Infrastructure Networks and Urban Inequality: The Political Geography of Water Flows in Bangalore

Alison E. Post
U.C. Berkeley
aepost@berkeley.edu

Tanu Kumar
U.C. Berkeley

Megan Otsuka
U.C. Berkeley

Francesc Pardo-Bosch
Escola Superior d'Administració i Direcció d'Empreses (ESADE)

Isha Ray
U.C Berkeley

April 20, 2018
Prepared for the Brown-Harvard-MIT Joint Seminar on South Asia

Infrastructure services such as water, electricity, and mass transit are central to urban livelihoods. While the political economy literature on local public goods provision has examined patterns of expenditure on and access to infrastructure, variation in service quality for those receiving networked services has received far less attention. In this paper, we examine the distribution of service *intermittency*, which detracts from service quality and imposes significant welfare costs. We disaggregate intermittency into four dimensions: predictability, frequency, duration, and throughput. We extend arguments from the distributive politics literature to predict the allocation of burdens associated with intermittency among households; we show that this literature has paid insufficient attention to how network structures affect the ability of state or city officials to differentially channel service flows. We illustrate the importance of different dimensions of intermittency and network structure through an analysis of the political geography of piped water supply in Bangalore, India. We find that variation occurs at the "valve area" level, or the smallest units at which water pressure can be distributed, and not at the household-level. Households in low-income valve areas receive more frequent and regular service than those in more affluent ones, contrary to predictions from the distributive politics literature. Our work suggests that the distributive politics of *network access* differ significantly from those affecting water flows *within the network*.

Acknowledgments:
This project was funded by the Development Impact Laboratory, U.C. Berkeley (USAID Cooperative Agreement AID-OAA-A-13- 00002). We thank C. Sharada Prasad and Zachary Burt for their contributions, Guadalupe Tunón, Eugenia Giraudy, Pranav Gupta, and Galen Tsongas for superb research assistance, and Joel Middleton, Malini Ranganathan, and Laura Stoker for advice. We also thank NextDrop, the Public Affairs Foundation, and the Bangalore Water Supply and Sewerage Board for their collaboration. Finally, we thank David Gordon, Robin Harding, Aila Matanock and Katerina Linos, and seminar participants at the University of Iowa and U.C. Berkeley for comments on previous drafts. The project has been approved through IRB protocol 2014-04-6259.

INTRODUCTION

Public services delivered through infrastructure, such as water, electricity, roads and mass transit, are central to urban lives and livelihoods. A vibrant literature in political economy analyzes the distribution of such services; it examines the extent to which politicians disproportionately channel vital infrastructure services to members of the same ethnic or racial groups, whether politicians are more likely to target swing or core voters, and other socio-political factors influencing allocation. Access to infrastructure, however, is not a guarantee of good quality service. Service quality varies dramatically within infrastructure networks, and this variation has received scant attention in the political economy literature.

Intermittency defines infrastructure services in the developing world. Intermittent services are those that would be delivered continuously in an ideal world, but are in fact delivered discontinuously, often with unpredictable start and end times. Water networks, for example, may be only partially pressurized, with segments of the network receiving water for short periods in rotation. Globally, approximately 300 million people with access to piped water receive services intermittently—often just one or two days a week, for a few hours at a time (van den Berg & Danilenko, 2010). Many electricity systems also deliver services discontinuously, with power interruptions occurring daily; in South Asia, an average firm experienced 25.5 outages per month in 2016.[1] Mass transit services are also often intermittent, with departure times diverging significantly from official schedules.

[1] World Bank Enterprise Surveys. Downloaded 3/27/2018 from http://data.worldbank.org /indicator/IC.ELC.OUTG.

Intermittency imposes disproportionate costs on the poor. Coping with electricity blackouts is more difficult for poorer households because they cannot afford private generators (UNDP, 2010). Low-income households receiving intermittent water services must wait for water to arrive and then fill household storage containers, as substitutes such as vended water are more expensive than municipal supplies. Buses that do not arrive on time make it difficult to arrive at work on time; lower income populations with no other transport options may develop reputations as unreliable employees under such circumstances (e.g., Smith, 2007).

In this paper, we provide one of the first analyses of the distributive politics of intermittent service delivery. We define the primary dimensions of intermittency that determine the extent to which households are burdened: the predictability of service arrival times; service frequency; service duration; and throughput (i.e. current for electricity, or pressure for water). We then investigate which of these dimensions affect which households, and whether their distributional patterns look similar or different from patterns of service access reported in the distributive politics literature. While Kramon and Posner (2013) have shown that allocation patterns vary across different services, we examine whether different dimensions of service quality can be distributed differently even within a single service.

We extend intuitions from the political economy and urban political ecology literatures to formulate hypotheses regarding the allocation of intermittently provided infrastructure services. These literatures suggest that politicians will target higher income or "in-group" households, as well as voters in strategically important electoral districts. We show that these literatures have paid little attention to how the *physical features* of infrastructure networks constrain, or otherwise influence, the political manipulation of public services. Network structure affects how services can be distributed: specifically, these services are allocated by geographic areas defined by network units, and household-level targeting within service area units is infeasible.

Our empirical analysis focuses on intermittently provided piped water supplies in Bangalore, India, a city of approximately 8.5 million residents.[2] We analyze a novel dataset containing geo-coded household-level information about the experience of intermittency. We also leverage unique, fine-grained maps of the boundaries of the segments of the city water network that are pressurized in rotation. In our main study area, we find that household-level characteristics do not predict variation in service frequency or predictability. Variation occurs at the "valve area" level, or the smallest network segments for which water pressure can be distributed. We find that low-income valve areas receive more predictable and frequent service, on average; this finding contrasts with with existing scholarship on infrastructural inequalities in India and elsewhere, which has focused primarily on access *to* and not *within* the network, and which has consistently found that social and economic exclusion is associated with poor water services.

The last section of our paper considers potential explanations for our counter-intuitive findings. These include strong relationships between street-level bureaucrats and low-income communities, who need predictable water supply most because they have little access to substitutes, and the relative political insulation of the state-government controlled water utility from local officials. We also discuss the broader implications of

[2] Population figure from the Indian census, 2011.

this study: that (a) intermittency represents a crucial yet understudied aspect of service delivery; (b) that intermittency (as well as other types of service quality) should be disaggregated into different dimensions, as they may not all be allocated according to the same political logic; and (c) network structure must be taken into account when analyzing the distributional consequences of infrastructure services; favored access to piped water or on-grid electricity cannot be targeted in the same way as favored access to hospital beds or ration cards.

THE DISTRIBUTIVE POLITICS OF INFRASTRUCTURE SERVICES

Why and How to Study Intermittency

Access to vital infrastructure services like water, sewerage, electricity, and transit, is conventionally structured by physical distribution networks. Political economy scholarship on "local public goods provision" has focused primarily on explaining levels of government expenditure and differing levels of access to services and distribution networks (e.g., Alesina, Baqir, & Easterly, 1999; Baldwin & Huber, 2010; Banerjee & Somanathan, 2007). Infrastructure services in low- and middle-income countries, however, are often delivered intermittently to those with network access. Table A.1 (online appendix), obtained through an exhaustive search, reports the focus of studies of local public goods in low-and-middle income countries; it shows that the extent and distribution of service intermittency are almost never mentioned in this literature.[3]

[3] Exceptions include Murillo (2009) and Min (2015) who do discuss the negative effects of intermittent electricity service. Min (2015, pp. 7, 47) also emphasizes that analyzing electricity distribution means looking at both network access ("stocks") and flows through the network, but the empirical analysis focuses on year-by-year electrification rates rather than the predictability and variability of supply on a daily basis.

A small body of sector-specific work, however, has highlighted the health and economic costs that intermittency can impose. Scholarship on the electricity sector, for instance, is well aware of the prevalence and negative effects of service disruptions, or "rolling blackouts."[4] Similarly, water policy scholarship has devoted attention to the prevalence, causes and consequences of water intermittency.[5] New research in the fields of civil engineering and public health suggests that intermittent water supply reduces household consumption levels to below internationally recommended levels (Kumpel, Woelfle-Erskine, Ray, & Nelson, 2017), and increases the likelihood that water is contaminated before reaching households (e.g., Kumpel & Nelson, 2013). Intermittent service may also be *unpredictable* as official supply schedules are often inaccurate because of aging infrastructure systems, power outages, and inefficiencies in the way in which the utility is administered.

Intermittency may impose differential costs on different subsets of the population, making its distribution an important object of study. Low-income households receiving intermittent and unpredictable water services, for example, must wait to collect and store water, whereas higher income households can afford pumps that automatically fill storage tanks when water services commence, as well as the load-bearing roofs that such tanks require. Alternative providers such as private water vendors emerge to "supplement" intermittent state provision (Kjellén & McGranahan, 2006; Solo, 1999), but water from these sources can be costly (see Post, Bronsoler, & Salman, 2017). Intermittency itself is multi-faceted. For example, several hours of water at low pressure and certain timing once a week is not at all the same service as a short duration of flow with good pressure,

[4] E.g. Crane and Roy (1992).
[5] See Kumpel and Nelson (2016) for a review of the literature.

arriving unreliably, but twice a week. Household circumstances will determine which of these leads to higher coping costs.

Scholarship from a variety of disciplines has shown that elected officials and political intermediaries influence which groups or communities gain access to infrastructure and other public services throughout the developing world (see Golden & Min, 2013). We argue that analyses of the political distribution of infrastructure services should also encompass the allocation of the burdens imposed by intermittency. To capture the range of these burdens, we identify four distinct dimensions of intermittency: (a) the **frequency** of service; (b) the **predictability** of arrival times; (c) **throughput**, (e.g. water pressure); and (d) the **duration** of supply intervals.[6] We expect elected officials to allocate these dimensions strategically across their constituencies, but their incentives and ability to do so will vary with local infrastructure conditions, the availability of substitutes for state services, and the socio-political characteristics of the populations to be served.

Deriving Predictors of Allocations from the Existing Literature

We build on the political economy literature on distributive politics and as well as on urban political ecology—paying particular attention to studies focused on India—to derive hypotheses regarding how government-owned or regulated utilities could allocate intermittent infrastructure services. The political economy literature highlights a number of variables that could predict which groups are more or less likely to be spared the costs associated with intermittency.

[6] Price and quality (for water) are two other important dimensions of service quality. We focus here only on dimensions of intermittency.

A first set of studies examines whether or not the allocation of local public services disproportionately benefits certain population subgroups, such as particular ethnic, racial, or caste groups (see Golden & Min, 2013). In the Indian case, for example, Besley, Pande, Rahman and Rao (2004) find that local government heads steer certain public goods to members of the same caste. Chandra (2004) argues that politicians in patronage democracies like India face strong incentives to favor voters of the same ethnicity.[7] Meanwhile, Bertorelli et al. (2017) find that lower caste and income groups receive worse public services in Bangalore.

Second, scholars of distributive politics debate the extent to which political actors steer allocations toward "core" supporters, as opposed to "swing" voters or districts (for a review, see Golden & Min, 2013). Recent years have witnessed an outpouring of scholarship examining which perspective is more relevant for the Indian context. The "core voter" hypothesis would suggest that elected officials strongly favor clear supporters (Breeding, 2011; Min, 2015), or areas with dense networks of local party operatives (Auerbach, 2016); to the extent to which parties have clear ethnic or caste identities, this argument is consistent with Chandra (2004)'s position that politicians tend to cater to members of their own groups. In India, parties such as the BJP and regional parties with strong caste affiliations have more clearly specified groups of core supporters than catch-all parties like the Congress (Chhibber & Jensenius, 2015).[8] Other research on distributive politics in India suggests that governing parties and elected officials target

[7] Recent scholarship suggests that caste favoritism, and even identification, may be decreasing in India, especially in urban areas (e.g., Banerjee & Somanathan, 2007; Dunning & Nilekani, 2013; Thachil, 2017).
[8] Note, however, that Breeding (2011, p. 75) argues that Congress is more likely to target minorities and lower caste groups in Karnataka.

electorally vulnerable "swing" districts, or swing voters within such districts (on electricity, Baskaran, Min, & Uppal, 2015; on roads, Bohlken, 2016; Golden & Min, 2013; on education, Vaishnav & Sircar, 2012). Throughout this literature, heads of governments allocate funds to districts controlled by members of their own party (i.e., aligned), whether they are swing or core districts.[9]

Research suggests that elected officials frequently rely on intermediaries to deliver social services to the groups they intend to target, rather than direct such targeting themselves (e.g., Stokes, Dunning, Nazareno, & Brusco, 2013). This means that access to such intermediaries, such as party workers or fixers, can influence an individual's or a community's ability to secure critical services. In the Indian context, the presence of informal local leaders--who often serve as party operatives--can help communities and households secure benefits (Auerbach, 2016; Jha, Rao, & Woolcock, 2007).

Urban political ecology and urban studies research focused on the water sector in India and beyond offer consistent theoretical arguments and ethnographic evidence. Because connections with politicians help to secure either formal or informal access to the water network, slum residents, and particularly very poor households in outlying slums, possess much lower rates of network connectivity. In Mumbai, for example, the poor (Gandy, 2008; Graham, Desai, & McFarlane, 2013) and Muslims (Contractor, 2012; Graham et al., 2013) have lower rates of network access . This literature also emphasizes that partisan alignment, political leverage, and group identity affect the allocation of water flows within networked parts of the city. In ethnographic studies of water

[9] One paper in the distributive politics literature points in a different direction: studying health services in India, Gulzar (2015) finds political alignment is associated with greater expenditure, yet lower quality services.

allocations in Mumbai, Anand (2012) and Björkman (2015, p. 161) argue that city councilors pressure utility employees to reallocate water from one neighborhood to another, to allocate less water less reliably to informal settlements than to other residential areas, and to discriminate against predominantly Muslim slums (Anand, 2011b, p. 430).[10] Anand (2012, p. 499) quotes one plumber's comments: "they [governing party politicians] are not interested in the Muslim vote. They never come into the settlement to see the problem." Rusca et al. (2017, p. 142) find similar conditions in Lilongwe, Malawi, where poor neighborhoods receive poor quality water and with lower frequency. In summary, consistent with the distributive politics literature, this body of work suggests that characteristics such as income, caste, religion, and political ties, affect household access to the water network, and to water allocations within the network.

These two literatures lead to the following predictions: *Less predictable, less frequent, lower-pressure, and shorter duration infrastructure services will be associated with economic marginality, social marginality, minority religious status. They will also be more prevalent when households lack political influence because the party they support does not hold office, or because they do not live in strategically important districts. The presence of local leaders may also be associated with better infrastructure services.*

Bringing Networks into the Picture

[10] Anand attributes these differences to biases held by utility engineers as well as to electoral calculations (Anand, 2012, pp. 497–500). Both Anand (2012, p. 503) and Björkman (2015) suggest that, in Mumbai, intermediaries or "plumbers" exert strong influences over *de facto* allocations.

We extend these literatures on infrastructure and services to show how the specific physical characteristics of infrastructure networks, and the material characteristics of the resources they carry, shape the socio-political targeting of services. Service allocations are routinely constrained by the physical features of infrastructure networks. In electricity networks, power is allocated by substation-level distribution feeders within the transmission system. Similarly, urban water networks are constrained by the location of the water mains connecting water treatment plants with different sections of the city. Elevation gradients within the system also affect flows.[11] Finally, when utilities do not possess sufficient water to fully pressurize the network at once, they pressurize small segments of the water network—"valve areas" servicing roughly 50 – 200 households—in rotation, thereby allocating water services to different neighborhoods at different points in time.

This means that utilities typically cannot target individual households, but must grant or withhold services from particular network segments at any one time. If a city cannot cut off power to a large hospital, for example, the homes on the same distribution feeder will not experience blackouts, whatever be their income, caste or political affiliation. Therefore while Golden and Min (2013; 2014), analyze electricity provision and line losses using data from utility service divisions, and aggregate these divisions into political units, there is actually no *a priori* reason to expect that the relevant physical segments will overlap with political units.

[11] Engineering research on water intermittency shows how network structure and elevation can contribute to inequitable allocations (e.g., De Marchis et al., 2011; Manohar & Mohan Kumar, 2014).

Given the segmented nature of infrastructure systems, the ability (or motivation) of governments to treat particular groups preferentially depends not only upon the network structure but also the underlying population distribution. To discriminate along caste, linguistic, religious, or class lines requires that out-groups be spatially concentrated (see Ejdemyr, Kramon, & Robinson, Forthcoming), and also that these spatial concentrations substantially overlap with isolatable partitions in the network in space and in scale. This condition may or may not hold. While low-income and marginalized groups tend to cluster together in many cities, this is not always the case. Cities such as Nairobi and Mumbai contain vast, contiguous slums with hundreds of thousands of residents, often clustered together by economic or linguistic characteristics, but "pocket" slums—at times quite diverse—are common in other cities.

If infrastructure networks constrain the extent to which officials can steer service allocations to particular groups, then what looks like a relationship between household characteristics and infrastructure allocations may, in fact, be a relationship between *network segment* characteristics and allocations. If government officials attempt to direct water or power flows disproportionately away from socially marginal households, or toward households of the dominant religion, this will occur at the smallest network segment rather than the household level. If the smallest network segment is heterogeneous, social marginality and service quality may not be strongly correlated. The relationship between network segment characteristics and allocations cannot be detected, of course, unless one collects data on household membership in network segments.

SITUATING OUR CASE: WATER SERVICES IN BANGALORE

The empirical focus of this paper is the distribution of water flows within a diverse section of Eastern Bangalore serviced by the utility's piped network. We describe Bangalore's water utility network, which does not (yet) service all households in the greater metropolitan area. While households receive somewhat better services than in much of urban India, water flows are allocated unequally within the city.

Piped water and sewerage services in Bangalore are provided by the Bangalore Water Supply and Sewage Board (BWSSB). Established in 1964, BWSSB is an organ of the Government of the state of Karnataka rather than of Bangalore's municipal government. BWSSB's chairman is always a senior member of the prestigious Indian Administrative Service. The utility is charged with providing services to one of India's largest metropolitan areas: the Census of 2011 put Bangalore's population at 8.5 million, but current (unconfirmed) estimates are closer to 11 million. Several studies have argued that, in comparison with other Indian cities, BWSSB is a well-functioning utility (e.g., Connors, 2005; McKenzie & Ray, 2009); comparisons with Delhi and Chennai from 2009, for example, show that Bangalore has good pipeline coverage, on average significantly more hours of water service per day (four times higher than Delhi, the country's capital city), and a high revenue collection ratio (i.e. water paid for as a proportion of water sold).[12] This being said, as late as 2000, roughly one-third of the population still had partial or no access to the piped water network, with a lack of access

[12] These data are from the urban water benchmarking group IB-NET; website http://database.ib-net.org/quick?goto=one_click accessed August 2017. Bangalore and Delhi data were only available for 2009. Ward-level data from Bangalore Patrol, collected in 2010, also confirm overall high rates of pipeline coverage for Bangalore (http://bangalorepatrol.com/scores.php; accessed August 2017).

concentrated among the poor (Benjamin, 2000, p. 39).[13] In 2014, Krishna et al. found that households in newly settled slums, concentrated disproportionately on the city outskirts and with predominately scheduled caste populations, possessed no access to the city's water network (Krishna, Sriram, & Prakash, 2014, p. 8).

Access to BWSSB's network does not ensure good service quality. The BWWSB network area is divided into six zones, each of which draws on different supply reservoirs that can provide differing levels of water to utility customers. The Eastern zone, for example, receives comparatively low levels of water per capita: 83 liters per day compared with 149 liters in the South (Manohar & Mohan Kumar, 2014, p. 614). Thus various dimensions of intermittency — supply frequency, duration of supply, predictability of arrival times – may themselves vary in quality from time to time and place to place.

We chose a study site within Bangalore that included a range of income, caste, and religious groups, as well as variation in service quality, so that we could examine the political as well as physical factors that shaped access to quality water services. In consultation with BWSSB and a local social enterprise called NextDrop, we decided to conduct our study in BWSSB subdivision E3 (see outline in Figure 1).[14] This is an outlying area with roughly 200,000 inhabitants in Eastern Bangalore that was connected to the utility's main network six years before our study.[15] The subdivision lies fully

[13] In some areas, populations received no services despite being on the network and paying for services (see Connors, 2005; Ranganathan, 2014).
[14] This study was conducted jointly with an impact evaluation of household water notification services provided by NextDrop (see Kumar, Post, & Ray, 2018). See below for more detail.
[15] A small set of areas still received service from legacy "borewell" systems (CMC supply) built by village and town governments before BBMP annexed this area.

within the utility's eastern zone, so the entire study area is served by a single reservoir. It is divided into 124 valve areas that are pressurized in rotation (Figure 2). Our 2015 survey confirmed that there was variable service quality in E3: over 85% of households received water services only once or twice a week, while some received services every day.[16] About 70% of households reported that their water did not come at a predictable time. The area also possessed significant economic, caste, and religious diversity. E3 also contained a range of settlement types, from areas dominated by middle-to-high income apartment blocks, to areas of lower middle class housing, to precarious settlements. Consistent with the overall pattern in Bangalore,[17] these clusters of low-income housing were very small, and sometimes contained religiously and ethnically mixed populations.

[INSERT FIGURES 1 and 2]

Given these background conditions in our Bangalore study area, we arrived at context-specific expectations regarding the allocation of different dimensions of intermittency. A first general expectation is that targeting by income level should be possible in Bangalore given that low-income neighborhoods—though smaller in Bangalore than in many cities—are typically larger than most valve areas, which contain only 50-200 households. Similarly, some valve areas had large concentrations of Muslim households, suggesting that targeting by religion would also be possible in Bangalore (Figure 3). Any correlations between these household characteristics and service quality

[16] Our 2015 survey is described in greater detail below.
[17] In 2011, Bangalore's officially recognized slums contained an average of only 1209 residents. Figure calculated from the Karnataka Slum Clearance Board's list of "declared slums." Slum Clearance Board lists are somewhat outdated, and do not include newer, unrecognized slums, which are typically smaller in size.

should be observable at the valve area level, rather than the household level, once network structure is accounted for in our models.

[INSERT FIGURE 3 ABOUT HERE]

Our second set of expectations relate to variation across different dimensions of intermittency. We expect service frequency to be allocated strategically by utility officials, and for targeting to be most visible at the valve area level. We also expect water service predictability to be allocated strategically across valve areas as well, especially given the manual nature of the system for opening and closing water valves. Water pressure may be harder to allocate strategically due to the prevalence of small hills throughout the city, which create elevation gradients within individual valve areas. We would also expect it to be less strategic to manipulate the duration of supply sessions than frequency or predictability, given that the vast majority of households in our study area possessed household connections, and thus did not need to queue for water; the most common supply session length of 2-3 hours would typically be enough time to fill a household's existing storage containers.

THE DISTRIBUTION OF INTERMITTENCY IN EASTERN BANGALORE

Data and Sampling

To assess empirical support for these propositions, we created a geo-coded dataset of households that we placed in valve areas, the smallest infrastructural units of allocation in intermittent water systems in India. This is the first time, to our knowledge, that such fine-grained data on the technical features of infrastructure has been incorporated into analyses of the distributive politics of water, or of the political distribution of infrastructure-based services more broadly.

We collected data in BWSSB subdivision E3 through a two-wave in-person survey administered to the same set of households in April-May and October-November of 2015 (Kumar, Post, & Ray, 2018).[18] The enumerator asked to speak with the person responsible for managing the household's water supply, as he/she would be most knowledgeable about service quality. For 80% of households, our respondents were women. Within E3, we defined 10 low income and 20 mixed income blocks to ensure that our specific study area was representative of the subdivision, and that it covered most of the residential area with piped water (Appendix Figure A1). We systematically sampled households within these blocks.[19] Given the nature and size of our sample (n = 2948), we expect that our study population did not deviate significantly from the underlying population in the area.[20] The income distribution was similar to the overall Bangalore population, with roughly 33% falling within the bottom third of the city income distribution,[21] and 14% including recent migrants from states such as Tamil Nadu

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[18] The surveys were part of a larger study to assess the impact of NextDrop's service providing households with advance notification regarding water arrival times, which is why we needed a two-wave survey. For this work we relied on the data in Wave 1. Water pressure data came from Wave 2, because we did not collect these data in the first wave.

[19] More specifically, for the purposes of the impact evaluation study, each block was divided into four clusters of similar socio-economic composition. Within each cluster, we followed a systematic sampling plan with a skip of three between households on every street (Appendix Figure A.1). The online appendix describes the survey in greater detail.

[20] Some households did not respond to all of the survey questions used to measure our dependent variables, so the N for each of the regression tables varies.

[21] The 2011-2012 India Human Development Survey (IHDS) reports that 63% of the Bangalore population possessed a scooter or other type of motorized vehicle; in our study area, approximately 70% did. This is a similar ratio to urban India overall (75% for metropolitan areas, 73% for other urban locations) according to the IHDS. See: https://ihds.umd.edu/.

and Andhra Pradesh. Table 1, which describes the independent variables in our analysis, shows the diversity of our sample with respect to socio-economic status, religion, and migration status.

[INSERT TABLES 1 and 2 HERE]

Our survey questions captured all four dimensions of water supply allocation in intermittent systems (Table 2): (i) predictability of water arrival times; (ii) service frequency; (iii) duration, or the length of service delivery intervals; and (iv) water pressure (i.e., throughput), which can greatly affect the availability of water for different household uses. Table 3 (below) shows our key dimensions, and the questions that operationalized them as dependent variables.

[INSERT TABLE 3 ABOUT HERE]

Our surveys allowed us to obtain measures of household characteristics that the literature suggests may be associated with more or less privileged access to services (see Table 1). These include household income, religious affiliation, scheduled caste or scheduled tribe (SC/ST) status, and partisan affiliation. We obtained information about household socio-economic status through a variety of measures, including questions about household assets (such as possession of a motorized vehicle), self-placement in income bands, floor and roof type of the home, and occupation. We also asked respondents whether or not they received water through the Cauvery system (i.e. through relatively new pipelines) rather than from the legacy borewell (CMC) systems; given its recent installation date, Cauvery service would likely be associated with better service on all of the dimensions in Table 3. Finally, we recorded the elevation of each household, as households at higher elevations are typically harder to service.

Since we contend that distributive politics in infrastructure networks will be constrained by physical networks, we measured not just household level variables, but *valve-area variables*. To create these measures, we relied on valve area maps created by NextDrop so that they could place households within the correct valve areas, thereby allowing them to send accurate text messages with water arrival times (see Figure 2). The utility itself did not possess maps of this infrastructure. Valve areas are not visible from the street level, and have been modified extensively over time. Therefore the "water valvemen" charged with opening and closing water valves to channel water into valve areas were the ones with the best knowledge of valve area boundaries. NextDrop personnel created the maps by walking the edges of the valve areas with the valvemen and taking GPS coordinates. The maps thus represent a unique data source.

We placed our surveyed households in their specific valve areas using household GPS readings we collected during our surveys.[22] This allowed us to characterize each valve area based on the survey responses from households residing in that area. We calculated measures for the proportion of Muslims, the proportion of households that are

[22] Three GPS readings with at least five-meter precision were taken for each household, and then averaged. We used QGIS to place households in valve areas based on these coordinates. See the online appendix for more detail.

low-income,[23] the proportion of residents that are recent migrants to Bangalore, whether there is a local leader to whom households take their concerns, and valve area elevation.[24] Figure 3 portrays valve area variation in the percentage low-income and Muslim households.

We also used our household survey responses to measure the specific dimensions of intermittency. Correlations between the responses of households living in the valve area suggest that respondents experienced (and sensed) similar supply conditions, particularly with respect to frequency and predictability.[25] Figure 4 illustrates variation across valve areas in the number of days between water supply sessions; notably, reported variation is far greater than is suggested by the water utility's official supply schedule.

[FIGURE 4 ABOUT HERE]

We also placed valve areas within wards, the main unit of political representation in Bangalore, so we could control for partisan alignment, residence in a competitive "swing" district, and the quality of water services, given the great weight placed upon these factors in the distributive politics literature. Eight of Bangalore's 198 wards fall in

[23] This continuous variable captures the percentage of respondents in each valve area that did not possess a motorized vehicle. Having a motorized vehicle is a common "marker" of lower- to middle-middle class in India.
[24] Households uniformly covered territory within valve areas to varying degrees. We therefore rated the "coverage" of each valve area so as to conduct robustness checks with our analysis, ensuring results were robust to including only valve areas with large numbers of household observations and good geographic distributions. Coding was conducted according to strict instructions. More details appear below.
[25] The ICC for the number of days between water supply sessions is 0.54, and for whether or not water arrives at a specific time is 0.29.

E3. We placed valve areas in the wards based on where the majority of populated territory fell.[26] For each ward we then collected data on the partisan affiliation of the ward representative (corporator), which told us whether s/he came from the same party as the party in control of the state in Spring 2015.[27] We also measured whether or not each ward was a "swing" district using a margin of victory measure, following Golden and Min (2013).[28] In our case, alignment was observationally equivalent with the observable implications of the core voter hypothesis, because the Congress (INC) controlled the state government; an INC-controlled state house interested in targeting its core voters would direct resources of INC-controlled wards. However, given the small number of wards in our dataset, we treat these primarily as control variables in the empirical analysis.

Modeling Strategy and Results

As our dependent variables are dichotomous or ordinal in nature, we estimated logit and ordinal logistic models to assess the relationship between household, valve area, and ward characteristics and five dependent variables capturing the four different dimensions of water intermittency: predictability (predictability of arrival time and

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[26] We used Google Earth satellite imagery to place valve areas in wards. If half a valve area was vacant land, based our decision on where the majority of the settled area fell. One valve area, however, was split evenly between two wards, so we dropped it from the analysis, reducing our sample size from 3002 to 2948.

[27] We focus here on state-level control because BWSSB is a parastatal controlled by the Karnataka state government rather than by Bangalore's municipal government.

[28] We subtract the number of votes secured by the runner-up from the number secured by the winner, and divide this by total votes for both candidates. We draw on data from the fall 2015 elections, even though these took place slightly after our survey, as they provide a better indicator of competitiveness during Spring 2015 than data from the 2010 city elections, when completely different patterns of competitiveness existed.

frequency of supply cancellations, frequency, supply duration, and throughput.[29] Our frequency score is based on the number of days between supplies, with more frequent service receiving a higher score.

We first estimate "naïve" models that examine the relationship between intermittency and household characteristics cited in the literature--such as religion on income--but ignore the fact that households belong to valve areas. The results of these analyses are presented in Table 4. They suggest that household characteristics are associated with differing service quality. Being a low-income household, for example increases the likelihood of receiving predictable supply. Being a Muslim household, on the other hand, is correlated with a lower likelihood of more frequent supply. Appendix Table A.1 presents results for dependent variables capturing the remaining measures of the quality of intermittent water supply: supply duration, the frequency of supply cancellations, and pressure levels. In these cases, no household-level predictors other than Cauvery supply exert a consistent effect; as we would expect, supply duration and water pressure is better for the relatively new Cauvery connections, and supply cancellations are less frequent.

[INSERT TABLE 4 ABOUT HERE]

We then employ a number of different model specifications that take the water network structure into account. This second set of models includes not only household-

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[29] There are several flavors of ordinal logistic regression. Ours uses the following parameterization:

$$\log\left(\frac{P(Y>j)}{1-P(Y>j)}\right) = S_j = \alpha_j + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p, \quad \text{j} = 2,\ldots, \text{J} - 1, \text{J}$$

where J represents the number of levels in the dependent variable, and p represents the number of independent variables. This cumulative logit parameterization specifies that the outcome of interest is observing a particular value of the dependent variable or greater (Parry, 2016).

level observations such as religion, but also valve area characteristics such as the percentage of Muslim households. Model 1 contains all of our household and valve-area predictors, and clusters standard errors by valve area. Model 2 substitutes ward fixed effects for clustered standard errors at the valve area level to ascertain if patterns are driven by unobserved ward-level heterogeneity. In Model 3, we add a variable reflecting whether or not the ward's corporator is aligned—i.e., from the same party as that which controls the state government (the INC for this period) --and again cluster standard errors by valve area. In Model 4, we control for political background conditions by interacting alignment with the margin of victory in a given ward during the 2015 election cycle.[30] In supplementary tables in the online appendix, we present two other specifications.[31]

The results of these analyses are presented in five separate tables, corresponding to each of our dependent variables. Our models of supply predictability and frequency provide strong evidence that targeting of specific groups occurs at the valve area level rather than at the household-level. Low-income valve areas—defined in terms of the percentage of households without a motorized vehicle—receive more, rather than less predictable water supply, and more frequent, rather than less frequent services. Household income level and religion are insignificant in these revised models, suggesting that authorities cannot easily privilege or deny households with particular characteristics when they do not live in valve areas with other group members. Predictability and

[30] Note that we cannot include ward fixed effects in Models 3 and 4 because our data is cross-sectional and we include ward-level variables. We do not have sufficient variation in the data to fit a model containing clustered standard errors in Model 4.
[31] A first model includes just household-level variables and valve area fixed effects, providing a fuller test of the association between these household-level variables and our dependent variables. A second model accounts for the possibility that our Cauvery Supply variable may be driving results through post-treatment bias by dropping the households living in areas with CMC supply.

frequency are arguably the two most important dimensions in reducing the time needed to wait for, collect and store water. Valve area characteristics appear less important for other indicators of service quality, as in the naïve models (Tables A.2-4), and in line with our expectations.

Table 5 reports results for our models for whether or not water comes at a specific time. Here, the main variable consistently associated with more predictable water arrival times across specifications is the percentage of households in the valve area that are low-income. For Model 1, this suggests that for a one standard deviation increase in the low-income valve area variable (a 19% increase in the proportion of low income households in each valve area), the odds of water arriving at a specific time are 56% greater (see Figure 5).[32] This is an unexpected finding, given the sizeable consensus in the literature that economically marginal populations receive worse water services. Other valve area characteristics we might expect to be important based on the literature, however, are not consistently associated with more predictable services: the existence of local leaders is not significant across specifications, suggesting that local leaders may not always be as important as the literature suggests; and variables reflecting a large Muslim or migrant population are not significant across all specifications. When we substitute household level and valve area level SC/ST variables for our low-income variables, they are also insignificant.[33] The strong association between the low-income valve area variable and predictable services remains strong even when we control for the margin of victory in the latest elections and the corporator's alignment with the party governing at the state level.

[32] To calculate the odds ratio, we used the formula OR = $e^{\beta * a}$, where β is the log-odds regression coefficient and a is the change in X for which we are calculating a change in the odds ratio.
[33] Results available upon request.

[INSERT TABLE 5, FIGURE 5 HERE]

Table 6 reports results from our models of weekly service frequency, also incorporating valve area boundaries. As with the first set of results, we observe no consistently significant relationships between household level variables (i.e. Muslim household, low-income household, or migrant household) and the dependent variable. Turning to valve area characteristics, however, a different story emerges. Here again, valve areas comprised more heavily of low-income households receive more frequent supply across all of our specifications. A one standard deviation increase in the percentage low-income valve area variable is associated with a 54% higher odds of more frequent water supply. The conditional relationship between the low-income valve area variable and frequency of supply is illustrated in Figure 6. Valve areas with proportionally larger Muslim populations, on the other hand, receive less frequent service, consistent with the existing literature. For a one standard deviation, or a 19.7% increase, in the valve area percentage Muslim variable, the odds of receiving a lower frequency of water supply is 39% higher (Figure 7). The existence of a local leader in the valve area is not consistently associated with more frequent service across specifications. Households living in valve areas with lower elevations receive services somewhat more frequently, which makes sense given the role of pressure and gravity in water distribution systems. For a one standard deviation (19 meters) increase in elevation, the odds of receiving a lower frequency of water supply is 1% higher. These relationships remain strong even when we include our controls variables for the margin of victory, alignment, and the interaction between the two. Results for our other dependent variables display less striking patterns of allocation, consistent with results in the naïve models (see Tables A.2 – A.4).

[INSERT TABLE 6, FIGURES 6 + 7 HERE]

The strong association between low-income valve areas and more predictable and frequent service remains strong and highly significant under a variety of additional robustness checks. To address possible measurement bias for our independent variables, we dropped from our analysis valve areas for which we had low levels of coverage by surveyed households.[34] Similarly, since many valve area characteristics were calculated based on household responses, we dropped valve areas with two or fewer household responses to questions regarding religion, household assets, migrant status, etc. A predominance of low-income populations remained strongly associated with more predictable and frequent service.

It could plausibly be argued that some respondents from households possessing automatically filling water tanks might be less informed about the frequency and predictability of water supply, and that this might have affected our results. We therefore repeated our analysis on the subset of our sample without automatically filling water tanks. It could also be argued that respondents from low-income households would be less likely to report dissatisfaction with their water service than middle- or high-income respondents, because their expectations of government bureaucracies are low in general,

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[34] To code the survey coverage of each valve area, we first calculated the total acreage comprised by each valve area using QGIS and categorized valve areas as small (under 10 acres), medium (10-20 acres), or large (greater than 20 acres). Coverage categories of poor, fair, good, or very good were then assigned to each valve area. Poor coverage valve areas were those with surveyed households only on the edges for small valve areas or in one corner for medium or large valve areas. Only areas occupied by households were included in this process; areas occupied by vacant land or a lake were ignored.

and / or they appreciate the recent improvements in service following the Cauvery extension project in E3 enough that service disruptions do not worry them.[35] Our household surveys did, in fact, report high levels of satisfaction with BWSSB as a utility across class and caste. We therefore also ran models without our low-income households. Finally, to address the concern that the new Cauvery pipelines in E3 might have been systematically extended to some groups and not others—and that our Cauvery variable might therefore introduce post-treatment bias—we estimated our models with the subset of households receiving only Cauvery supply.[36] We then removed the valve area elevation variable from the Cauvery-only dataset to ensure that our results were not dependent on an interaction between Cauvery service and valve area elevation. Results in all of these cases were similar to those of our main models. [37]

Additional robustness checks addressed further potential concerns about possible measurement error. We checked if our results were robust to using alternative measures for household income (and thus valve area income).[38] To address concerns that our

[35] Franceys and Jalakam (2010) found that low-income populations in Hubli, India, adjusted their expectations after becoming accustomed to poor service quality.
[36] An example helps illustrate the possibility of post-treatment bias: if lower income areas were less likely to receive Cauvery service, then a regression estimating the association between low-income valve area status that controls for Cauvery service might underestimate the impact of low-income valve area status on service quality. Model 6 in Tables A.I-AV drops households with only CMC supply, leaving households with only Cauvery supply and with multiple supply – both Cauvery supply and CMC supply. We also dropped households with only CMC supply and with multiple supply, leaving households with only Cauvery supply. Due to the relatively small number of households with CMC service, we could not look at CMC households only.
[37] Results available upon request.
[38] We substituted reported average monthly income for our main measure, ownership of a motor vehicle. We then categorized households earning less than Rs. 10,000 a month as low-income.

elevation data might be inaccurate, we also removed the household and valve area elevation variables one at a time from the models, and then together.

DISCUSSION AND CONCLUSION

In this paper, we highlighted the importance of studying service intermittency, and the uneven distribution of service quality more broadly. Because the politics of allocation may vary across different dimensions of service quality, we disaggregated water intermittency into four components, and analyzed the distribution of these components across a diverse subdivision of Bangalore's water utility. Our work has several implications for future research on distributive politics, especially for studies of infrastructure services.

Our analysis highlights the importance of studying not just service access, but service quality. Service quality can be disaggregated into multiple dimensions, not all of which may allocated according to the same criteria. Piped water services, for example, are composed of many dimensions of importance to households: quantity, quality, frequency of arrival, time of arrival, predictability of arrival, duration of delivery, the frequency of supply cancellations, and, of course, price. Different dimensions matter more or less to specific consumers. For instance, seven hours of water delivered once a week is a different service than those same seven hours split over two or three days a week if the consumer is storage-constrained. Intermittent but predictable services at a lower price are preferred by some consumers to continuous, good quality supplies at higher prices (e.g., Burt & Ray, 2014). Scholars examining the politics of distribution in other infrastructure sectors—like electricity and public transit—would profit from examining the dimensions of intermittency we explore here, and scholars of distributive politics in other areas could fruitfully disaggregate other types of services into multiple dimensions as well.

Our work suggests that different technical and political factors will affect how these different dimensions of water services are experienced by households. We find *that all dimensions of service quality may not be correlated– some areas may receive services that are good on one dimension and poor on others.*[39] Our findings highlight the extent to which the benefits and burdens associated with these delivery dimensions can be distributed differently. While low-income valve areas in our study experienced more predictable and frequent services, for instance, they did not receive noticeably different water pressure levels or fewer supply cancellations. Studies of the distribution of other infrastructure services, and perhaps even other types of public policies, could benefit from employing such disaggregated analyses; in effect, our work indicates that different dimensions of inequality can (and do) co-exist within one composite "service".

The strong and significant association between low-income populations and more frequent and predictable services is in sharp contrast to almost all the literature on income groups and infrastructure access. One possible reason for this, building on the distributive politics literature, could be that elected officials know that low-income households struggle most with water intermittency, and therefore direct water valvemen (through their supervisors) to deliver more frequent and reliable services to low-income neighborhoods. Moderate- to high-income households are more likely to have automatic tanks, so these groups are less exposed to the costs associated with intermittent supply. They may be less likely to shift their political support in response to improvements (or

[39] For the inverse logic, stressing that patterns of distribution vary across broad policy areas, see Kramon and Posner (2013).

deteriorations) in supply, whereas low-income voters may be more likely to do so. While we did observe that particularly competitive wards received better services for some of our outcome variables, this relationship did not hold across all models. Our survey respondents also did not report approaching local leaders or elected officials regarding their water-related concerns (see below).

We consider two complementary explanations to be more likely based on our research. A first reason why low-income valve areas may enjoy better service is that the street-level bureaucrats (or "valvemen") responsible for opening and closing water valves exercise discretion. Indian utilities lack accurate, fine-grained maps of their water systems; the most accurate information about valve area boundaries, pipe locations, etc. lies with the valvemen who often have years of experience in their valve areas. Valvemen can use this discretion to provide more frequent and predictable services to communities they know to be most in need of them. Our ethnographic research in another district in Bangalore found that water valvemen felt strong connections with low income communities, often viewing them as their most important "clients" (Hyun, Post, & Ray, 2018); this explanation is consistent with Björkman (2015), who found that valvemen in Mumbai could modify their schedules to better serve low-income households. Our survey data from E3 also suggests that households trust valvemen—rather than elected officials or local leaders—to address their water needs; while more than 60% of our respondents in low-income neighborhoods reported contacting water valvemen about service problems, less than 10% contacted a local leader or city corporator. Moreover, very few individuals reported paying "tip" money to valvemen in return to their services, although we did learn of informal payments in exchange for regularly turning on water valves in other parts of the city.[40]

A related possibility is that the BWSSB management exercises a substantial degree of autonomy from local elected officials, and uses this independence to prioritize services for populations it knows to be in need. Several factors could explain BWSSB's independence. First, BWSSB—unlike the Mumbai water utility examined by Anand (2011a) and Björkman (2015)—is an organ of the state, rather than the city, government. Yet the elected representatives most active at the neighborhood level are corporators—city ward representatives. Their links with BWSSB officials are generally informal and indirect.[41] State legislative representatives (MLAs) appear to be completely inactive in this service area; in our surveys, 0% of households reported ever contacting an MLA regarding water problems. In addition, BWSSB is a legally independent, professionalized enterprise rather than a line ministry, which means that even state-level elected officials may be more restricted in terms of the types of pressures they can apply relative to standard government departments.[42] This formal insulation from political pressure, as well as the indirect links between corporators and state officials, may partially explain the patterns we observed. Taken together, the pivotal role played by valvemen in water allocation and the BWSSB management's relative insulation from local politics may help explain why the patterns of allocation we observe *within* the water

[40] Interviews with low-income households in other parts of the city suggested that informal payments existed in other districts, and were not a topic respondents were reticent to discuss with researchers.
[41] Our conversations with BWSSB engineers corroborated this point.
[42] See Herrera and Post (2014) on different institutional arrangement for the management of water services, including corporatized utilities. Benjamin (2000) critiques this institutional format for service provision in Bangalore precisely because elected officials are bypassed.

network diverge strongly from patterns of *access to* the water network observed by other scholars.

More broadly, our results demonstrate how crucial it is to ground any analyses of the politics of service delivery in the physical networks through which these services are delivered. Social scientists have rightly critiqued the engineering and planning literatures for focusing exclusively on the technical aspects of water system mapping, delivery, and quality. But social scientists, in turn, have underplayed the significance of the design principles of, and the material nature of the resource behind, networked services. Piped water systems, for instance, are designed to deliver area by area rather than household by household, and these areas are shaped not only by socio-economic considerations but also by elevation and hydraulic features. We argue that, within the piped water network, the unit of distribution – and therefore of discrimination – is a hydraulically isolatable area. Our study of patterns of water distribution in Eastern Bangalore illustrate the extent to which valve areas, rather than households, are the units that public officials can target. In our full specifications, household-level characteristics commonly cited in the literature, such as income, religion, and caste were not strongly associated with better predictability and frequency, while valve area characteristics were.

It follows that the extent to which officials can successfully target particular groups, such as swing voters or favored ethnic groups, will depend upon underlying population distributions and how these overlap with infrastructure network structure. Previous studies that have found a negative association between socio-cultural marginalization and *networked* public services, therefore, rely on a high level of spatial clustering within these groups; this reliance, however, is usually assumed rather than made explicit. In the Bangalore case we examine, low-income settlements are small and often quite diverse. Targeting on the basis of social and economic characteristics would be even easier, we imagine, in a city with larger, more segregated slums, such as Mumbai. It would also be easier outside the reach of infrastructure networks, where governments can deliver water more flexibly using tanker trucks.

Whether street-level bureaucrats are playing independent roles in targeting water services, or the utility itself is operating on a political and financial calculus that is somewhat independent of city- and state-level partisan politics, or both, the implications of our work are significant. We conclude that, to understand how inequalities within networked services can be produced or alleviated, it is essential for researchers and policy analysts to (i) "see" infrastructure services through the joint lenses of social structure and physical (network) structure; (ii) disaggregate services into their key components and examine which service components vary together, for whom, and why; and (iii) understand at a granular scale – meaning, at the scale of a valve area (or a sub-station feeder) – the relationships between settlement patterns and access to services.

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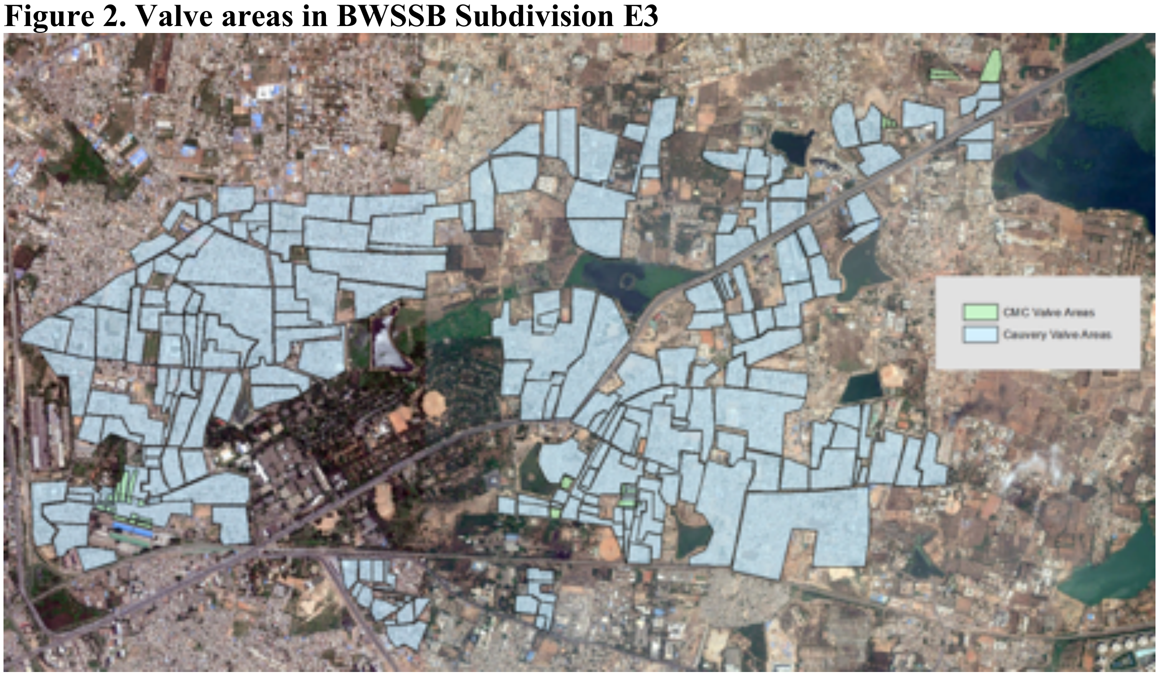
Figure 1. BWSSB Subdivision E3

Figure 2. Valve areas in BWSSB Subdivision E3



Source: Valve area maps courtesy of NextDrop, superimposed over google satellite imagery.

Figure 3. Religious and Economic Composition of Valve areas in BWSSB Subdivision E3

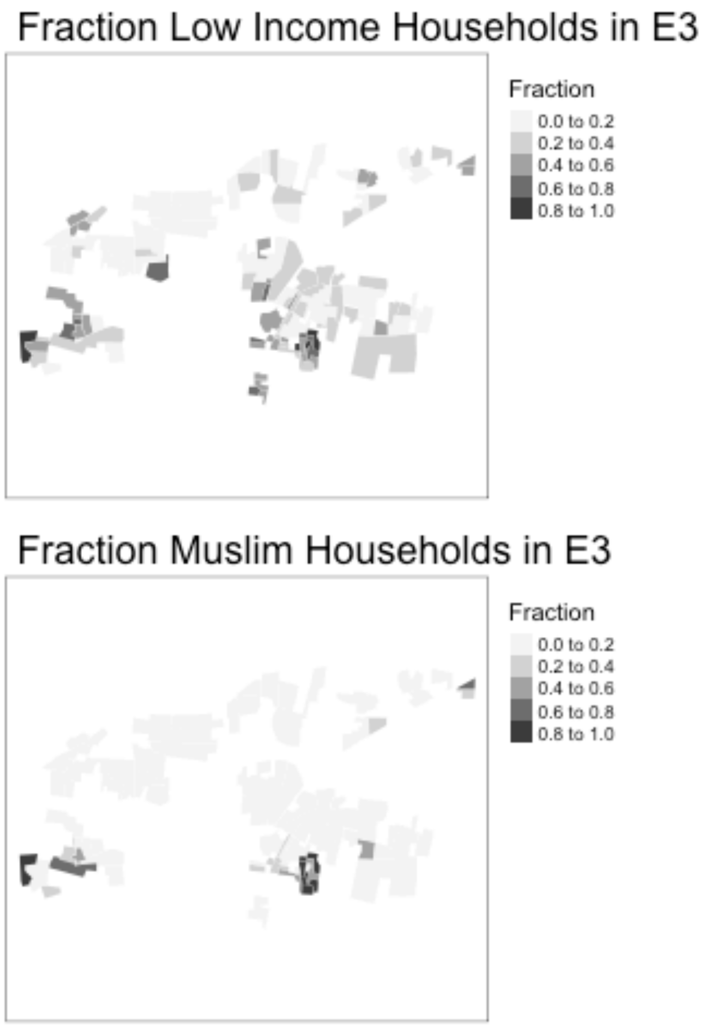
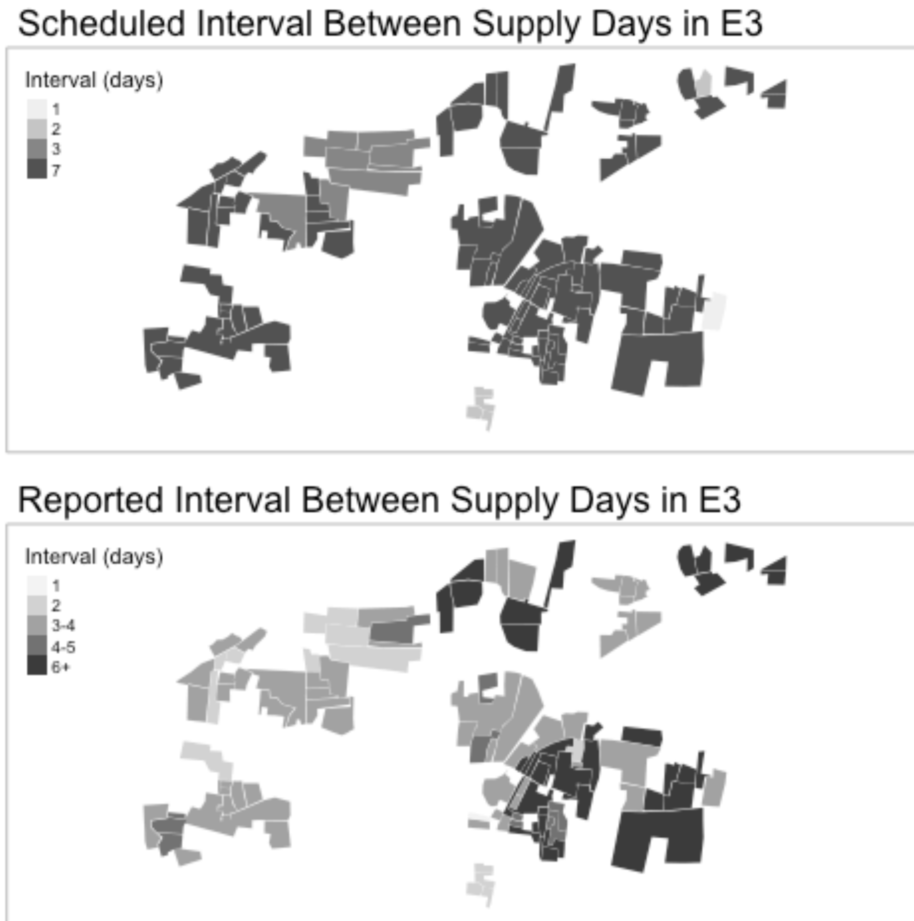


Figure 4. Day Intervals Between Water Supply in BWSSB Subdivision E3



Note: Scheduled supply day intervals from BWSSB. Reported interval map displays modal responses from household surveys geo-located in each valve area.

Figure 5.

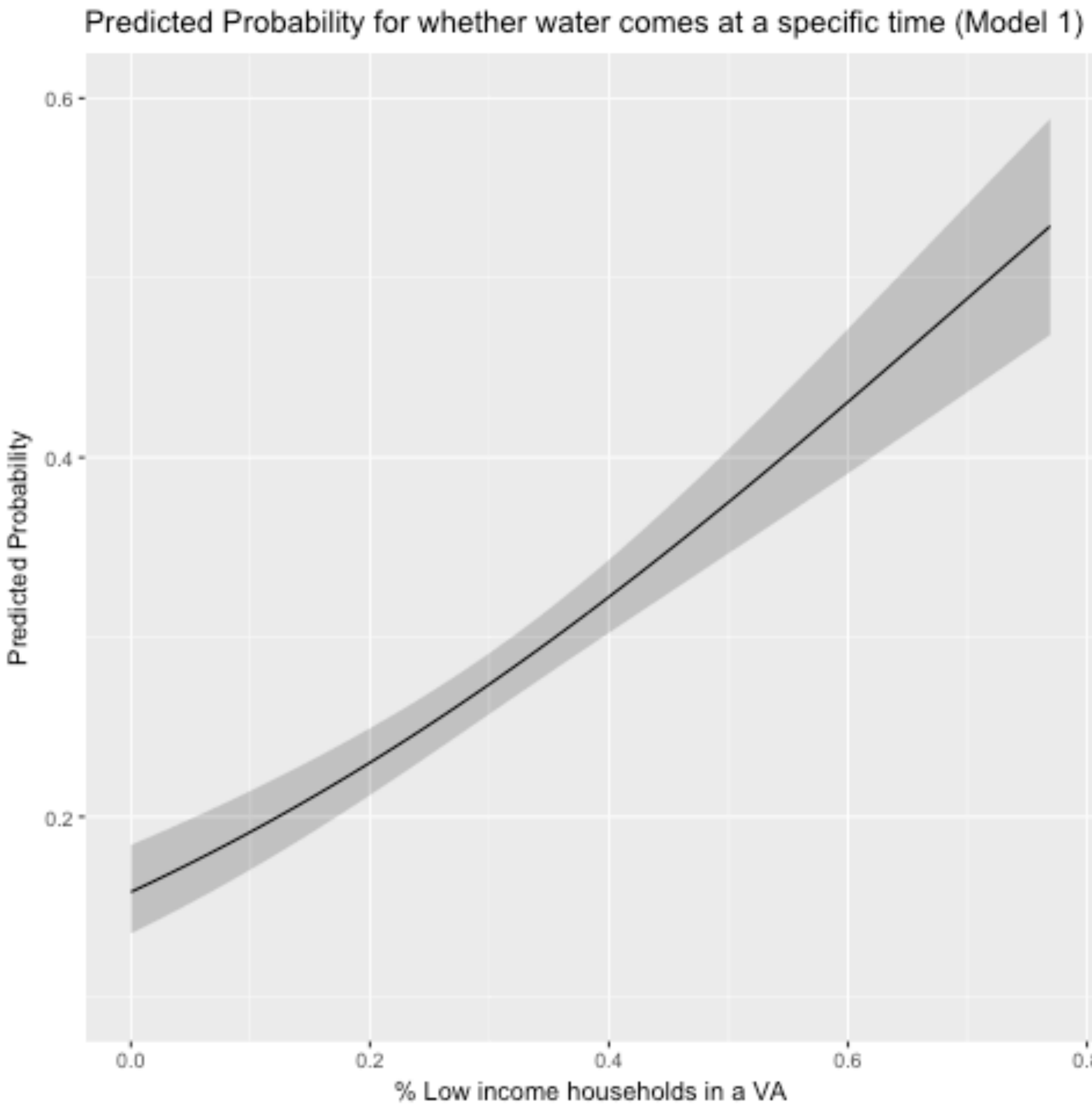

Predicted Probability for whether water comes at a specific time (Model 1)
Predicted Probability
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
% Low income households in a VA

Figure 6.

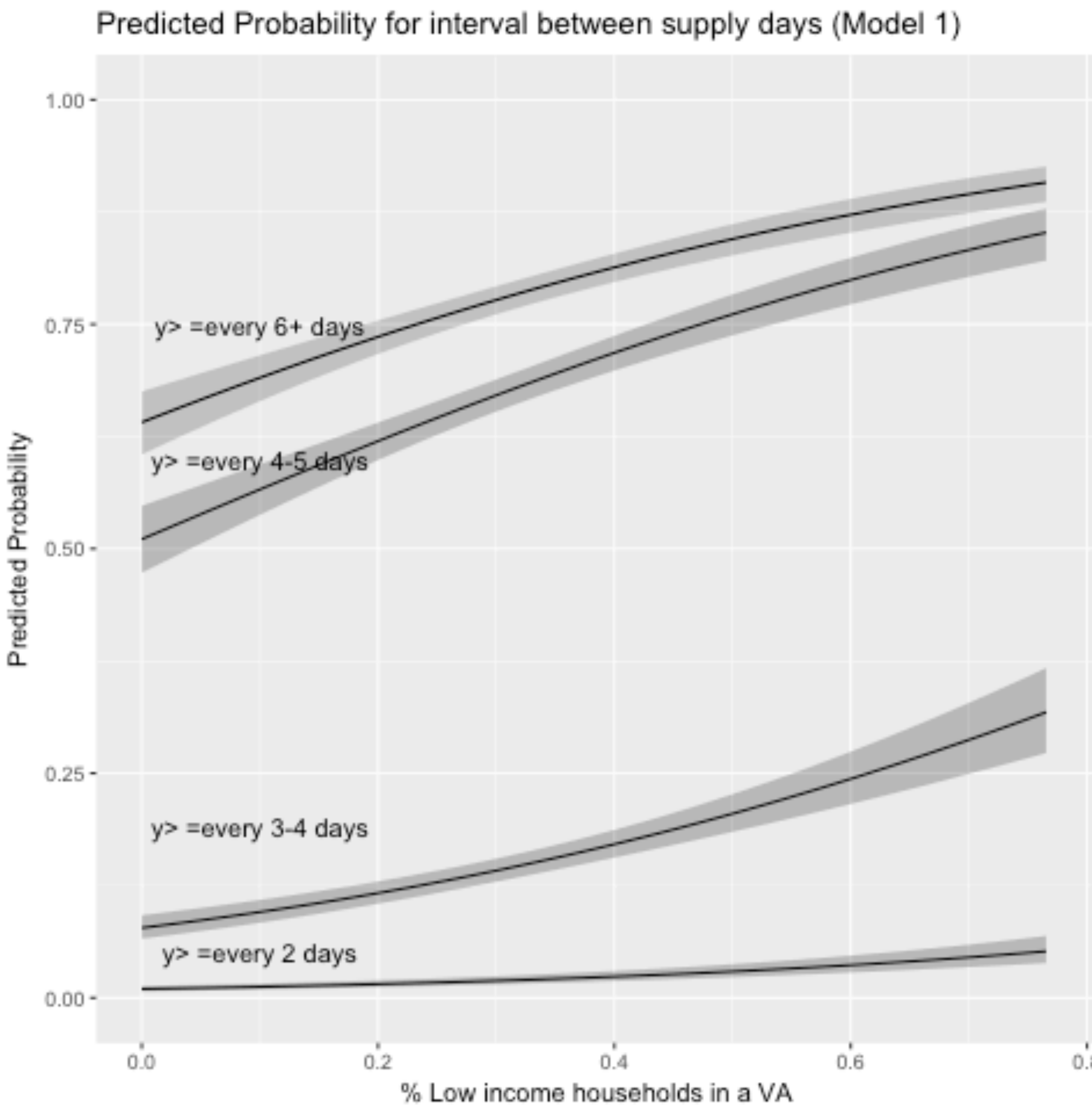

Predicted Probability for interval between supply days (Model 1)
Predicted Probability
1.00
0.75
0.50
0.25
0.00
y> =every 6+ days
y> =every 4-5 days
y> =every 3-4 days
y> =every 2 days
0.0
0.2
0.4
0.6
0.8
% Low income households in a VA

Figure 7.

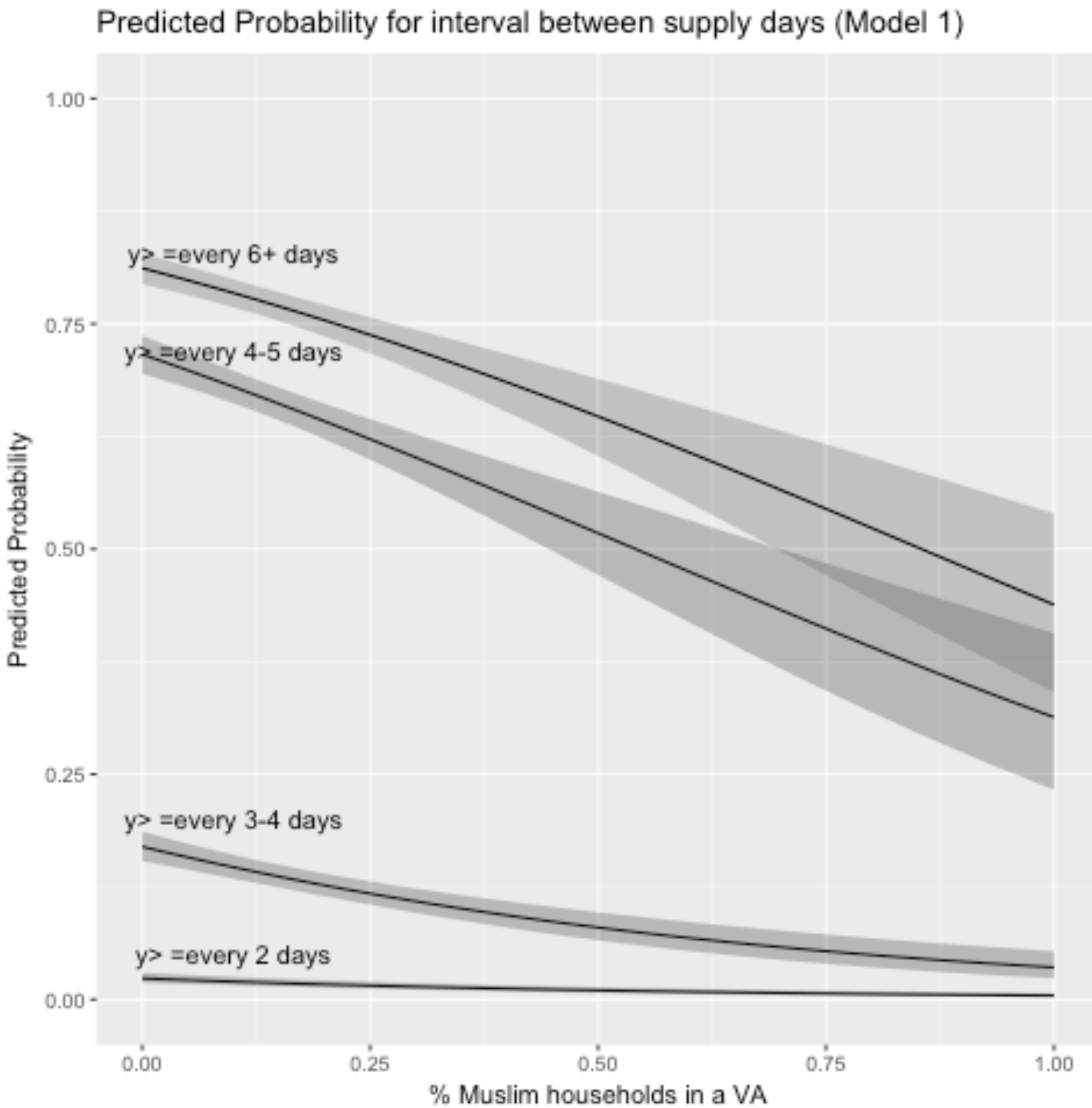

Predicted Probability for interval between supply days (Model 1)
1.00
0.75
0.50
0.25
0.00
Predicted Probability
y> =every 6+ days
y> =every 4-5 days
y> =every 3-4 days
y> =every 2 days
0.00
0.25
0.50
0.75
1.00
% Muslim households in a VA

Table 1. Descriptive Statistics for Independent Variables

Variable	Mean	St. Dev.	Min	Max
HH level variables				
Elevation	905.789	62.116	211.533	1,389.800
Cauvery Supply	0.857	0.350	0	1
CMC Supply Only	0.048	0.214	0	1
Muslim	0.125	0.331	0	1
Low income	0.300	0.458	0	1
VA level variables				
Elevation	905.789	19.599	731.850	1,145.883
Muslim	0.125	0.193	0.000	1.000
Urban Migrant	0.338	0.166	0.000	1.000
Low Income	0.300	0.192	0.000	1.000
Local leader	0.546	0.498	0	1
Ward level variables				
Margin of victory	0.097	0.096	0.0005	0.237
Corporator Aligned	0.206	0.405	0	1

Table 2. Tabulated Responses for Dependent Variables

Variable Response option	N individuals choosing response
Whether water comes at a specific time	
Yes	805
No	2045
Interval between supply days	
Everyday	69
Every 2 days	409
Every 3-4 days	1434
Every 4-5 days	286
Every 6+ days	705
Duration of water when it comes on	
Less than 2 hours	548
2-3 hours	956
3-4 hours	771
4+ hours	584
Whether or not service is cancelled on supply days	
No	1030
Rarely	750
Yes	712
Water pressure level	
Weak	240
Moderate	1748
Strong	444

Table 3. Water Intermittency: Dimensions of Household Impact

Dimension	**Operationalization**
Predictability	• Does water come at a specific time of day or specific day of the week? • Are scheduled supplies ever cancelled?
Frequency	• How many times a week does the water arrive?
Duration	• How long does the water stay on when it comes?
Thoughput	• How strong is the water pressure during supply sessions?

Table 4. Water Supply Predictability and Frequency in Eastern Bangalore, April-May 2015 (no valve area characteristics)

	Whether water comes at a specific time[1]		Service Frequency[2]	
	Model 1	Model 2	Model 1	Model 2
Household level variables				
Elevation	-0.001*	-0.002**	0.002***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	0.182	0.164	-0.272**	-0.366***
	(0.127)	(0.132)	(0.126)	(0.136)
Muslim	0.305**	0.060	-0.246***	-0.346***
	(0.125)	(0.131)	(0.094)	(0.103)
Low income	0.440***	0.309***	0.314***	0.157*
	(0.093)	(0.095)	(0.082)	(0.086)
Ward level variables				
Margin of victory		-5.898***		-2.187***
		(0.613)		(0.438)
INC Corporator		-0.471***		-2.715***
		(0.126)		(0.125)
Margin X INC Corp.		-107.225***		-29.430
		(6.100)		(77.163)
N	2,831	2,831	2,884	2,884
R^2	0.018	0.083	0.014	0.252
chi^2	35.860*** (df = 4)	167.725*** (df = 7)	35.720*** (df = 4)	756.932*** (df = 7)

Notes: 1) Logistic regressions were used to estimate outcomes. A higher category indicates better service. All models include bootstrapped standard errors. Intercept has been omitted. 2) Ordinal logistic regressions were used to estimate outcomes. A higher category indicates better service. All models include bootstrapped standard errors. Intercepts have been omitted.
*p < .1; **p < .05; ***p < .01

Table 5. Predictability of Water Supply in Eastern Bangalore, April-May 2015

	Whether water comes at a specific time[1]			
	Model 1[2]	Model 2	Model 3[2]	Model 4
Constant	3.373	11.360***	1.648	8.172***
	(4.746)	(2.649)	(4.612)	(2.396)
HH level variables				
Elevation	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	0.251	0.239*	0.271	0.225*
	(0.352)	(0.130)	(0.367)	(0.128)
Muslim	0.188	0.217	0.188	0.196
	(0.162)	(0.171)	(0.165)	(0.161)
Low income	0.078	0.090	0.078	0.086
	(0.103)	(0.103)	(0.102)	(0.100)
VA level variables				
Elevation	-0.005	-0.013***	-0.003	-0.009***
	(0.005)	(0.003)	(0.005)	(0.003)
Muslim	-0.273	-0.808**	-0.371	-0.914***
	(0.574)	(0.318)	(0.561)	(0.278)
Urban Migrant	-0.682	-1.436***	-1.075	-1.754***
	(0.834)	(0.360)	(0.945)	(0.318)
Low Income	2.324***	1.874***	2.459***	1.544***
	(0.789)	(0.317)	(0.780)	(0.277)
Local leader	-0.176	-0.206**	-0.201	-0.165*
	(0.253)	(0.102)	(0.249)	(0.096)
Ward level variables				
Margin of victory				-6.133***
				(0.680)
INC Corporator			0.430	-0.149
			(0.330)	(0.142)
Margin X INC Corp.				-108.159***
				(5.354)
Ward dummies?	No	Yes	No	No
N	2,831	2,831	2,831	2,831
R^2	0.068	0.148	0.074	0.126
chi^2	137.914*** (df = 9)	307.404*** (df = 15)	150.584*** (df = 10)	259.989*** (df = 12

Notes: 1) Ordinal logistic regressions were used to estimate outcomes. A higher category indicates better service. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. All models include bootstrapped standard errors. 2) Standard errors clustered at the valve area level using the Bootcov function in R.
*p < .1; **p < .05; ***p < .01

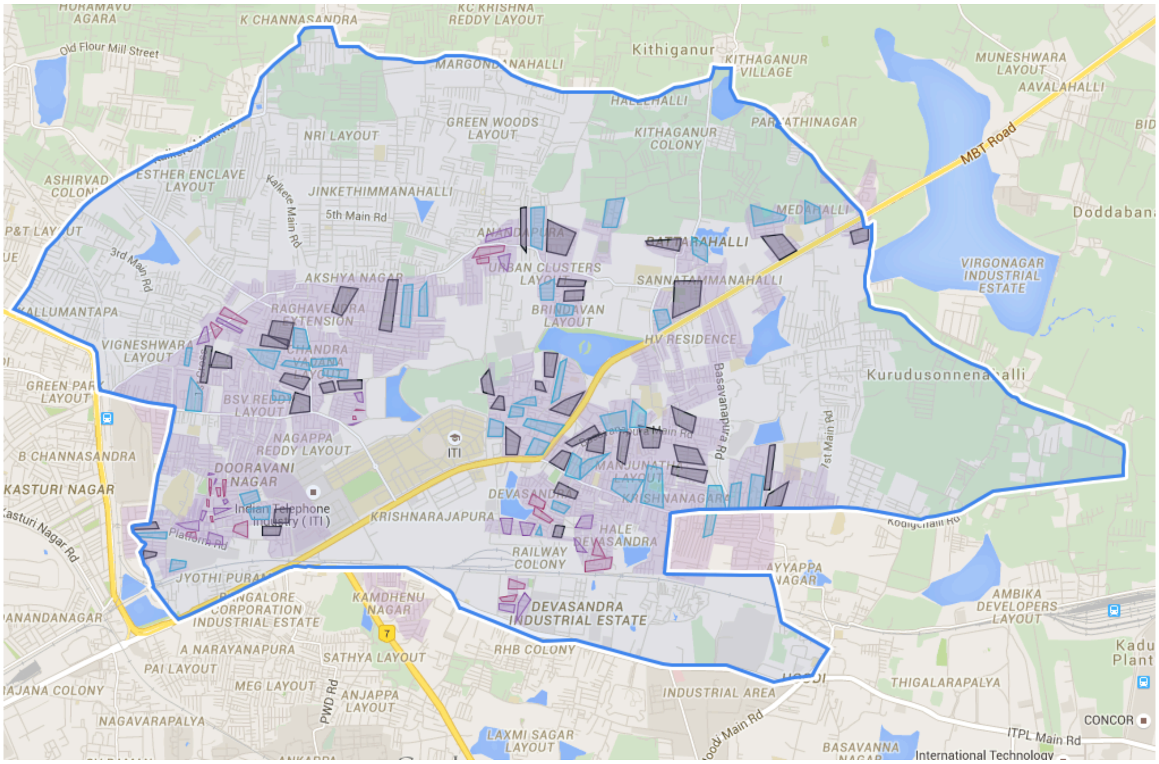
Table 6. Water Service Frequency, Eastern Bangalore, April-May 2015

	Service Frequency[1]			
	Model 1[2]	Model 2	Model 3[2]	Model 4
y> =every 2 days	-23.220***	-15.359***	-15.526***	-13.875***
	(7.454)	(2.236)	(5.966)	(2.150)
y> =every 3-4 days	-23.756***	-16.023***	-16.187***	-14.540***
	(7.454)	(2.238)	(5.947)	(2.152)
y> =every 4-5 days	-26.270***	-18.793***	-18.909***	-17.263***
	(7.513)	(2.251)	(5.960)	(2.165)
y> =every 6+ days	-28.414***	-20.994***	-21.063***	-19.413***
	(7.500)	(2.259)	(5.940)	(2.175)
HH level variables				
Elevation	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	-0.264	-0.398***	-0.396	-0.405***
	(0.346)	(0.139)	(0.406)	(0.136)
Muslim	-0.009	-0.009	-0.020	-0.020
	(0.105)	(0.116)	(0.115)	(0.113)
Low income	0.025	0.008	0.010	0.009
	(0.078)	(0.086)	(0.087)	(0.087)
VA level variables				
Elevation	0.028***	0.017***	0.020***	0.018***
	(0.008)	(0.003)	(0.006)	(0.002)
Muslim	-1.710**	-1.239***	-1.374*	-1.508***
	(0.833)	(0.279)	(0.754)	(0.241)
Urban Migrant	-1.339	0.717***	0.592	0.500**
	(0.952)	(0.270)	(0.880)	(0.242)
Low Income	2.232**	1.409***	1.771*	1.549***
	(1.010)	(0.257)	(0.964)	(0.253)
Local leader	-0.021	0.350***	0.141	0.148*
	(0.343)	(0.092)	(0.328)	(0.080)
Ward level variables				
Margin of victory				-1.290***
				(0.487)
INC Corporator			-2.371***	-2.483***
			(0.399)	(0.125)
Margin X INC Corp.				-26.128
				(76.032)
Ward dummies?	No	Yes	No	No
N	2,884	2,884	2,884	2,884
R^2	0.130	0.301	0.283	0.287
chi^2	367.841*** (df = 9)	937.417*** (df = 15)	873.333*** (df = 10)	887.857*** (df = 12

Notes: 1) Ordinal logistic regressions were used to estimate outcomes. A higher category indicates better service. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being

in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. All models include bootstrapped standard errors. 2) Standard errors clustered at the valve area level using the Bootcov function in R.
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$

Figure A.1 Survey Clusters within BWSSB Subdivision E3



Note: The BWSSB E3 subdivision boundary is shown in blue, while areas receiving piped water supply are denoted in lavender. Pink and purple polygons denote low-income clusters (treatment and control); black and blue polygons denote mixed income clusters (treatment and control). There are four clusters per block.

Table A.1. Duration of Water Supply, Prevalence of Cancellations, and Water Pressure, Eastern Bangalore, April-May 15 2015

	Duration of water when it arrives		Prevalence of supply cancellations		Water Pressure	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Household level variables						
Elevation	-0.001	-0.001	-0.00003	0.0001	-0.00002	-0.0002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	0.599***	0.582***	-0.504***	-0.532***	0.428***	0.403***
	(0.096)	(0.096)	(0.101)	(0.103)	(0.146)	(0.149)
Muslim	-0.104	-0.318***	-0.208*	-0.148	0.228	0.165
	(0.105)	(0.109)	(0.110)	(0.114)	(0.140)	(0.139)
Low income	-0.074	-0.227***	0.014	0.026	0.054	-0.012
	(0.073)	(0.076)	(0.083)	(0.084)	(0.097)	(0.100)
Ward level variables						
Margin of victory		-5.211***		1.186**		-1.828***
		(0.429)		(0.467)		(0.587)
INC Corporator		-0.548***		-0.208*		-0.495***
		(0.102)		(0.111)		(0.132)
Margin X INC Corp.		22.258***		29.014***		10.850
		(5.781)		(5.833)		(8.286)
N	2,841	2,841	2,474	2,474	2,420	2,420
R^2	0.016	0.075	0.012	0.033	0.007	0.016
chi^2	41.943*** (df = 4)	207.118*** (df = 7)	27.383*** (df = 4)	74.055*** (df = 7)	13.870*** (df = 4)	31.080*** (df = 7)

Notes: 1) Ordinal logistic regressions were used to estimate outcomes. A higher category indicates better service. All models include bootstrapped standard errors. Intercepts have been omitted.
*p < .1; **p < .05; ***p < .01

Table A.2. Duration of Water Supply, Eastern Bangalore, April-May 2015

	Duration of water when it comes on[1]			
	Model 1[2]	Model 2	Model 3[2]	Model 4
y> =every 2-3 hours	2.486	9.002***	2.599	8.552***
	(3.976)	(1.778)	(4.014)	(1.721)
y> =3-4 hours	0.900	7.330***	1.014	6.887***
	(3.966)	(1.774)	(3.999)	(1.717)
y> =4+hours	-0.389	5.971***	-0.276	5.536***
	(3.961)	(1.773)	(3.995)	(1.717)
HH level variables				
Elevation	-0.0005	-0.0005	-0.0005	-0.0004
	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	0.585**	0.594***	0.583**	0.527***
	(0.262)	(0.103)	(0.266)	(0.099)
Muslim	0.044	0.043	0.044	0.041
	(0.173)	(0.129)	(0.179)	(0.128)
Low income	0.039	0.042	0.038	0.045
	(0.082)	(0.081)	(0.080)	(0.083)
VA level variables				
Elevation	-0.001	-0.008***	-0.001	-0.006***
	(0.004)	(0.002)	(0.004)	(0.002)
Muslim	-0.155	-0.861***	-0.148	-0.833***
	(0.705)	(0.266)	(0.695)	(0.253)
Urban Migrant	0.787	-0.016	0.822	0.059
	(0.563)	(0.237)	(0.611)	(0.224)
Low Income	-0.295	-1.887***	-0.306	-1.666***
	(0.567)	(0.247)	(0.584)	(0.247)
Local leader	-0.399*	-0.215***	-0.397*	-0.271***
	(0.227)	(0.079)	(0.233)	(0.074)
Ward level variables				
Margin of victory				-7.181***
				(0.507)
INC Corporator			-0.038	-0.968***
			(0.248)	(0.123)
Margin X INC Corp.				20.323***
Margin of victory				-7.181***
Ward dummies?	No	Yes	No	No
N	2,841	2,841	2,841	2,841
R2	0.041	0.122	0.041	0.117
chi2	110.086*** (df = 9)	343.891*** (df = 15)	110.244*** (df = 10)	327.475*** (df = 12

Notes: 1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. All models include bootstrapped standard errors. 2) Standard errors clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Table A.3. Prevalence of Supply Cancellations, Eastern Bangalore, April-May 2015

	Whether or not service is cancelled on supply days[1]			
	Model 1[2]	Model 2	Model 3[2]	Model 4
y> =rarely	5.335	4.181**	5.489	3.827**
	(4.747)	(2.060)	(4.813)	(1.896)
y> =yes	4.044	2.859	4.197	2.521
	(4.744)	(2.058)	(4.802)	(1.895)
HH level variables				
Elevation	0.0002	0.0002	0.0001	0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	-0.444**	-0.395***	-0.446**	-0.471***
	(0.213)	(0.108)	(0.213)	(0.106)
Muslim	-0.174	-0.179	-0.174	-0.182
	(0.195)	(0.147)	(0.194)	(0.149)
Low income	0.049	0.048	0.049	0.049
	(0.094)	(0.093)	(0.093)	(0.089)
VA level variables				
Elevation	-0.004	-0.003	-0.005	-0.003
	(0.005)	(0.002)	(0.005)	(0.002)
Muslim	-0.094	-0.220	-0.087	-0.047
	(0.439)	(0.273)	(0.452)	(0.262)
Urban Migrant	-1.673**	-2.017***	-1.631**	-1.682***
	(0.661)	(0.282)	(0.710)	(0.274)
Low Income	-0.311	-0.783***	-0.324	-0.292
	(0.486)	(0.273)	(0.511)	(0.250)
Local leader	-0.125	-0.065	-0.122	-0.081
	(0.212)	(0.092)	(0.215)	(0.084)
Ward level variables				
Margin of victory				0.373
				(0.527)
INC Corporator			-0.044	-0.091
			(0.263)	(0.127)
Margin X INC Corp.				31.179***
				(8.914)
Ward dummies?	No	Yes	No	No
N	2,474	2,474	2,474	2,474
R2	0.035	0.066	0.035	0.051
chi2	78.611*** (df = 9)	149.582*** (df = 15)	78.782*** (df = 10)	114.837*** (df = 12)

Notes: 1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. All models include bootstrapped standard errors. 2) Standard errors clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Table A.4. Water Pressure, Eastern Bangalore, April-May 2015

	Water pressure level[1]			
	Model 1[2]	Model 2	Model 3[2]	Model 4
y> =moderate	3.653	5.283**	4.375	5.616**
	(3.267)	(2.438)	(3.222)	(2.366)
y> =strong	-0.111	1.497	0.605	1.835
	(3.273)	(2.434)	(3.226)	(2.361
HH level variables				
Elevation	0.0003	0.0003	0.0003	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
Cauvery Supply	0.457**	0.464***	0.444**	0.421***
	(0.189)	(0.146)	(0.194)	(0.149)
Muslim	0.211	0.217	0.209	0.223
	(0.240)	(0.183)	(0.238)	(0.176)
Low income	-0.077	-0.082	-0.078	-0.080
	(0.103)	(0.103)	(0.101)	(0.105)
VA level variables				
Elevation	-0.002	-0.004	-0.003	-0.004
	(0.004)	(0.003)	(0.004)	(0.003)
Muslim	-0.123	-0.364	-0.070	-0.220
	(0.431)	(0.279)	(0.423)	(0.263)
Urban Migrant	-0.024	-0.161	0.230	0.018
	(0.427)	(0.353)	(0.472)	(0.343)
Low Income	0.932*	0.415	0.848	0.561*
	(0.545)	(0.327)	(0.556)	(0.314)
Local leader	-0.233	-0.205**	-0.220	-0.193**
	(0.186)	(0.102)	(0.189)	(0.097)
Ward level variables				
Margin of victory				-1.660**
				(0.674)
INC Corporator			-0.256	-0.471***
			(0.190)	(0.147)
Margin X INC Corp.				7.940
				(8.548)
Ward dummies?	No	Yes	No	No
N	2,420	2,420	2,420	2,420
R2	0.016	0.024	0.018	0.022
chi2	30.083*** (df = 9)	45.817*** (df = 15)	34.060*** (df = 10)	41.722*** (df = 12)

Notes: 1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. All models include bootstrapped standard errors. 2) Standard errors clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Supplemental Information for:

"Infrastructure Networks and Urban Inequality: The Political Geography of Water Flows in Bangalore"

Table A.1
Empirical Studies* of Local Public Goods Provision in the Developing World**

Author/Date	Country Focus	Sector/service	Dependent Variable(s)	Intermittency or Service Predictability one of main DVs?
Agostini, C., Brown, P., Zhang, X. (2016)	China	Broad public projects - electricity, drainage, land, agriculture, others (based on specific survey of public goods spending in villages)	Spending	No
Ahlborg, H., Borang, F., Jagers, S., & Soderholm P. (2015)	Cross-country (Africa)	Electricity	Consumption	No
Akin, J., Hutchinson, P., & Strumpf, K. (2005).	Uganda	Social services (health)	Spending	No
Alesina, Devleeshauwer, Easterly, Kurlat, and Wacziarg (2003).	Cross-country	Variety of public goods	Infrastructure quality index, log infant mortality, illiteracy	No
Anbarci, N., Escaleras, M., & Register, C. A. (2009).	Cross-country	Infrastructure (water, sanitation)	Access	No
Arvate, P. R. (2012).	Brazil	Social services (health, education)	Outcomes - Immunizations, reading at grade level, etc.	No
Auerbach, Adam. (2016).	India	Trash, Health care, roads, street lighting	Quality	No

Baldwin, K. (2013)	Zambia	Education	Access (classroom construction)	No
Baldwin, K., & Huber, J. D. (2010).	Cross-country	Business (contract enforcement), infrastructure (water, sanitation, roads, telephones), social services (health, education)	Spending, Access	No
Bandiera, O., & Levy, G. (2011).	Indonesia	Infrastructure (roads, utilities, etc.), social services (health, education, police, government employment)	Spending	No
Banerjee, A., & Somanathan, R. (2007).	India	Infrastructure (roads, libraries, wells, etc.), social services (schools, hospitals, etc.)	Outcomes - Facilities built	No
Banerjee, A., Iyer, L., & Somanathan, R. (2005).	India	Infrastructure (roads, libraries, wells, telephones, etc.), social services (schools, hospitals, etc.) and	Access	No
Barr, A., Lindelow, M., & Serneels, P. (2009).	Ethiopia	Generic - game tokens	Spending	No
Baumgärtner, S., Drupp, M. A., Meya, J. N., Munz, J. M., & Quaas, M. F. (2016).	Sweden and Cross-country	Environment Public Goods	Willingness to Pay	No
Beekman, G., Bulte, E., & Nillesen E (2014)	Liberia	Agriculture	Voluntary contributions to public good	No
Bell, C. (2011)	Cross-country	Education, health, welfare	Expenditures	No
Bernauer, T., Koubi, V. (2009)	Cross-country	Environment (air quality)	SO2 concentrations	No

Besley, T., Pande, R., & Rao, V. (2007).	India	Infrastructure (roads, village transport, water, sanitation, irrigation, electricity), social services (BPL cards, health, education)	Spending, Other - targeting of BPL cards	No
Besley, T., Pande, R., Rahman, L., & Rao, V. (2004)	India	Infrastructure (toilets, wells, electrical connections, roads, drains, streetlights)	Other - Type and Amount of Good Received	No
Bhavnani, Rikhil, and Alexander Lee. (2018)	India	Social Services (Health and Education)	Access	No
Boräng, Frida, Sverker C. Jagers, and Marina Povitkina. (2016)	Small Island Developing States	Infrastructure - Electricity	Per Capita Electricity Consumption	Yes
Bunte, Jonas B., and Alisha A. Kim. (2017)	Nigeria	Infrastructure and Social Services	Expenditure	No
Burgess, R., Gedwab R., Miguel E., Morjaria A., Padro I Miquel G. (2015).	Kenya	Roads	Spending, road construction	No
Burns, J. & Keswell M. (2015)	South Africa	Broad examples	Other - player strategy	No
Caldeira, E., Foucault, M. & Rota-Graziosi, G. (2015)	Benin	Local public spending	Expenditures	No
Cammett, Melani and Sukriti Issar. (2010).	Lebanon	Education, health care	Location of welfare agencies	No
Carlsson, F., Johannson-Stenman O., Khanh Nam P. (2015).	Vietnam	Infrastructure (bridge)	Other - Player Strategy	No
Carpenter, J., Daniere, A., & Takahashi, L. (2004)	Thailand, Vietnam	Broad examples	Contribution in public goods games	No
Caselli, F. & Michaels, G. (2013)	Brazil	Housing, education, health,	Infrastructure,	No

		transportation, transfers	expenditures, quality	
Casey, K., Glennerster, R., & Miguel, E. (2012)	Sierra Leone	Public infrastructure, education, water, sanitation, health, roads	Index of outcome components (includes infrastructure and quality)	No
Casini, Paolo, Lore Vandewalle, and Zaki Wahhaj. (2017).	India	Infrastructure and Social Services	Probability of ward member addressing the issue	No
Cecchi, Francesco, Jan Duchoslav, and Erwin Bulte. (2016).	Uganda	Insurance	Adoption of insurance and contribution in PG game (No Institutional context in the game)	No
Chattopadhyay, R. & Duflo, E. (2004)	India	Water, roads, irrigation, education	Infrastructure, quality, access	No
Chaudhary, Latika, and Jared Rubin. (2016)	India	Infrastructure (Railroad, Postoffice) and Social Services (Education)	Education Outcomes and Access	No
Chauvet, L., Gubert, F., Mercier, M., Mesple-Somps, S. (2015)	Mali	Education, health, water	Access, infrastructure	No
Chen, J. & Huhe, N. (2013)	China	Education, social welfare, transportation, agricultural infrastructure, health	Expenditures	No
Chhibber, P., & Nooruddin, I. (2004).	India	Club goods (salaries), infrastructure (electricity, drinking water)	Spending, Other - voter perceptions of quality	No

Chu, J. & Zheng, X-P. (2013)	China	Infrastructure, education	Expenditures	No
Churchill, Sefa Awaworyi, Janet Exornam Ocloo, and Diana Siawor-Robertson. (2017).	Cross-country	Social Services - Health	Health outcomes and Access	No
Cooray, A. (2014)	Sri Lanka	Education, health, roads, water, electricity	Access, infrastructure, outcome (health)	No
Cruz, Cesi, Julien Labonne, and Pablo Querubin. (2017).	Philippines	Social Services (Health, Food security, child care etc.)	Access	No
Czyzewski, Bazyli, Jan Polcyn, and Anna Hnatyszyn-Dzikowska. (2016).	Poland	Social Services - Education	Quality	No
D'Arcy, Michelle, and Marina Nistotskaya. (2016).	Democracies	Social Services (Health and Education) and Infrastructure	Composite index on quality of public goods, health and education expenditure and outcomes	No
d'Adda, Giovanna. (2017).	Colombia	Conservation	Player-strategy (with local context)	No
Deacon, R. (2009)	Cross-country	Education, environment, sanitation, roads, water	Access, infrastructure, outcomes	No
Deininger, K., & Mpuga, P. (2005).	Uganda	Infrastructure (broadly defined), social services (education, health)	Quality	No
Dell, M. (2010)	Peru	Education, roads	Infrastructure, education outcomes & attainment	No
Desmet, K., Ortuno-Ortin, I., Wacziarg, R. (2012)	Cross-country	Health, education, water, electricity, roads	Access, quality, infrastructure, infant	No

			mortality, immunization rates	
Desmet, Klaus, Ignacio Ortuño-Ortín, and Romain Wacziarg. (2017)	Cross-country	Infrastructure and Social Services	Composite index based on access and quality of ten public goods	No
Desmet, Klaus, Ignacio Ortuño-Ortín, and Shlomo Weber. (2017)	Cross-country	Infrastructure (Roads, and Sanitation) and Social Services (Health and Education)	Health and education outcomes and Access	No
Dickson, Bruce, Pierre Landry, Mingming Shen, and Jie Yan. (2016)	China	Social Services (Health and Education)	Expenditure	No
Dincă, Marius Sorin, Gheorghiţa Dincă, and Maria Letiţia Andronic. (2016)	Romania	Social Services and Infrastructure	Access/Supply	No
Dıaz-Cayeros, A., Magaloni, B., & Euler, A. R.	Mexico	Infrastructure (water, sanitation, electricity)	Access, Other - political participation	No
Duan, H. & Zhan, J. (2011)	China	Local public spending	Expenditures	No
Duquette-Rury, L. (2014)	Mexico	Public sanitation, drainage, water, electricity	Access	No
Egel, D. (2013)	Yemen	Education	Infrastructure	No
Enikolopov, R. & Zhuravskaya, E. (2007)	Cross-country	Health, education	Access, health & education outcomes	No
Faguet, J. P. (2004).	Bolivia	Broad - any government spending	Spending	
Fang, Wang, and Chen Shuo. (2017)	China	Social Services (Health and Education)	Access	No
Finnoff, Kade. (2016)	Rwanda	Social Services – Health	Enrolment in	No

			community health insurance, access to healthcare	
Foa, Roberto, and Anna Nemirovskaya. (2016)	US, Canada, Russia, and Brazil	Social Services (Health)	Infant Mortality Rate	No
Franck, R. & Rainer I. (2012).	Cross-country (Africa)	Education, Infant Mortality	Access, Outcomes	No
Gajwani, K. & Zhang, X. (2014).	India	Education, roads, sanitation, health	Access, infrastructure	No
Gennaioli, N. & Rainer, I. (2007)	Cross-country (Africa)	Roads, Health, Education	Infrastructure, access	No
Gibson, C. & Hoffman, B. (2013)	Zambia	Broad public expenditures	Expenditures	No
Gisselquist, R., Leiderer S., Nino-Zarazua M. (2016)	Zambia	Education, Health	Spending, enrollment, infrastructure, immunization and mortality rates	No
Glennerster, R., Miguel, E., & Rothenberg, A. D. (2013).	Sierra Leone	Infrastructure (roads, school facilities), social services (education)	Outcomes - Facilities built, community participation, etc.	Yes
Golooba-Mutebi, F. (2012).	Rwanda, Uganda	Infrastructure (water, sanitation)	Access	No
Gonzalez M. (2002).	Mexico	Public Infrastructure	Spending	No
Grigoriadis, Theocharis. (2017).	Russia	Public Goods Game (with local context)	Player Strategy	No

Grossman, G. (2014).	Uganda	Broad examples	Level of cooperative behavior	No
Habyarimana, J., Humphreys, M., Posner, D. N., & Weinstein, J. M. (2007).	Uganda	Broad - examples include low crime rates, access to drinking water	Other - Player Strategy	No
Han, Enze, and Christopher Paik. (2017)	China	Infrastructure - Electricity	Supply	No
He, Chunyan, Li Peng, Shaoquan Liu, Dingde Xu, and Peng Xue. (2016)	China	Efficiency of Public Goods Investment	Efficiency of Public Goods Investment	No
Hoop, T., Kempen, L. & Fort, R. (2012)	Peru	Health education (discuss broader applications as well)	Level of voluntary contribution	No
Huang, Jian, Longjin Chen, Jianjun Li, and Wim Groot. (2017).	China	Social Services- Health	Satisfaction with services	No
Huhe, N., Chen, J., & Tang, M. (2015)	China	Public health, social welfare, infrastructure	Access (water), expenditures (welfare & infrastructure)	No
Jack, B. & Recalde, M. (2015)	Bolivia	Education	Voluntary contributions	No
Jackson, K. (2013)	Cross-country (Africa)	Water, electricity, education	Access	No
Javaid, A. & Falk, T. (2015)	Pakistan	Water (irrigation)	Other - Player Strategy	No
Joshi, M. & Mason, T. (2011)	Nepal	Sanitation, education, health	Access, outcomes	No
Khwaja, A. (2009)	Pakistan	Infrastructure projects (irrigation, electricity, roads, walls)	Project maintenance by community	No
Kochar, A. (2008)	India	Education	Expenditures (number of teachers sanctioned for	No

			public primary school at village level)	
Kochar, A., Singh, K., & Singh, S. (2009).	India	Infrastructure (broadly defined), social services (education)	Spending	No
Kramon, E. & Posner D. (2016)	Kenya	Education	Education attainment	No
Kung, J., Cai, Y., Sun, X. (2009)	China	Education, infrastructure, water, electricity, other	Expenditures	No
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. (1999).	Cross-country	Infrastructure (broadly defined), social services (education, health)	Quality	No
Lee, M., Walter-Drop, G., & Wiesel, J. (2014)	Cross-country (Developing & Developed)	Health, education, water, electricity	Access, Health outcomes	No
Li, Y. (2014)	China	Education, health	Access, expenditure	No
Liu, Ying, Tang Yao, Yunli Bai, and Yu Liu. (2016)	China	Infrastructure – water	Service Provider	No
Lu, X. (2015)	China	Education	Spending	No
Luo, R., Zhang, L., Huang, J., & Rozelle, S. (2007).	China	Infrastructure (broadly defined), social services (education)	Spending	No
Luo, R., Zhang, L., Huang, J., & Rozelle, S. (2010).	China	Infrastructure (broadly defined), social services (education)	Spending	No
MacLean, L. M. (2011)	Cross-country (Africa)	Social services (health, education)	Access	No
Martinez-Bravo, Monica. (2017)	Indonesia	Social Services and Infrastructure	Access	No
Martinez-Bravo, Monica, Priya Mukherjee, and Andreas Stegmann. (2017)	Indonesia	Social Services (Health and Education)	Expenditure	No

Martinsson P., Villegas-Palacio C., & Wollbrant C. (2015).	Colombia		Other - Player strategy	No
Meng, X. & Zhang, L. (2011)	China	Local public spending	Expenditures	No
Meseguer, C. & Aparicio, F. (2012)	Mexico	Public Infrastructure projects (electrification, paving, water, roads, health, education, ecological preservation)	Spending	No
Miguel, E. (2004)	Kenya, Tanzania	Education, Sanitation, Water	Expenditures, infrastructure	Yes
Miguel, E., & Gugerty, M. K. (2005)	Kenya	Infrastructure (water facilities), social services (education)	Other - Participation in PGP activities and organizations	Yes
Milner, Helen, Daniel Nielson, and Michael Findley. (2016)	Uganda	Provider of Public Goods	Preference between government and foreign donor	No
Mu, R. & Zhang, X. (2014)	China	Broad public spending	Expenditures	No
Mussacchio, A., Fritscher, A., & Viarengo, M. (2014)	Brazil	Education	Expenditures	No
Nooruddin, I. & Simmons, J. (2015)	India	Development, education, civil administration	Expenditures	No
Okten, C. & Osili, U. (2004)	Indonesia	Community Organizations that produce a broad array of local public goods	Money & time contributions, prevalence	No
Olken, B. A. (2007)	Indonesia	Infrastructure (roads)	Spending, Other - Corruption	No
Olken, B. A. (2010).	Indonesia	Infrastructure (water, sanitation,	Access	No

		roads)		
Olken, Benjamin and Monica Singhal. (2009)	Cross-country	Informal taxation (community contributions)		No
Pal, Sarmistha, and Zaki Wahhaj. (2017)	Indonesia	Infrastructure and Social Services	Access	No
Pesqué-Cela, V., Tao, R., Liu, Y., & Sun, L. (2009)	China	Generic	Other - Participation in PGP activities and organizations	No
Petrick, M., & Gramzow, A. (2012).	Poland	Business (market access for farmers, pro-small business legislation, tourism development), infrastructure (telecommunications)	Access	No
Qian, Tao, and Qi Zhang. 2017.	China	Social Services (Health and Education) and Infrastructure (Roads)	Expenditure and Access/supply	No
Rosas, G., Johnston N., & Hawkins K. (2014)	Venezuela	Education, Social programs	Access (scholarships, Mercal stores)	No
Rosenzweig, S. (2015)	Tanzania	Electricity, Piped Water	Access	No
Sacks, A., & Levi, M. (2010)	Cross-country (Africa)	Food Security	Access	Yes
Sarkhel, P. (2015)	India	River embankments	Private expenditure on embankments	No
Sato, H. (2008)	China	Broad - not precisely defined	Spending	No
Shenoy, Ajay. (2018)	India	Infrastructure (Electricity,	Access	No

		Housing, Sanitation)		
Silva-Ochoa, E. (2009)	Mexico	Infrastructure (water, sanitation, electricity), social services (health, education)	Outcomes - literacy rate, child mortality, new sewer connections	No
Soifer, Hillel. (2016)	Ecuador and Colombia	Infrastructure (Railroad) and Social Services (Education)	Railroad Development and Literacy	No
Taale, Francis, and Christian Kyeremeh. (2016)	Ghana	Infrastructure - Electricity	Willingnes to Pay	No
Thachil, T. & Teitelbaum, E. (2015)	India	Development	Expenditures	No
Trotter, Philipp. (2016)	Sub-saharan Africa	Infrastructure - Electricity	Access	No
Tsai, L. L. (2007)	China	Infrastructure (water, roads), social services (education, etc.)	Access, Outcomes - Facilities built, etc.	No
Tsai, L. L. (2011)	China	Infrastructure (roads, irrigation, sanitation, electricity, telecommunication)	Other - Government assessment of ability to provide public good	No
Tu, Q., Mol, A., Zhang, L., Ruben, R. (2011)	China	Agriculture	Other - cooperation	No
Uchimura, H. & Jutting, J. (2009)	China	Health	Outcome (infant mortality)	No
Visser, M. & Burns, J. (2015)	South Africa	Fishing	Other - player strategy	No
Waring, T. (2011)	India	Irrigation	Access, quality	No
Wimmer, Andreas. 2016.	Asia and Africa	Social Services (Health and Education) and Infrastructure (Railroads)	Quality and access	No
Wong, Ho Lun, Yu Wang, Renfu Luo, Linxiu Zhang, and Scott	China	Infrastructure - Roads	Quality	No

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Xu, Y. & Yao Y. (2015)	China	Schooling, road & sanitation, electricity, irrigation, forestation	Spending	No
Yi, H., Hare, D., & Zhang, L. (2011).	China	Infrastructure (water, roads, irrigation), social services (education, health)	Spending, Access	No
Zeneli, Fjona. (2016)	Albania	Infrastructure - water	Demand	No
Zhan, J., Duan H., Zeng M. (2015)	China	Education, health care	Spending	No
Zhang, L., Luo, R., Liu, C., & Rozelle, S. (2006)	China	Broad - public goods projects	Projects (count)	No
Zhang, X., Fan, S., Zhang, L., & Huang, J. (2004).	China	Infrastructure (water, irrigation, roads, electricity), social services (education), transfers to poor	Spending	No
Zheng, S., & Kahn, M. E. (2012).	China	Transport, green space	Other - Gentrification	No
Zhu, Lin, and Yongshun Cai. (2016)	China	Social Services and Infrastructure	Access and Expenditure	No

*Table only includes laboratory or "laboratory in the field" experiments if they were tailored to specific institutional or organizational contexts. Such experiments are noted with an asterisk.
**Contains results of article searches using the term "public good" and "local public goods," using major academic search engines.

II. Further Background on Data Collection and Dataset Assembly:

The surveys were conducted to collect data not only to assess the aforementioned hypotheses about water allocations within utility networks, but also to assess the impact of a service providing households with advance notification regarding water arrival times. The study took the form of a cluster-randomized experiment, with clusters separated by 1-2 streets to avoid spillover effects. Within E3, we defined 10 low income and 20 mixed income blocks, and four clusters of similar socio-economic composition within each block. Within each cluster, we followed a systematic sampling plan with a skip of three between households on every street. This sampling method gave us 25 households per cluster, even though our clusters were small.

In the data analysis performed for this paper, we rely predominantly upon Wave 1 data. Wave 2 data was used in instances in which Wave 1 data was not suitable. Data used from Wave 2 includes one dependent variable (water pressure level) and two independent variables (the presence of a local leader and political party preference). Our Wave 1 survey did not ask about water pressure, but it was an important indicator to be studied. Nextdrop implementation should not have affected water pressure. Wave 1 data regarding presence of a local leader and party affiliation was unreliable because of unclear question wording, so we included improved questions in Wave 2. Since the presence of a local leader and political party preference were unlikely to change between wave 1 and wave 2, it did not present problems to use these data instead.

We placed our households in valve areas using household-specific GPS coordinates and the valve area boundary maps we obtained from NextDrop. Each household survey was conducted on a tablet computer. The surveys were programmed using Open Data Kit (ODK). We configured the ODK so that enumerators were forced to take 3 separate GPS readings for each household. These readings needed to reach 5-meter precision before the enumerator could proceed to conduct an interview. We averaged these three readings to obtain a more precise estimate for each household. We then used these averaged GPS coordinates to place households inside valve areas using QGIS, which assigned households to valve areas based on their coordinates.

Table A.II. Predictability of Water Supply in Eastern Bangalore, April-May 2015 (additional models)

	Whether water comes at a specific time[1]	
	Model 5[2]	Model 6[3]
HH level variables		
Elevation	-0.001	-0.0005
	(0.001)	(0.001)
Cauvery Supply	0.608***	0.224
	(0.201)	(0.494)
Muslim	0.277	0.258
	(0.188)	(0.166)
Low income	0.099	0.061
	(0.123)	(0.113)
VA level variables		
Elevation		-0.006
		(0.006)
Muslim		-0.329
		(0.565)
Urban Migrant		-0.736
		(0.870)
Low Income		2.458***
		(0.799)
Local leader		-0.170
		(0.269)
Constant	-12.118	4.106
	(192.269)	(5.458)
VA dummies?	Yes	No
N	2,641	2,511
R2	0.430	0.078
chi2	941.706*** (df = 121)	140.137*** (df = 9)

1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. 2) Model tolerance increased to 1 X 10^8. 3) Households with only CMC service dropped. Standard errors bootstrapped and clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Table A.III Water Supply Frequency, Eastern Bangalore, April-May 2015 (additional models)

	Interval between supply days[1]	
	Model 5[2]	Model 6[3]
y> =every 2 days		37.564***
		(9.502)
y> =every 3-4 days		35.233***
		(9.533)
y> =every 4-5 days		32.577***
		(9.434)
y> =every 6+ days		31.991***
		(9.436)
HH level variables		
Elevation		-0.0001
		(0.001)
Cauvery Supply		0.399
		(0.427)
Muslim		0.029
		(0.111)
Low income		0.023
		(0.079)
VA level variables		
Elevation		-0.037***
		(0.010)
Muslim		1.795**
		(0.913)
Urban Migrant		1.483
		(1.074)
Low Income		-2.599**
		(1.149)
Local leader		0.049
		(0.391)
Constant		
VA dummies?		No
N		2,574
R^2		0.166
chi^2		427.389*** (df = 9)

1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. 2) VA fixed effects model will not converge even if tolerance increased to 1 X 10^8. 3) Households with only CMC service dropped. Standard errors bootstrapped and clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Table A.IV Duration of Water Supply, Eastern Bangalore, April-May 2015 (additional models)

	Duration of water when it comes on[1]	
	Model 5[2]	Model 6[3]
y> =every 2-3 hours	2.616***	2.103
	(0.979)	(4.358)
y> =3-4 hours	0.523	0.471
	(0.977)	(4.342)
y> =4+hours	-1.133	-0.826
	(0.978)	(4.337)
HH level variables		
Elevation	-0.001	-0.0002
	(0.001)	(0.001)
Cauvery Supply	0.469***	0.251
	(0.142)	(0.242)
Muslim	0.081	0.058
	(0.135)	(0.170)
Low income	0.051	0.089
	(0.088)	(0.085)
VA level variables		
Elevation		-0.001
		(0.005)
Muslim		-0.443
		(0.668)
Urban Migrant		0.792
		(0.628)
Low Income		-0.358
		(0.560)
Local leader		-0.405*
		(0.240)
VA dummies?	Yes	No
N	2,669	2,542
R^2	0.382	0.033
chi^2	1,179.562*** (df = 121)	80.634*** (df = 9)

1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. 2) Model tolerance increased to 1 X 10^8. 3) Households with only CMC service dropped. Standard errors bootstrapped and clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Table A.V Prevalence of Supply Cancellations, Eastern Bangalore, April-May 2015 (additional models)

	Whether or not service is cancelled on supply days[1]	
	Model 5[2]	Model 6[3]
y> =rarely	-0.760	6.832
	(1.009)	(4.878)
y> =yes	-2.329**	5.552
	(1.010)	(4.867)
y> =4+hours	0.001	0.0003
	(0.001)	(0.001)
HH level variables		
Elevation	-0.398***	-0.258
	(0.148)	(0.218)
Cauvery Supply	-0.241	-0.264
	(0.156)	(0.196)
Muslim	0.067	0.016
	(0.099)	(0.095)
Low income		-0.006
		(0.005)
VA level variables		
Elevation		0.212
		(0.446)
Muslim		-1.812***
		(0.653)
Urban Migrant		-0.357
		(0.508)
Low Income		-0.126
		(0.220)
VA dummies?	Yes	No
N	2,317	2,205
R^2	0.287	0.032
chi^2	679.818*** (df = 121)	62.735*** (df = 9)

1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. 2) Model tolerance increased to 1 X 10^8. 3) Households with only CMC service dropped. Standard errors bootstrapped and clustered at the valve area level.
*p < .1; **p < .05; ***p < .01

Table A.VI Water Pressure, Eastern Bangalore, April-May 2015 (additional models)

	Water pressure level[1]	
	Model 1[2]	Model 2[3]
y> =moderate	1.514	3.004
	(1.215)	(3.663)
y> =strong	-2.752**	-0.857
	(1.217)	(3.670)
HH level variables		
Elevation	0.0004	0.0005
	(0.001)	(0.001)
Cauvery Supply	0.301	0.294
	(0.185)	(0.205)
Muslim	0.274	0.254
	(0.177)	(0.261)
Low income	-0.085	-0.047
	(0.116)	(0.106)
VA level variables		
Elevation		-0.002
		(0.004)
Muslim		-0.187
		(0.434)
Urban Migrant		-0.125
		(0.446)
Low Income		0.848
		(0.570)
Local leader		-0.248
		(0.197)
VA dummies?	Yes	No
N	2,260	2,159
R^2	0.167	0.011
chi^2	317.896*** (df = 121)	19.253** (df = 9)

1) Ordinal logistic regressions were used to estimate outcomes. A positive log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable increases. In the same way, a negative log odds coefficient indicates that as the value of the independent variable increases, the likelihood of being in a higher category of the dependent variable decreases. 2) Model tolerance increased to 1 X 10^8. 3) Households with only CMC service dropped. Standard errors bootstrapped and clustered at the valve area level.
*p < .1; **p < .05; ***p < .01