extent, public expenditure, and electricity supply and demand, among other variables (Henderson, Storeygard, and Weil 2011; Baum-Snow et al. 2017; Bleakley and Lin 2012; Min et al. 2013; Hodler and Raschky 2014; Baskaran, Min, and Uppal 2015; Burlig and Preonas 2016; Harari 2020; Mahadevan 2021). Our results suggest that all of these proxies are valid, but researchers have no guarantee that night-lights are proxying the specific variable that they would like to measure and not a different one.

Second, we find that night-light elasticities vary substantially across the level of geographic aggregation and across contexts. Importantly, we find that night-light elasticities are an order of magnitude smaller in the time series than they are in the cross section. Night-light elasticities with most variables are also considerably higher in electrified villages than in non-electrified villages. This finding suggests that researchers should use extreme caution in applying regional luminosity-to-GDP elasticities from the literature to microgeographic contexts without additional information, because these elasticities may be wildly different. Applying cross-sectional elasticities to time series night-light coefficients is likely to result in a substantial upward bias on GDP estimates.

Moving beyond night-lights, we next examine the distribution of manufacturing and services employment across space. Economic activity is often highly agglomerated and firm-size distributions are known to follow power laws (Ellison and Glaeser 1997; Gabaix 2016). The amount of concentration affects the extent to which regional averages reflect the access to opportunity of the majority of a region's residents. We show that the distribution of firms across space also follows a power law, such that some regions have orders of magnitude more employment density than others. The extent of employment concentration is higher for manufacturing than for services firms, and the highest by far for manufacturing employment in rural areas. The mean Indian village has 15 manufacturing jobs per 1,000 people, but the median has fewer than 5. Almost 80 percent of rural Indians live in villages with fewer manufacturing job opportunities than the rural mean. Regional employment opportunities, especially for women, may be of limited relevance if

urban local bodies for towns, and rural panchayats, which are on average comprised of two or three villages. Legislative constituencies are geographic areas, usually comprised of multiple towns and villages, that send one representative each to India's Vidhan Sabhas (state legislatures).

- 2 Henderson, Storeygard, and Weil (2011) show that elasticities are similar across countries and across large regions within countries, but they do not measure elasticities at finer geographic levels. And yet the primary use of night-lights in research is precisely to generate outcome variables at very high geographic resolution.

they are not geographically proximate. This analysis demonstrates that analysis of employment at aggregate geographic scales may fail to register the lack of labor-market opportunities for most rural workers.

Finally, we conduct a poverty mapping exercise, considering the problem of a policy maker targeting a program to poor geographic regions (Ravallion 1993; Baker and Grosh 1994; Bigman et al. 2000; Bigman and Srinivasan 2002; Elbers et al. 2007; Brown, Ravallion, and van de Walle 2019). We measure the efficiency gain that could arise from the ability to allocate a program reaching 25 percent of the population at increasingly finer geography. If the policy maker can observe poverty only at the district level ($n = 618$), then allocating the program to the poorest districts would cover 37 percent of the rural poor. Allocating the same program at the village level would cover 44 percent of the rural poor. There is likely a trade-off between precise geographic targeting and administrative cost; highly localized data make it possible to estimate the parameters of this trade-off.

The SHRUG has a number of strengths and weaknesses as an analytic platform. Its primary strengths are its geographic resolution and consistent location identifiers over a period of dramatic economic change. There are few other data sources in developing countries that allow tracking of public goods, economic activity, politician characteristics, election results, and many other outcomes at the village and town level for almost 600,000 consistently bounded geographic units.³ The key comparative disadvantages of the SHRUG are that (a) most of the underlying data sources are based on narrow surveys with a few dozen questions rather than hundreds and (b) the SHRUG describes locational aggregates, rather than individual or firm microdata.⁴ Researchers interested in detailed characteristics of individual households and firms may thus be better served by traditional data sources.

There are a number of contexts in which the SHRUG may have a comparative advantage:

- Programs with highly local variation are difficult to evaluate with aggregate data. Examples of analysis of such programs using administrative data (some of which are now in the SHRUG) include Lehne, Shapiro, and Vanden Eynde (2018), Chhibber and Jensenius (2016), Burlig and Preonas (2016), Asher and Novosad (2017), Adukia, Asher, and Novosad (2020), Asher and Novosad (2020), and Muralidharan, Niehaus, and Sukhtankar (2020).
- Analysis at the city/town and legislative constituency levels is challenging because neither of these units are identified in India's conventional data sources. SHRUG data are aggregated to both of these levels.
- Researchers running field experiments typically use national population censuses as sampling frames for new field experiments, but have limited additional data on sample locations before collecting their own baseline surveys. The SHRUG increases the scope of what is known at a local level. Field experimentalists can begin to test for divergent trends in field locations even before conducting a baseline survey.

Most of the data underlying both the SHRUG and the papers using administrative data described above are public. The primary constraint to using data like these is the time input required to assemble, clean, and match them to other data sources. The returns to this activity are increasing in the number of other localized data sources that they can be matched to. We therefore hope that the existence of the SHRUG makes it worthwhile for researchers to assemble and share other administrative and microgeographic datasets describing additional dimensions of development in India.

We structured the SHRUG to maximize the ease and benefit to researchers of sharing new data. First, by providing a broad spectrum of data under a consistent set of identifiers, we hope to create a standard set of location identifiers for India. Such standardization can lower the cost of merging datasets for all researchers. Second, we have structured downloads from the SHRUG to credit individual contributors.

3 There are approximately 605,000 towns and villages in India. We collapse these to about 590,000 unique, consistent locations that can be tracked over time.

4 Note that it can be rapidly linked to firm-level data in the Economic Census, which is openly available.

When researchers download data from the SHRUG, they are asked to cite the authors who created each component of the SHRUG that they are using.⁵ This citation structure is intended to give researchers an incentive to contribute, because clean data integrated into the SHRUG will receive more users and generate more citations than data on journal websites that are suitable for replication only.⁶

Finally, SHRUG data are released to non-commercial users under a copyleft license (the Open Database License, or ODbL), which commits researchers who link the SHRUG to non-proprietary data to also post that non-proprietary data in a complete form with SHRUG identifiers at the time that their research is published.⁷ Given the long publication lags in economics, this license gives researchers ample lead time to work on additional projects with the data that they have collected, but commits them to sharing data in a reasonable time horizon. Like the limited protection time offered by a patent, this approach trades off the private incentive to researchers of developing unique data sources with the much greater public good of making those data sources available to the full network of researchers that can make use of them.⁸

The current release of the SHRUG (version 1.5) describes (a) demographic and public goods data on every town and village in India from 1991 to 2011, (b) employment and location of every non-farm firm in India from 1990 to 2013, (c) legislative election results from 1980 to 2018 (Jenselius 2017), (d) assets, liabilities, and criminal charges of all politicians in office and many additional candidates from 2004 to 2017 (Prakash, Rockmore, and Uppal 2019), (e) remotely sensed night-lights from 1994 to 2013, (f) remotely sensed forest cover from 2000 to 2019, (g) the share of labor force in agriculture and small area estimates of consumption from the Socioeconomic and Caste Census (SECC) of 2012, and (h) administrative data from the implementation of India's national rural roads program. As new census, remote sensing, and administrative datasets are released, the breadth of this panel will continue to grow.

This paper first describes the construction of the SHRUG in some detail, along with several validation exercises. Next, the analyses of night-lights, agglomeration, and poverty are presented, followed by a discussion of the strengths and weaknesses of the SHRUG as an analytical tool. To conclude, there is a discussion of the copyleft license and framework for improving institutions of data sharing between researchers.

2. Data: A 25-Year Multidimensional Panel of Locations

All variables in the SHRUG are disaggregated to the level of the village ($n = 590,648$), the town ($n = 7,528$), and the state legislative constituency ($n = 2,800$), covering the entire country. The different components are summarized briefly in table 2 and in detail in the SHRUG metadata table.⁹

All of these data sources were initially generated with diverse geographic identifiers that were not straightforward to link. The Population and Economic Censuses are published with town and village codes with incomplete correspondences across different rounds. Pradhan Mantri Gram Sadak Yojana (PMGSY) data are published at the habitation level; most villages consist of between one and three habitations. Remote sensing data are published in grid cells, while political data are published at the constituency level; constituencies are approximately the size of subdistricts (a standard unit in the Population Censuses), but with different and overlapping boundaries.

Any pair of these datasets can be reconciled and matched to each other, albeit with significant labor input. Sources of information used to match data include numeric identifiers, names, maps, data contents,

5 For instance, users of the data in the SHRUG on the criminal charges facing Members of Legislative Assemblies should cite Prakash, Rockmore, and Uppal (2019).

6 The present version of the SHRUG already includes contributions from two groups of researchers other than ourselves. Since making the data public in September 2019, three additional groups of researchers have begun working on additional data sources that they plan to integrate with the SHRUG.

7 More information on the ODbL is available at <https://opendatacommons.org/licenses/odbl/index.html>.

8 Data under formal proprietary contracts that restrict sharing are excluded from this commitment at this time.

9 The SHRUG metadata table can be found at devdatalab.org/shrug-metadata.

and external data sources. In most cases, none of these information sources provides a perfect match. Identifiers are rarely consistent across datasets; sometimes they are consistent across some states but not others. Locations may be known by multiple names, and names may change over time; they virtually always have different spellings across and even within data sources. Maps are supplied with different projections and different degrees of error; boundaries that should be identical in different mapping sources often are not. Locations themselves change, splitting, merging, and realigning boundaries in complex ways.

The process of matching these datasets consists of developing algorithms to use as many of these information sources as possible, and then tuning those algorithms based on manual verification of samples of data. Individual verification of every match is however not feasible when observations number in the hundreds of thousands. Some units cannot be matched even with manual verification because there is insufficient information available. Some degree of incorrect matches is inevitable.

The core contribution of the SHRUG is a set of universal location identifiers (one at the town and village level and one at the constituency level) that span the entire sample period from 1990 to 2018. All of the datasets above can be rapidly linked to these identifiers in every period. When using the SHRUG, linking disparate data sources takes seconds rather than months. By releasing the data with these universal identifiers, our hope is to make them a standard for economic research in India, allowing future data sources to be linked to the data sources described here with ease.

This section describes the process of creating the universal identifiers that are at the heart of the SHRUG. The definitions of individual data fields are described in detail in the SHRUG codebook.¹⁰

To keep its size reasonable, the SHRUG 1.5 data package includes only a subset of the fields in the Economic and Population Censuses. We provide linking keys to each of these source datasets to make it easy for users to bring in additional fields from these open data sources.

Building the Town and Village SHRUG

The key challenge in creating time series administrative data in India is in dealing with changing unit boundaries. Faced with the challenge of villages being split, merged, and integrated with cities and towns, the decennial census has opted to create new location identifiers in every decade since 1991. Further complicating the process of matching locations over time, district boundaries have changed substantially, with hundreds of new districts created between 1991 and 2011. The census provides digital keys to link villages and towns to prior censuses, but they are highly incomplete. The census district handbooks contain detailed descriptions of boundary changes in narrative format only. All of these sources have errors and inconsistencies.

We used both the digital linking keys and the district handbooks to create the best possible correspondence of villages and towns across the 1991, 2001, and 2011 censuses.¹¹ We supplemented this with a custom fuzzy string matching program to match village and town names over time.¹² We conducted a hierarchical match from the largest to the smallest administrative units. We began with a match of districts across Population Censuses. A 1991–2001 district correspondence was shared with us by Kumar and Somanathan (2017). We constructed the 2001–2011 district match based on the back-referenced village identifiers in the 2011 census, which provided a 2001 census village identifier for the majority of 2011 villages. Within districts, we then matched subdistricts on the basis of names where possible, and then we matched villages within subdistricts, again on the basis of names. Where the district and subdistrict maps indicated substantial changes in district and subdistrict boundaries, we matched villages and towns within higher-level aggregates of districts and subdistricts. We validated the data using internal

10 The SHRUG codebook can be found at <http://www.devdatalab.org/shrug>.

11 The census district handbooks are 500+ page books describing all changes to boundaries in a given census district in an intercensal period. There is one book like this for each of India's ~700 districts.

12 The program is called "masala-merge" and is available at <http://github.org/devdatalab/masala-merge>. It performs a Levenshtein string match, customized for common string substitutions used in Indian languages.

consistency checks and data from multiple sources, including geospatial village and town data assembled by other research groups. Table S1.1 in the supplementary online appendix summarizes the share of population from each Population Census that is matched at the village and town level to the SHRUG by state. Virtually all towns and villages were matched across the census periods: the match rate is 98 percent or higher for all but two small states in 1991.

To match the Economic Censuses to the Population Censuses we used the location directories for 1998 and 2005, which were shared with us by the Ministry of Statistics (MOSPI). For 2013 we used the fact that the Economic Census location codes corresponded to the Population Census short codes, which were available with village and town names on the Population Census website. The final step in all these cases was a match using location names with the algorithm described above.

MOSPI was not able to provide a location directory for the 1990 Economic Census. The EC district codes were the same as those used in the 1991 Population Census, but the lower-level codes were different in some states. We worked with MOSPI to identify the set of states that used the same identifiers in the 1991 Population Census and the 1990 Economic Census. It was straightforward in the data to distinguish these states from those that created new codes, and we matched villages and towns on the basis of identifiers in these places. For towns that could not be reliably matched on the basis of the town codes, we obtained a number of additional matches in situations where three conditions all held: (a) towns could be uniquely matched within districts to the 1991 Population Census based on the number of wards,¹³ (b) their within-district size rank was the same in the Economic and Population Censuses, and (c) the number of people per Economic Census job was within an order of magnitude of the dataset mean, which was approximately 20. Table S1.2 in the supplementary online appendix summarizes the share of employment in each Economic Census that is matched to the SHRUG, by state. Because of the absence of the 1990 location directory, the match rate for the 1990 Economic Census is much lower than for the other censuses.

Additional administrative datasets (such as the PMGSY road data and the SECC) were matched using a similar approach. These matches are described in more detail in [Asher and Novosad \(2020\)](#).

Location splitting and merging over time results in an inordinately complex set of linking keys. To create a dataset that was unique on the same locations for all of the different underlying data sources, we aggregated location units until a set of boundaries could be found that was unique across all years. We gave each of these units a unique SHRUG identifier, or a *shrid*.

A shrid describes a geographical unit that can be mapped consistently across all rounds of the Indian Population and Economic Censuses from 1990 to 2013. In the majority of cases, a shrid describes a single village or town. When villages or towns have merged or separated in the sample period, we have aggregated them in the periods where they appear separately, such that the aggregation is represented by a single consistent shrid in all of the data. Some shrids are thus composed of multiple Population Census villages or towns, or a combination of villages and towns.

In some cases, village and town boundaries have changed so dramatically that the aggregated constant boundary unit is quite large. In the case of New Delhi and Chandigarh, whose internal boundaries have changed frequently since 1991, the shrid is the entire city-state. In the case of Mumbai, a shrid is a district, which is the smallest non-changing unit. Creating time-consistent data within urban boundaries is a challenging and distinct project that we are also working on, but is beyond the scope of this iteration of the SHRUG.

The use of a single consistent unit for each geographic location is a critical simplification for the researcher. Without a one-to-one relationship between locations across datasets, each additional bilateral merge requires an increasingly complex task of handling splits, joins, and unit duplications. When working with shrids, any number of datasets can be merged without increasing complexity.

13 For instance, if a district had two towns in the 1991 Population Census, with respectively four and seven wards, we matched them to the 1990 Economic Census towns with the same number of wards.

The complete keys linking shrlds to their original Population and Economic Census codes and location names are posted with the SHRUG, making it easy to bring in additional data that are already linked to Population Census codes. As described in the codebook, we have designed a naming convention for shrlds that will be forward-compatible with future censuses as well. New keys will be posted as future censuses are released.

Creating a Constituency-Level Panel

The boundaries of India's 543 parliamentary and some 4,000 legislative constituencies do not align with the aggregate administrative boundaries used by India's data collection agencies. To create a constituency-level dataset with economic outcomes, we matched villages and towns to constituencies using digital maps and collapsed the data to the legislative boundaries.¹⁴ We created a set of time-invariant constituency identifiers for the third and fourth delimitations.¹⁵

Creating a constituency-level panel from town and village microdata poses a number of challenges. First, because of the fuzzy matching process, there are some villages that were matched to some censuses and not to others. Simply aggregating employment in matched villages to the constituency level would thus overstate employment gain in constituencies that have improving match rates over time. We corrected these errors with an imputation process which we describe here.

In the 2011 Population Census we have matched 100 percent of towns and villages to constituencies, while the match rates in 1991 and 2001 are very high but imperfect. For each constituency we therefore know the 2011 population in towns and villages that were matched to the other censuses and the 2011 population in towns and villages that were not matched. We impute the prior years' population in unmatched locations by assuming that the within-constituency 2001–2011 population growth rate is the same in towns and villages that we did *not* match in 2001 as it is in the towns and villages that we *did* match. We can repeat the process to obtain the full set of populations in 1991. Because the match rates in 1991 and 2001 are so high, any error in this imputation process is likely to be minimal. This process will cause the aggregated constituency population to be closer to the truth than if we counted missing locations as having zero population.

We repeated the process to aggregate the employment count in the Economic Censuses, and the public goods counts in the Town and Village Directories. For each Economic Census we assumed that the employment-to-population ratio for missing locations is the same as it is for non-missing locations within the same constituency. For location amenities that are aggregated with means rather than sums (such as the mean number of hours of electricity), we generated an aggregate based on the population-weighted mean in non-missing locations. To avoid excess dependence on imputed values, we set fields to missing in constituencies where locations covering more than 25 percent of the population would be imputed. This means that different constituencies may be missing different fields depending on the underlying structure of the data.

Figure S1.1 in the supplementary online appendix runs a simulation to calculate error rates associated with the imputation process. We randomly drop additional locations from the 2001 Population Census and then compare the calculated constituency population to what would be observed if no locations were dropped. When 25 percent of shrlds are dropped (the upper limit of what we include in the data), the average constituency population is within 2 percent of the true value with a slightly negative bias of

14 SHRUG 1.5 does not include electoral data for parliamentary constituencies or panchayats, but these will be included in the future. Boundary data were obtained from ML Infomap.

15 This was necessary because the Election Commission of India (ECI) does not always use consistent numeric identifiers over time. The keys provided with the constituency-level data make it possible to link to the ECI data and thus to any other dataset that uses those identifiers.

0.015 percent.¹⁶ It is important to note that this imputation process applies only to the constituency-level data; when Economic or Population Census data are missing in the town and village data, they are reported as missing in the SHRUG.

Another challenge that arises is that the available polygon shapefiles for constituencies and towns/villages are not perfectly aligned, even though they all use the same WGS84 projection and were obtained from the same firm. The misalignment is small—of the order of several hundred meters in the worst cases—but it is enough that some villages and towns cannot be unambiguously assigned to a single constituency. We dropped constituencies in which more than 25 percent of 2011 population is in villages or towns that cannot be decisively assigned. We have explored several alternate sources of data and spoken with several other experts on Indian spatial data, and to our knowledge there are currently no higher accuracy shapefiles than these, so this amount of error is unavoidable. There are several ongoing projects to assign villages to constituencies by digitizing electoral rolls; as these data become available, we aim to integrate them into future versions of the SHRUG.

A third challenge is that some towns contain multiple constituencies. Because the Population Censuses do not report consistent identifiers at the ward level or below, it is difficult to identify the population or other characteristics of these constituencies—we know only the aggregate population of the combined constituencies.¹⁷ We therefore exclude constituencies that include any part of towns that cross constituency boundaries. Constituencies in large urban areas are therefore missing population and economic data in the SHRUG. However, the election and remote sensing measures are included for all villages because they are not aggregated from village and town data.

The *constituency* SHRUG is therefore not representative—in particular, it excludes large cities. However, we are not aware of other research that measures or exploits socioeconomic data at the constituency level for large urban constituencies (other than the remote sensing measures described above), presumably due to the same boundary misalignment issues that we face here. Constructing such a dataset using ward maps for India's largest cities would be a valuable contribution that would enable better study of politics in India's growing cities.

Finally, India periodically redraws constituencies to account for population changes. The third delimitation came into effect in 1976 and the fourth in 2008, in the middle of the period covered by the SHRUG (Iyer and Reddy 2013). This is not a problem for data construction, since constituencies are simply defined as polygons. We therefore match both sets of polygons to villages/towns and create separate complete constituency-level panels from 1990–2018 for the old and the new constituency delimitations. Researchers can thus make their own decisions regarding which polygons to use for which periods. We provide separate identifiers for the third and fourth delimitations; there is no correspondence between these as nearly all of the constituency boundaries were changed.

Remote Sensing Data

At present, the SHRUG includes data from two remote sensing sources: nighttime luminosity (Henderson, Storeygard, and Weil 2011) and forest cover (Asher, Garg, and Novosad 2020; Townshend et al. 2011). Nighttime luminosity data are from the National Oceanic and Atmospheric Administration (NOAA), and

16 Imputed values for constituencies with high imputation rates are available from the authors, as is the share of imputed data in each constituency field. These are not included in the online SHRUG package because the files are extremely large and have relatively narrow usefulness. While it would be desirable to use these values to econometrically adjust for the partial imputation that took place in calculating these values to adjust for the partial imputation of some constituency values, we are not aware of an out-of-the-box method that is well matched to this partial imputation structure. The simulated error rates suggest that this source of error is small relative to other sources of error in the collection of administrative data in India, and thus not a major concern.

17 The Population Census reports data at the ward level, but the wards change across rounds and do not necessarily share boundaries with constituencies.

provide a luminosity value from 0 to 63 for each 1 km × 1 km grid cell. Forest cover data come from Vegetation Continuous Fields (VCF), a Moderate Resolution Imaging Spectroradiometer (MODIS) product that measures tree cover at a 250 m resolution from 2000 to 2019. VCF is predicted from a machine-learning algorithm based on broad spectrum satellite images and trained with human-categorized data, which can distinguish between crops, plantations, and primary forest cover.

Gridded data from both of these sources were matched and aggregated to village, town, and constituency boundaries. About 90 percent of towns and villages were georeferenced with polygons, permitting accurate measurement of night-lights and forest cover. About 10 percent of locations, especially in the northeast, were georeferenced in the mapping data only by points; we constructed Thiessen polygons to match these to the forest cover and night-light rasters. Locations mapped with Thiessen polygons are flagged in the data.

Imputation of Consumption Expenditure

We created a measure of village- and town-level consumption expenditure using data from the SECC, a universal enumeration of household assets conducted in 2012. Asset censuses like this are commissioned by the federal government approximately every decade to determine individual eligibility for means-tested poverty relief programs. The SECC enumerates a list of household assets that can be rapidly assessed (including roof and wall material, number of rooms, and assets such as agricultural equipment, vehicles, and mobile phones).

We used this asset data to generate small area estimates of consumption expenditure, following the method of [Elbers, Lanjouw, and Lanjouw \(2003\)](#). Using the 2011–2012 IHDS-II (Indian Human Development Survey, 2011–2012, available at <https://ihds.umd.edu>), we regressed total household consumption on a set of continuous and dummy variables that are equivalent to all asset and earnings information contained in the SECC. We then used the coefficients (shown in tables S1.3 and S1.4 in the supplementary online appendix) to predict household-level consumption in the SECC microdata. We aggregate this to create a village- and town-level measure of annual per capita consumption expenditure. Because the urban and rural asset lists are different, we use separate estimations depending on whether households were identified as rural or urban in the SECC.¹⁸ Village- and town-level asset ownership shares are also available in the house listing for the 2011 Population Census and match the asset shares in the SHRUG closely.

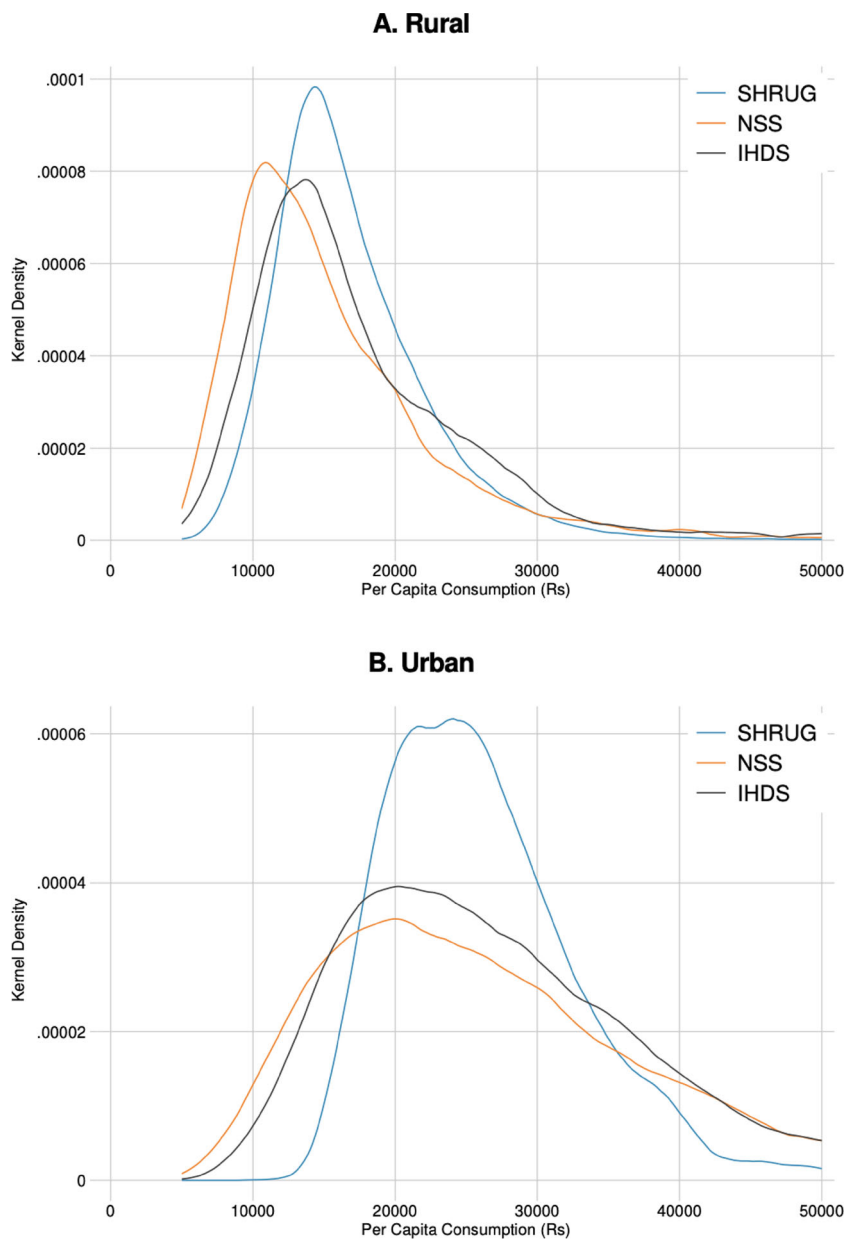
In addition to average per capita consumption, we included the share of individuals in each town and village who live in households with per capita consumption below the 2012 national poverty rate, defined in two ways: below \$2, or below Rs. 27.2 per day in villages and Rs. 33.33 in cities and towns.¹⁹

We have validated these consumption estimates in three ways. First, we affirmed that the consumption distribution broadly matches the 2011–2012 IHDS and the 2012 National Sample Survey (NSS). The consumption distribution in each dataset is shown in [fig. 1](#). For the sake of comparability, the locations used are Population Census villages in the SHRUG and the closest analog in the other two datasets (first

18 The consumption model is estimated with statistical error. To allow researchers to account for these errors, we used a bootstrap approach, drawing households from the IHDS with replacement and re-estimating village-level per capita consumption 1,000 times. These 1,000 draws are available as a SHRUG package for download and reflect the distribution of per capita consumption that arises from the first-stage estimation process. Researchers can use these 1,000 draws in a second bootstrap process to account for the consumption model is estimated with statistical error. The data appendix in [Asher and Novosad \(2020\)](#) describes this process in additional detail.

19 The \$2 threshold is converted in PPP to Indian rupees in the following way. It should be noted that GDP per capita (current US\$) of India in 2012 is 1,446.985, GDP per capita PPP of India in 2012 is 4,916.486, and the exchange rate between the Indian rupee and US\$ in 2012 is 53.427 according to the World Bank. Thus, \$2 PPP is equal to 31 rupees ($2 \times 1,446.985/4,916.486 \times 53.427$) or 31 rupees per day, while the 27.2/33.33 rural/urban classification is from the 2011 Suresh Tendulkar Committee report ([Planning Commission of India 2009](#)).

Figure 1. SHRUG, IHDS, and NSS Consumption Per Capita



Source: Authors' analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India (SHRUG), the National Sample Survey (NSS), and the India Human Development Survey (IHDS).

Note: The figure shows the distribution of location-level annual consumption per capita from the NSS, the IHDS, and the SHRUG. Consumption in each location is a mean across households, calculated with sampling weights. Location units are primary sampling units in the IHDS, first stage units in the NSS, and towns or villages in the SHRUG.

stage unit in the NSS and primary sampling unit in the IHDS).²⁰ The figure shows that the SHRUG has lower variance than the IHDS and NSS but otherwise a similar distribution. These differences are mechanically related to the construction process of small area estimates through several channels. First, the SHRUG uses predicted consumption and is thus lacking the error term found in the other datasets. Second, the observation counts per location in the NSS and IHDS are far lower than in the SHRUG, so outlier households have a smaller effect on the variance in village-level consumption in the SHRUG. Third, the SECC asset measures aim to identify poor households and do not include luxury goods. Households in the top percentiles of the consumption distribution are thus effectively topcoded in the SHRUG. Similarly, the structure of the asset regression is such that there is a minimum estimated household consumption quantity, which is the same for all households with none of the assets on the asset list. But in the NSS and IHDS there is no mechanical lower limit for household consumption. The SHRUG therefore has no households with either extremely high or extremely low consumption.

As a second exercise, we compared average consumption in SHRUG districts and IHDS districts. Figure 2 presents a binscatter showing that average consumption covaries very strongly across these two datasets in both rural and urban areas. Finally, we decomposed the difference in average consumption between the SHRUG and IHDS. Tables S1.3 and S1.4 in the supplementary online appendix compare the means of each component of the consumption index in the SHRUG and the IHDS. Columns (1) and (2) show the share of households with each characteristic in both datasets; Column (3) shows the difference. Column (4) shows the coefficient on consumption from the prediction regression in the IHDS. Column (5) shows the average difference in Indian rupees between consumption estimates in the SHRUG and consumption as measured by the IHDS, which is driven by this component of the regression.²¹ There are some large differences in the roof and wall material variables, suggesting that the two datasets have classified materials slightly differently; but these differences cancel each other out and thus create little spread between the SHRUG and IHDS.

The transformation of household assets into consumption values assumes a similar relationship between consumption and asset ownership in the IHDS and the SHRUG. But there is no mechanical link between the asset ownership shares in the two datasets; the similarity in the estimated consumption distributions is therefore informative and gives us confidence that the consumption measures in the SHRUG are good proxies for these direct survey measures.

3. Analysis: The High-Resolution Geography of Development

What Do Night-Lights Proxy?

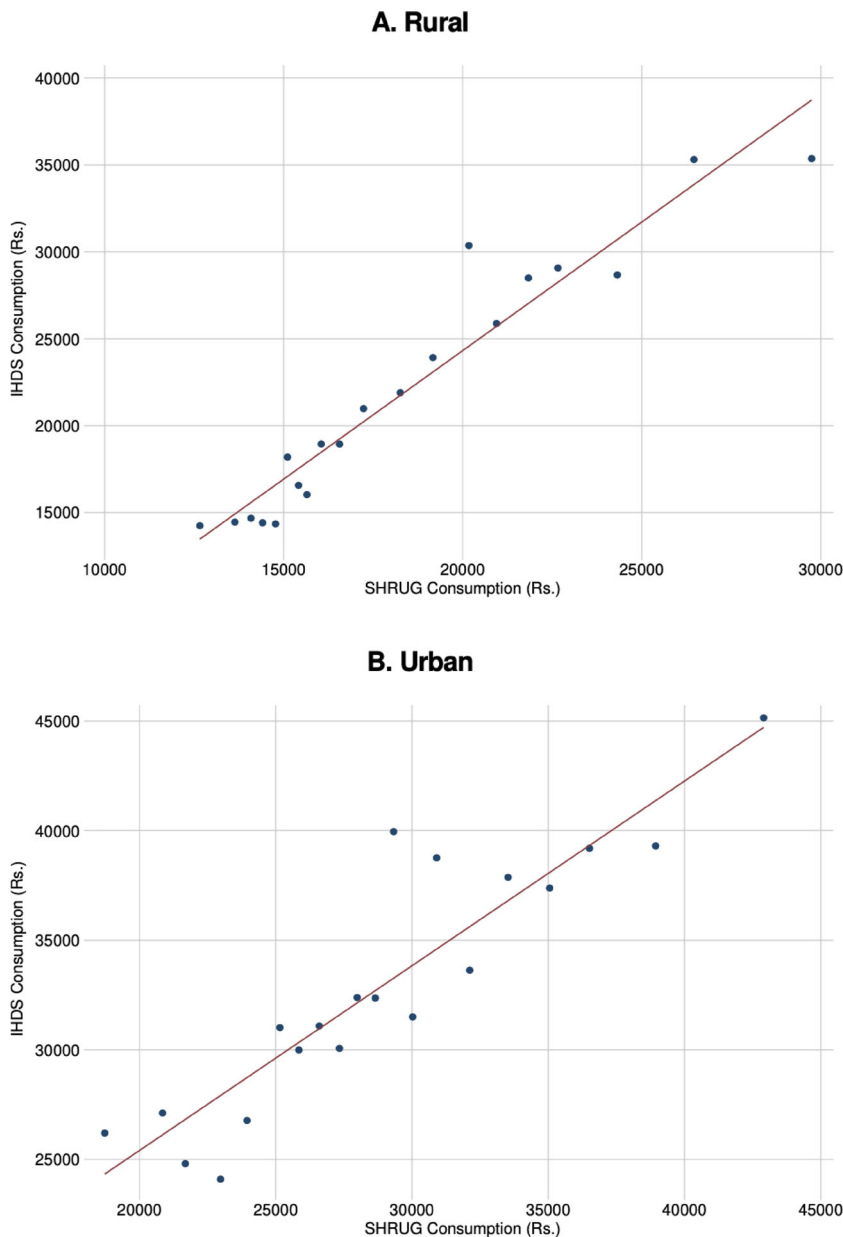
The use of satellite imagery as a data source on local development has been a major innovation in the last 20 years. The most popular form of satellite imagery in economics has been the use of night-lights as a proxy for cross-national GDP (Henderson, Storeygard, and Weil 2011). Night-lights have been particularly valuable for the study of low-income countries because they offer a high geographic resolution proxy of development where no other data may be available.

The research has not been entirely consistent on what exactly night-lights are proxying. Night-lights have been assumed in various studies to represent GDP growth (Henderson, Storeygard, and Weil 2011), cross-sectional GDP (Bleakley and Lin 2012), urban extent (Harari 2020; Baum-Snow et al. 2017), public expenditure (Hodler and Raschky 2014), rural electrification (either supply or demand) (Min et al. 2013; Baskaran, Min, and Uppal 2015; Burlig and Preonas 2016; Mahadevan 2021). Many of these studies work from an underlying assumption of a constant elasticity between night-lights and the outcome of interest in the cross section and in the time series, as well as across different geographic scales of analysis.

20 Each observation in this density plot is a village. For the sample surveys, we apply sampling weights when calculating village means (to take into account stratification on affluence and occupation) and when plotting densities (taking into account cross-village stratification on village size and oversampling in some states).

21 The average exchange rate in 2012 was INR 53 to USD.

Figure 2. District-Level SHRUG Consumption versus IHDS Consumption



Source: Authors’ analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India (SHRUG) and the India Human Development Survey (IHDS).
Note: The figure is a binned scatterplot of district-level average annual per capita consumption in the IHDS and the SHRUG, weighted by the count of individuals in each survey. The SHRUG sample has been restricted to the 331 districts where the IHDS matches the Indian Population Census.

A common approach is to show that night-lights are correlated with outcomes at an aggregate scale (e.g., across countries) and then to use night-lights as a proxy for the same variable at a microgeographic scale, where data to test the relationship between night-lights and the outcome do not exist.

In this section we show that (a) night-lights are indeed strongly and significantly correlated with many of their presumed proxies even at the highest geographic resolution, (b) because night-lights are

Table 3. Cross-Sectional Correlates of Night-Lights

	(1) District	(2) Subdistrict	(3) Town	(4) Village	(5) Village
Log population	0.971*** (0.067)	0.794*** (0.023)	0.958*** (0.025)	0.371*** (0.003)	0.342*** (0.003)
Log non-farm employment	1.559*** (0.075)	1.411*** (0.034)	1.068*** (0.031)	0.614*** (0.004)	0.592*** (0.005)
Log manufacturing employment	2.025*** (0.077)	1.779*** (0.036)	1.087*** (0.036)	0.612*** (0.005)	0.578*** (0.006)
Log services employment	1.446*** (0.076)	1.330*** (0.033)	1.048*** (0.032)	0.591*** (0.004)	0.559*** (0.005)
Log consumption	0.317*** (0.014)	0.279*** (0.005)	0.150*** (0.003)	0.093*** (0.004)	0.075*** (0.003)
Log hours electricity (rural)	0.937*** (0.055)	0.930*** (0.023)		0.235*** (0.003)	0.187*** (0.004)
Share of HH with electricity (urban)			0.049*** (0.006)		
N	632	5,761	3,525	460,297	460,129
Fixed effects	None	None	District	District	Subdistrict

Source: Authors' analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India.

Note: The table shows the cross-sectional relationship between a set of rural development outcomes and nighttime luminosity at various levels of aggregation. Each coefficient in the table is from a separate estimation of equation (1)—a regression of the log outcome variable on log luminosity and the log polygon size (the number of 1 km × 1 km cells in the geographic unit). Column (1) aggregates data to the district level, column (2) to the subdistrict level, column (3) to the town level (urban only), and Columns (4) and (5) to the village level (rural only). Columns (2)–(5) are clustered at the district level. Standard errors on consumption are calculated using 1,000 bootstraps as described in Imputation of Consumption Expenditure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

independently correlated with a wide range of correlates of development, it is difficult from light data alone to determine exactly which proxy is being measured, (c) night-light elasticities vary widely across outcome and across context, and (d) high-geographic-resolution night-light elasticities are an order of magnitude smaller in the time series than in the cross section.

We combine data on village/town-level luminosity with population, employment in manufacturing and services (or combined), electricity supply, and per capita consumption. The night-lights variable in each case is the log of average luminosity in a location polygon, where luminosity is a value from 0 to 63 observed in each 1 km × 1 km grid cell.²²

Night-Light and Development in Cross Section

Table 3 describes the relationship between each outcome variable and luminosity, controlling only for the area of the geographic unit. The estimating equation, based on Henderson, Storeygard, and Weil (2011), is

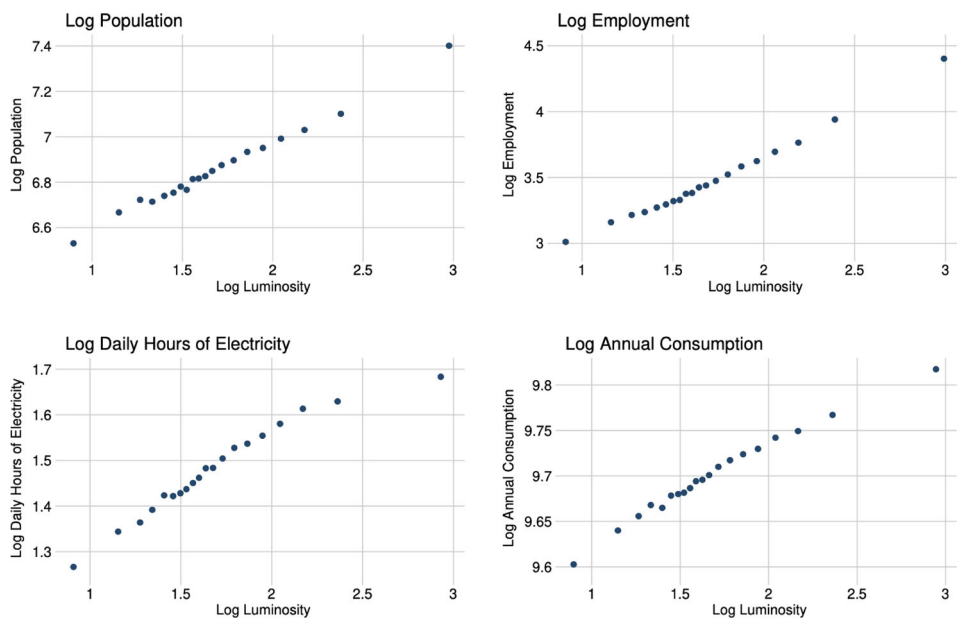
$$\ln(Y_i) = \beta_0 + \beta_1 \ln(\text{light}_i) + \beta_2 \ln(\text{numcells}_i) + \epsilon_i, \quad (1)$$

where Y_i is the outcome variable, light_i is the average pixel luminosity in the geographic polygon, numcells_i is the village area, and ϵ_i is an error term.²³ The unit of analysis i is a district (column 1),

22 In villages in 1991 and 2001 we use an indicator variable for whether the village had any power supply. In 2011 we use the number of hours of electricity available per day. The 2011 Village Directory reports hours available in winter and in summer; we take the mean of these measures. All of these power variables are normalized in this analysis to make their spatial variation maximally comparable; however, it is difficult to determine whether power has increased between 2001 and 2011 because of the change in the measure used. The electrification measures used in the Town Directory (i.e., for urban locations) are the numbers of electricity connections for different types of users; we use the share of households that have electricity in each period.

23 The area control is the number of 1 km × 1 km cells in the geographic unit. We include this to omit mechanical effects of geographic size of administrative units. Columns (2)–(4) are clustered at the district level.

Figure 3. Cross-Sectional Night-Lights versus Development Proxies



Source: Authors’ analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India.
Note: The figure shows the cross-sectional relationship between log night-lights and log population (top left), log employment (top right), log hours of electricity (bottom left), and log annual consumption (bottom right). The graphs are generated by binscatter, which shows the mean Y-variable in equally dense bins across the distribution of log night-lights. All graphs are run at the town/village level (except for log daily hours of electricity, which is only available for villages) and include district fixed effects.

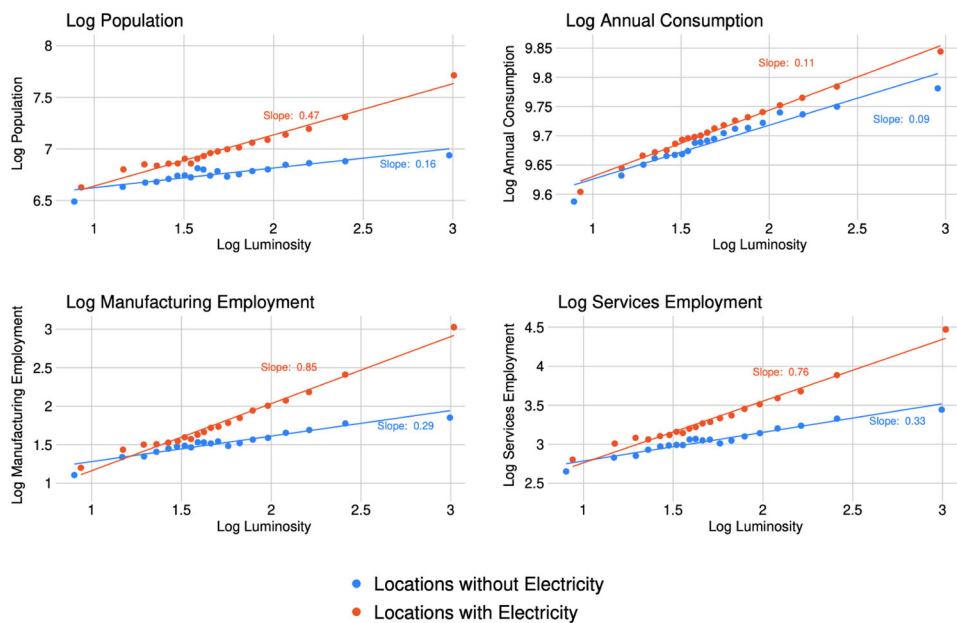
subdistrict (column 2), town (column 3), or village (columns 4 and 5). Columns (3) and (4) include district fixed effects, and column (5) includes subdistrict fixed effects, to limit variation in the analysis to microgeographic variation *within* these larger units. Each entry in the table shows a coefficient β_1 from a separate regression. All variables are measured in logs, so the coefficients can be interpreted as elasticities.²⁴ The one exception is for urban electricity, where the best variable available is the share of households with electrical connections.

Night-lights are extremely highly correlated with local population, employment in manufacturing and services, electrification, and per capita consumption, at all levels of geographic aggregation. Even when variation is limited to be within each of India’s over 5,000 subdistricts (approximately 100 hundred villages each, column 5), night-lights are extremely strong predictors of all six variables.²⁵ The validity of night-lights at high geographic resolution for all these outcomes has been presumed to be true by a large number of papers using night-lights as local proxies of development, but has seen little testing in a developing country context. Further, the log-log relationship between the outcomes and night-lights is broadly linear across the distribution for all of the variables, as shown in fig. 3, even at the lowest levels of development.

24 In all log specifications, we add 1 to the employment and power variables before taking logs (reflecting respectively, one job and one hour of daily electricity), so that zeros are not dropped. Results are virtually identical if we use the inverse hyperbolic sine transformation or add a different quantity (e.g., 0.1 hours of electricity). Population and consumption are never zero, and none of the quantities are zero at the aggregate levels of subdistrict and district.

25 These results are robust to using both level and standardized measures of population, employment, consumption, and power. Measuring population and employment in levels results in a much worse fit (lower correlations, regression coefficients, and r-squared) because of the presence of outliers.

Figure 4. Cross-Sectional Relationship between Night-Lights and Development Proxies as a Function of Electrification



Source: Authors' analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India.
Note: The figure shows the village/town-level cross-sectional relationship between four development proxies (population, annual consumption, manufacturing, and services employment), with separate series plotted for locations that do and do not report access to electricity. The graphs are generated by binscatter, which shows the mean Y-variable in equally dense bins across the distribution of log night-lights. All graphs include district fixed effects.

However, the elasticities are far from constant across geographic scales, and vary widely across variables. The cross-district and cross-subdistrict elasticities of population with respect to night-lights are 0.97 and 0.79 respectively; the within-district and within-subdistrict elasticities for villages are far lower at 0.37 and 0.34. For employment, per capita consumption, and power supply, we also find that elasticities at aggregate levels are more than twice as high as the local elasticities in rural areas. Towns (urban areas) with district fixed effects generate elasticities that are lower than those for more aggregate areas but much higher than those for rural areas.

The ordering of the elasticities across variables is consistent across all four specifications. The outcome with the highest elasticity with respect to night-lights is employment, followed by population, then power supply, and finally per capita consumption. In all specifications, the employment elasticity is more than five times higher than the consumption elasticity. At the village level, with subdistrict fixed effects, a 50 percent increase in night-lights is associated with a 36 percent increase in non-farm employment, an 18 percent increase in population, a 33 percent increase in power, and a 9 percent increase in per capita consumption.

At high geographic resolution, all of these elasticities remain statistically significant even after controlling for the other potential proxy variables, with the partial elasticities ranging between 0.08 (for consumption) and 0.69 (for non-farm employment) (table S1.5 (column 4) in the supplementary online appendix). A key result is that night-lights cannot be interpreted as a specific proxy for only one of these outcomes in isolation; they reflect a combination of development outcomes. In any given context where night-lights are used as a proxy for development, it is difficult to determine whether they are describing population, employment, power, or expenditure. They could be performing different roles in different places, making interpretation difficult.

Table 4. Time Series Correlates of Night-Lights

	District (1)	Subdistrict (2)	Town (3)	Village (4)	Village (5)
Log population	0.023 [*] (0.012)	0.030 ^{**} (0.008)	0.018 ^{***} (0.005)	0.005 ^{***} (0.001)	0.003 ^{***} (0.001)
Log non-farm employment	0.588 ^{***} (0.131)	0.343 ^{***} (0.088)	0.037 (0.025)	0.016 ^{**} (0.003)	0.017 ^{***} (0.002)
Log manufacturing employment	0.452 ^{***} (0.117)	0.234 ^{**} (0.079)	0.045 (0.030)	0.001 (0.004)	0.004 (0.003)
Log services employment	0.538 ^{***} (0.124)	0.325 ^{***} (0.083)	0.024 (0.026)	0.016 ^{**} (0.003)	0.017 ^{***} (0.002)
Electricity (rural)	−0.129 ^{**} (0.057)	−0.097 ^{**} (0.041)		0.056 ^{***} (0.005)	0.050 ^{***} (0.004)
Electricity (urban)			−0.007 (0.009)		
N	2,358	21,988	7,372	1,551,314	1,550,915
Fixed effects	District, year	Subdistrict, year	Town, district * year	Village, district * year	Village, subdistrict * year

Source: Authors’ analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India.
Note: The table shows the time series relationship between a set of development outcomes and nighttime luminosity at various levels of aggregation, controlling for location fixed effects. Each coefficient in the table is from a separate estimation of equation (2)—a regression of the log outcome variable on log luminosity, with location and time fixed effects. The one exception is electricity, which is measured differently over both time and towns/villages; we describe the construction of these measures in the section on What Do Night-Lights Proxy? Column (1) aggregates data to the district level, column (2) to the subdistrict level, column (3) to the town level, and columns (4) and (5) to the village level. All regressions are clustered at the district level. ^{*} $p < 0.10$, ^{**} $p < 0.05$, ^{***} $p < 0.01$.

We also find that night-light elasticities are not constant across place. Figure 4 shows that for all outcomes other than consumption, night-light elasticities are 2–3 times higher in electrified villages; for consumption, the elasticity is similar in electrified and non-electrified villages.²⁶

Night-Light and Development in the Time Series

Many of the papers that use night-lights as an outcome variable focus on *changes* in light rather than cross-sectional differences in light across space.²⁷ It is therefore important to understand whether elasticities in the time series are similar to elasticities in the cross section. This relationship might not hold if the elasticities above are driven in part by correlations with additional unobserved variables. It also might not hold if the covariates have different variance in cross section and time series; for instance, in a period where there are very few changes in electricity supply, time series night-light elasticities with respect to electricity supply will be relatively smaller compared with the other elasticities. In this section we estimate night-light elasticities in a time series setup with village fixed effects.

To align the years across data sources, we extrapolate the values from the 1991, 2001, and 2011 Population Censuses (population and electricity) to the Economic Census years of 1990, 1998, 2005, and 2013.²⁸ Our only measure of per capita consumption is in 2012, so it is not possible to include changes in consumption in this analysis.

Table 4 shows the partial correlation between each outcome variable and luminosity, at various levels of geographic aggregation. Each coefficient in the table is the coefficient β_1 from a single regression that

26 Specifically, the sample is split according to whether or not a village reports non-zero hours of electricity; it is assumed that all towns are electrified.
27 For instance, many programs are evaluated with models with location fixed effects, which effectively compare night-light changes in treated places to non-treated places.
28 We assume a constant rate of population growth between census years and extrapolate the 1991–2001 growth rate for 1990 and the 2001–2011 growth rate for 2013. We use a linear extrapolation/interpolation for the standardized electrification measure.

takes the form

$$\ln(Y_{i,t}) = \beta_0 + \beta_1 \ln(\text{light}_{i,t}) + v_i + \psi_t + \epsilon_{i,t}, \quad (2)$$

where $Y_{i,t}$ and $\text{light}_{i,t}$ are defined as above. This specification includes fixed effects for year (ψ_t) and location (v_i), such that all variation picked up by β_1 is within the analysis unit over time. Columns (1) and (2) show the aggregate district and subdistrict level regressions, column (3) town-level regressions with district * year fixed effects, and columns (4) and (5) show village-level regressions with district * year and subdistrict * year fixed effects respectively. These fixed effects isolate the relationship between changes in light and development outcomes from regional changes.

Elasticities vary substantially at different geographic scales. Non-farm employment elasticities are substantially higher at higher levels of aggregation than at more geographically fine units. At the village level, once district-year fixed effects are taken out and variation is restricted to changes across villages within districts, the employment elasticities fall below 0.02, less than 1/20 of the district and subdistrict level elasticities. The population elasticities are very small in all specifications and are less than 0.01 at the village level. Changes in power supply are in fact negatively correlated with changes in night-lights at aggregate geographic scales, but have an elasticity of 0.05–0.06 at the village level.

In spite of substantially smaller elasticities, the relationship between night-lights and all covariates remains highly significant in the expected direction at the village level, with the exception of manufacturing employment. Across all specifications, night-lights have higher elasticities with respect to employment in the services sector than in the manufacturing sector, reversing the pattern observed in the cross section. Services employment in rural India is concentrated in education, health, and retail; the higher elasticity of lights with respect to services may suggest that night-lights are picking up changes in consumption and expenditure patterns (because higher demand results in a larger retail sector), rather than concentrations of production.²⁹ In contrast, in urban areas only population is significantly correlated with luminosity in the time series, although the coefficients are generally similar to the village-level estimates.

Discussion: What Can We Learn from Night-Lights?

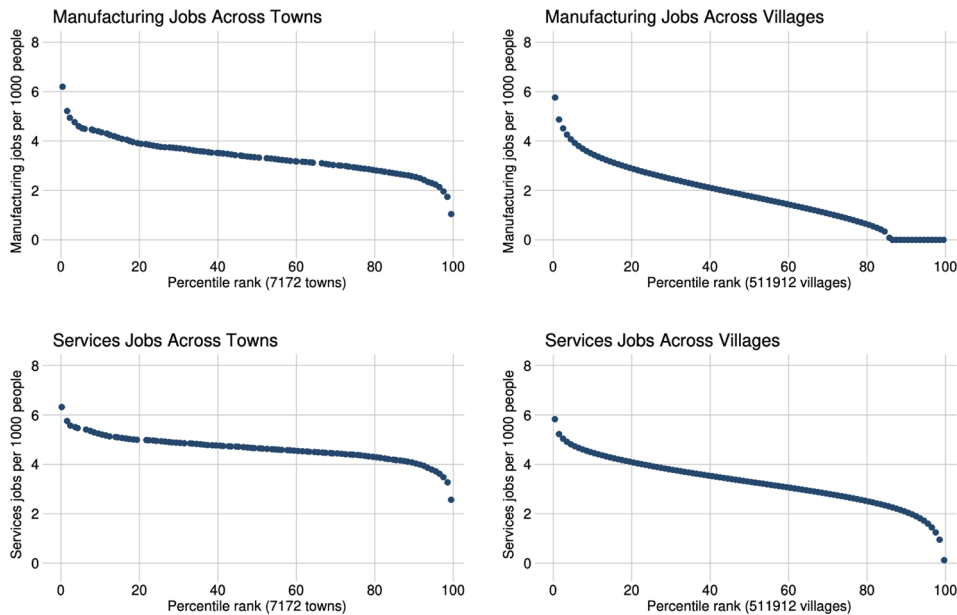
The results in this section provide clarification and nuance for analyses that use night-lights as a proxy for development. Night-lights are predominantly used to estimate measures of development at high geographic resolution where other development proxies are unavailable. As such, they are often used exactly in contexts where the assumption that lights will be associated with various development measures at a fine geographic scale is difficult to test.

The results shown here support the idea that night-lights do indeed describe highly local variation in development in contexts where little data are available. We have shown that night-lights have strong cross-sectional associations with all of the variables that they are presumed to proxy in the literature, even at a highly local scale and in a very rural environment. These correlations are to some extent independent: population, employment, electricity, and per capita consumption are all strongly correlated with lights, even after controlling for each other. The relationships are strongly log-linear in the cross section, holding equally for both rich and poor places, as well as well-lit and poorly lit places. This finding is therefore supportive of the dominant methodology in the research of interpreting night-lights as a valid high geographic resolution proxy for a range of development outcomes.

However, transforming the coefficients from night-lights into specific development measures is a fraught exercise. Night-lights are independently correlated with all of the covariates described here. If a policy or program is found to be correlated with increased luminosity, then it will be difficult for

29 In table S1.6 in the supplementary online appendix we show that these results are robust to limiting the analysis to the census years with the highest quality data (2001–2013) and to weighting regressions by population.

Figure 5. Distribution of Job Density across Space



Source: Authors’ analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India and Economic Census.
Note: The figure describes the distribution of non-farm jobs per 1,000 people across villages and towns. The Y-axes show the log number of manufacturing- or service-sector jobs per 1,000 people. The X-axes show the town or village rank on the same measure. The rank is population weighted such that a village with rank 50 has more manufacturing or services jobs per 1,000 people than villages representing 50 percent of the Indian population. Each point represents the mean of the measure in one percentile bin, or approximately either 70 towns or 5,000 villages.

researchers to determine whether that correlation is proxying for population, employment, electrification, per capita consumption, or something else.

Importantly, our results have implications for the application of luminosity-to-GDP elasticities from the literature to new contexts. Many studies of night-lights estimate time series regressions with place and year fixed effects. Our results suggest that time series elasticities in these contexts may be an order of magnitude smaller than the widely reported cross-sectional elasticities. This would imply that program effects measured with night-lights may in fact be much smaller than presumed.

Further, night-light elasticities with respect to various development measures are highly variable across different levels of aggregation and in different places. For instance, we found that elasticities are generally higher in urban areas, and can be twice as large in rural areas that are electrified compared to those that are not. Our analysis suggests that the application of rule of thumb conversions between night-lights and GDP at highly disaggregated geographic levels in developing countries should be used with extreme caution.

What Is the Distribution of Jobs across Villages and Towns?

Economic opportunities are strongly contingent on local labor and goods markets. Given high transportation costs in developing countries, the relevant labor market for an individual may be geographically very small. Analysis of regional opportunities based on large geographic aggregates may therefore not reflect the opportunities available to most individuals in a region, especially if economic opportunities are not evenly distributed across space.

In fig. 5 we rank each town and village according to the number of non-farm jobs per 1,000 people (henceforth job density) and plot this measure in logs against the town and village rank.³⁰ Rank percentiles

30 On average there are 22 manufacturing jobs and 61 service jobs per 1,000 people in India.

Table 5. Concentration of Non-Farm Employment in Villages and Towns

	Mean employment per 1,000 ppl	Median employment per 1,000 ppl	Slope (national)	Slope (within district)
Towns				
Manufacturing	39.5	27.1	−0.019	−0.012
Services	115.8	104.0	−0.012	−0.009
Villages				
Manufacturing	15.4	4.9	−0.040	−0.035
Services	40.2	26.0	−0.027	−0.021

Source: Authors' analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India and Economic Census.

Note: The table shows several statistics describing the distribution of non-farm employment in rural and urban municipalities (villages and towns, respectively), disaggregated by manufacturing and services. Columns (1) and (2) are mean and median employment per 1,000 people, across the distribution of towns and villages. The mean is population weighted, and the median refers to the town or village with the median individual, so that 50 percent of the national population lives in places with above-median employment per capita. Column (3) shows the slope from a regression of employment per 1,000 people on the town or village rank, where each location's rank is a function of employment per 1,000 people in the same category. Column (4) shows the slope from the same regression, but with district fixed effects.

are adjusted for population, such that the 20th percentile village has higher job density than villages representing the most job-dense 20 percent of the rural population. If jobs were equally distributed across space, the job density would be constant and these lines would have a slope of zero. Instead, the distribution of job density follows a power law as evidenced by the linearity of the function across most of its support. In other words, highly ranked places have orders of magnitude higher job density than lower ranked places.

One way to characterize this relationship is with the coefficient from a regression of location job density on location density rank; this is the slope of the curve in [fig. 5](#). We estimate the slope of this function within percentiles 10 and 90 to mitigate the effect of outliers, though we find similar estimates if we include all data points.

For urban manufacturing jobs, the coefficient is −0.019. Moving from the 20th percentile town to the 80th percentile town changes the manufacturing job density from 48 jobs per 1,000 people to 16 jobs per 1,000 people. Urban service sector jobs are more evenly distributed, with a regression coefficient of −0.012. Jobs in rural areas are much more concentrated, especially in manufacturing; the coefficients for rural manufacturing and services jobs are respectively −0.04 and −0.027. The 20th percentile village has 17 manufacturing jobs per 1,000 people (just above the national rural average), while the 80th percentile village has less than 1. [Table 5](#) summarizes the concentration of job density, showing the difference between mean and median job density, as well as the slope of the regression function described above with and without district fixed effects.

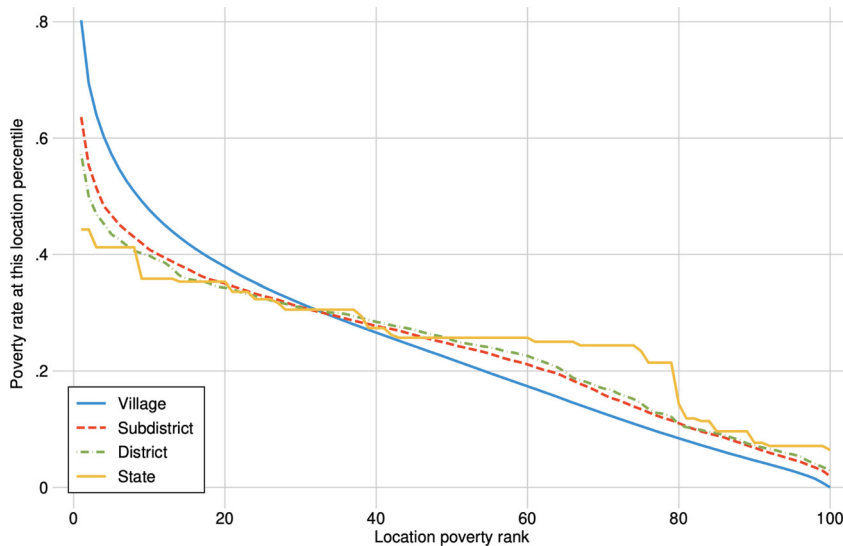
The uneven distribution of jobs, especially rural manufacturing, is consequential for local labor markets. The mean village has 15 manufacturing jobs per 1,000 people, but the median has only a third of that. Seventy-nine percent of rural Indians live in villages with fewer manufacturing sector opportunities than what is implied by mean values. These results are not driven by variation across districts; as shown in [table 5](#), the concentration measures are very similar when calculated with district fixed effects.

The power law distribution of rural manufacturing is important in many domains and implies that analysis at higher geographic aggregations may be misleading. District means may not reflect the experiences of the overwhelming majority of individuals.

How Localized Is Poverty?

Development programs are often geographic in scope, targeting regions that are underserved, poor, or populated by marginalized groups. In India, policies are often targeted to the district and subdistrict level; for instance, India's District Primary Education Program (DPEP) built schools, hired teachers, and improved infrastructure in districts with below median literacy rates ([Khanna 2017](#)). India's national and

Figure 6. Concentration of Poverty at Different Levels of Aggregation



Source: Authors’ analysis based on data in the Socioeconomic High-Resolution Rural-Urban Geographic Dataset on India.
Note: The figure plots locations’ average poverty rates against their poverty rate ranking. The four data series represent four different level of aggregation: state ($n = 35$), district ($n = 600$), subdistrict ($n = 5,600$), and village/town ($n = 590,000$). The graph shows, for instance, that the poverty rate in the fifth percentile district is 37 percent, while the poverty rate in the fifth percentile village is 50 percent.

state governments have long maintained lists of so-called “backward” districts and blocks, which affect eligibility for a range of programs (Kumar 2020).³¹

Targeting programs at high levels of geographic aggregation may be desirable for implementation reasons or simply because higher-resolution data are not available to policy makers. The cost of allocating programs at aggregate levels is that needy individuals will be left out if they live in better-off regions.

Both policy planning and evaluation are difficult in the absence of high-geographic-resolution data, such that the extent of mistargeting driven by geographic aggregation is often not even known. If poverty is primarily a phenomenon of broad regions, then district-level targeting may be almost as efficient as village-level targeting. If variation in poverty is mostly local, then district-level targeting could be much worse. India’s primary sample survey with broad geographic coverage, the NSS, is minimally helpful in this regard because it is representative at the district level and does not sample enough individuals within primary sampling units to describe the geographic distribution of development at geographically finer levels.

In this subsection we examine the effects of using different geographic aggregations on the efficiency of a hypothetical program targeting individuals who live below the poverty line. Our analysis follows an established literature examining the social benefit of targeting anti-poverty programs at various geographic scales (Ravallion 1993; Baker and Grosh 1994; Bigman et al. 2000; Bigman and Srinivasan 2002; Elbers et al. 2007; Brown, Ravallion, and van de Walle 2019).

For each level of aggregation (district, subdistrict, and village) we rank the locations by poverty rate. Ranks are adjusted for population such that a rank X implies that X percent of the national population lives in a location with a higher poverty rate. Figure 6 shows the average poverty rate at each rank, based on the geographical granularity of the ranking unit. The poverty rate in the fifth percentile district is 43 percent; it is 47 percent in the fifth percentile subdistrict, and 57 percent in the fifth percentile village.

31 There are on average 10 blocks per district (compared with 1,000 villages per district), making them comparable to subdistricts, the primary intermediate unit in the Indian Census and used here.

If the hypothetical program was targeted to the bottom 25 percent of the population as ranked by the regional poverty rate, then it would reach 34.6 percent of poor people if targeted by state, 40.4 percent if targeted by district, 42.4 percent if targeted by subdistrict, and 49.1 percent if targeted by village. Relative to district targeting, we find that targeting at the village level could allow an additional 21 percent more individuals below the poverty line to receive program benefits, a greater improvement than that of moving from state to district targeting.

Even though subdistricts are 10 times smaller than districts, the targeting gain in moving from district to subdistrict is small, but the gain in moving to village-level targeting is much higher. This effect size is not something that could be measured from district-level data because the geographic aggregate at which poverty is most concentrated is not known *a priori*.

A caveat to all of these measures is that targeting exercises based on small area estimates necessarily rely on assumptions of a uniform relationship between assets and consumption that may not hold (Tarozzi and Deaton 2009). Standard errors on targeting estimates are therefore likely to be underestimated.

4. Comparative Advantages and Disadvantages of the SHRUG

The SHRUG has two main advantages relative to other data sources. First, it describes a wide set of socioeconomic outcomes over a long period for a wider set of high geographic resolution locations than any other Indian panel dataset with broad scope.³² This enables analysis of outcomes at the level of policy and program variation, which is often at the village, town, or constituency level.

Second, because the SHRUG's geographic coverage is comprehensive, it is particularly valuable when used in tandem with other datasets. Each new administrative or remote sensing data source that is linked to the SHRUG can be fully integrated with all the other data sources in the SHRUG, expanding the scope of potential analysis. In contrast, sample surveys run by different research teams do not have the same complementarities because there is rarely enough sample overlap for the same locations to appear in both datasets. Two research teams integrating new administrative or remote sensing data into the framework of the SHRUG will immediately be able to benefit from each others' work due to the linked identifiers and comprehensive geographic coverage. For this reason, the utility of the SHRUG will increase over time as we continue to extend its breadth.

Like every data source, the SHRUG has several limitations. First, the lengths of most of the surveys underlying the SHRUG are smaller than in many other data sources. Because the administrative censuses are implemented for every household and non-farm firm in India, they are necessarily based on much shorter surveys than detailed sample surveys like the NSS and Annual Survey of Industries (ASI). This disadvantage is traded off against the high geographic precision and wide breadth of data available for towns and villages across all of the modules of the SHRUG. An NSS consumption survey is much more detailed than the SECC, but the short asset survey in the SHRUG can be analyzed in conjunction with data on night-lights, forest cover, administrative programs, public goods, and local firms, across several hundred thousand villages.

Second, the SHRUG consists of locational aggregates, rather than individual or firm microdata. It is thus not suitable for studying variation across individuals or firms *within* locations. Note that we have provided keys to link the SHRUG to the firm-level Economic Censuses, which describe every non-farm establishment in India in four cross sections from 1990 to 2013.

32 Other specialized data sources have high geographic resolution but cover more narrow topics. For example, Prowess (maintained by the Center for Monitoring of the Indian Economy) describes the operations of large firms and contains headquarters addresses. The SHRUG can in principle be linked to Prowess at the village and town level using georeferences, but we have not yet created a key. There are also several village-level time series datasets with broad and deep surveys, chiefly ARIS-REDS and ICRISAT. The data in these surveys are much more detailed than the data found in the SHRUG, but they cover at most a few hundred villages.

Third, not all villages and towns are matched in all periods. If a researcher's goal was to estimate the number of non-agricultural firms in India, for example, then aggregating from NSS or ASI samples is arguably a better approach because there are no missing locations. Economic Census data in the SHRUG have a slight rural bias because rural boundaries are more easily tracked over time than urban boundaries, and many towns are missing economic data for 1990. Similarly, as noted above, we were not able to obtain census-based data for predominantly urban constituencies.

Fourth, the SHRUG is only as good as the collection process for the administrative data that underlie it. The NSS enumerators spend far more time with each firm owner than the Economic Census enumerators and have more quality checks and cross validations in their survey process. Some of the outliers in the Economic Census (and thus the SHRUG) are almost surely incorrect. This is inherent in the nature of the process of collecting data from hundreds of millions of respondents in a short time period. We offer some suggestions in the codebook on how to deal with these observations.

Finally, most of the data in the SHRUG are available only for the years when large-scale administrative data were collected. Consumption data are available only in 2012, and none of the four Economic Census years are exact matches for the Population Census years. The remote sensing data, however, are available annually.

Administrative data by no means obviate the need for high-quality sample field surveys. Whether the strengths or the limitations of the SHRUG dominate will depend on the particular research question. The SHRUG is particularly well suited for research requiring high-resolution geographic variation, rich location information, or socioeconomic outcomes in units with political boundaries.

5. Conclusions: A Model for Collaborative Data Sharing

Most researcher-initiated data collection projects have a relatively narrow scope. A local survey is conducted for the purpose of an experimental or observational study, one or several research papers are written, and the data are reused only for replication or in rare cases, for long-term follow-up.

The existence of comprehensive administrative data makes possible a paradigm where investments in data yield many more positive externalities for other researchers. Because administrative data are often comprehensive at the state or the national level, one researcher's efforts at collecting and rationalizing an administrative dataset may yield dividends to many other researchers. Many researchers are already making use of administrative data in India and in other developing countries. In the absence of a common platform to link these datasets to each other, there is considerable duplication of effort and many potential complementarities and externalities across projects are not being realized.³³ Our aim in building the SHRUG is to create a common geographic frame for all these datasets, standardizing their location identifiers and lowering the cost to researchers of creating positive externalities for each other.

Researchers often face a trade-off between sharing data, which enables more socially valuable research, and keeping data restricted, which ensures that they will not be scooped on future projects with those data. Some balance between these objectives is needed; private returns to developing new data sources are desirable as motivating factors.

The increasingly stringent data policies of economics journals have been effective in generating replication data, but those data are often posted without sufficient documentation or identifiers to be usable for other research projects. Replication files often describe only the researcher's final sample, which may be a small subset of the national data on which it is based. This is not the result of malign

33 Some examples of Indian administrative programs that have been studied with administrative data include the NREGS public works and wage support program, the RGGVY rural electrification program, and the ongoing Total Sanitation Campaign, all of which are the subjects of multiple research papers. And yet none of these programs (or research projects) have easily accessible or linkable data frames, causing each new researcher to have to reinvent the wheel, and limiting the scope of each research project to the amount of data that its research team is willing to clean.

intent; rather, it can take weeks or months of effort to make replication data useful for future projects, and researchers may not see rewards for doing so.³⁴

In creating the SHRUG, we aim to both lower the transaction costs of sharing data and to change the institutional incentives around data sharing. Researchers who create data sources that are compatible with the SHRUG will have their work cited because the data will be more valuable when linked with the range of fields in the SHRUG. To add weight to this incentive, the SHRUG is released under a copyleft license that commits users to share any data that they link to the SHRUG when their papers are accepted for publication. The time lag to publication in economics all but ensures that researchers who develop new non-proprietary SHRUG-linked data sources will have a large lead on any other projects working with their data.³⁵ Our project aims to raise the returns of data assembly, resulting in new public goods for the research and policy-making communities.

The open source software universe has demonstrated that an equilibrium can exist where highly skilled individuals freely share the fruits of their labors, creating valuable externalities but also receiving enough private benefits to make these contributions worth their while. The work underlying the SHRUG aims to model a set of norms and protocols to facilitate a similar equilibrium around the sharing of data for social science research.

We conclude by reiterating our request to users of the SHRUG to cite all of the research papers that underlie the different components of the SHRUG. When data are downloaded from the SHRUG platform, a list of citations underlying the download is automatically generated. Citing these appropriately will further increase the returns to other researchers to investing in developing new data sources and making them easily usable by others, creating positive externalities for all.

The SHRUG will be regularly updated as new data are brought online and inevitable errors are found and corrected. The latest version will be maintained at the SHRUG website, and all prior versions will be archived on the Harvard Dataverse, so that researchers can always replicate an exact prior download.³⁶

Researchers wishing to make their data easily linkable to the SHRUG need only to post their data with unique SHRUG identifiers. We aim to maintain a listing of external datasets that can be linked directly to the SHRUG in this way. Following the data organization standards and protocols described on the SHRUG website will help to make these contributions as accessible as possible to outside researchers.³⁷

Research teams that assemble national datasets at the shrid or constituency level that are of wide general interest and are extremely clean and consistent with the SHRUG format can request to have their data maintained and released directly via our website, which will maximize the availability of those data to others. We have made every effort to ensure that users downloading data from our site will appropriately reference all contributors to the specific datasets being downloaded, ensuring proper attribution.

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- 34 The low average quality of public replication data further creates a lemons problem: researchers who become accustomed to finding minimally useful data on journal websites may be discouraged from searching for the gems that do exist.
- 35 Even in the case of proprietary microdata, it is often possible to share village/town aggregates that strike a balance between respecting restrictions on data sharing and benefiting the wider research community.
- 36 The SHRUG website is <http://devdatalab.org/shrug>. The URL for the archived versions at the Harvard Dataverse is <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DPESAK>.
- 37 Contribution protocols are described in more detail at http://devdatalab.org/shrug_contribute.

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