Pre-Analysis Plan

The Household Welfare and Political Impacts of Increasing Service Predictability: An Experimental Intervention in Bangalore's Water Sector

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Abstract: Throughout the developing world, intermittency and unpredictability are the hallmarks of public service delivery: buses do not run on a standard schedule, water supplies are variable in terms of arrival times, and electricity blackouts occur unexpectedly. Surprisingly, the causes and consequences of unpredictable urban services have received much less attention than patterns of access to, or government expenditures on, these services. While addressing the underlying causes of service unpredictability tends to be very costly (e.g., replacing leaky water pipes or increasing capacity to improve water pressure levels), low-cost informational interventions can potentially help households to cope with service unpredictability. Alleviating coping costs may also change the way in which citizens relate to their local governments.

Through a cluster-randomized experiment in Bangalore, we will evaluate a text-message based notification scheme providing households with advance warning of the timing of water services and supply cancellations, and a dedicated contact number for reporting problems. We assess whether the notification system reduces: a) the time spent waiting for water; b) expenditures on substitutes for piped water services; and c) stress levels on account of uncertain and irregular deliveries and uncertainty. We hypothesize that lower-income households will see greater welfare impacts because they have few affordable and accessible alternative water sources. We also examine if, and how, the receipt of real-time information changes how citizens "see the state," whom they hold responsible for service quality and problems, and whom they approach about service concerns. We hypothesize that the advance notification system will prompt citizens to see the state as more modern and responsive when compared with the status quo, in which the state can only be accessed through intermediaries and low level bureaucrats. This research thus develops a framework within which the material, stress-related, and political impacts of greater predictability in urban services can be assessed.

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Introduction

Throughout the developing world, intermittency and unpredictability are the hallmarks of public service delivery: buses do not run on a standard schedule, water supplies are variable in terms of arrival times, and electricity blackouts occur unexpectedly. For instance, worldwide, 400 million people rely on intermittent water, often receiving services only a few days a week for a few hours (van den Berg and Danilenko 2011). The poor state of the underlying urban infrastructure—prone to unexpected pipe leaks and power outages that put pumps out of service—often means that services are not only intermittently delivered, but are also unpredictable. Yet the causes and consequences of unpredictable urban services have received much less attention than patterns of access to, or government expenditures on, these services.

Service unpredictability can be particularly onerous for low-income populations. Relying on buses that do not arrive on time or on a standard schedule can make it difficult to consistently arrive at work on time; lower income populations who cannot afford substitutes such as personal cars or private taxis are more likely to develop reputations for unreliability with employers under such circumstances.[1] Coping with electricity blackouts is also more difficult for poorer households, who often cannot afford private generators.[2] Similarly, low-income households receiving intermittent and unpredictable water services suffer in a number of ways: they must spend time waiting at home for water arrival so as to be able to fill household storage containers, as substitutes such as vended water tend to be much more expensive than municipal water. Higher income households, in contrast, can afford pumps that automatically fill household tanks when water services commence, as well as the load-bearing roofs that such tanks require.

There are many reasons to believe that service unpredictability, in addition to imposing material and financial hardship, also weakens bonds between individuals the state. Citizens who cannot depend upon regular services, one might argue, will be less likely to view government service providers as competent and respectful of citizen concerns. If citizens must attempt to contact low-level bureaucrats or local political bosses on multiple occasions in order to obtain information regarding when services might resume, such feelings will only be magnified. Often, lay citizens do not know whom to contact at all. Under such circumstances, we would also expect citizens receiving unpredictable services to be far less willing to pay user fees--especially ones in line with delivery costs--than those receiving services with regularity.[3]

This project examines the effect of increasing service predictability on household welfare and on citizens' relationship with the local state. It does so through an impact analysis of an information-based intervention being piloted in India's water sector. Through a cluster-randomized experiment in Bangalore, we evaluate the impact of a service developed by a social enterprise called NextDrop, which provides households with text message notifications regarding water arrival times and supply cancellations. Water utilities in urban India typically do not possess sensors that allow them to monitor exactly where water is within their network, so NextDrop has developed a novel system

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[1] E.g. Smith (2007).

[2] United Nations Development Programme. 2010. Human Development Report. New York: UNDP.

[3] See, for instance, Savedoff and Spiller (1999) regarding the water and sanitation sector.

in which the utility employees, who operate the valves allowing water to flow into areas of 50-200 households, notify them when they are opening and closing valves. NextDrop then sends notifications to individual households, which they have cataloged by "valve area" through the collection of household GPS coordinates, letting them know when their water will arrive.

Our field experiment—which is taking place in the context of NextDrop's rollout in Bangalore—examines two sets of potential impacts. The study is designed to assess household level welfare impacts such as: a) the time spent waiting for water; b) expenditures on substitutes for piped water services; and c) stress levels on account of uncertain deliveries. The study will also examine how (and if) NextDrop delivery notifications impact how citizens "see the state," [4] whom they hold responsible for service quality and problems, and whom they approach about service concerns.

This paper proceeds as follows. First, we provide a more thorough description of the intervention to be evaluated. We then locate our study within the theoretical perspectives that inform our hypotheses. We proceed to outline the main hypotheses we will examine in the course of the study with respect to our outcomes of interest, including our expectations regarding heterogeneous treatment effects. Finally, we describe our research design and review the power calculations used to determine sample size, and the allocation of our sample between different populations of interest.

The Intervention Our Study Will Evaluate

We evaluate the impact of a particular intervention that may increase the predictability of urban services: text-message based notifications regarding the timing of water delivery in intermittent water systems. NextDrop, a start-up venture launched by recent UC Berkeley graduates (among others), has developed and initiated an SMS-based notification system to help consumers and small businesses reduce the coping costs of water intermittency. NextDrop's cell-phone based system is innovative in its use of employee- and crowd-sourced data collected through low-cost and ubiquitous cell phones. The notification system potentially represents a more reliable form of information to households regarding when water will be available than the published schedules in newspapers or on the walls of local service stations, which our preliminary data collection in Bangalore suggests depart significantly from actual practice.

NextDrop obtains information regarding the timing of water delivery in particular "valve areas" of 50-200 households by collecting water flow information from valvemen—the individuals responsible for opening and closing the valves controlling water into particular districts—and disseminating notifications to NextDrop customers 30 minutes to an hour before the water turns on. The notifications are provided free of charge to households.[5]

NextDrop has already piloted their system in a second-tier Indian city, Hubli-Dharwad (population 1 million), in the southern Indian state of Karnataka. The enterprise

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[4] Corbridge *et al*. (2005).

[5] NextDrop's revenue model involves charging utilities for information-based services, including real-time information of water flows and sending water arrival notifications to consumers.

has since refined its incentive schemes for valvemen (whose cooperation is essential for the accurate data collection),[6] refined the ability to notify customers via a geocoding system and created a 'dashboard' for the utility for real-time information about water flow and allocation within the system. It is currently rolling out services in the cities of Mysore and Bangalore.

Theoretical Discussion and Hypotheses

This project draws on two literatures that speak to the potential effects of improving the predictability of urban services—and NextDrop's notifications in particular—on: a) household welfare; and b) citizens' relationship with the state. Building on these literatures, we propose to examine eight related hypotheses regarding household welfare effects and six on political effects.

A. *Household Welfare Effects*

The water policy literatures suggest that intermittent water supply imposes significant costs on households. While some researchers have studied the effects of water service intermittency on water quality and human health (e.g. Kumpel and Nelson 2013; Ercumen *et al*. forthcoming), few have quantified or modeled the coping costs and inefficiencies of unreliable water deliveries.[7] This is the first study, to our knowledge, that will empirically estimate the impacts of greater predictability of intermittent water services. Our hypotheses thus build on a broader literature, including behavioral economics and development studies.

The first set of costs we examine relate to the time spent waiting for water services to commence. In low income households that cannot afford maids or automatically-filling storage tanks, household members—and particularly women—may need to restrict their activities to the household for substantial periods of time in order to ensure they are at home, and thus able to store water, whenever water services commence (e.g. Zérah 2000). The "waiter" thus devotes time to waiting for water that might otherwise be spent on work, community activities, religious functions, etc. Receiving notifications regarding the time of water delivery on a given supply day, or a notification of supply cancellation, it stands to reason, would reduce the amount of time spent waiting and allow more time for these other activities. This leads us to a first set of hypotheses:

H1: Household members in charge of managing a household's water supply will spend less time waiting for water on a weekly basis if they receive accurate prior notifications regarding delivery times and service disruptions.

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[6] The accuracy of valvemen reports is monitored through a system of callbacks with consumers. We are evaluating the efficacy of alternative incentives schemes for the water utility's valvemen in a related project.
[7] For exceptions, see Zérah (2000) or Baisa *et al*. (2010).

H2: *Household members in charge of managing water supply will be better able to participate in community, social, or religious activities if they receive accurate prior notifications regarding delivery times and service disruptions.*

H3: Household members in charge of managing water supply will be less likely to forego earnings if they receive accurate prior notifications regarding delivery times and service disruptions.

The literature on urban water supply also documents the extent to water obtained through a city's piped water network costs less than substitutes such as bottled water and bulk water from water vendors (e.g. Estache *et al*., 2001). Obtaining substitute sources, especially at short notice, requires time and energy spent fetching and carrying water from wells, or arranging for special deliveries with vendors, etc. (Kjellén and McGranahan 2006). In light of these studies, we would expect that notifications regarding the timing of water delivery would reduce the necessity to rely upon substitutes, because they would decrease the probability of missing a supply period. This leads us to a second set of hypotheses:

H4: Receiving accurate prior notifications regarding water delivery times and service disruptions will reduce household expenditures on substitutes, such as bottled, vended or tanker water.

H5: Receiving accurate prior notifications regarding water delivery times and service disruptions will reduce the effort households spend securing alternative sources of water.

Finally, waiting for water and supply unpredictability may impose psychological costs. Given that water is such a vital resource for households, and that substitutes for piped water can be much more expensive or less desirable, the household member responsible for obtaining and managing a household's water supply may incur a great deal of stress when services are unpredictable or water storage cannot be planned. This argument builds directly on empirical studies of water stress (e.g. Wutich and Ragsdale 2008), as well as the behavioral economics literature, which has shown that many dimensions of poverty impose cognitive and other stresses upon the poor (e.g. Mullainathan and Shafir 2013). Such stresses manifest themselves in a number of ways: consciously worrying about water provision, preoccupation (i.e. thinking about water delivery while doing other things), or stress incurred through the hassle of repeatedly trying to obtain information regarding supply timing from street level bureaucrats or local intermediaries. This leads us to a third set of hypotheses:

H6: Receiving accurate prior notifications regarding water delivery times and service disruptions will reduce respondents' sense that missing or delayed water supply is a constant worry.

H7: Receiving accurate prior notifications regarding water delivery times and service disruptions will reduce the extent to which respondents finding themselves thinking about water supply while doing other things, such as household chores or paid work.

H8: Receiving accurate prior notifications regarding water delivery times and service disruptions will reduce the effort households must expend to secure important information regarding the timing of water deliveries.

While we hypothesize that these effects may be observable across the entire urban population in developing country cities with water intermittency, we expect these effects to be particularly pronounced under certain circumstances:

- For *low-income households*, because the cost of substitutes for piped water as a fraction of household income is greater, and because poverty itself exacerbates stress (see Mullainathan and Shafir 2013). We will measure income not only in terms of monthly cash income, but also in terms of the types of assets that a household possesses. Income may correlate strongly with religion or scheduled caste/tribe status; if so, we are likely to observe that effects vary along these lines as well);
- For *households living in structures without automatically-filling overhead tanks*, which often cannot be supported in 1-2 level structures of poor construction quality;[8]
- For *households where someone spends a significant amount of time waiting or worrying about water* prior to the intervention. (We expect this to be closely related to the above conditions.)
- For *households receiving water services that typically arrive on a scheduled supply day within an interval of less than 4 hours*. Our intuition is that notifications are most useful when they occur within an interval of four hours or less, because individuals would be more likely to stay at home and wait for water under such circumstances. If arrival times are less predictable than this, household members are unlikely to stay at home waiting for the water to arrive.
- In *households where the person responsible for managing and storing water is of working age*, and especially where this person is a male of working age, receiving accuracy notifications from NextDrop may reduce the economic cost of water intermittency. On the other hand, stress levels for women "waiters" may be reduced more dramatically than those for male "waiters" because domestic water is traditionally a "female" responsibility. Therefore if the water does not arrive on time, or does not arrive at all, it is more likely to be the female head-of-household who will need to find alternative sources.

We thus expect to observe *heterogeneous treatment effects* when we subset our analysis according to these intuitions.[9]

B. Political Effects

[8] There may be overlap between low-income households and households living without automatically filling storage tanks.

[9] In some cases we may not have sufficient sample size for heterogeneous treatment effects to be visible or statistically significant.

In this project, we also ask whether--even in the absence of substantive service improvements, such as better water quality, or more frequent deliveries--better information alone lead to a more favorable view of the local state and its agencies. In doing so, we build on a broader literature investigating what determines how citizens "see" and relate to the state (Corbridge *et al*. 2005; Ferguson and Gupta 2002; Evans 2008). This question connects both the political science and public goods literatures to a rich body of research on the role of information, and information technologies, in development. Here it has been argued that better information, through information technologies, on government schemes, commodity prices, or water quality, directly influences citizens' views of the state (though not necessarily in a positive direction) (Madon and Sahay 2002; Tolbert and Mossberger 2006).

Our first intuition is that increasing the predictability of services will lead citizens to revise their judgments of state competence. Even if services are still delivered intermittently, and with less frequency than citizens may desire, receiving accurate, prior information regarding service timing (and cancellations) should not only make services easier to access, but also convey greater state capacity and control. In addition, the innovative application of text messaging to disseminate service schedule information to citizens could make the state seem more "modern," and thus further improve citizen perceptions of governmental competence (Harriss 2006; Kuriyan and Ray 2009; Ghertner 2011). This leads us to the following hypotheses:

H9: Receiving accurate prior notifications regarding water delivery times and service disruptions will improve citizen perceptions of the competence of state water providers.

H10: Receiving accurate prior notifications regarding water delivery times and service disruptions will lead citizens to perceive state water providers as more innovative and modern than previously.

We also expect notifications that increase service predictability to shift citizen perceptions regarding who is responsible for addressing their concerns regarding services, and the state's level of universalism. The literature on citizen-state interactions in the developing world suggests that citizens (and especially low and middle income populations) tend to turn to lower level bureaucrats or political intermediaries regarding service problems.[10] When such mechanisms do not work, a group of households and community leaders may collectively protest at government offices.[11] These patterns may slowly shift with the introduction of a universally administered notification system that connects citizens more directly to the urban service provider. Citizens are more likely to view government agencies themselves, rather than their local intermediaries, as responsible for addressing their problems, and redirect their complaints (or lodge additional complaints) with government bureaucracies.

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[10] On the Bangalore case, see Ranganathan (2014); on the importance of intermediaries within clientelistic party systems in the developing world, see Stokes *et al*. (2013) for a review.

[11] See Ranganathan (2014) regarding water protests in Bangalore; see also Auerbach (2014) regarding urban services in Northern Indian cities.

This shift will be tied, at least in part, to an increasing sense that notifications are sent not just to favored groups, but also to marginalized populations. It will also stem from the fact that information is arriving automatically, without effort on the part of the citizen; it no longer requires cumbersome and time-consuming efforts to proactively solicit information—which may even involve reliance upon personal connections, favors, or bribes. To the extent that this perceptual shift occurs, we would expect that more people will lodge individual (rather than group-only) complaints, thinking that their complaints will be heard. These intuitions lead us to the following hypotheses:

H11: Receiving accurate prior notifications regarding water delivery times and service disruptions will lead citizens to be more likely to perceive state water providers as more universalistic service providers that care about "people like us."

H12: Receiving accurate prior notifications regarding water delivery times and service disruptions will lead citizens to view state water providers as directly responsible for correcting service problems than previously, when local political leaders and/or intermediaries might have been held responsible.

H13: Receiving accurate prior notifications regarding water delivery times and service disruptions will lead citizens to be more likely to contact the central water bureaucracy directly (through text or phone) than previously.

Building on the preceding arguments, it stands to reason that when water utility services become easier to utilize because they become more predictable, and as perceptions of state competence and universalism increase, citizens may be more disposed to pay for services. This line of argument is consistent with, yet extends, the consensus in the urban water literature, which suggests that poor service quality detracts from consumer willingness to pay for services (Whittington, et al 1990; Hensher, et al 2005). These intuitions also build on the literature on the politics of the welfare state, which suggests that citizens of countries with more universalistic welfare states are more supportive of devoting general tax expenditures to social services *because* they perceive themselves as benefiting or potentially benefiting from the service regime (e.g. Esping-Anderson 1990). Hence, we may observe the following:

H14: Receiving accurate, prior notifications regarding water delivery times and service disruptions will lead citizens to pay their water bills at a greater rate than citizens who *do not receive such notifications.*

While we hypothesize that these effects may be observable across the entire urban population in developing country cities with water intermittency, we expect these effects to be particularly pronounced under certain circumstances:

- For *marginal households (low income, religious minority, low caste, etc.)*, because they are less likely to have had influential political intermediaries prior to the intervention.[12]
- For *low-income households living in structures without automatically filling overhead tanks* (see previous section)
- For *households where someone spends a significant amount of time waiting or worrying about water* prior to the intervention. (We expect this to be closely related to the above conditions.)
- For *households receiving water services that typically arrive on a scheduled supply day within an interval of less than 4 hours*. Our intuition is that notifications are most useful when they occur within an interval of four hours or less, because individuals would be more likely to stay at or near home and wait for water under such circumstances. If arrival times are less predictable than this, household members are unlikely to stay close to home waiting for the water to arrive.
- For *effects to vary by neighborhood* type (level of cohesion, presence of neighborhood association, etc.)[13]

As in the previous section, then, we expect to observe *heterogeneous treatment effects* when we subset our analysis according to these intuitions.

Research Design

The effects of this informational intervention will be assessed in the context of a cluster-randomized experiment to be conducted in Bangalore, India, between May 2015 and December 2015. This section provides more detail on the nature of the intervention to be evaluated, the rationale chosen for our study site, our randomization and sampling strategy, the specific indicators to assess the variety of impacts we have outlined above, and power calculations for determination of sample size.

A. *Study Site and Timeline*

We will evaluate the hypothesized household-level impacts of NextDrop's services in the context of its ongoing rollout in the Indian city of Bangalore, a megacity of over 8 million, often called India's Silicon Valley. NextDrop signed a memorandum of understanding with the state water utility providing water and sanitation services in the city, Bangalore Water Supply and Sewerage Board (BWSSB), in May 2014, allowing it to collect information from BWSSB valvemen and provide notifications throughout the city.

Our research design takes advantage of the fact that NextDrop's rollout is taking place in stages. We focus our evaluation on a portion of the city where NextDrop does not yet operate: BWSSB's E3 subdivision, a socio-economically diverse district (roughly

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[12] We expect this to be the case even though recent studies suggest that India's marginal populations are now better able to exert pressure upon the state than previously (e.g. Corbridge *et al*. 2005; Banerjee & Somanathan 2007).

[13] We are currently assessing whether or not it will be possible for us to gather data on relevant neighborhood characteristics.

20 km squared) in the eastern part of the city. Because NextDrop is required to serve at least 2/3 of the city by the end of 2014 under the terms of a DFID grant—in addition to the firm's desire to respond to BWSSB's request to roll out quickly—we were asked to restrict our evaluation to only one of the utility's 32 subdivisions. Exploratory fieldwork during summer 2014 increased our confidence in our original intuitions that the impact of NextDrop's services were likely to be higher in low income areas with residential structures of 1-2 stories, and where water delivery is variable in timing (yet not *completely* unpredictable). We thus sought a utility subdivision that contained a diverse population (where roughly 1/3 of our sample could be drawn from the bottom third of the city's income distribution), and that still possessed a reasonable number of low rise structures—a type of building environment that is growing less common in megacities like Bangalore, but is typical of urban India more generally. We limited ourselves to consideration of subdivisions that BWSSB had not specifically requested NextDrop to expand into immediately, because we did not want our research to interfere with NextDrop's relationship with Bangalore's water utility.

After review of the limited (and only somewhat accurate) available government data on low-income settlements and population densities in Bangalore, and extensive site visits throughout the city in the summer and fall of 2014, we chose utility subdivision E3. This subdivision possessed the ideal combination of some low-rise residential neighborhoods, as well as several low and middle-income neighborhoods of sufficient size.[14] Our estimates suggest that approximately 20% of the area's residents – who include recent migrants from Tamil Nadu and Andhra Pradesh -- could be classified as Bangalore's bottom third of the income distribution. We estimate that roughly 25% of the population lives in low-rise structures (and therefore do not have overhead water tanks). Residents receive services 1-2 times a week, which is typical for urban India and also frequent enough that it is likely we will observe the notifications having an effect on our outcomes of interest if they are indeed useful for households. The area thus promises to allow us to analyze how the impact of NextDrop's intervention may vary according to the variety of criteria we outline, and in a setting that is reasonably representative for urban India.[15]

The main means of evaluating the effects of the intervention involves two surveys to the treatment group as well as to the control group, a baseline one prior to the intervention and a follow-up one for both groups after the treatment group has received services for 6 months. We will conduct the baseline survey and enroll households into the survey in May of 2015. We will then conduct the follow-up survey in November of 2015.We chose to run the trial for 6 months because this will allow households sufficient time to adapt their daily routines to the service. Allowing the trial to run longer would mean that we risk losing a larger portion of our study participants due to household moves, etc.

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[14] As subsequent sections will explain, we employ a skip of 3 between sampled households, which increases the size of the low-income areas required to obtain a sufficiently large sample from low-income groups.

[15] Data from our baseline survey will allow us to compare in more precise terms the E3 population with the Indian urban population more generally.

B. *Varying Treatment "Dosage"*

We make three disclaimers about the nature of the "treatment" in BWSSB subdivision E3. As mentioned above, NextDrop depends on the water utility's valvemen to send it information regarding water valve opening and closing times. NextDrop is working closely with both the valvemen and BWSSB to ensure that information is actually sent to NextDrop in the first place, and that such information is completely accurate. Yet the accuracy of this information cannot be assumed, and must be investigated explicitly—something that we will do in this study through questions in our follow-up survey. We expect that notifications will have a greater effect when they are accurate.

Second, NextDrop only provides notifications for water supplied by Bangalore's central water utility, BWSSB. Bangalore, however, has been growing outwards for several decades and has been incorporating existing townships and municipalities into its borders. As a result, households in some areas—including some within E3—receive piped water from both the main BWSSB network and a local source.[16] In such cases, NextDrop only provides notifications for water supplied by BWSSB. This means that while some households in Bangalore will receive notifications on every water supply day, others may only receive notifications every second supply day. Therefore, we must also investigate the frequency of NextDrop notifications relative to the frequency of supply.

Third, NextDrop notifications may not always arrive a significant amount of time before water services commence. NextDrop estimates that notifications arrive 30 – 60 minutes before water service commence in Bangalore, but given that our study is taking place in a new area, detailed data on the elapsed time between notifications and water services is unavailable. There may also be some variation within E3 associated with differing distances between households and the main valve for a particular valve area. We will obtain data on the amount of warning households typically receive through their NextDrop notifications through our follow-up survey. We expect that households receiving notifications more in advance will value them more.

We plan to obtain data on the accuracy, frequency, and timing of NextDrop's services in order to examine the extent to which households receive varying "doses" of our treatment through specific questions in our follow-up survey. We conceive of the largest "dose" as one consisting of accurate and frequent notifications issues more than 30 minutes before water arrives. If significant variation exists, we will examine the extent to which stronger effects as associated with larger "doses" of our treatment. As this "dosage" is likely to vary mainly with some variable related to geography, we may use propensity score analysis to estimate counterfactuals through a single scalar of

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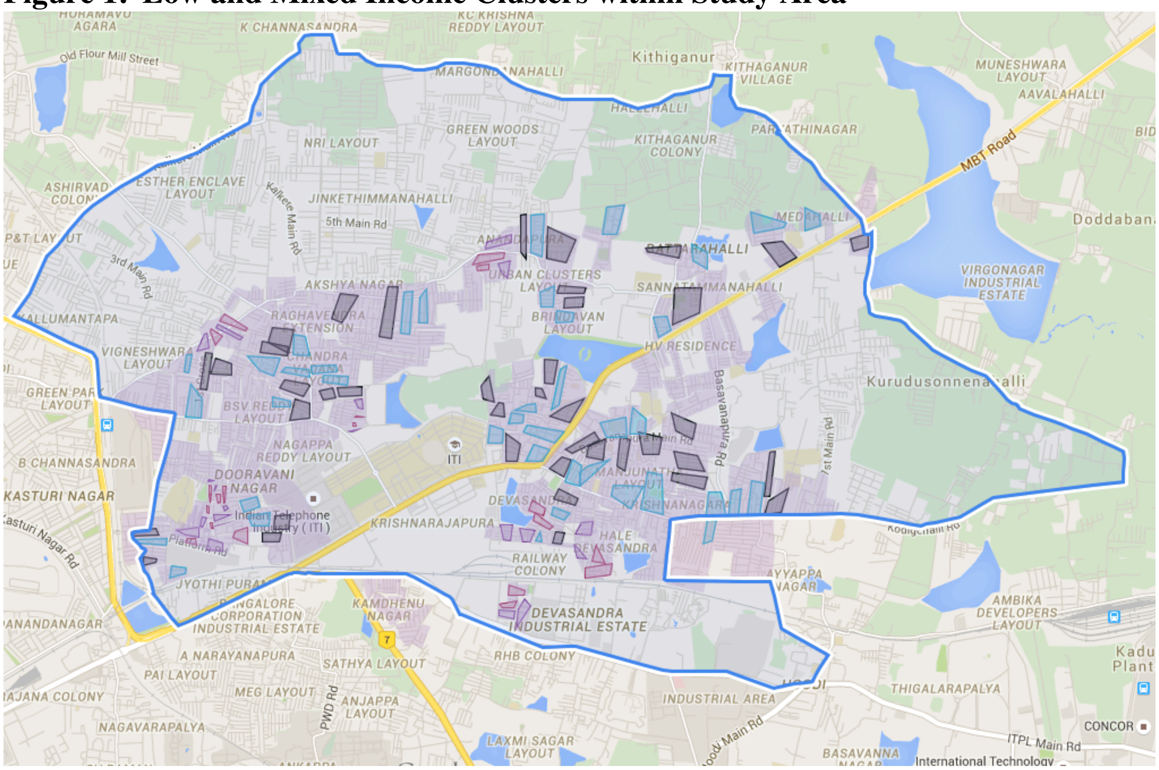
[16] BWSSB supplies households with piped water from two sources in E3: "Cauvery" or "Kaveri" water (surface water from the Cauvery river) and "CMC water" (water piped from local borewells). CMC water used to be administered by local municipalities. Following the Bangalore government's annexation of outlying towns, BWSSB has been assuming control of CMC systems. It is in the process of assuming responsibility for the CMC systems in E3. In E3, NextDrop trains valvemen to send notifications for Cauvery water, and for CMC water where no Cauvery water is supplied. Where households receive both Cauvery and CMC water, BWSSB valvemen only send notifications for Cauvery water.

propensity scores (Imbens 2000; Joffe and Rosenbaum 1999; Rosenbaum and Rubin 1983).

C. *Randomization and Sampling Strategy*

Within BWSSB subdivision E3, we are evaluating the impact of NextDrop's services through a cluster-randomized experiment. We chose a cluster-randomized design, rather than one with household-level randomization, because of concerns regarding information sharing between treatment and control households.[17] The 120 clusters of households in our study are separated from one another by at least two streets so as to create a physical buffer preventing information sharing between our treatment and control groups (see Figure 1). Within each cluster, we will utilize systematic sampling—i.e., employing a skip—between households in order to choose study participants. After piloting the survey in low-income areas, we decided that a skip of at least 3 between households would be sufficient to avoid "group interview" sessions in which neighbors group together to help respondents answer survey questions.

Figure 1. Low and Mixed Income Clusters within Study Area



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

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[17] Our concerns regarding interference under household-level randomization were heightened when we conducted a small phone survey of existing NextDrop consumers in utility subdivision NE3, which specifically asked if information was shared with immediate neighbors. Small survey pilots in E3, conducted by the authors, also found that information of various types is shared between immediate neighbors, particularly in low-income neighborhoods.

clusters (treatment and control), while black and blue polygons denote mixed income clusters (treatment and control). There are four clusters per block.

Because blocking on a variable associated with the outcome of interest can improve the precision of causal estimates in the context of cluster-randomized experiments (Imbens 2011), we employed a geographic approach to stratification, or "blocking." Based on site surveys, we designated 30 geographic areas with a particular socio-economic character, either low income (10 blocks) or mixed income (20 blocks). We expect blocks in either one of these two categories to be similar not only in socio-economic terms, but also in terms of the state of the underlying water infrastructure. By blocking on socio-economic geography, we thus lay the groundwork for analyses of subsets of the data corresponding to areas where we expect to observe stronger effects: areas with poorer residents and with poorer quality water infrastructure.

Blocks were designated by our survey research organization following preliminary fieldwork by our team based on extensive site visits throughout E3.[18] Within each of these blocks, we outlined four clusters separated by two streets or lanes from one another.[19] Cluster boundaries were drawn so that clusters within a block were very similar to one another in terms of socio-economic mix. Within each block, we randomized two clusters to treatment and two to control. As mentioned above, within each cluster, survey enumerators will visit every third household. For both treatment and control groups, interviews will be conducted with the person responsible for managing and storing water for the household. Enumerators will interview a constant number of respondents per cluster.[20] GPS coordinates will be collected for each household to ensure compliance with the cluster design, to allow for the enrollment of treatment households in NextDrop's system (and especially the correct placement of treatment group members in valve areas), and facilitate follow-up surveys after six months.

Noncompliance is always a challenge for experimental researchers. In the case of this evaluation, the concern is that some households in our treatment group may not desire to enroll in NextDrop's notification services when our survey enumerators give them the opportunity to do so. In theoretical terms, what is of most interest to us is the impact of receipt of NextDrop notifications upon those that genuinely want to receive them, or the compliers. We will therefore employ a placebo design that involves asking

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[18] As mentioned previously, fine-grained census data on income does not exist for urban India. Our team therefore relied on visual cues such as dwelling type, number and type of vehicles parked along streets, and conversations with local residents to designate low and mixed income blocks.

[19] We include four clusters per block rather than two (the pairwise approach to blocking), following Imbens (2011).

[20] Note that attrition between wave 1 and wave 2 may mean that final counts will differ a little bit between clusters. Analyses will be weighted to account for this. The aim, however is equalize the N per cluster. We are collecting phone numbers for households in both the treatment and control group, which should help us avoid uneven attrition between treatment and control if treatment group members are enabled to work more outside the home because of NextDrop's notifications. (Individuals can be contacted via phone and enumerators can meet them after work.)

respondents in both treatment and control group households whether they would like to receive notifications *when services are available in their area*, and will collect contact information for "compliers" in both the treatment and control group. NextDrop will enroll the treatment group compliers as soon as they receive their mobile phone numbers and GPS coordinates; they will then enroll the control group compliers in their system after six months, after we have conducted the follow-up survey that will be used for our impact analysis and collected other related data (details below, section E)). This research design will thus allow us to not only calculate treatment effects utilizing the ITT, but also calculate the Complier Average Causal Effect (CACE).

D. *Power Calculations*

Our power estimates focus on *one* of our outcome variables: reductions in the amount of time spent waiting for water on a weekly basis.[21] We focus on wait time because any changes in this are likely to generate changes in other outcomes of interest, such as stress levels and political attitudes. It is also an outcome measure for which we could obtain preliminary data prior to our study. Analyses regarding sample size, including the allocation of households between low-income and other clusters, were calculated on the basis of our preliminary estimates of the effects for the sub-population that we hypothesize will be most affected: low-income households, and particularly those living in low-rise structures. Based on our site visits to E3, and census data, we identified five major low-income areas, which could be divided into *10 blocks, each containing 4 clusters* of similar socio-economic character. (Making clusters smaller would not have been feasible given the small size of these areas, the need to accommodate at least four clusters within each low-income area for blocking, and the need to leave two streets between clusters to prevent information sharing.)

In addition to the number of clusters, we also need estimates for the size and spread of the effects we hope to capture through our study. Unfortunately, prior surveys on wait times for water in Bangalore do not exist, and the effect of an intervention like that offered by NextDrop has not been evaluated in another location. We therefore relied on a few different data sources to estimate the expected size and standard deviation of our expected effects for this population. First, we conducted a very small pilot survey within two low-income areas in E3, within which we asked how much time, on average, household members currently spend at home on supply days because they expect the water to arrive. We then calculated expected reductions for these households based on the assumption that wait time could be reduced to one hour on a given supply day if households received NextDrop notifications.[22] These inquiries yielded estimates of 30-minute (s.d. = 1 hour) and 45 minute (s.d. = 1.76 hour) weekly reductions for the two areas. We also analyzed NextDrop's valvemen report data regarding valve opening times for a subdivision in which they have operated for over a year, NE3. We drew a

[21] One typically powers a study for one primary outcome of interest, even if multiple outcomes will be analyzed. As a result, we may not obtain statistically significant differences between treatment and control groups for some of our outcomes of interest.

[22] We assumed that households would stop waiting after 3.5 hours, and would not bother staying at home continuously if arrival times were so unpredictable that one could not anticipate if services would start in the morning or afternoon.

systematic sample from among the valve areas, and estimated a mean wait time for each valve area based on deviations from the beginning of the most common start time for services on supply days. (In other words, in the absence of household level data, we sampled from valve areas, assuming these serve as an acceptable proxy for household level data for preliminary estimates.) Relying on similar assumptions as in the previous exercise, we calculated a mean reduction of 2 hours a week (s.d. = 2). We treat this set of estimates from different sources as lower and upper bound estimates for our treatment effect in power calculations.

For cluster-randomized experiments, power calculations must also include estimates of the intra-cluster correlation (ICC). In this case, as before, we could not build on insights from pre-existing surveys. We therefore consulted the literature on health studies related to household interventions in contexts with varying socio-economic background conditions and from various countries. We observed that ICC values typically fall in the 0.01 – 0.15 range, and thus use these as lower and upper bounds for our calculations.[23]

To detect a CACE of the size discussed above through an experiment with forty clusters, with 80% power, and at the 0.05 significance level (two-tailed test), calculations suggest we would need between 150 and 500 respondents falling in our "high impact" population, or 4-13 households per cluster. Given our estimates that only 2/3 – 4/5 of the population in these low income clusters actually fall in our hypothesized "high impact" group, this suggests the need to sample 5-16 households per cluster. If we assume an 80% compliance rate with our intervention (agreement to enroll in NextDrop services), and a 20% attrition rate between the baseline and follow-up services, this suggests we need to sample 7-22 households per cluster to detect an effect within this group in these areas.[24]

To detect an effect through an ITT analysis would require more households per cluster, as our original expectations regarding the size of the average effect for treatment areas would be lower due to the inclusion of noncompliers, which we estimate to be roughly 20% of our sample. When we down-weight the size of our expected effect (and modify the standard deviation) accordingly and conduct power analyses, calculations suggest that we would need to observe 230-700 households, or between 6 and 17.5 households per cluster, in order to observe an effect. Note that these calculations assume that *everyone* surveyed in these clusters will experience a reduction in wait time. We have estimated that only 2/3 – 4/5 of the population in our identified low-income areas falls in our target population (low income and low rise). So to obtain a yield of 6-17.5 low income/low rise households within these clusters, we should ultimately survey (and retain as compliers) 8-25 households per cluster. Moreover, if we experience 20% attrition between wave 1 and wave 2, we would need to survey 10 – 31 households per cluster to detect an effect. Overall, this analysis suggests that an original *sample size of 25 HH per cluster in our 40 low income clusters*, or 1000 HH total, will be sufficient for

[23] E.g., Groves *et. al.* (2013, Chapter 4); Smeeth *et al.* (2002).

[24] We expect to experience some attrition because households may move to another part of the city or back to their home villages. To capture the ITT, we would need a roughly 20% larger sample size in these areas, as the mean expected effect would be reduced to account for the inclusion of noncompliers.

us to detect an effect (either CACE or ITT) of the size we expect if there is indeed one at work.

Because the remit for our study includes evaluating the effect of NextDrop's intervention *across income groups*, we also examined how many households would be required to detect an effect roughly half the size of that we observed through our pre-piloting among low income groups. Overall, this analysis suggests that sample size of 2000 HH, split between 80 clusters with 25 HH each, would allow us to assess whether or not NextDrop is having an impact on wait times within the mixed income clusters.

E. *Specific Indicators*

The impacts of NextDrop's services will be assessed by observing differences between our treatment and control groups on behavioral and survey-based indicators. While most impacts will be measured through responses to questions in the baseline and post-intervention surveys, we plan to draw on at least one behavior measure. This behavioral measure is outlined in Table 1.

Table 1: Behavioral Indicator for Treatment Effects

Hypothesis	*Indicators*
H14: Receiving prior notifications regarding water delivery times and service disruptions will lead citizens to pay their water bills at a greater rate than citizens who do not receive such notifications.	-We will examine differences in changes in monthly payment rates and arrears between our treatment and control groups through examining BWSSB billing records

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Appendix including copy of survey, flyers, etc. to be included with the Pre-Analysis Plan upon registration with EGAP during Winter 2014