Using auctions to improve sanitation at scale

Joshua W. Deutschmann[1], Jared Gars[2], Jean-François Houde[3,8], Terence Johnson[4], Molly Lipscomb[4], Mbaye Mbeguere[5], Sarah Nehrling[6], Laura Schechter[3], and Jessica Zhu[7]

[1]*University of Chicago*
[2]*University of Florida*
[3]*University of Wisconsin–Madison*
[4]*University of Virginia*
[5]*Bill & Melinda Gates Foundation*
[6]*Garabam Consulting*
[7]*Precision Development*
[8]*NBER*

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Abstract

Decentralized markets can lead to inefficiency as the lowest cost service providers and the highest value purchasers have trouble finding each other. We created a centralized auction platform for sanitation services with the government in Dakar, Senegal to increase competition and reduce prices with the goal of increasing take-up and improving welfare. We test the impact of the call center on prices using an encouragement design randomized controlled trial and four rounds of household survey data from 9,672 households. Using variation induced by randomized advertisements, we find that for every auction conducted in a neighborhood in a month, nearby households pay 1.5% less for sanitation services and are 8% more likely to choose the more sanitary option. Scaling up access to the platform could lead to substantial reductions in diarrhea incidence.

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Rapid urbanization and increasing population density in peri-urban areas of low-income countries have created a growing sanitation problem with important health impacts, contributing to the high rate of under-5 mortality from diarrheal diseases. The United Nations Economic and Social Council (2020) estimates that nearly 24% of the world's population living in urban areas live in slums.[1] In most urban and peri-urban areas of low-income countries, households rely on individual sanitation systems such as septic tanks and unimproved pits because expansion of the sewer network is expensive and resource intensive (Ross et al., 2016). These isolated systems need to be periodically emptied in order to continue to function, and emptying services are often provided by independent truck operators. Markets for goods and services in low-income countries often exhibit imperfect competition (Barrett, 1997; Bergquist and Dinerstein, 2020; Houde et al., 2022). For markets such as sanitation services, high prices affect household choices and neighborhood health, reducing overall welfare. We test the extent to which a centralized platform for trading services can affect household choices by providing better information about prices and increasing competition.

We worked with the government of Senegal's National Sanitation office (ONAS) to intervene in the market for sanitation services in Dakar. Households face two options when choosing to empty (or "desludge") their pits: mechanized desludging by a vacuum truck which takes the sludge far away, or manual desludging by a person with a shovel who leaves the sludge nearby. As with many service industries in low-income countries, there is little competition between mechanized service providers, leading to high prices and low adoption (Houde et al., 2022). The alternative option, manual desludging, is less expensive but imposes large health costs on neighbors as the sludge is typically left in a trench in the street near the house. Fifty-seven percent of households in our sample state that they have most recently desludged manually, driven largely by the difference in price between a mechanized and manual desludging.[2] Many countries have worked to improve sanitation practices in rural areas, but relatively little has been done about the related urban issue of latrine waste disposal (Kresch et al., 2020).[3]

[1] According to the UN, a slum is a group of more than one individual living under the same roof that lack access to at least one of the following: durable housing, sufficient living space, access to safe water, adequate sanitation, security of tenure (UN-Habitat, 2019).

[2] Among households which have never hired a mechanized desludging operator, 65% state that the primary reason they have not hired one is the higher price. Among those who desludge manually, 56% do it themselves rather than hiring a worker.

[3] Previous efforts to improve sanitation in Senegal and beyond include encouragement campaigns, advertisements, informational meetings, and the outlawing of manual desludging, with little impact on manual desludging rates (Water and Sanitation for Africa, 2012). In Ghana, attempts by the government to regulate the price and quality of sanitation services have been unsuccessful (Agyei et al., 2011). Rather than relying on information, fines, or regulation, our intervention is market-based

Improved sanitation has important impacts on well-being. Neighborhoods with high rates of manual desludging also have high rates of diarrhea. In our baseline survey data, a household which reported using a manual desludging in the last month was 23% more likely to report at least one case of household diarrhea in the last week and 39% more likely to report a case of diarrhea among children. This is consistent with the large impact of manual desludging on health found by the literature: Johnson and Lipscomb (2021) finds that a price targeting program which increases the market share of mechanized desludging by 4.7% also decreases diarrhea in poor households by 6%. In a large RCT offering desludging subsidies, Deutschmann et al. (2024) finds that each additional subsidy among the households in the immediate neighborhood decreases the likelihood of a report of diarrhea by 3.9%. This problem is increasing in importance as these neighborhoods grow quickly. Pikine, the largest peri-urban neighborhood in Dakar, grew by 43% from 770,000 residents in 2002 to 1,102,000 residents in 2013 (ANSD, 2020).

As is common in many sanitation markets worldwide, prior to our intervention the supply side of the desludging market in Dakar was rife with inefficiency. Service providers exercised market power, households were unable to find the lowest cost operator, and low-cost operators had difficulty finding jobs. In 2013, the desludging market was composed of approximately 74 companies and independent operators who controlled 152 trucks. Most operators work out of one of the 22 garages located around Dakar, and operators are typically unwilling to compete for business with other operators from their own garage. The lack of competition and resulting high prices depress demand for mechanized desludging and lead to excess capacity among the desludging operators. Conversations with operators suggest a truck could manage four to five jobs per day. Data compiled from Dakar's three sewage treatment centers confirms this estimate, with the 95th percentile truck handling five jobs per day. And yet, the treatment center data shows operators performing an average of two jobs per day. If demand did increase, there would be capacity to serve additional households.

We implemented a call center linked to a centralized platform to increase competition in the market. The platform used just-in-time auctions to match households in need of a desludging with service providers.[4] The call center may impact the market in several ways. First, it provides households with an easily-accessible option for procurement of their desludging service. Households can get this price quote with a phone call, rather than the costly process of visiting a garage and bargaining with a service provider directly. This could allow households to avoid the costly search

and focuses on high prices caused by a lack of competition between trucking companies.

[4] For more information on the design and operation of the platform, please see the Materials and Methods section.

process entirely, or to use the information from the call center to bargain for a better price from another provider. Second, the platform offers the job to 7-15 desludgers at once, so desludgers with low opportunity costs (either because of distance to the job, availability, or efficiency at the work) are able to compete for jobs. This could improve the efficiency of matching between households and service providers and result in lower prices. Third, desludgers know that households have the option of calling the call center, which disciplines their prices and service offerings in the wider market.

We first characterize the difference between mechanized desludging prices received by the households through the call center and those that they receive in the traditional market. The histogram of the distribution of the price difference is shown in Figure 1. 28% of the sample has auction prices lower than median neighborhood traditional market prices. The median household receives the same price in the call center as the median market price in their neighborhood. While 49% of households receive a higher price than the median neighborhood market price, 26% of these higher prices were accepted while 46% of the lower-than-median neighborhood prices were accepted. Higher prices may be palatable to households either because they find searching for a desludger costly, or because households that called the call center tended to expect higher prices in the traditional market as well–ie higher cost households (those with less maintained tanks farther from the road) may be more likely to call the call center in order to "pool" with the rest of the sample. In addition, desludgers do price discriminate against wealthier households, and would have a harder time discriminating in the context of an auction.[5]

We use our survey data to estimate expected market prices for households that call the call center. The average price for a job completed through the call center is 24,646 CFA, whereas the expected market price for households that call the platform is significantly higher at 26,100 CFA.[6] The platform thus provides prices 5.6% lower than the market for the higher-price customers who tend to call.

In addition to the lower prices received directly through the platform, competition through the platform may lead to more competitive pricing in the traditional market. Households can use the call center to get a reference price and then negotiate a lower price in the traditional market. Firms may respond by offering lower prices in the traditional market, understanding that households may choose to exit negotiations and instead call the call center. This would both increase the impact of the platform to *all* households in the desludging market, and lead to an under-estimate in the impact

[5]This may under-estimate the price effects of the auctions as we have not corrected for inflation, and we are comparing auction prices from 2013-2017 to reported market prices from 2012-2014.

[6]This is calculated by using phone numbers to match the survey and administrative data, using LASSO to estimate the probability a surveyed household calls the platform, and weighting the market prices by the probability a household calls in.

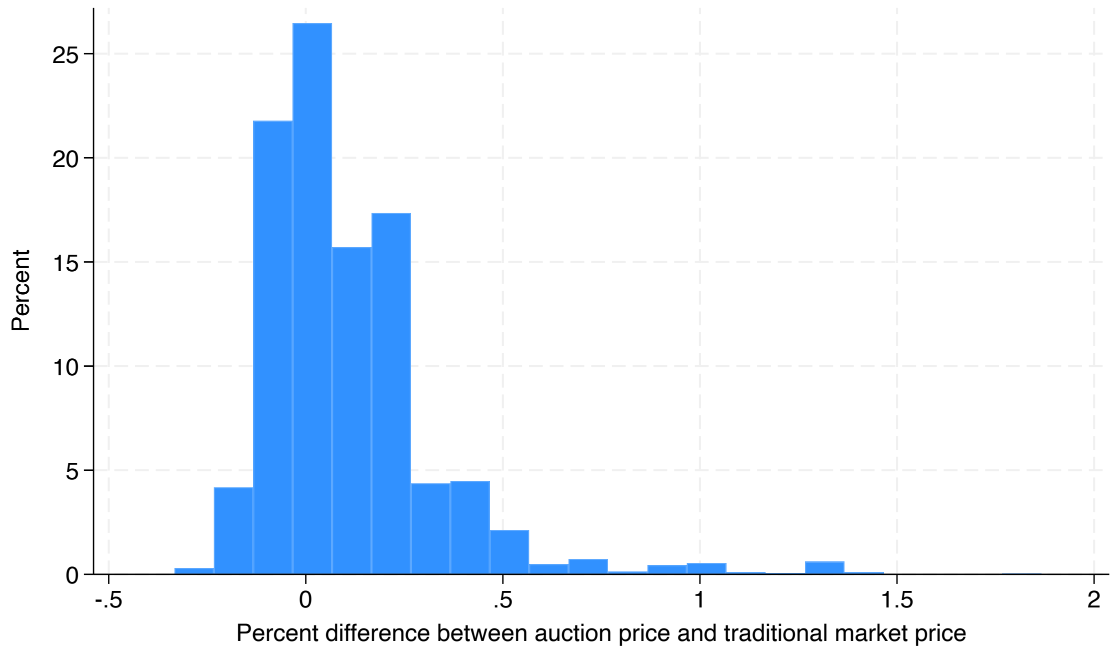

Figure 1: Difference between platform and traditional market prices

of the platform on prices. We conducted a small follow-up survey with households who declined the price offered by the call center. 77 percent of households did not have a price quote from the traditional market when they called the call center, suggesting they could have used the call center quote when bargaining with another provider. The median household who called the call center and ultimately sourced a mechanical desludging elsewhere obtained a price that was 12 percent lower than the neighborhood average market price.

In order to test the impact of use of the call center on traditional market prices, we use an encouragement design randomized controlled trial exploiting random variation in the quantity of SMS ads sent to households in different neighborhoods. Together with ONAS, we initiated a direct advertising campaign to approximately 60,000 households. Each day we randomly chose up to 2,000 households to send SMS messages advertising the call center. Table 1 demonstrates that in areas which received more SMS messages, more customers called to request service. An extra 1000 SMS ads in a neighborhood in a month led to an additional 2.2 customers calling in. For every additional auction in a neighborhood induced by the advertising, we observe a decrease in the price of desludgings in the traditional market of approximately 350 CFA (about 1.5%), and an increase of 8% (4 p.p.) in the probability that households in the neighborhood use mechanized desludging.

Our data allow us to further explore whether these effects are concentrated in areas with relatively high prices before the launch of the call center. Table 2 shows that the price decrease driven by increased call center use was concentrated in neighborhoods with higher prices at baseline: above median price neighborhoods had a decrease in price of 1,210 CFA per 1000 ads, relative to an average price decrease of 758 CFA per 1000 ads. Despite the concentration of price changes, we observe that the advertising affected mechanical desludging choices broadly, including in relatively lower-priced neighborhoods at baseline. This would be consistent with the call center also making it more convenient for households to use mechanized desludging, inducing switching above and beyond what we might expect due to the price decrease.

Using survey data on prices of mechanized and manual desludgings, we estimate how sensitive consumers are to increases in the price of a mechanized desludging. We find a price elasticity of demand of -2.2, implying that a price decrease of 1% would lead to a 2.2% increase in use of mechanized desludgings as households switch from manual services.

In sum, we conduct a large-scale policy experiment in collaboration with the government of Senegal and show that centralizing the desludging market through an auction platform can have important impacts on both price and take-up. The overall impact on market prices during our randomized trial is approximately 1.5 percent. When combined with the elasticity of demand estimated at 2.2, this suggests a 3.3 percent increase in take-up of mechanized desludging over manual desludging, with a much larger effect in neighborhoods and for households that had high prices in the traditional market. In related work, Houde et al. (2020) show that a better optimized platform could reduce prices further. The broader impacts on the market are also important. The platform reduces prices most in neighborhoods where prices were higher at baseline, and knowledge of the call center through advertising leads to lower prices in the traditional market and increases adoption of mechanized desludging.

Although the platform has a larger impact on wealthier households who are most likely to use mechanized desludging even at higher prices, the centralized platform can be particularly helpful in allowing the government to subsidize jobs for those least likely to take up on their own. The elasticity of government procurement to price is typically quite low, allowing organized service providers to increase the price in response to a subsidy. A platform "hides" government jobs among household jobs making the true elasticity of demand difficult to estimate for any particular job as a desludger. In addition, the preferential take-up rate by wealthy consumers suggests that cross-subsidization of the type suggested by Johnson and Lipscomb (2021) could be particularly successful in this type of environment.

Centralizing the market through a platform provides a relatively low-cost and scalable way for the government to intervene in the market and encourage households to adopt services which improve sanitation and health.

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1 Figures and Tables

Table 1: Impact of auctions on traditional market prices

	Num Auctions	Price (CFA)		Last used mechanical	
	(1)	(2)	(3)	(4)	(5)
		OLS	2SLS	OLS	2SLS
Ads in neighborhood	2.18***	-758.39		0.35***	
(thousands)	(0.72)	(495.85)		(0.06)	
Auctions			-347.28**		0.04***
			(153.04)		(0.01)
Observations	1438	1438	1438	2056	2056
Mean Dep. Var	12.98	23758.42	23758.42	0.49	0.49

Neighborhood and month fixed effects included in all regressions but not shown. Standard errors are clustered at the neighborhood level. Observations are at the household level and restricted to households reporting a desludging in 2014 for all regressions. Columns 2 and 3 further restrict to households reporting that they last used a mechanical desludging. The outcome in column 1 is the number of auctions run in the household's neighborhood in 2014. The outcome in columns 2 and 3 is the price the household reported paying for their most recent mechanical desludging in CFA in 2014. The outcome in columns 4 and 5 is an indicator variable equal to one if the household last used a mechanical deslduging.

Table 2: Impact of auctions on traditional market prices (with heterogeneity by baseline prices)

	Num Auctions	Price (CFA)		Last used mechanical	
	(1)	(2)	(3)	(4)	(5)
		OLS	2SLS	OLS	2SLS
Ads in neighborhood	3.08***	372.59		0.47***	
(thousands)	(0.83)	(401.57)		(0.08)	
High mean mech price	-0.96	-1210.64***		-0.13	
2012-2012=1 $\times$ Ads in neighborhood (thousands)	(0.69)	(420.31)		(0.11)	
Auctions			121.96		0.05***
			(124.40)		(0.00)
High mean mech price			-341.02***		-0.01
2012-2012=1 $\times$ Auctions			(112.62)		(0.01)
Observations	1438	1438	1438	2056	2056
Mean Dep. Var	12.98	23758.42	23758.42	0.49	0.49

Neighborhood and month fixed effects included in all regressions but not shown. Standard errors are clustered at the neighborhood level. Observations are at the household level and restricted to households reporting a desludging in 2014 for all regressions. The outcome is the price the household reported paying for their most recent mechanical desludging in CFA in 2014. High mean mech price 2010-2012 is a dummy equal to one if the neighborhood had an above-median mean mechanical price over the period 2010-2012.

2 Materials and Methods

2.1 Data

Household survey: We ran four rounds of surveys, surveying a total of 9,672 households at least once (overlapping samples of households were interviewed in each round). The surveys were conducted in late 2012, early 2014, and two rounds in early 2015. Arrondissements with access to the sewer network, with high levels of industrial activity, with primarily newly constructed residences, and with consistent flooding problems were avoided. In the remaining five (out of 19) *arrondissements*, sampling was done by randomly selecting points on a grid overlaid on a map of Dakar, and then omitting grid points in uninhabited areas and areas served by the city sewer network.

Survey of desludging service providers: We conducted a baseline survey covering 121 desludging truck operators in mid-2012, and an endline survey of 152 operators in mid-2015. These surveys include data from truck operators who both did and did not choose to participate in the auction platform.

Auction platform administrative data: We use data from a just-in-time auction platform for the procurement of residential desludging jobs. Together with Water and Sanitation for Africa (WSA) and the National Office of Sanitation in Senegal (ONAS), we ran the call-center from July 2013-September 2015. The call center has since been scaled up by ONAS and is now managed by a private sector provider, Delvic. Call center activity is clustered around the peri-urban areas of Dakar, but calls have come from downtown Dakar as well as further out of the city.

We use administrative data from these auctions, including the identities of the desludgers who were invited to bid (invitations were randomized), whether or not they bid, the time and amount of their bid(s) if they made one, the format of the auction (auction format was randomized), the location of the household job that they were bidding on, and the winning bid.

2.2 Impact of manual desludging on diarrhea

We estimate the relationship between manual desludging use and diarrhea rates using the household survey. The survey collected information on whether any children or adults had experienced diarrhea in the past week. Using this information, we construct a dummy variable equal to one if any child, or any household member, experienced diarrhea in the week before the survey. The survey also collected information on the household's most recent manual desludging.

We estimate the following regression for household i in grid point cluster j in subzone z:

$$\begin{aligned}Y_{ijz} =& \alpha + \beta_1[\text{HH Manual Last } X \text{ Months}]_{ijz} + \beta_2[\text{Share of Cluster Manual Last } X \text{ Months}]_{ijz} \\ &+ \beta_3 K_{jz} + \gamma_z + \epsilon_{ijz}\end{aligned}$$

where K_{jz} is the total number of households in the cluster, γ_z is a subzone fixed effect, and ϵ_{ijz} is clustered at the grid point cluster level. The coefficient β_1 measures the relationship between a household's diarrhea outcome and whether or not it reported a manual desludging in the last month, and β_2 measures the relationship between the share of other households in the cluster which used manual in the last month. The results of these regressions, found in Table 3 are robust to using longer time horizons (e.g., manual desludgings in the last 3 or 6 months) with comparable magnitudes.

Table 3: Diarrhea incidence in last week and manual desludgings in last X months

	Children			Any in household		
	(1)	(2)	(3)	(4)	(5)	(6)
HH Manual Last Month	0.089***			0.078***		
	(0.017)			(0.018)		
HH Manual Last 3 Months		0.067***			0.067***	
		(0.013)			(0.014)	
HH Manual Last 6 Months			0.061***			0.063***
			(0.011)			(0.012)
Frac. Oth. HH Manual Last Month	0.105*			0.155**		
	(0.056)			(0.064)		
Frac. Oth. HH Manual Last 3 Months		0.101***			0.140***	
		(0.036)			(0.043)	
Frac. Oth. HH Manual Last 6 Months			0.120***			0.165***
			(0.030)			(0.035)
Observations	8901	8901	8901	8379	8379	8379
R^2	0.030	0.031	0.033	0.045	0.047	0.050
Outcome mean	0.230	0.230	0.230	0.350	0.350	0.350
Commune FE	Y	Y	Y	Y	Y	Y

Results in this table are from linear regressions of the outcome variables (diarrhea incidence in last week among children or anyone in household) on own-household manual desludging in the last X months and other households in the cluster. All regressions additionally control for number of surveyed households in grid point cluster. Outcome mean is the mean incidence of the outcome variable among all grid point clusters. Standard errors (in parentheses) clustered at grid point cluster level.

Table 4: Diarrhea incidence in last week and manual desludgings in last X months

	Children			Any in household		
	(1)	(2)	(3)	(4)	(5)	(6)
HH Manual Last Month	0.014			0.005		
	(0.009)			(0.005)		
HH Manual Last 3 Months		0.007			0.005	
		(0.007)			(0.004)	
HH Manual Last 6 Months			0.006			0.009^{**}
			(0.006)			(0.004)
Frac. Oth. HH Manual Last Month	0.059^{*}			0.041^{**}		
	(0.032)			(0.018)		
Frac. Oth. HH Manual Last 3 Months		0.042^{**}			0.026^{**}	
		(0.021)			(0.012)	
Frac. Oth. HH Manual Last 6 Months			0.046^{***}			0.036^{***}
			(0.017)			(0.010)
Observations	7617	7617	7617	8708	8708	8708
R^2	0.021	0.021	0.022	0.032	0.032	0.034
Outcome mean	0.112	0.112	0.112	0.071	0.071	0.071
Commune FE	Y	Y	Y	Y	Y	Y

Results in this table are from linear regressions of the outcome variables (rate of diarrhea occurence in last week among children or anyone in household) on own-household manual desludging in the last X months and other households in the cluster. All regressions additionally control for number of surveyed households in grid point cluster. Outcome mean is the mean incidence of the outcome variable among all grid point clusters. Standard errors (in parentheses) clustered at grid point cluster level.

2.3 Elasticity of demand for mechanized desludging

When a household needs a desludging, they make the choice between purchasing a mechanized desludging and purchasing a less expensive less sanitary manual desludging. In order to estimate the demand for mechanized desludgings, we develop a selection model which predicts which households will switch to mechanized over manual based on the prices they are likely to face in the market.

Let r_i denote the reservation price of consumer i, and p_i denote the best offer that i receives for the mechanized service. We do not observe the reservation price since consumers are choosing between mechanized and one of two manual options (family or baay pell). Similarly, we don't observe the mechanized price that *would have been* offered to consumers who use a manual desludging. As in Houde et al. (2022) we follow Heckman (1979), and construct an endogenous selection model to address this problem and measure the demand for mechanized services:

$$\begin{pmatrix} r_i \\ p_i \end{pmatrix} = \begin{pmatrix} z_i\alpha + x_i\beta_0 \\ x_i\beta_1 \end{pmatrix} + \begin{pmatrix} e_{i0} \\ e_{i1} \end{pmatrix}$$

where $\mathbf{e}_i \sim N(0, \Sigma)$, and z_i is a variable that affects the reservation price, but does not directly affect the mechanized price. Let σ_j denote the standard-deviation of e_{ij}, and σ_{01} the covariance between e_{i0} and e_{i1}. After receiving offer p_i, consumers choose the mechanized option if the surplus, v_i, is positive:

$$y_i = 1 \text{ if } v_i = r_i - p_i > 0 \rightarrow z_i\alpha + x_i(\beta_0 - \beta_1) + e_{i0} - e_{i1} = \underbrace{z_i\alpha + x_i\gamma}_{\bar{v}_i} + u_i > 0 \quad (1)$$

We estimate the model using maximum likelihood after normalizing $\sigma_u = 1$. For the variable z which affects the household's reservation price r, but not the price they are actually charged p, we use the predicted manual price charged to household i's neighbors. We construct this variable in two steps. Fist, we estimate the conditional mean of manual baay pell prices by OLS using variables x_i as regressors. Let $\hat{p}^b(x)$ denote this predicted cost of a manual desludging for a household with characteristics x. We then calculate the sample average of $\hat{p}^b(x)$ among other households living on the same block as household i; on average there are four households per block in our sample. This variable varies across households based on the observed characteristics of their neighbors. The identifying assumption is that those attributes are independent of the distribution of mechanized price offers that household i receives (conditional on its own characteristics x_i), and are correlated with the reservation price r_i.

To compute the price elasticity of demand for mechanized services, we calculate the effect of raising the average mechanized price $\bar{p}_{i,1} = x_{i,1}\hat{\beta}_1$ on the probability of choosing the mechanized option:

$$\text{Elasticity}_i = \frac{1}{n}\sum_i \frac{\partial \Pr(y_i = 1|z_i)}{\partial \bar{p}_{i1}} \frac{\bar{p}_{i,1}}{\bar{s}_1} = -\phi(z_i\hat{\gamma})\frac{1}{\hat{\sigma}_u}\frac{\bar{p}_{i,1}}{\bar{s}_1}. \quad (2)$$

where $\bar{s}_1$ is the aggregate share of consumers choosing the mechanized option. We obtain an estimate of the variance of u_i by assuming that the distance to the nearest treatment center affects the probability of choosing the mechanized option only through its effect on prices: $\gamma_{\text{distance}} = \beta_{1,\text{distance}}/\sigma_u$ or $\hat{\sigma}_u = \hat{\beta}_{1,\text{distance}}/\hat{\gamma}_{\text{distance}}$. We find an elasticity of -2.2 which can be interpreted as for a 1 percent reduction in price, there is a 2.2 percent increase in quantity.

2.4 The operation of the call center

The call center centralizes the market by providing desludgers with the opportunity to bid on jobs. Households call when their latrine pit is full and supply basic information on the location of the pit to be desludged. [7] The call-center operator submits the job to the platform, and the platform automatically chooses between 7 and 15 randomly chosen desludgers to invite to bid on the job. Desludgers have one hour to bid and receive reminder messages every 15 minutes and then again five minutes before the close of the auction. Households are then informed of the winning bid and chose whether or not to accept it.

To encourage good behavior by truckers, customers were called with follow-up surveys. If truckers arrived late for their scheduled job, failed to respect the price they offered in the auction, or serviced the household poorly, they were penalized. Truckers with an active penalty had their bids artificially inflated, requiring them to bid even more aggressively to win jobs and work off the penalty. This was effective: 98% of clients polled after a completed job rated the service highly, and 76% of jobs were completed by truckers within two hours of the expected time, many of the slower jobs were a result of scheduling issues with the household.

2.5 Impact of call center on prices using randomized advertisements

In 2014, together with ONAS, we initiated a direct advertising campaign via SMS messages to approximately 60,000 households.[8] ONAS had collected the phone numbers and GPS coordinates of people living in each zone in an earlier campaign to have a census of all latrines. Each weekday during each of two rounds of advertising, up to 2,000 households were sent an SMS message with basic information about the call center. Each household in our database received one SMS message in the first round of advertising which ran from late February to early May 2014, and one SMS message in the second round which ran from late July to mid September 2014. The order in which households received SMS messages was randomized, and drawn independently for each round of advertising.

We combine information on how many households received text messages from the advertising campaign in each month in each neighborhood with survey data on prices households in targeted zones recall receiving in 2014. Outcome variables

[7] Because Dakar does not have a popularly-used address system, we developed a custom landmark-based system to pinpoint households and communicate that location to truckers. Call-center operators use a hierarchical system, first asking the caller for the neighborhood name, then finding a large (primary) landmark nearest the household, followed by a smaller (secondary) landmark closer to the household. These three pieces of information are included in the SMS messages sent to truckers.

[8] The call center was also advertised on TV and radio, but this was not directly targeted.

include the number of auctions (from the auction data) and the average price for a mechanized desludging and propensity to use mechanized desludging (both from the survey data) in subzone z and month m (for household i in the survey). We use the following specification to estimate the impact of these advertising messages:

$$Y_{izm} = \alpha + \beta_1 NumberAds_{zm} + \beta_2 X_{izm} + \gamma_z + \mu_m + \epsilon_{nm} \tag{3}$$

We include subzone and month fixed effects. Outcomes from the survey include additional household level controls X_{izm}. For the survey outcome propensity to use a mechanized desludging, the level of observation is the most recent desludging of each household, where the sample is restricted to desludgings which occurred in 2014. When analyzing the price of mechanized desludgings, we restrict the sample to mechanized desludgings which occurred in 2014. This causes the number of observations to vary across columns. Standard errors are clustered by subzone which is the level of randomization of the advertising.

We hypothesize that the auction platform makes it easier for desludgers to locate and compete for jobs outside their usual territories, which should in turn decrease prices and increase uptake of mechanized desludgings. We estimate the impact of the number of auctions in a neighborhood on traditional market prices and the take-up of the improved sanitation services. Because the number of auctions is endogenous and may be correlated with the wealth or sanitation preferences of local households, we use the randomized ads as an instrument for the number of auctions.

2.6 Auction and traditional prices for households in the auctions

Households that call the call center may be those who would have received a higher price in the traditional mechanized market. This may be because it is more costly for desludgers to access their house - for example due to narrow or sandy roads. It may be because they can not search as well - for example due to being time constrained or not knowing a desludger. Finally, it may be because deludgers price discriminate against wealthier households.

We combine one round of survey data with the administrative data from the call center to predict the probability that each household will call the call center. We then compare the average price in the call center to the expected price in the traditional market for the average caller "type."[9] We use phone numbers to match households in the survey and call center data. Our number of matches (91 out of 3209 households surveyed) is a lower bound since households may provide one phone number in the

[9] We can only use one survey round since we limit the analysis to desludgings done after 2010 by households without access to subsidies.

survey and use a different phone number when calling the call center. We use machine learning (LASSO) to select predictors of calling the call center (Ahrens et al., 2020). From 25 demographic and 23 location variables, the machine learning procedure selects 15.

We use the selected predictors to predict the probability that each household calls, and generate a weighted average traditional open market mechanized price, weighed by the estimated probability that each household calls in. The average auction price for non-subsidized auctions outside of Rufisque where the client did not cancel was 24,359 CFA with a median of 25,000 CFA. Weighted average prices for similar clients in the survey data was 26,040 CFA, suggesting that auction prices are lower by 1,681 CFA, or 6.9%.

Table 5: Maximum likelihood estimates of the selection model

VARIABLES	(1) Mechanical Price	(2) Choice
Nbh. Baaybell price (avg)		0.147[a]
		(0.0169)
Nearest center (Km)	0.842[a]	-0.149[a]
	(0.117)	(0.0154)
Nearest garage (Km)	0.718[a]	-0.148[a]
	(0.236)	(0.0300)
Num. trucks (3km)	0.0289[a]	-0.00558[a]
	(0.00552)	(0.000752)
Wide road	-0.236	-0.493[a]
	(0.677)	(0.0689)
Tube meters	0.0512[a]	-0.00540[a]
	(0.0198)	(0.00134)
Number of rooms	0.148[a]	0.0287[a]
	(0.0570)	(0.00743)
1(Own Refrigerator)	1.132[a]	0.245[a]
	(0.321)	(0.0395)
ρ_{u,e_1}	-0.270[a]	
	(0.0444)	
Observations	6,647	6,647

Robust standard errors in parentheses
[a] p<0.01, [b] p<0.05, [c] p<0.1
Controls: Arrondissement and month/year FEs,
additional household characteristics (see Table **??**)

Note: Additional controls include arrondissement and month-year fixed effects and all household characteristics listed in the control variables X_i. The dependent variables are the mechanized desludging price and an indicator for choosing mechanized rather than manual. The parameter ρ_{u,e_1} represents the correlation between the error in the two regressions. Robust standard errors in parentheses: $c \ p < 0.10$, $b \ p < 0.05$, $a \ p < 0.01$.