Imperfect Competition and Sanitation: Evidence from randomized auctions in Senegal*

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1 Introduction

As of 2015, only 28 percent of sub-Saharan Africa had access to even basic sanitation (Organization and the United Nations Children's Fund, 2017). Rapid urbanization and increasing population density in peri-urban areas of developing countries has created a growing sanitation problem with important health impacts, contributing to the high rate of under-5 mortality from diarrheal diseases. One of these problems is under-investment in modern sewage systems.

In most peri-urban areas of Dakar (Senegal), households rely on individual sanitation systems such as septic tanks and unimproved pits because expansion of the sewer network is expensive and resource-intensive (Plummer and Cross, 2006). These isolated sanitation systems need to be emptied periodically (on average twice per year); a service that we refer to as *desludging*. Households choose between two options: manual workers who enter the pit and extract the sludge using shovels and buckets and dump the sludge in the street; and truckers capable of pumping the sludge and then take it out of the neighborhood, usually to one of the four treatment centers. Survey evidence suggest that slightly more than half of desludgings are performed using the manual option, which creates important environmental and health externalities (Deutschman, Gars, Griffith, Houde, Johnson, Lipscomb, Mbeguere, Schechter, and Zhu (2016)).

In this paper, we analyze the role that imperfect competition plays in explaining the low-takeup of mechanical desludging. We examine this question empirically, by measuring the extent to which truckers behave non-competitively in the market.

Several features of the market structure are consistent with limited competition and collusion between providers. Based on household surveys, we know that the average mechanical price is roughly 60% higher than the price of the manual option, and that financial constraints is the main factor determining the timing and technology choice that households make. Moreover, the largest companies in Dakar are member of a trade association (ASSA), which coordinates equipment purchases and bid for non-residential desludging contracts. The leaders of the association also control the main garages where truckers park and meet residential clients. Finally, the location of those garages, and the fact that prices are negotiated bilaterally between clients and truckers, lead to important search frictions that limit the scope for competition between truckers.

We proceed in two steps to test the hypothesis that prices are set non-competitively. We first exploit a large household survey of demand and prices covering most peri-urban areas of Dakar to analyze the distribution of transaction prices and demand across competitive and potentially collusive neighborhoods. We exploit the fact that the Association is not present in one neighborhood of the city (Rufisque). Companies in this area use a posted-price schedule, and charge mechanical prices that are about 10% higher than manual prices. As a result, nearly 100% of the population use the mechanical desludging option. To investigate wether high-prices in the Association-controlled area are due to differences in competitive conduct (as opposed to cost), we compare transaction prices for households living on either sides of the Rufisque boundary. Controlling for observed households characteristics (proxy for cost), we show that average prices increase sharply as we move away from the boundary. Similarly, demand and price dispersion are significantly different between the two areas; consistent with the idea that supply is rationed in areas controlled by the Association, and that consumers are price discriminated against. Finally, we also show that truckers in the less competitive area have substantial excess capacity, compared to truckers operating in the Rufisque neighborhood.

Our second (and main) empirical test uses data from a real-time auction platform deployed in the city in an effort to improve access to mechanical desludging. The auctions were designed to incentivize firms to behave competitively, without being detected. We partnered with the state government to introduce two sources of randomization in the design. When a client calls, he/she is assigned to a randomly selected group of potential bidders ranging from 8 to 20. In addition, the format of the auctions is itself random across clients. In 50 percent of auctions, the platform uses a revisable format which provides information about the current lowest-standing bid received, and allowed bidders to revise their bid (as in Hortaçsu and Kastl (2012)). The remain auctions are conducted using a sealed-bid format. In the both cases, the lowest bid is presented to the client, who has the option to accept or reject (the average acceptance frequency is 30%). Our data covers slightly more than 5,000 auctions conducted over the course of three years.

We use random variation across formats and invitation lists to test the null hypothesis that invited bidders behave competitively in the platform. Since each auction is anonymous and performed over a short period of time (60 minutes), the platform offers an opportunity for truckers to generate more revenues, and break from tacit collusion.

To test this hypothesis, we first identify strategies that are inconsistent with competitive bidding (e.g. Porter and Zona (1993), Porter and Zona (1999), Chassang, Kawai, Nakabayashi, and Ortner (2019)). An action is defined as "collusive" if a bidder submits a bid that does not maximize its expected profit in an effort to suppress competition among cartel members (i.e. avoidance of competition). This identification strategy relies on documenting the prevalence of strategies that are either dominated and dominant for all bidders, irrespectively of their cost. Since the platform randomizes the auction format, we focus on identifying dominant/dominated actions that are specific to each strategic environment.

We analyze two types of strategies. The first one is the propensity of bidders to avoid ties in the sealed-bid auctions. Round prices are common in the market, since most transactions are cash-based. This leads to a small number of focal prices for bidders to use. Targeting focal prices used in the residential market softens competition by turning the auction into a lottery and allocating the good to participants who submit early bids. This is clearly a dominated strategy from the point of view of a profit maximizing bidder.

The second strategy is the propensity of bidders to submit a late bid in the revisable auction format. In this format, bidders are informed about the currently lowest bid, and have the option of submitting a sealed bid in the last 15 minutes of each auction. Bidding in the closed portion of the revisable auction is a dominant strategy. Since winning bidders pay their bid, it is optimal for firms to wait until the closed portion to submit their bid. Doing so limits the likelihood that the bid is undercut, and to the extent that bidding is costly, firms are better off learning about rival bids before submitting a bid. In contrast, submitting an early bid can be viewed as an effort to coordinate prices by sending a signal to rivals.

Our results suggest that the market is composed of a small group of profit maximizing bidders (roughly 1/3), competing with a larger group of firms whose behavior is consistent with tacit collusion. Consistent with the presence of competitive bidders, we show that the frequency of ties and early winning bids is reduced significantly when auctions are conducted using the revisable format (compared to sealed). However, the two fractions are non-zero, suggesting that a large number of firms submit non-competitive bids in both formats.

In addition, we show that there exists a strong positive correlation between firms' conducts in both formats. In particular, the results show that bidders who are likely to tie in the sealed-bid auctions are also submitting lower bids on average, and are more likely to bid late and undercut other bidders in the revisable auctions. This implies that non-competitive bids are not due to random errors or inattentions. In other words, non-competitive bidders systematically use dominated strategies (and conversely for competitive bidders). Crucially, we obtain this result by comparing frequent bidders in the auctions, which reduces the importance of learning or insincere bidding as alternatively interpretations for these results.

Finally, we evaluate the potential damages from collusion in this market by measuring the counter-factual demand for mechanical desludging under the assumption that households had access to more competitive price distributions. We consider two competitive scenarios: (i) the observed distribution of prices in the Rufisque neighborhood, and (ii) the auction price distribution under more competitive invitation lists. The results show that demand would increase substantially in both cases: from 42% to 71% using Rufisque prices, and to 54% using the auctions. These two experiments are partial equilibrium simulations, that do not account changes in bidding strategies if all transactions were conducted using the auction platform. In a companion paper, Houde, Johnson, Lipscomb, and Schechter (2020), we use the auction data to estimate the distribution of desludging cost, and simulate the equilibrium effect of eliminating non-competitive strategies and using competitive invitation lists on prices and take-up.

Our paper is part of a growing set of papers using tools from Industrial Organization to study the functioning of markets in developing countries (e.g. Keniston (2011) and Bjorkegren (2019)). Among those, our paper is closest to two recent papers studying market frictions using data from field experiments. Falcao Bergquist and Dinerstein (2019) analysis of pass-through and market power in a wholesale market for agricultural products in Kenya. The paper uses field-experiment in Kenya to analyze the pass-through of cost shocks on prices and demand, and identify a model of imperfect competition. Johnson and Lipscomb (2020) uses market-design tools evaluate the optimal targeted subsidies for improved sanitation in Burkina Faso.

Our paper also contributes to the literature on diagnosis tests for collusion.[1] There are two strands of literature studying collusion in auction environments. The first one relies on testing implications of efficient models collusions (e.g. Baldwin, Marshall, and Richard (1997), Bajari and Ye (2003), Asker (2010)), and the second identifies strategies that are inconsistent with competitive bidding (e.g. Porter and Zona (1993), Porter and Zona (1999), Chassang et al. (2019)). We follow the second approach here. An action is defined as "collusive" if a bidder submits a non-meaningful bid in an effort to suppress competition among cartel members (i.e. avoidance of competition).

The paper is also connected to the literature that focusses on identifying "mistakes" by firms in strategic environments (see Della Vigna (2018) for a discussion). Failure to maximize individual profit can arise also for other reasons than limiting competition. For instance, Hortaçsu, Luco, Puller, and Zhu identifies the importance of bounded-rationality in electricity auctions, assuming competitive bidding. Although we cannot rule out completely that sub-optimal bids are caused bounded-rationality (as opposed to tacit collusion), our results similarly show that an increase in the fraction of bidders avoiding dominated strategies can lead to important efficiency gains. Similarly, as in Doraszelski, Lewis, and Pakes (2018), we show that bidders quickly how to behave strategically in this new competitive environment.

[1]See Hendricks and Porter (1989), Porter (2005) and Abrantes-Metz and Bajari (2009) for discussions of this literature.

The rest of the paper is organized as follows. We first describe the data and the structure of the market. We take a first look at the importance of collusion by analyzing the distribution of prices between areas that are controlled by the association, compared to our competitive control. The next section analysis non-competitive behavior in the auction platform. The final section evaluates the effect of imperfect competition on demand and consumer surplus.

2 Data

We use three datasets to conduct our empirical analysis: (i) a household survey of technology choice and price, (ii) a provider survey, and (iii) administrative data from the just-in-time auctions.

We conducted four sets of household surveys spanning November 2012-June 2015. We interviewed 9,672 households, randomly selecting some neighborhoods for repeat interviews to create a panel dataset, generating 16,255 observations in total. We drop observations with missing responses on key variables including those who did not receive a desludging over the past year (either mechanical or manual). The final sample size includes 7,824 observations, and 5,242 unique households.[2] We use the household surveys to measure the distribution of prices and demand across neighborhoods. An observation corresponds to a household's most recent desludging transaction.

We constructed our random sample of households from areas farther removed from the sewage network, using geographic sampling techniques: we overlaid grid points on a map of Dakar, dropped grid points which were in uninhabited areas or served by the city sewer network, randomly selected grid points for sampling from the remaining points, and used a spiral method to select households for the sample starting from each randomly selected neighborhood grid point. Figure 11 in the Appendix displays the distribution of households' locations. Our analysis focuses on five of the 19 *Arrondissements* of Dakar.[3] The majority of households surveyed are located in five neighborhoods: Pikine Dagoudane (center-west, 14%), Thiaroye (center, 30%), Guédiawaye (center-east, 13.5%), Niayes (north-east, 37%), and Rufisque (south-east, 4.8%). Note that households in Rufisque were not sampled in the second and third wave of the surveys, which explains the smaller number of observations

[2] Some households were surveyed over multiple years in order to measure their response to a direct subsidy program (or serve as a control group). Households who were part of the subsidy intervention program are excluded from our data.

[3] Arrondissements are subdivided into 43 *Communes d'Arrondissement* or CAs (admin3 and 4 on the map).

(i.e. 250 unique households).[4]

On the firm side, we conducted a baseline survey covering 121 desludging truck operators in May and June 2012, and an endline survey of 152 drivers (of which 13 owned their own truck), 75 truck-owners, and 20 managers were surveyed in June 2015. We refer to an operator either as a manager of a fleet of trucks, or a driver associated with a single license plate. These two surveys include data from several truck operators who decided not to participate in the auction platform as well as most operators associated with the call center. In addition, we also collected information on the truck size and location of most license plates active in the market (≈ 350). We use the provider survey to identify the main location of each truck in the market to measure the distance between households and truckers.

Finally, 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. Call center activity is clustered around the peri-urban areas of Dakar, particularly Pikine and Guediawaye, but calls have come from downtown Dakar as well as further out of the city.

We have access to the administrative data from these auctions: 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 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.

3 Residential desludging in Dakar

In this section, we describe the functioning of the residential market for desludging in Dakar. Section 5.1 describes the functioning of the call center.

3.1 Demand

When a household latrine fills, the household must empty it (getting a desludging) in order to restore it to working order. Households have a choice between three types of desludging services: (i) manual, performed by a family member, (ii) manual, performed by a hired worker (called a "baay pell" in Senegal), and (iii) mechanical, using a vacuum truck. Manual

[4] We also surveyed a small number of households in the Dakar Département, which corresponds to the historical center of the city. We dropped those observations in this paper because households tend to be wealthier and is closer to the city sewage network.

Table 1: Summary statistics on desludging choices and prices

	mean	sd	p25	p50	p75
Choice: Mechanical	.468	.499	0	0	1
Choice: Baaypell	.242	.429	0	0	0
Choice: Family	.29	.454	0	0	1
Mechanical price	23.8	7.7	19	25	30
Baaypell price	14.2	5.86	10	15	17
Family price	.501	2.51	0	0	0
Truck find: Garage	.235	.424	0	0	0
Truck find: Phone	.189	.391	0	0	0
Truck find: Referral	.439	.496	0	0	1
Truck find: Street	.108	.31	0	0	0
Truck find: Other	.0296	.17	0	0	0
Observations	7824				

All prices are measured in 1,000 CFA. Summary statistics on prices and shopping variables are conditional on the service being chosen.

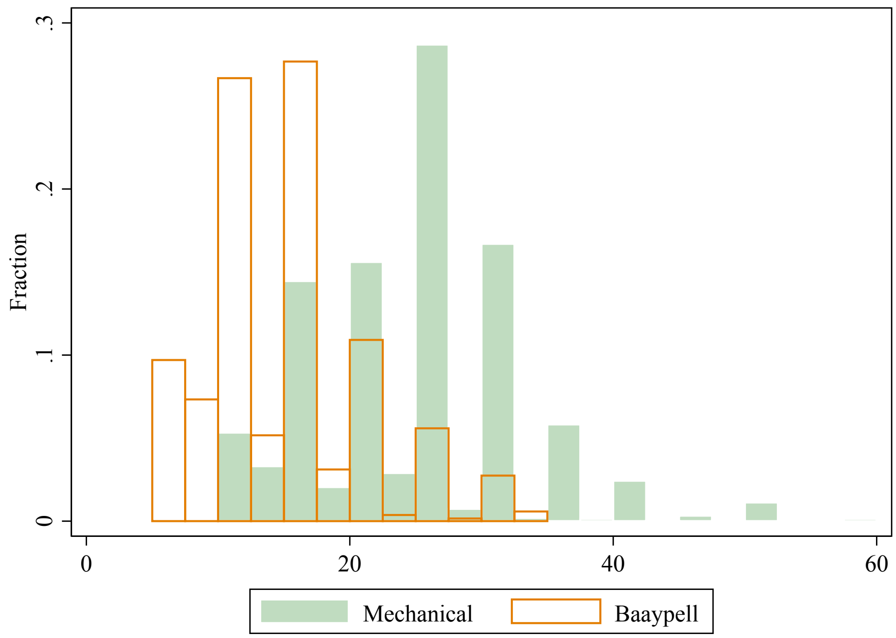
desludging consists of removing the sludge using a shovel, and placing it in a pit dug in the street near the house. The manual option increases the risk of health-related sanitation problems (for the client and for the workers). Manual desludging is technically illegal– though is rarely fined it is often a source of controversy among neighbors when it is used as the impact on the neighborhood is substantial. Mechanical desludgings are done by two to three workers with a vacuum truck. The truck pumps as much liquid out of the pit as they are able, and then dumps it either in a treatment-center (legal) or in the river/ocean (illegal).

Mechanical desludging is performed by small/medium sized companies, with many independent-operators, and most companies owning 2-3 trucks. The manual option is competitively provided throughout the city. Manual desludging providers are typically sole owner/operators who often engage in other manual labor as well, and meet clients through referrals and family connections.

Table 1 presents summary statistics on the transaction price and desludging technology choice. Despite the health hazards associated with manual desludging, the market share of the mechanical service is only 47%. This is mostly due to the price difference between the two options. All prices are expressed in 10,000 CFA francs, and reported on per trip basis.[5] Typically, households using family members for desludging do not report paying directly for

[5] Our household survey reveals that about 8% of households require multiple trips.

Figure 1: Distribution of transaction prices for mechanical and manual technologies



the service, and so there are many 0's in the family desludging price. The price of manual desludging ranges between 12,000-16,000 ($24-$32), and average price is 14,212 CFA. In contrast, households report paying on average 23,800 CFA per trip (approximately $46) for mechanical desludging. To put these numbers in perspective, we estimate that the cost of utilities is about 40,000 CFA per month for the median household in our sample.

Figure 1 shows the distribution of transaction prices in our sample. The histogram for the mechanical technology shows that most transaction prices are reported in increments of 5,000 CFA. The modal/median price is 25,000. Roughly 30% of transactions reported are at this price, and 56% of transaction prices reported are at 20, 25 or 30 thousand CFA. While it can certainly be more efficient to use round numbers when performing cash-based transactions, the fact that more than 20% of transactions use other increments than 5,000 CFA suggests that this does not represent a hard constraint for all providers.

The gap between the price of manual and mechanical is due in part to cost differences in providing the service. The added expense of providing the mechanical option varies significantly across households based on distance and accessibility. Manual desludging is time consuming and often involves multiple workers. Mechanical desludging is typically much faster (between 1 and 2 hours), and exhibits economies of scale due to large fixed costs and the possibility of serving multiple households with the same trip (for larger trucks). Fixed

Table 2: Market structure summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
1(Domestic revenue> 50%)	0.82	0.39	0	1	180
Total domestic trips (last 10 days)	5.22	4.01	0	12	163
Total trips (last 10 days)	12.82	11.75	1	53.5	133
Num. different nbh.	2.02	0.45	1	3	143
Distance treatment center (km)	4.74	2.51	0.46	16.07	352
Truck size	9.93	2.12	4	17	280
Education (indicator)	0.64	0.48	0	1	157
Experience (years)	10.2	6.05	0	31	157
Num. trucks per garage	38.34	28.72	1	84	352
Num. companies in garage	19.37	20.91	1	56	352
HHI garage	0.3	0.25	0.03	1	352
AAAS member	0.48	0.5	0	1	352

costs include the maintenance and/or rental cost of the truck, as well as fixed payment to the driver and trade association. Variable costs for mechanical desludging providers include fuel, worker time both at the house and in traffic, and fees for disposal of the sludge at a treatment-center (approximately 3,000 CFA). While the efficiency of the trucks varies substantially by truck size and age, trucks get between 3 and 6 kilometers per liter of diesel.[6] Diesel prices averaged 750 CFA per liter over the period. This suggests that the average truck spend up to 2,500 CFA for the average round-trip to the clients' location and treatment-center.[7] These added variable costs for mechanical of approximately 5,500 CFA on average explain only 51% of the price differential between the manual and mechanical options suggesting that mechanical may be a less competitive market.

3.2 Supply

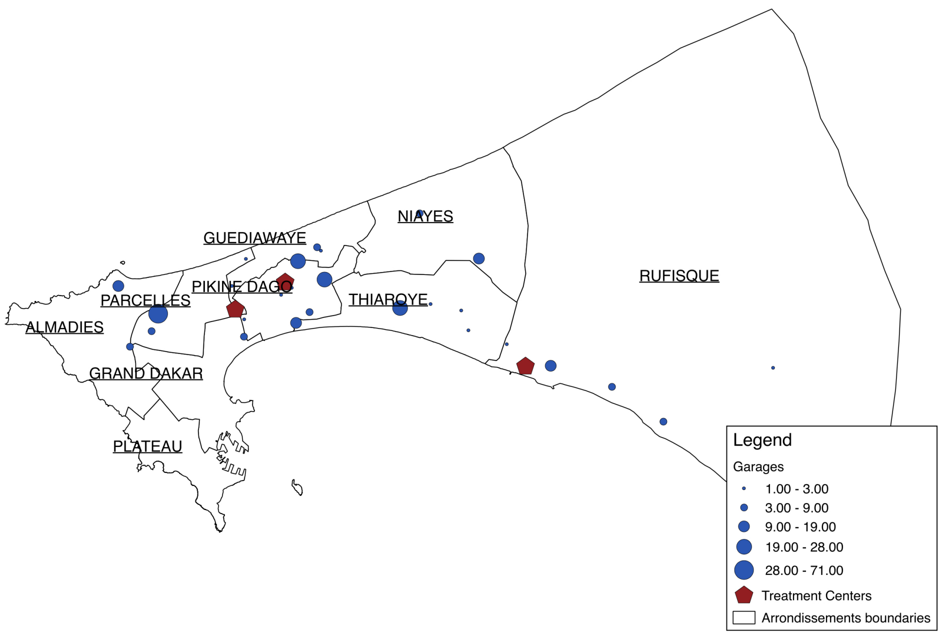
The supply-side of the market for desludging services is organized around a network of garages (or parking-lots) where clients meet service providers.

We use the provider survey to assign each truck to a garage. Figure 2 shows the location of garages and treatment-centers, and Table 2 gives summary statistics on distance and provider characteristics. The unit of observation is a truck license plate. The market includes

[6] In order to estimate the amount of diesel necessary per kilometer for a job, we sent an enumerator for ride-alongs with two truck drivers, filling the tank at the beginning and end of the day and recording their kilometers traveled and diesel used.

[7] The average distance from garages to the nearest treatment-center is 4.74 Km, while the average distances from garages to households and households to treatment-center are equal to 4.5 Km and 1.21 Km respectively. Therefore, the average round trip is roughly 10 Km.

Figure 2: Distribution of garages and treatment-centers



three treatment-centers scattered across the city. The figure also illustrates the uneven size distribution of garages. The largest garage located in Pikine (Foire) includes nearly 80 trucks, while some more informal garages include a handful of trucks. There are also a group of independent truckers who operate outside of the garage system, typically picking-up clients on the street or via cell-phone. Although our survey provides limited coverage for those truckers, discussions with market participants revealed that they tend to operate older and less fuel-efficient trucks on average.

Fourteen garages located across Dakar provide the focal point of the desludgers' businesses. Each operator typically belongs to one garage, and stations his truck there between jobs while he is waiting for additional business. Walk-in clients at the parking lot are allocated on a first-come/first-serve basis, and prices are bilaterally negotiated with the client.

The spatial differentiation of garages gives operators some pricing power, since households must incur sizable search costs when turning down an offer. Even if the customer is able to find an alternative garage somewhat further away, they will face additional costs as a result of the longer distance to the household, so instigating competition between garages is difficult. Moreover, competition from independent truckers unaffiliated with a garage is limited by search frictions.

A walk-in visit to a garage is not the only method used by households to find truckers.

For instance, member-drivers find business privately without reporting jobs to the garage dispatcher. The bottom half of Table 1 provides statistics on how consumers find truckers. Since households must repeatedly order the service (every 6 or 12 months on average), 44% of matches are realized via referrals or repeat use (e.g. household members or neighbors). Note that households do not sign long-term contracts with providers, and prices are negotiated for each trip. The second most common method is by visiting a garage where idle trucks are parked.

To estimate the productivity of each truck, we ask operators the number of desludging trips performed over the last 10 days. Table 2 summarizes this information. Although non-residential work is an important component of profits, 82% of trucks obtain the majority of their revenue from residential desludging services. On average, trucks perform slightly more than 1 trip per day (residential/non-residential combined), but we find substantial heterogeneity. The top 10 percent trucks in terms of productivity perform more than 3 jobs per day, and the most productive truck performed over 50 trips over a 10 day period. Based on this and discussions with provider, we estimate that a typical job takes between 1 and 2 hours from start to finish. Most truckers therefore operate with excess capacity, while a small fraction operate at full capacity. Eighty-five percent of desludging operators in the baseline provider survey stated that they could find more jobs if they wanted to make more money.

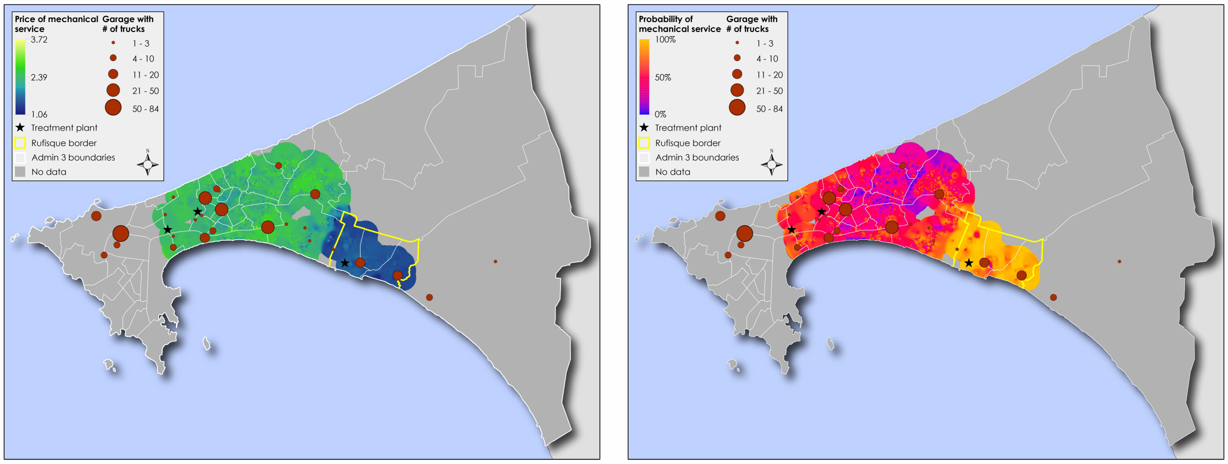
The compensation of drivers is consistent with under-provision of the service and limited competition. 92% are paid on salary, and about half of desludgers report paying a commission for jobs are referred to them from the garage ($\approx$ 3,000 CFA/day). A portion of these revenues is redistributed to company owners in the form of revenue-sharing agreements. For instance, desludgers in the largest garages report being paid by the parking lot on days when they do not find work. Similarly, among desludgers paid on commission, approximately 50% receive some payment even on days on which they do no desludgings.

4 A first look at collusion in areas controlled by the trade association

In this section we evaluate empirically the importance of imperfect competition in the market, contrasting prices and take-up rates of mechanical desludgings in the area controlled by the main garages in Dakar with an area of Dakar with much higher levels of competition. The ability of one area in the city to sustain market power while another has high levels of

Figure 3: Distribution of prices and demand for mechanical desludging across neighborhoods

(a) Average transaction prices (b) Transaction probabilities



competition is in theory sustainable because of spatial differentiation and limited capacity. Our objective is to contrast the pricing behavior in competitive regions of Dakar with the pricing behavior in regions controlled by the garages and more susceptible to market power.

To test the hypothesis that there is imperfect competition in the market, we study the spatial distribution of prices and demand across neighborhoods controlled by the garages (Pikine Dagoudane, Thiaroye, Guédiawaye and Niayes), with areas in which the garage structure is more conducive to competition (Rufisque). We use the Rufisque arrondissement as our competitive control.

Figure 3 plots the (smoothed) distribution of prices and demand across those two different neighborhoods. The boundaries of the competitive area are highlighted in yellow (south-east). The median price in Rufisque is 15,000 CFA, compared to 25,000 CFA in the rest of the city. Therefore, the Rufisque median price roughly corresponds to the price of manual desludging. As a result of this price difference, nearly all Rufisque households who required desludging during our sample chose the mechanical option, compared to 40% in the rest of the city. Our understanding of the functioning of the Rufisque sub-market is that firms set a base mechanical price that is slightly above the price of the manual option. This allows the companies to operate their truck at capacity and realize economies of scale. Firms therefore appear to behave competitively in this area.

Table 3: Mean differences in characteristics across neighborhoods

	Rufisque	Others	Difference	P-Value

Nearest center (Km)	4.55	2.84	1.71	0
Nearest garage (Km)	1.23	1	.23	0
Num. trucks (3km)	50.11	28.91	21.2	0
Wide road	.12	.05	.07	0
Tube meters	15.97	14.74	1.23	.15
Shopping: Street	.11	.12	-.01	.594
Shopping: Phone	.18	.22	-.04	.056
Concrete, no storage	.65	.75	-.1	0
Concrete, storage	.32	.22	.09	0
Slate roof	.34	.23	.11	0
Tile floor	.41	.54	-.13	0
Number of rooms	7.27	7.35	-.08	.698
1(Multi HH)	.24	.17	.07	.002
Num. other HH	1.08	.75	.33	.003
Household size	11.69	11.78	-.09	.805
Adult share	.67	.66	.01	.205
Children share	.33	.34	-.01	.305
Women share	.34	.34	0	.893
Room used (%)	.77	.79	-.02	.298
1(Own Motorcycle)	.08	.06	.01	.294
1(Own Fan)	.8	.85	-.05	.01
1(Own Refrigerator)	.51	.57	-.06	.014
1(Own Car)	.16	.18	-.03	.182
Own house	.78	.87	-.09	0
Num. earners	3.57	3.27	.31	.019
Num. other earners	.48	.54	-.06	.272
1(Other earners)	.27	.27	0	.887
Adult earners (%)	.51	.5	.02	.271

These differences do not necessarily imply that the rest of the market is collusive, since there are important differences between the two areas, which could in principle explain the lower prices in Rufisque. Table 3 summarizes the main household characteristics. We separate households living in the four largest neighborhoods from those living in the competitive control (Rufisque). The average household includes 11 members with a standard deviation of 7. Most households include several adults, and multiple earners. Since we have limited information on income, we proxy the wealth of the household using ownership of durable goods (e.g. fans, refrigerator, car), as well as characteristics of the building itself.

The last two columns calculate the average differences between households in Rufisque relative to the rest of the market. Although the size and composition of households are nearly identical across groups, Rufisque households tend to be poorer. In particular, they are less likely to own their house or other durable goods. House materials are also different. Rufisque residents also have easier access to desludgers than the rest of the market. The number of trucks within 3km of their house is much larger, and the fraction of households living on a wide road is more than double. On the other hand, the distance to the nearest treatment-center is larger on average in Rufisque. This statistic is a bit misleading however, since most households outside of Rufisque live closer to the Niayes treatment-center (north-east), although Niayes has less capacity and is more likely to be closed during high demand periods.

Boundary effects Our main hypothesis is that the markup on mechanical transactions is discontinuous near the Rufisque boundary; our proxy for differences in the degree of collusion. Assuming that the cost of desludging is continuous around the boundary, if there exists a difference in conduct between the two areas, only households living close to the boundary should be able to negotiate better terms. Note that we use the administrative boundary of the Rufisque Arrondissement to delineate the markets. Because of this, we should not expect a sharp discontinuity in prices.

We also test for two additional implications. If markups are lower, the number of mechanical transactions should be larger near the boundary, compared to areas far from Rufisque. We also study the effect of the boundary on the dispersion of prices. The fact that collusion is likely partial in the areas controlled by the association, should lead to a larger dispersion in markup as we move away from Rufisque.

To implement this test, we assume that conditional on observable characteristics of households, the distribution of mechanical desludging cost is the same in Rufisque and the rest of the city. Since we do not observe household-level cost, we rely on observed neighborhood and household characteristics to proxy for observed cost differences. This leads to the following pricing equation:

$$p_{it} = g^k\left(\text{Distance to rufisque}_i\right) + x_{it}\beta^k + \epsilon_{it}, \quad k = \text{Rufisque, Other.} \tag{1}$$

Controlling for observed household characteristics is important to obtain a consistent estimate of $g^k(\cdot)$. We estimate this pricing function separately for the two regions, and approximate $g^k(\cdot)$ using a step function of distance with 500 meters increments. We estimate a similar linear-probability specification to quantify the effect of distance to Rufisque on the probability of choosing mechanical over the two manual options. Note that since Rufisque is located in the East portion of the city, we measure the distance to Rufisque using distance to the west and north boundary connecting the neighborhoods of Niayes and Thiaroye.

Table 14 in the Appendix reports the estimates of $\hat{\beta}$ for the two regions.[8] The bottom two rows present the test results associated with the null hypothesis that the distance coefficients are equal to zero, and that the slope coefficients are equal across the two regions. The first hypothesis is strongly rejected in the rest of the market, but not in the Rufisque area; confirming that distance to Rufisque is a strong predictor of negotiated prices in the areas controlled by AAAS. We also reject the common slopes assumption. This is consistent with the fact that transactions are mostly performed using posted-prices in Rufisque, while they are negotiated in the rest of the city. Price negotiation opens the door to price discrimination (e.g. wealthier consumers pay more). For instance, we observe that households outside of Rufisque who own a refrigerator pay more on average, conditional on other variables proxying for the quantity of sludge. These results confirm our first hypothesis that competitive conduct are different between the two regions.

Figure 4 presents the relationship between distance to Rufisque and market conditions. To account for observed differences across the two areas, we compute the predicted outcomes evaluated at the average x's of households living in Rufisque. Each regression line corresponds to the predicted dependent variable for a representative household living in Rufisque. The green line presents the predicted outcomes in Rufisque, and the orange line presents the predicted outcome in the collusive region.

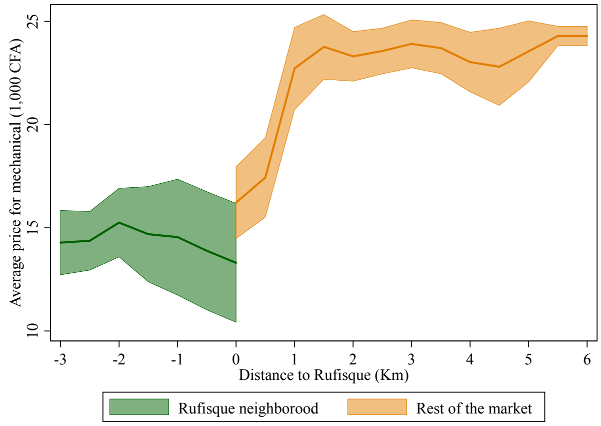
Figure 4a confirms that mechanical prices are increasing in distance in the areas controlled by AAAS, but flat in Rufisque. Households living within 500 meters of Rufisque pay nearly the same price as their neighbors; roughly 15,000 CFA. The gap widens significantly as we move more than 1 Km away from the boundary. For distances greater than 1.5 Km, the average transaction prices reaches close to 25,000 CFA, and the price schedule is independent of distance to the competitive region.

In contrast, Figure 4b shows that manual prices are independent of distance, and are roughly the same throughout the city. This is consistent with our hypothesis that the market for manual desludging is competitive. Note that the confidence-interval in Rufisque

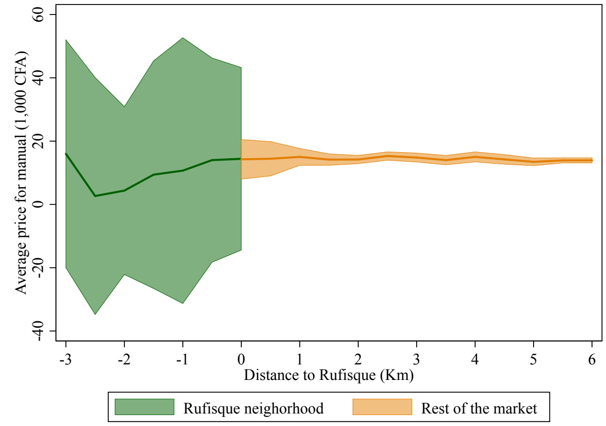
[8]The table omitted the coefficients associated with the distance group dummies, and with time/survey fixed-effects.

Figure 4: Predicted prices and demand as function of distance to the competitive region (Rufisque)

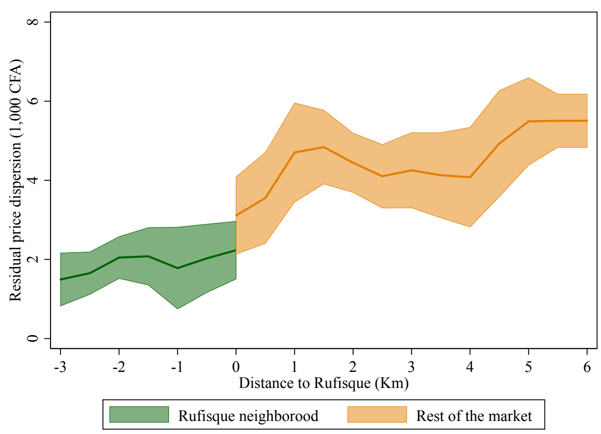
(a) Predicted mechanical prices



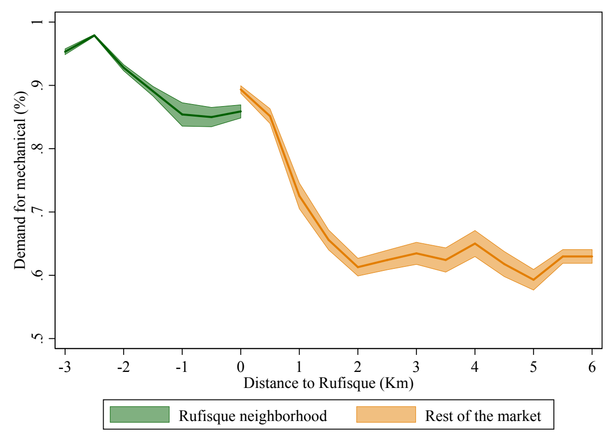
(b) Predicted manual prices



(c) Residual dispersion mechanical prices



(d) Predicted probability of choosing mechanical



is large because of the small number of manual desludging observations.

Figure 4c presents the effect of distance on the residual dispersion of prices. We estimate the conditional variance of the residual by regressing the absolute value of the residual obtained from equation (1) on distance and characteristics:

$$|\hat{\epsilon}_{it}^{k}| = g^{k}\left(\text{Distance to rufisque}_i\right) + x_{it}\beta^{k} + \epsilon_{it}, \quad k = \text{Rufisque, Other.} \tag{2}$$

Although the relationship between price dispersion and distance is relatively noisy, we observe a pattern consistent with the price level results. The predicted values can be interpreted as the standard-deviation of prices, conditional on distance and characteristics. In neighborhoods controlled by AAAS ("rest of the market"), this standard-deviation is roughly equal to 5,000 CFA, compared to less than 2,000 CFA in the competitive area. Dispersion is also increasing in distance from the boundary. These results are consistent with the hypothesis that prices are set more competitively in Rufisque. In the rest of the market, the observed increase in residual dispersion is consistent with models of price discrimination and search frictions.

The dispersion result is also consistent with the existence of a competitive fringe active in the collusive areas. Although our data does not identify sellers directly, in Table 14 we are able to control for how consumers find their desludger (i.e. phone or street hailing). Interestingly, households who find their supplier outside of the "regular" channels are paying significantly lower prices; between 500 CFA and 1,150 CFA respectively. Importantly, this difference is only present in the region controlled by AAAS. Although this variable could capture unobserved buyer heterogeneity, together with the dispersion results, this is consistent with the idea that some consumers are able to pay more competitive prices by avoiding garages controlled by AAAS.

Finally, Figure 4d analyzes the effect of distance to Rufisque on the probability of choosing the mechanical option (over both manual options). As before, this transaction probability is evaluated at the mean characteristics of households in Rufisque, to eliminate any compositional effects. The effect of distance on demand mimics the price results, suggesting that demand for mechanical desludging is elastic. Households within one kilometer of the boundary are choosing using mechanical desludging at a much higher rate than in the rest of the AAAS-controlled areas. The predicted probability in and around Rufisque is estimated at roughly 95%, compared to about 60% in the rest of the city. Note that this predicted fraction of users is larger than the unconditional probability reported in Figure 3. This is because Rufisque households have an easier access to mechanical services (i.e. predicted probability is evaluated at the average x of Rufisque households).

Productivity and profitability Table 4 investigates the difference the number of trips per truck across the two regions; our measure of firm productivity. We use information from the operator survey to estimate differences in productivity across Rufisque and other regions. We control for a large number of variables characterizing the trucker and the garages they are affiliated with.

Truckers in Rufisque perform on average 29 more trips over a 10 day horizon. This is despite the fact that the number of trucks per capita is larger in Rufisque (see Table 3). Recall that the average number of trips in the full sample is 12.82. Truckers in Rufisque

Table 4: Desludging truck usage regression results

VARIABLES	(1) Total trips	(2) 1(Dom. rev.>50%)	(3) Domestic trips	(4) Num. Arrond.
Rufisque	29.2***	0.58***	8.62***	-0.85***
	(5.41)	(0.12)	(1.60)	(0.26)
AAAS member	1.25	0.064*	2.15***	0.0022
	(2.09)	(0.033)	(0.79)	(0.082)
Constant	-1.00	0.19	0.38	2.99***
	(8.59)	(0.25)	(2.90)	(0.34)
Observations	133	156	154	143
R-squared	0.265	0.757	0.364	0.404

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Additional controls: Experience, distance to center, truck size, education, garage size garage HHI, population density, area size.

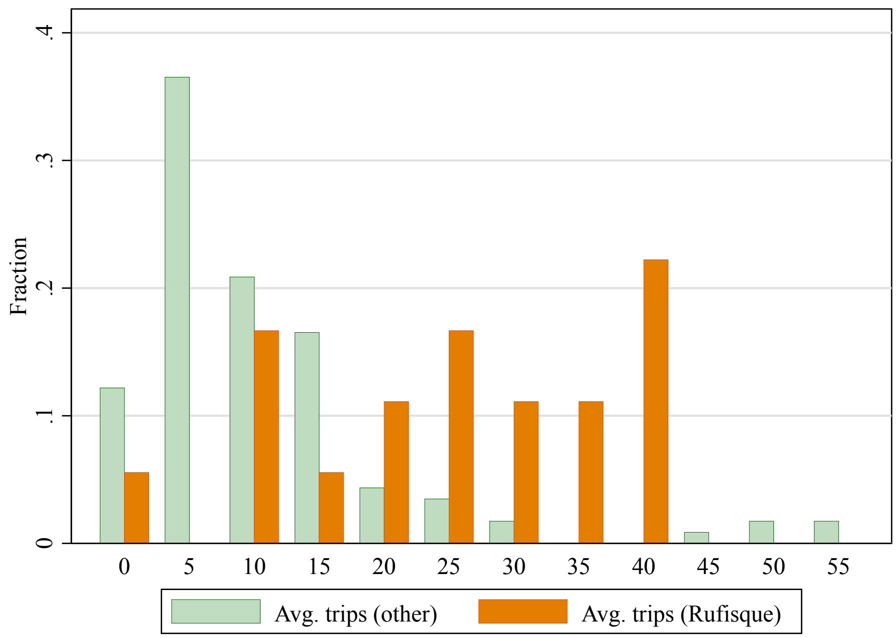
are therefore used at nearly full capacity. Figure 5 illustrates this point by plotting the distribution of trips across the two regions. The median truck in Rufisque performed 2.5 trips per day during our survey period, compared to 1 trips per day in the rest of the market. Note that the nature of non-residential trips in Rufisque are different from those performed in most other neighborhoods, because of the proximity of Rufisque to the ocean. Many desludging trucks in Rufisque are used for to clean up fish markets for instance.

We observe the same increase in magnitude in the number of domestic trips. A larger fraction of Rufisque trucks are doing mostly residential desludging, and perform on average 8.62 additional domestic jobs over a 10 day horizon. Finally, Rufisque trucks are less likely to do business in other neighborhoods than trucks in other regions. This is consistent with the price results around the boundary: Rufisque trucks are unlikely to serve clients outside of their neighborhood.

Note also that the AAAS dummy is imprecisely estimated, but positive across all specifications. In other words, we do not find evidence that companies directly associated with AAAS are less productive than others operating in the same neighborhood; where productivity is measured as jobs per truck. This is likely because trucks affiliated with the main garages tend to be better located, and more likely to match with consumers. Independent truckers are forced to pick-up clients from more isolated locations, or directly on the street.

Finally, we combine the reported trips measures for each truck with the the average

Figure 5: Distribution of trips per trucks across arrondissements (last 10 days)



transaction price per neighborhood, to construct a back-of-the-envelope measure of variable profits. In particular, for each truck in the provider survey, we calculate the average round-trip distance and transaction price among households surveyed. We use a 3 Km distance radius to define the territory around each garage. The total distance is calculated as the sum of the average distance from the driver's garage to each household within 3 Km, and the distance from households to the nearest treatment center, and from the treatment center to the garage. We use a fuel efficiency of 4 liters per Km, and a diesel price equal to 750 CFA/liter. We also account for a 3,000 commission fee paid to the garage, as well as a dumping fee of 300 CFA per cubic liter (or 3,000 for the average truck size). These three cost components approximate the marginal cost of the average trip.

Table 5 presents the results. The bottom panel summarizes the distribution of profit margins across the two regions. On average, the margin is slightly more than twice as large in the rest of the market, as in Rufisque ($16,900$ vs $8,180$). However, since Rufisque trucks perform more trips per day, the difference in variable profits is much smaller. The estimated daily profit for residential trips is *lower* in Rufisque, by about 2,000 CFA. When using the total trips measure (i.e. residential + commercial), Rufisque trucks are slightly more profitable. This difference should be interpreted with caution however, since since we

Table 5: Distribution of average daily profit margins and variable profits across regions

		N	Mean	SD	P10	Median	P90
Variable profits	**Residential trips**						
	Rest of the market	81	10.2	5.94	2.88	9.97	17.4
	Rufisque	18	7.57	2.12	5.48	8.34	9.48
	All trips						
	Rest of the market	81	19.5	20	3.6	13.4	38.2
	Rufisque	18	20.5	11.1	5.48	23	34.3
Profit margins	Rest of the market	81	16.9	.765	16	17.1	17.8
	Rufisque	18	8.18	1.25	6.25	8.67	9.48

Variable profit for truck i is: $\pi_i = \text{Trips}_i \times \left(\hat{p}_i - \text{Fuel} \times \widehat{\text{Distance}}_i - \text{Fee}\right)$. The price and distance are calculated using the survey of households living within 3Km of the garage. The fee corresponds to the average garage commission (3,000 CFA). All prices are expressed in $1,000$ CFA.

do not observe the profit margin on non-residential trips.

The percentiles also reveal interesting differences. The difference in profitability is mostly concentrated at the top of the productivity distribution. The most productive trucks in the rest of the market are nearly twice as profitable as in Rufisque. However, in the areas controlled by AAAS, there exists a large number of under-utilized trucks, which are significantly less profitable than trucks in Rufisque; despite charging higher prices.

5 Tacit collusion in the auction platform

In this section, we use data from the auction platform to evaluate the stability of tacit collusion in the market. We do so by inviting potentially collusive firms to participate in a new controlled competitive environment. We designed the auctions to incentivize firms behave competitively, without being detected. Firms were randomly invited to submit anonymous bids for over 5,000 clients over the course of three years. In 50 percent of the auctions, the platform also facilitates coordination by providing information about the current lowest-standing bid received and allowing bidders to revise their bid (as in **?**). By repeatedly observing bidding and participation behavior, we can measure firms' incentives to deviate from the collusive arrangement.

We start by describing the structure of the auction platform, and the source of random variation. We then use the outcome of these auctions to test for the presence of competitive behavior (or lack thereof).

5.1 Description of the auction platform

The design of the platform is simple and intuitive. When a household head needs a desludging service, he/she calls the center and gives the dispatcher basic information about the location of the pit to be desludged. The platform was designed to compete with the current supply organized around the garage system, by reducing search frictions and creating competition between sellers.

Jobs are made as homogeneous as possible through the rules of the call center: Households are told to expect the desludger to remove up to 8 cubic meters of sludge, and the winning operator is required to be available to do the job within two hours of the end of the auction.[9]

The call center dispatcher sends the job out for bidding to 8-20 desludging operators via text message. Both independent and affiliated operators are invited to bid on every job, and bidding is done anonymously. The platform informs the bidder as to the number of operators who have been invited and the number that are single truck operators versus those affiliated with larger companies, but not the specific identities of the other bidders.

The timing of each auction proceeds as follows. The invited desludging operators have one hour to bid on the job using text messages, and the operator with the lowest offer wins the job. In case of a tie, the bidder who sent the earlier bid wins, encouraging prompt bidding. The dispatcher then calls the household, informs them of the winning bid, and asks if the household accepts that price. If the household accepts, the desludging operator is given the household-specific information, and plans the remainder of the transaction directly with the household. Households pay desludgers directly.[10] The final winning bid is sent to all desludgers who have been invited to participate in the auction, but not the identity of the winner.

There are three main layers of randomization in the auction platform: (1) the auction format, (2) the number of bidders invited to the auction, and (3) the identities of the bidders invited to the auction. We exploit this randomization in order to measure how the desludgers change their bidding strategies across formats, and how competition and the identity of bidders affect auction prices.

[9]These rules were made so that desludgers could form expectations on the requirements of the service before submitting a bid. Desludgers with trucks less than 8 cubic meters are allowed to participate, but they must be ready to do more then one trip to empty a household's tank. Similarly, desludgers with tanks larger than 8 cubic meters are not required to take more than 8 cubic meters when they perform the service.

[10]After the job has been completed, customers respond to customer satisfaction surveys conducted by phone in order to ensure that quality of desludgings contracted through the call center remain high. In cases where the customer is dissatisfied or reports paying a price higher than the final auction bid, the job is investigated and the desludger is penalized in terms of future invitations to auctions if they are found to be at fault.

The auction format is randomized between a closed and revisable bidding format; each selected with 50-50 probability. In the first, the "sealed-bid format", bidders receive no updates after the auction begins and have one hour to submit a single bid. Bidders in this format are not allowed to change their bids after they have been submitted. In the second, the "revisable format", bidders are given updates about the standing low bid every 15 minutes and 5 minutes before the auction closes, and can submit a new, lower bid any time. In both cases, desludgers receive text messages reminding them that they have been invited to the auction at the same interval (every 15 minutes and 5 minutes before the end of the auction).

Invitations are randomized between the 104 desludging operators in the system. The number of invited bidders is uniformly distributed between 8 and 20. Invitation probabilities are independent of the distance to the caller, but differ across bidders as a function of past participations. We calculate the invitation probability as a piece-wise linear function of the number of valid bids submit by a truckers in the prior months. This probability is truncated at the bottom and top to ensure that the invitation probability bounded away from zero, and less than 50%.

We ran auctions for desludging services through the call center in collaboration with the Senegalese Office of Sanitation (ONAS) from July 2013 through April 2017, totaling 4005 auctions. We made one change to the platform in January 2015. At that time, the management of the platform was transferred to ONAS, and the invitation rule was modified. In particular, rather than over-sampling "active" participants, the probability of being invited became IID across truckers. Also, the number of invited bidders decreased on average from 14 to 11. Although these two changes affected the performance of the platform (less competition), it did not affect the random assignment of bidders to formats or clients.

Figure 6 illustrates the distribution of auctions across the period of analysis. Starting in March 2014, the platform was heavily advertised across our target region, which led to an increase in the number of calls per month. At the peek, the platform ran between 300 and 400 auctions per month. The platform was much less advertised after the transfer to ONAS, and as a result the number of callers dropped. The figure also highlights seasonalities in demand. The high-demand months corresponds to the rainy season in Senegal.

Table 6 summarizes the number of auctions and participants before and after the platform design change. The number of completed desludging is smaller than the number of callers. On average the acceptance probability is about 30%. This is in part because the platform was not designed to match clients with the most competitive set of potential bidders. The randomization implies that clients often receive a small number of quotes, or are matched

Figure 6: Distribution of auctions across months

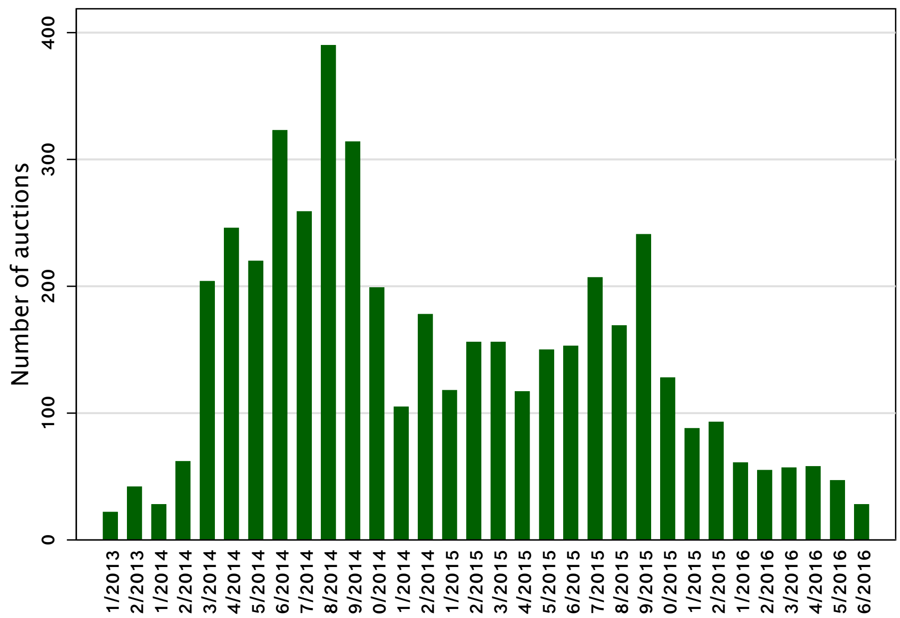


Table 6: Summary statistics on the auction platform

	Old paltform		New platform	
	Average	SD	Average	SD
Nb. of auctions	2669		2005	
Nb. of clients	2488		1680	
Nb. of completed jobs	862		481	
Auction format = Open	0.501	0.500	0.495	0.500
Probability of bidding	0.115	0.153	0.102	0.140
Invited auctions per firm	352	240	239	102
Number of firms	109		92	
Number of potential bidders	14	2	11	2
Valid bids per successful auction	2.878	1.529	1.848	1.042
Auctions with zero bids (%)	0.069	0.254	0.283	0.450

with distant truckers. Below we exploit this variation to identify demand for desludging at the platform.

The table also illustrates the experience and participation rate of bidders. The average bidder was invited to bid in 352 auctions prior to 2015, and 240 auctions afterwards. The participation rate is fairly low. Across both platforms, the probability of submitting a bid is about 10%, which leads to nearly three valid bids per auction. This hides substantial heterogeneity across bidders however, as we discuss below.

5.2 Hypothesis and identification strategy

We measure the stability of the cartel by identifying bidders behaving competitively in the auctions. We do so by exploiting the random assignment of bidders to clients and auction formats to test the null hypothesis of competitive bidding. Since each auction is anonymous and performed over a short period of time, it is unlikely that bidders are able to organize a "strong" cartel ring to suppress competition and select the lowest-cost firm. Instead, a rejection of this hypothesis is consistent with tacit collusion.

To test this hypothesis, we first identify strategies that are inconsistent with competitive bidding (e.g. Porter and Zona (1993), Porter and Zona (1999), Chassang et al. (2019)). An action is defined as "collusive" if a bidder submits a non-meaningful bid in an effort to suppress competition among cartel members (i.e. avoidance of competition). Conversely, we classify dominant strategies as "competitive", since they are associated with individual profit maximization. This identification strategy relies on documenting the prevalence of strategies that are either dominated and dominant for all bidders, irrespectively of their cost. Since the platform randomizes the auction format, we focus on identifying dominant/dominated actions that are specific to each strategic environment.

The first one focuses on the presence of identical bids (or tie) in sealed-bid first-price auctions. Excessive correlation in bids is a common "red-flag" used by antitrust authorities.[11] In our setting, under the collusion interpretation, identical bids reflect a tacit agreement between firms to focal prices in certain neighborhoods. Targeting focal prices used in the residential market softens competition by turning the auction into a lottery and allocating the good to participants who submit early bids. This is a dominated strategy, since a bidder can do strictly better by bidding below those focal prices, and increasing its probability of

[11] Since antitrust laws are not well enforced in Senegal, and the fear of being detected does not play an important role. Mund (1960) and Comanor and Schankerman (1976) provide early analysis of identical bids used in cartel cases, and McAfee and McMillan (1990) provide a theoretical discussion of the efficiency of this type of strategies.

winning the auction.

In the revisable auction format, firms can avoid "tying" by submitting a bid that undercuts the current lowest standing bid. As discussed in Haile and Tamer (2001), if a firm chooses to submit a bid it must be that his/her cost is lower than the previously advertised "bid to beat". In contrast a firm can avoid competing by matching the current lowest bid, bidding above, or not bidding at all.[12] Conditional on submitting an offer after a prior bid was placed, matching or bidding above the current lowest bid is analogous to submitting a "fantom" or losing bid. Note that this strategy can still lead to a transaction, because some bidders are penalized after providing low service quality in the past (penalty = 1,000 CFA). Rival bidders are only informed about the bid amount, and not about the penalty status of rivals. Given this uncertainty, a competitive player should bid slightly below to increase the probability of winning the contract.[13]

The timing of bid and the probability of sending a revised bid also reveals information about the competitiveness of a player. Bidding in the closed portion of the revisable auction is a dominant strategy if firms are maximizing individual profits.[14] Recall that unlike on eBay, sniping in the platform only affects the information provided to other bidders, and not the probability that a bid is rejected by the platform. Bidders have 10 minutes to submit a bid after the last message, and the platform gives an additional 5 minutes "grace" period to ensure that all bids are received. Since winning bidders pay their bid, it is optimal for firms to wait until the closed portion to submit their bid. Doing so limits the likelihood that the bid is undercut. Also, if bidding is costly, firms are better off learning about rival bids before bidding, rather than having to submit multiple offers over the course of the auction. In contrast, submitting an early bid can be viewed as an effort to coordinate prices by sending a signal to rivals.

This approach relies on identifying behavior that fail to maximize expected profit, and **does not** identify the intensions of bidders when committing those mistakes. Errors can arise also for other reasons than tacit collusion. For instance Hortaçsu et al. identifies the importance of bounded-rationality in electricity auctions, assuming competitive bidding.

[12]Not submitting a bid when the cost is lower than the current lowest bid is also a violation of profit maximization, but it is not testable without observing the private cost of each bidder.

[13]This argument assumes that the density of cost is continuous along the real time. If costs are discrete, and a bidder happens to face a cost exactly equal to the lowest-standing bid, matching is consistent with profit maximization. Given that bidder heterogeneity is most likely caused by capacity utilization and proximity to the client, it is more likely that the underlying distribution is continuous.

[14]Sniping on eBay is typically interpreted as evidence of common-value. See Roth and Ockenfels (2002) and Bajari and Hortaçsu (2003) for an analysis. This is unlikely to be the case in our context, since heterogeneity in cost is driven mostly by idiosyncratic factors such as distance or future commitments.

More generally, the presence tying and early bidding is consistent with the possibility that firms occasionally submit non-serious bids; either because of bounded-rationality or due market conditions (e.g. good outside option or high opportunity cost of time). This is an important caveat that applies to our approach, as well as much of the literature on testing for collusion. We discuss below how some of our results rule out alternative models "mistakes", but ultimately we cannot fully rule out some other interpretations.

To provide further evidence consistent with tacit collusion we leverage the panel dimension of the data to assess the persistence in bidders' propensity to behave competitively. Recall that we see the same bidders being invited to a large number of auctions (nearly 600 on average). We use this to measure the extent to which bidders that systematically choose dominated strategies in one format, are do so in the other format as well. Similarly, we identify "competitive types" as bidders who have a high propensity to choose dominant strategies across both formats, by adjusting their bidding strategy depending on the invitation. For instance, a negative correlation between the propensity to tie in the sealed-bid auction and bidding late in the open auction is consistent with the existence of a group of collusive bidders. A zero (or positive) correlation would be consistent with non-serious bidding.

5.3 Empirical analysis

Our detection strategy relies first on comparing auction outcomes across the two formats. Since the format is randomly assigned, this leads to a simple treatment effect regression estimated using auction-level observations:

$$y_t = \alpha 1\left(\text{Revisable}_t\right) + x_t\beta + \epsilon_t \tag{3}$$

where t indexes an auction, and y_t measures four different auction outcomes. We analyze the effect of the auction format on five outcomes variables: (i) winning bid amount, (i) winning bid is tied, (ii) winning bid is a round number (5,000 CFA increment), (iii) winning bid occurs in the last time interval, and (iv) timing of the first bid. We include observed characteristics in the regression for efficiency reasons, and to analyze their impact on auction outcomes. The results are unaffected by their inclusion, since the treatment assignment is balanced on covariates.[15]

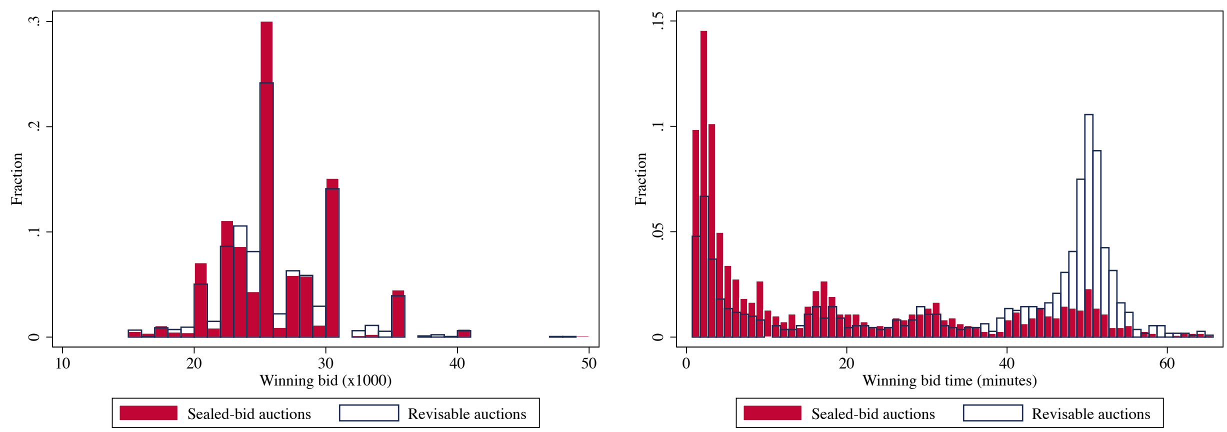
We start by analyzing the distribution of winning bid amounts and time. Figure 7

[15]Balance test results are available upon request.

Figure 7: Distribution of winning bid amounts and time across the two formats

(a) Distribution of winning bids

(b) Distribution of winning bid time



contrasts those two distributions using separate histograms for revisable and sealed-auctions. The winning bid distribution closely resembles the negotiated price distribution displayed in Figure 1, especially for bids coming from the sealed-bid format. The distribution exhibits clear mass points at common focal prices used in the regular market: 20, 22, 25, 30 and 35. The same mass points are present in the revisable format sample, but there are clear differences. Winning bidders in the revisable format are much more likely to under-cut those focal prices by 1,000, which leads to a higher density at 23, 24 and 29. This implies that cash-transaction frictions cannot fully explain the use of focal prices. The distribution of bids clearly shows that there exists a group of bidders willing to use a finer price grid to undercut the current lowest standing bid.

Figure 7b similarly suggests the existence of a group of competitive bidders. In the sealed-bid auctions, roughly 30% of winning bids are placed in the first 5 minutes. Since the tie-breaking rule favors early bidders, this is optimal for competitive and non-competitive types. In the revisable auctions, the mass of "early" winning bids is reduced substantially, and the modal winning bid is placed after the last message (i.e. minute 50). In between these two extremes, the distribution of bid time reflects the nudges created by the new messages.[16]

[16]Note that the distribution of bid time appears continuous around the message time. This is because the initial platform recorded arrival time with a slight error. This is not the case in the revised platform. In that sub-sample, we observe clear discontinuities around the message times. To classify bids "last minute bids", we round the arrival time up by two minutes if the bid time was recorded two minutes or less before the last message. Figure 7b plots the distribution of winning bid time for auctions performed under the initial design (i.e. prior to 2015). The revised format changed slightly the timing of reminder messages, which would introduce additional noise in the graphs. The bi-modality of the distribution persisted after the change.

Table 7: Effect of auction format on auction outcomes

VARIABLES	(1) Winning bid	(2) 1(Ties)	(3) 1(Round)	(4) 1(Last message)	(5) First bid (min.)
1(Revisable)	0.101	-0.0892[a]	-0.0927[a]	0.281[a]	3.216[a]
	(0.112)	(0.0156)	(0.0162)	(0.0141)	(0.571)
Observations	3,627	2,501	3,627	3,627	3,627
R-squared	0.353	0.054	0.082	0.145	0.220
Mean dep. variable	25.73	0.191	0.526	0.279	17.17

Robust standard errors in parentheses
[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

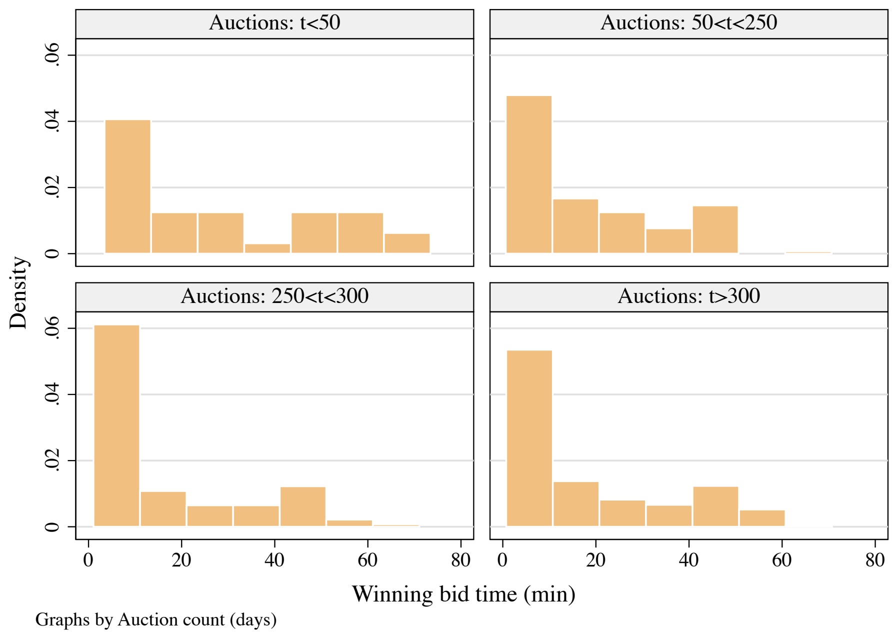
The fact that the winning bid time distribution does not look like the eBay platform where over 90% of bids are received in the last minute, but is instead a mixture of two distributions, is consistent with the idea that there exists a group of bidders who are not behaving competitively. If all bidders were behaving competitively by maximizing expected profits, the open auction would converge to a single mass after the 50th minute. The fact that the distribution remains bi-modal is consistent with the presence of a group of competitive bidders (last-minute bidders), competing with a group of non-competitive types (early bidders). Since the platform randomly invites a subset of potential bidders, the number of "competitive" bidders is not large enough to shift the entire distribution right and eliminate the early winning bids.

Interestingly, Figure 8 shows that bidders learned fairly quickly how to adjust their strategies in the open format. Late bidding was nearly inexistent in the first 100 auctions, and became the modal outcome starting with the 200th auction. The mass of early winning bids fluctuate somewhat over time and eventually stabilized around 18%. Learning also took place in the sealed-bid format: the fraction of early bids monotonically increased over time during the first 500 auctions; from about 30-40% in the first 200 auctions to more than 50% after the 500th auction. In the first 100 auctions, the bid times mostly reflected the timing of reminder messages in both formats, but the two distributions diverged over time: the sealed-bid times converged to a distribution with declining density density, while the open auctions converged to a bi-modal density.

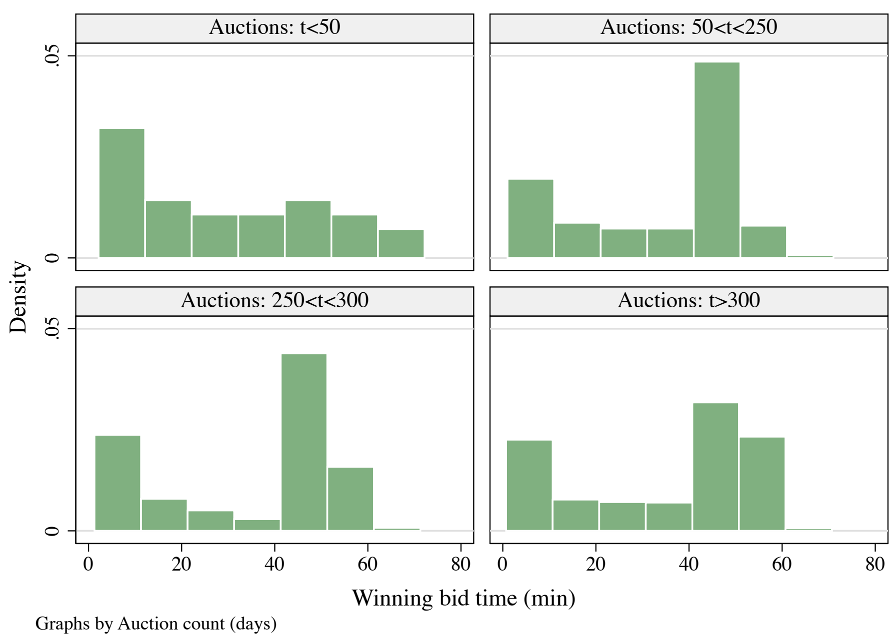
Table 7 reports the results of the regression analysis associated with (3). We report only the coefficients associated the auction format and the characteristics of invited bidders. Each regression includes additional auction and client characteristics. All five specifications are estimated using the full sample of closed and revisable auctions. Specification (2) (ties)

Figure 8: Distribution of winning bid times across auction

(a) Sealed-bid auctions



(b) Revisable auctions



uses the smaller subsample of auctions with at least two bids (i.e. 2892 instead of 4188 observations). This potentially creates a selection bias if revisable auctions are less likely to produce at least two valid bids. We account for this by including a polynomial function of the predicted probability of observing two or more bids estimated using the same set of control variables. The results are unaffected.

The first column tests the equality of wining bids across the two formats. The point estimates suggest that revisable auctions lead to offers that are on average 160 CFA larger than sealed-bid auctions, but the difference is not statistically significant (p-value is about 12%).[17] Although it is interesting to learn about the effect of the format on average winning bids, from a theory perspective there is no reason to believe that the two formats should be revenue equivalent (under collusion or competition). This is because the revisable auction format has a "hard close", and bids submitted in the last 10 minutes are not observed by rivals. The revisable auction is best described as a sequential auction: open followed by closed.

The next two specifications analyze the importance of ties and round bids. The probability that the winning bidder ties in the sealed-bid auction is significantly higher (i.e. 9 percent). As column (3) illustrates, this is explained by the fact that firms are significantly less likely to use round bids in the open format. This is consistent with Figure 7a above. By revealing the current lowest at the 50th minute, the revisable auction allows competitive bidders to submit bids that are "in the money" relative to the standing low bid as of minute 50, and win the auction more often.

Importantly, the fraction of round bids and ties does not go to zero in the revisable format. Table 15 in the Appendix presents the mean of each outcomes across the two formats. On average, 16.5% of revisable auctions end in a tie, compared to 25.6% for sealed. This is consistent the presence of a group of non-competitive bidders, but is inconsistent with the hypothesis that biased beliefs cause ties. It is likely that consumers do not have correct believes in the sealed-bid auction, which could explain the presence of ties. This is less likely in the revisable format, since firms learn quickly that failing to revise their bid down will result in a tie.

The last two specifications analyze the timing of bids. As Figure 7b suggested, winning bidders in the revisable format are significantly more likely to submit a bid in the last 10 minutes of the auction. The difference is 28 percentage point (i.e. 42% vs 14%). Similarly

[17] In general, collusion is thought to be easier to sustain in open auctions environments (without hard close). See Robinson (1985), Graham and Marshall (1987), Marshall and Marx (2007), Athey, Levin, and Seira (2011) for theoretical and empirical analysis of this in the context of english auctions.

the first bid is received earlier in the sealed-bid format (i.e. 19% vs 15.6%). The fact that the first bid arrives quickly on average in both formats explains the bimodal shape of the distribution of winning bid times. Both estimates confirm that the auctions are composed of two groups of bidders: early bidders in both formats ("non-competitive"), and bidders who submit late bids in the revisable format ("competitive").

Next, we investigate the correlation in bidding strategies across formats to provide support for the collusion interpretation. Specifically, we test the hypothesis that bidders who avoid dominated strategies behave competitively in both formats. To test this hypothesis we first construct a "collusive-index" by estimating the probability that a bidder tie the sealed-bid auction. We estimate this probability by estimating the following Probit model:

$$\Pr(\text{Tie}_{it}|x_{it}, \theta_i) = \Phi(-x_{it}\beta - \theta_i) \tag{4}$$

where θ_i is bidder i's fixed-effect. This fixed-effect measures the bidder's propensity to tie. We interpret this variable as a continuous measure of the incentive of firms to deviate from the collusive agreement. High θ bidders are less likely to deviate.

To reduce the measurement error in θ_i, we focus on active bidders submitting at least 30 bids in the sealed-bid auctions. Since those bidders are participating at a much higher rate than the average (30% compared to 10%), this sample includes the most experienced and attentive group of bidders.[18] 40 bidders satisfy this criteria (out of roughly 109 participating bidders).

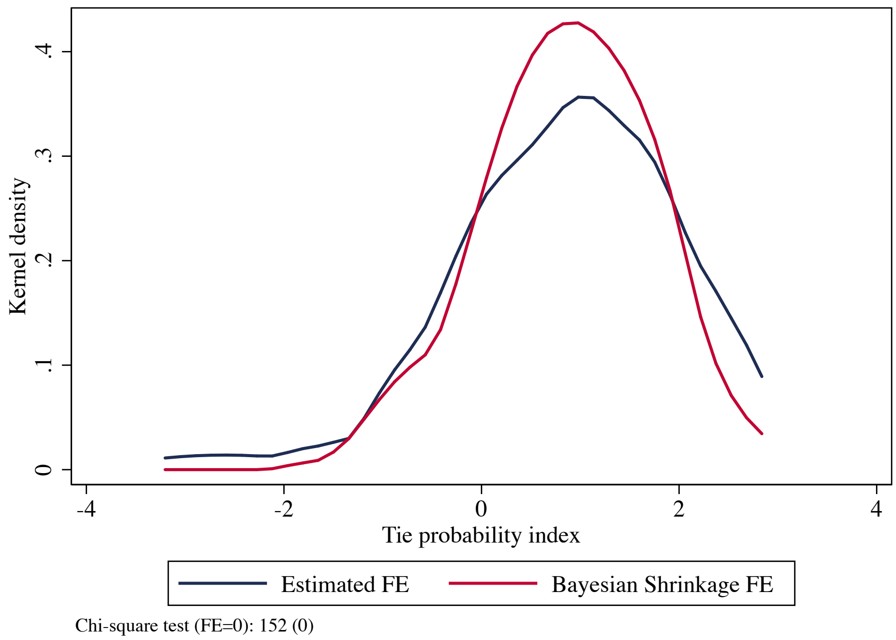
We estimate equation (4) using the sample of auctions with at least two valid bids. We control for observed characteristics of the auction that affects the sample selection (e.g. time/neighborhood fixed-effects, distance from garage and treatment center, aggregate time trends). We also control for the experience of bidders to account for learning effects (i.e. number of auctions invited prior to auction t).

Figure 9 illustrates the distribution of the collusion index across active bidders. The chi-square statistic (169) clearly rejects the null hypothesis of equal fixed-effects, which confirms the importance of bidder unobserved heterogeneity. To facilitate the interpretation, we normalized the index by its standard-deviation. We also report results using a *Bayesian Shrinkage* correction following the approach discussed in Chandra, Finkelstein, Sacarny, and Syverson (2016). This attenuates the importance of measurement error.[19] The sample includes a group of 11 bidders with a negative or close to zero propensity to tie (more com-

[18]The results are robust to varying the activity threshold from 20 to 40.

[19]To implement this correction, we project the estimated fixed-effects on observed bidder characteristics: garage FE, number of trucks, and truck size.

Figure 9: Distribution of the collusive index across active bidders



petitive types). The majority of bidders have a positive propensity to tie (less competitive types). Fifteen bidders have an index above 1.5, and the remainders have indices between 0.5 and 1.5.

To analyze the correlation between bidders' collusive type and bidding strategies, we estimate the following OLS regression estimated at the bid level:

$$y_{it} = \alpha\hat{\theta}_i + x_{it}\beta + \epsilon_{it} \tag{5}$$

where x_{it} is a set of control variables describing the auction and the client. The parameter α measures the correlation between the bidder collusive index ($\hat{\theta}$) and the choice variable y. We consider five outcome variables controlled by the bidder: (i) bid amount in the sealed-bid auction, (ii) indicator for round bid (5,000 increment), (iii) indicator for late bidding, (iv) indicator for bids that are "out of the money", and (v) time of first bid in the revisable auction.

Table 8 presents the main regression results using the shrinkage correction. Table **??** in the Appendix presents the same specifications without the shrinkage correction. Standard errors are clustered at the bidder level (40). Table 8a includes the results associated with bidding strategies in the sealed-bid auctions. The first column shows that bidders with

Table 8: Relationship between bidders' propensity to tie and bidding strategies (with shrinkage correction)

(a) Sealed-bid auctions

	(1)	(2)	(3)
VARIABLES	Bid amount	1(Round bid)	1(Late bid)
Tie FE	1.11^b	0.19^a	-0.049
	(0.51)	(0.050)	(0.066)
Observations	3,992	3,992	3,992
R-squared	0.222	0.143	0.062
Mean variable	27	0.60	0.21
Nb cluster	40	40	40

Robust standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

(b) Revisable auctions

	(1)	(2)	(3)	(4)
VARIABLES	1(Undercut)	1(Bid above)	1(Late bid)	Bid time
Tie FE	-0.093^b	0.058^b	-0.27^a	-12.0^a
	(0.042)	(0.024)	(0.068)	(2.75)
Observations	1,741	1,741	3,490	3,490
R-squared	0.083	0.052	0.240	0.230
Mean variable	0.37	0.043	0.21	26.7
Nb cluster	40	40	40	40

Robust standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

The control variables include: time and arrondissement fixed-effects, distance from garage to client (1km bins), number of invited bidders, auction hour, morning and lunch time indicator, distance to treatment center, client lat/long coordinates, population size, aggregate trend (cubic), new platform indicator, and experience of the bidder.

a high propensity to tie are submitting significantly higher bids. The difference between competitive types ($\theta = -2$) and collusive types ($\theta = 2$) is 4,400 CFA, or about 17% of the average bid placed. The second column confirms that bidders who are more likely to tie, are also more likely to submit "focal" bids using a grid with 5,000 CFA increments. However, all bidder types are equally (un)likely to submit a late bid in the sealed-bid auction (column 3). This os consistent with the idea that both collusive and competitive types have an incentive to bid early in the sealed auction due to the tie-breaking rule.

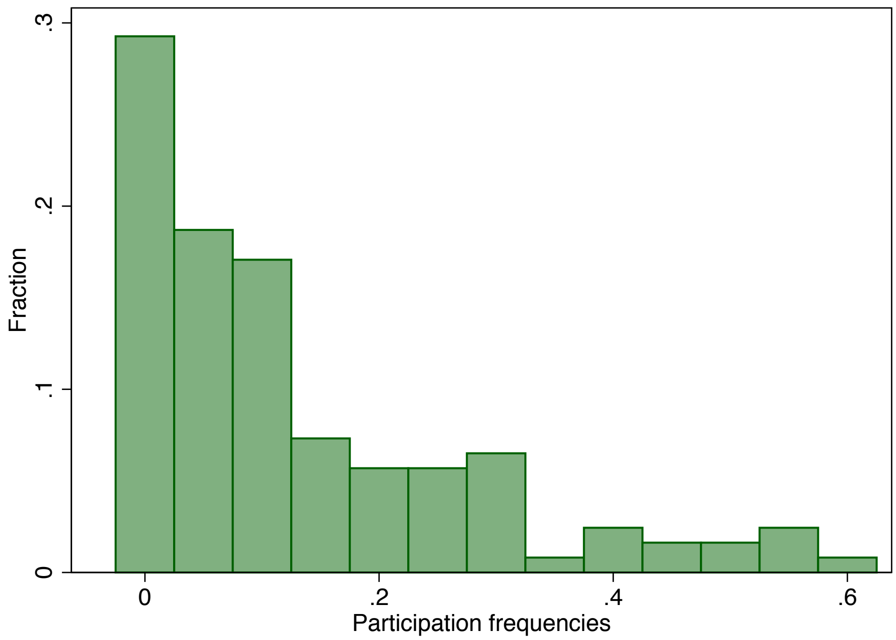
Table 8b shows similar results in the revisable auction sample. The first two columns analyze the probability of submitting losing bids. To estimate this regression, we further restrict the sample to bids placed after a price information message. Bidders who have a high propensity to tie in the sealed-bid auction (high $\hat{\theta}$), are also more likely to submit a losing bid in the revisable auction. Conditional on submitting a bid, those bidders are 9.3% less likely to undercut and 5.8% more likely to bid above the current lowest standing bid. Since those bids were placed *knowing* the value of the "bid to beat", this result shows that bidders behaving non-competitively in the sealed-bid auction, are also more likely to avoid competition in the revisable auction.

The correlation between "tying" and "late bidding" is also negative. The point estimates (-0.27) reveal that **only** bidders who have a low collusive index tend to submit bids after the last message. The first bid placed by non-competitive bidders also arrive much earlier: the difference between $\hat{\theta} = -2$ and $\hat{\theta} = 2$ is 48 minutes. This is in line with the idea that "collusive" types are using their first bid as a signal to other collusive bidders invited to the auction.

One obvious way firms can suppress competition is by refusing to bid. Figure 10 presents the distribution of participation frequencies across bidders. Indeed we observe that roughly 30% of bidders never bid, and another 30% participate in in less than 20% of auctions they were invited to. The group of active bidders represents the rest of the players; participation probabilities between 20 and 60 percent.

Table 16 analyses the relationship between bidders' propensity to tie, and the decision to participate in the auctions. Recall that we are only studying the participation decision of active bidders, and so it is reasonable to expect that those bidders pay attention to the invitation message, and endogenously decide to enter or not the auction. Columns (1)-(4) estimate a series of linear probability models accounting for observed differences across auctions, and the collusive index. Each specification flexibly controls for the distance between the bidder's garage and the client. In specification (2) we interact $\hat{\theta}_i$ with an indicator variable equal to one if the client lives within 2 Km of the garage; our proxy for

Figure 10: Distribution of participation frequencies across bidders



the territories associated with each garage.

In columns (1) and (3), we see that non-competitive types are less likely to submit a bid, although the point estimate is not statistically significant from zero with the shrinkage correction (it is different from zero only with the unadjusted index). The interaction with distance to garage shows however that bidders' types strongly predict the participation probability for clients located near the bidder's garage. For bidders with a propensity to tie greater than 1, the participation probability increases by more than 25 percentage point for clients located within 2 km. The average participation probability for active bidders is 27%. Therefore, the non-competitive types are bidding in nearly every auctions that located near their garage. Competitive types on the other hand are equally likely to bid on clients close or far from their own garage.This is consistent with the idea that collusive firms are more likely to get business through the garage system, while competitive firms match with clients using referrals and street hailing.

In summary, the previous results establish two patterns. First, the auction outcomes reveal the existence of deviations form the competitive model in both auction formats. Second, by measuring the propensity of a bidder to behave non-competitively, we show that there exist a group of competitive types that adjust their strategies across formats, and most often choose dominant strategies. This group quickly learned how to use the platform to win

Table 9: Relationship between bidders' propensity to tie and participation decision (with shrinkage correction)

VARIABLES	(1) Cutoff: 1 Km	(2) Cutoff: 2 Km	(3) Cutoff: 3 Km	(4) Cutoff: 4 Km	(5) Cutoff: 5 Km
Tie FE	0.28[a]	0.25[a]	0.17[a]	0.15[a]	0.11[b]
x Dist. $\leq$ Cutoff	(0.052)	(0.055)	(0.048)	(0.049)	(0.046)
Tie FE	-0.0061	-0.014	-0.017	-0.021	-0.023
	(0.044)	(0.043)	(0.042)	(0.041)	(0.042)
1(Open)	-0.013	-0.013	-0.013	-0.013	-0.013
	(0.0080)	(0.0080)	(0.0080)	(0.0080)	(0.0080)
Observations	26,279	26,279	26,279	26,279	26,279
R-squared	0.018	0.022	0.021	0.021	0.020
Mean variable	0.31	0.31	0.31	0.31	0.31
Nb cluster	40	40	40	40	40

Robust standard errors in parentheses

[a] p<0.01, [b] p<0.05, [c] p<0.1

clients, and offered lower prices. A second group of active bidders on the other hand systematically chose dominated strategies, and placed higher bids on average. It is important to acknowledge that we cannot rule out alternative interpretations for the presence of non-competitive behavior, for instance inattention or non-serious bidding. However, given our earlier analysis of the price and output differences across competitive and non-competitive neighborhoods, we conclude that a significant portion of non-competitive behavior that we document here are caused by tacit collusion in the market.

6 Measuring economic damages from collusion

In this section, we evaluate the economic damages of collusion in the market, by evaluating the price and quantity effects of collusion. We do so by measuring the change in consumer surplus and demand allowing all consumers to access more competitive prices.

We construct two counter-factual distributions that approximate more competitive environments. In the first one, we give consumers in the collusive neighborhoods access to the Rufisque price distribution (competitive control). In the second scenario, we give all consumers access to offers from auctions with competitive invitation lists (i.e. more competitive bidders and lower distance). This exercise is a partial equilibrium calculation of the effect of making the auctions more competitive.

Demand mechanical desludging We use a discrete-choice model to measure demand and willingness-to-pay. Let r_i denotes the reservation price of consumer i, and p_i denotes the best offer that i receives for the mechanical service. Since consumers are choosing between mechanical and one of two manual option (family or Baaypell), the reservation price is unobserved. Similarly, the mechanical price offer is unobserved for consumers choosing the manual option.

This leads to an endogenous selection model. Following (Heckman, 1979), we parametrize the distribution of reservation prices and offers as a bivariate normal distribution:

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

where $\mathbf{e}_i \sim N(0, \Sigma)$, and z_i is a variable that affects the mean reservation price, but does not directly affect the mechanical price. Let σ_j denotes the standard-deviation of e_{ij}, and σ_{01} the covariance between e_{i1} and e_{i0}.

After receiving an offer p_i, consumers choose the mechanical option if the surplus is positive:

$$y_i = 1 \text{ If } v_i = r_i - p_i > 0 \rightarrow z_i\alpha + x_i(\beta_0 - \beta_1) + e_{i0} - e_{i1} = \underbrace{z_i\alpha + x_i\gamma}_{\bar{v}_i} + u_i > 0 \tag{6}$$

We estimate the model by MLE after normalizing $\sigma_u = 1$. Let α, γ, σ_1 and ρ_{u,e_1} denote the parameters corresponding to the surplus distribution in the collusive area.

To identify σ_1 and ρ_{u,e_1}, we impose an exclusion restriction that the characteristics of household i's neighbors are uncorrelated with e_{i1}. We construct our instrument in two steps. Fist, we estimate by OLS the conditional mean of Baaypell prices in the city, using variables x_i as regressors. Let $\hat{p}^b(x)$ denotes this predicted for a household with characteristic x. We then calculate the sample average of $\hat{p}^b(x)$ among other households living in the same block as household i; on average there 4 households per block in our sample. This variable varies across households based on the observed characteristics of i's neighbors. The identifying assumption is that those attributes are independent of the distribution of mechanical price offers that household i receives (conditional on its own characteristics x_i), and are correlated with the reserve price r_i.

Table 10 reports the estimation results. The specification includes additional of household and neighborhood characteristics (see Table 3 for a detailed list). The model is estimated in the sample of household living more than 1 km away from the Rufisque boundary. As before

Table 10: 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 3)

the table highlights the role of distance to garages and treatment centers in determining prices and demand. The average price of Baaypell (manual) is a strong predictor of the mechanical choice, confirming that the two services are substitutes. The bottom two rows report correlation between u_i and e_{i1}, as well as the inverse-mills ratio coefficient. We can easily reject the null hypothesis of no endogenous selection. The correlation coefficient ($\hat{\rho}_{u,e_1} = -0.27$) suggest that consumers who receive high-price offers have low net surplus (i.e. high reservation price), consistent with models of price discrimination.

Counterfactual price distributions To calculate the effect of making the price distribution more competitive, we assume that the counter-factual offers are normally distributed with a different means and variances. Let β^{comp} and σ_1^{comp} denote the new location and spread parameters. We use the superscript "obs" to indicate parameters that the reflect the observed market equilibrium.

We use two counter-factual distributions to measure the effect of collusion on demand for mechanical desludging. The first one assumes that consumers in the collusive area have access to the Rufisque price distribution (conditional on x_i). Since there is essentially no endogenous selection in that market (i.e. take-up is nearly 100%), we estimate this price distribution via OLS. See specification (2) in Table 14 (Appendix) for the results. Let $\bar{p}_i^{\text{comp}} = x_i \hat{\beta}_1^{\text{comp}}$ denotes the mean offer that a consumer i living outside of Rufisque would receive in this counter-factual environment. We use $\hat{\sigma}_1^{\text{comp}}$ as an estimate of the standard-deviation of $e_{i,1}$ in the competitive environment.

We obtain the second counter-factual distribution using the results of the auctions. In particular, we estimate by OLS the mean and variance of the winning bid distribution, conditional on observed characteristics of the client, and measures of competition in the auction. To control the invitation list, we use the number of invited bidders, as well as the distance from the client to nearest invited bidders' garage. We measure both variables using the full list of invited bidders, as well as the list of active bidders invited. To account for the presence of competitive and collusive types, we also control for the number of bidders with difference levels of the collusive index (i.e. propensity to tie). We use five equally spaced groups.

Table 11 presents the results of this regression. The number and distance to nearest garage variables are strong predictors of the winning bid. Column (2) shows that controlling for the number of competitive and collusive types helps explain differences in bids across auctions. Adding one "very" competitive bidder to the auction leads to a 1,000 reduction in the winning bid. The marginal effect is monotonically increasing in the collusiveness of the group. The marginal effect of inviting more bidders in the top two groups actually leads to *higher* offers for consumers.

To construct a "competitive" auction, we construct an invitation list in which all competitive types are invited (i.e. 12 active bidders in the first three groups). We set the minimum distance to 500 meters, and set the total number of invited bidders to 20 (maximum). Table 12 summarizes the results of this exercise among all auctions that were conducted. Using this competitive bidder list would lead to a reduction of 5,290 CFA in the average winning bid.

We aggregate these predicted auction prices at the neighborhood level. Let $\bar{p}_i^{\text{comp}}$ denotes the mean of the offer distribution for all households in the survey. Since we observe limited characteristics of the platform clients, we assume that the mean of the distribution of offers is common to all households within a neighborhood. The variance of the residual of the winning

Table 11: Effect of competition and collusion on winning bids

VARIABLES	(1) Bid	(2) Bid	(3) Bid (log)	(4) Bid (log)
# bidders: Very competitive		-0.96^{a}		-0.040^{a}
		(0.13)		(0.0050)
# bidders: Competitive		-0.35^{a}		-0.014^{a}
		(0.10)		(0.0039)
# bidders: Mildly competitive		-0.077		-0.0023
		(0.053)		(0.0020)
# bidders: Somewhat collusive		0.031		0.0020
		(0.055)		(0.0021)
# bidders: Very collusive		0.083		0.0039^{c}
		(0.054)		(0.0020)
Min distance (Km)	0.063	0.060	0.0023	0.0021
	(0.048)	(0.048)	(0.0018)	(0.0018)
Nb. Bidders	-0.097^{a}	-0.068^{c}	-0.0033^{a}	-0.0024^{c}
	(0.031)	(0.035)	(0.0012)	(0.0013)
Active bidders x Less 10KM	-0.21^{a}	-0.23^{a}	-0.0093^{a}	-0.011^{a}
	(0.040)	(0.045)	(0.0016)	(0.0017)
Min. distance (active)	0.094^{a}	0.10^{a}	0.0036^{a}	0.0039^{a}
	(0.030)	(0.029)	(0.0011)	(0.0011)
1(Open)	0.13	0.10	0.0053	0.0044
	(0.11)	(0.11)	(0.0043)	(0.0043)
R-squared	0.313	0.325	0.327	0.342
Competition effect (sd)	0.77	0.99	0.031	0.040

Robust standard errors in parentheses
^{a} p<0.01, ^{b} p<0.05, ^{c} p<0.1

Table 12: Change in the winning bid distribution and acceptance probability from increasing competition within all auctions

	mean	sd	p25	p50	p75
Price difference	-5.29	1.00	-5.92	-5.26	-4.61
Accept prob. (observed)	0.29	0.12	0.21	0.28	0.35
Accept prob. (competition)	0.48	0.14	0.40	0.48	0.56
Δ Accept prob. (%)	0.81	0.55	0.47	0.69	1.01
Observations	3626				

bid regression similarly gives us an estimate of σ_1^{comp}. Note that there is no truncation in this sample, since we observe both accepted and rejected offers.

Counterfactual demand and consumer-surplus We use the two competitive price distributions to predict the take-up rate of households in the survey. To construct this counter-factual, we need to obtain an estimate of σ_u^{obs} (normalized to 1 in the estimation). Recall that the unconditional mean of v_i is the average difference between the reserve price r_i and mechanical price p_i. Assuming that distance to the nearest treatment center (mechanical cost shifter) does not affect the manual price, the effect of distance on participation identifies the scale of u:

$$\gamma_{dist} = \beta_{1,dist}/\sigma_u \to \hat{\sigma}_u^{\text{obs}} = \frac{\hat{\beta}_{1,dist}^{\text{obs}}}{\hat{\gamma}_{dist}^{\text{obs}}}.$$

We use this calculate the mean and variance of the reserve price using the following two identities:

$$\bar{r}_i = \underbrace{\hat{\sigma}_u^{\text{obs}} \cdot (z_i\hat{\alpha} + x_i\hat{\gamma})}_{\bar{v}_i^{\text{obs}}} + x_i\hat{\beta}_1^{\text{obs}} \text{ and } \sigma_u^{\text{obs}} = \sqrt{\sigma_0^2 - 2\sigma_{01}^{\text{obs}} + \sigma_1^{\text{obs}2}}.$$

We assume that $(\bar{r}_i, \sigma_0)$ are invariant to the change in competition. This is justified by our assumption that the manual service is competitively provided.

Putting these pieces together, we can calculate the distribution of consumer surplus in the counter-factual environment as follows:

$$v_i^{\text{comp}} \sim N\left(\bar{r}_i - \bar{p}_i^{\text{comp}}, \sigma_u^{\text{comp}2}\right).$$

The expected take-up probability and surplus for consumer i in the competitive environment can be written as:

$$s_i^{\text{comp}} = \Pr(v_i^{\text{comp}} > 0) = 1 - \Phi(-(\bar{r}_i - \bar{p}_i^{\text{comp}})/\sigma_u^{\text{comp}}) \tag{7}$$

$$E(v_i) = s^{\text{comp}} \times \left(\bar{r}_i - \bar{p}_i^{\text{comp}} + \sigma_u^{\text{comp}} \frac{\phi(-(\bar{r}_i - \bar{p}_i^{\text{comp}})/\sigma_u^{\text{comp}})}{1 - \Phi(-(\bar{r}_i - \bar{p}_i^{\text{comp}})/\sigma_u^{\text{comp}})}\right) \tag{8}$$

Table 13 reports the results of the two counterfactual experiments. Both scenarios lead to sizable decrease in prices. Not surprisingly, the Rufisque price distribution yields the larges price decline (i.e. 42% compared to 17% from the auction). This translates into large reduction in residual price dispersion, and increase in consumer surplus. The Rufisque experiment increase the average surplus fivefold, while the surplus increase from the auction corresponds to 160% of the baseline allocation.

Table 13: Effect of increasing competition in the market on prices and takeup

	Mechanical price distribution			Percent change	
	Observed	Rufisque	Auction	(2)-(1)	(3)-(1)
Mean offers	26.14	15.02	23.10	-0.42	-0.11
SD offers	7.00	3.04	3.43	-0.57	-0.51
CS	1.72	13.36	8.34	28.34	16.87
Takeup	0.42	0.71	0.54	2.69	1.70

Finally, the bottom row shows the effect of collusion on the takeup probability. If consumers in the collusive region had access to the Rufisque price distribution, the average takeup probability would increase from 42% to 71%. This new equilibrium would still be lower than in Rufisque, mostly because the area is more geographically dispersed, and some consumers do not have an easy access to mechanical desludging (i.e. narrow streets or distant from treatment centers). The increase in takeup from the auction is also large. The fraction of households choosing mechanical desludging increases to 54%. Importantly, this is a lower bound on the effect of removing collusion in the market, since many invited bidders appear to behave collusively.

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Figure 11: Distribution of survey households across neighborhoods

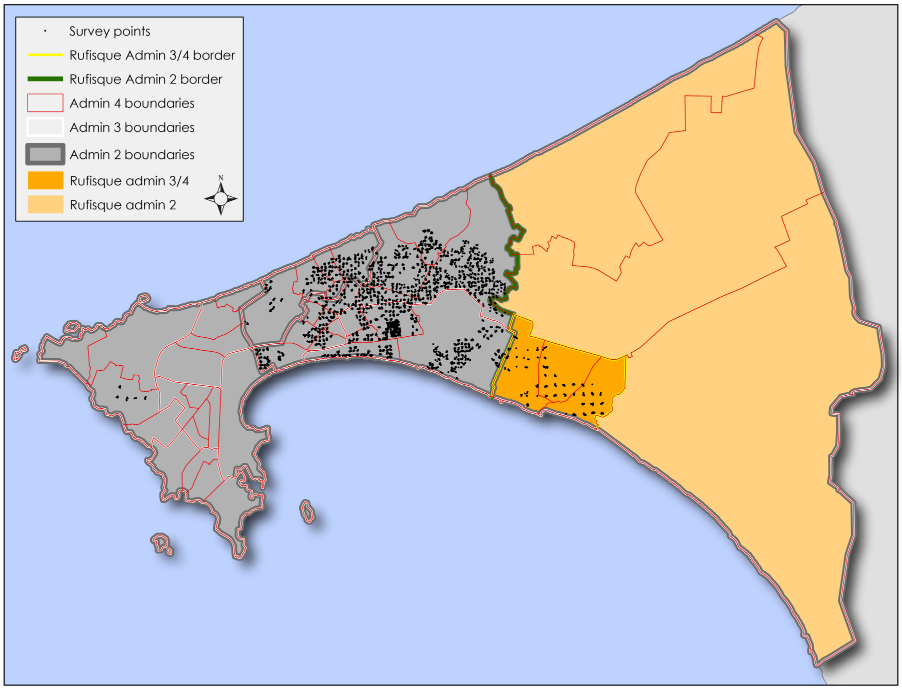

Table 14: Mechanical price regression across neighborhoods

	(1)	(2)
VARIABLES	Rest of the market	Rufisque
Shopping: Street	-1.15***	0.76
	(0.42)	(0.57)
Shopping: Phone	-0.54*	-0.47
	(0.32)	(0.42)
Nearest center (Km)	1.25***	-2.17
	(0.25)	(1.35)
Nearest garage (Km)	0.50**	1.26
	(0.22)	(1.03)
Num. trucks (3km)	0.020***	0.0048
	(0.0078)	(0.051)
Wide road	-1.16*	1.50
	(0.67)	(1.07)
Tube meters	0.045***	0.027
	(0.014)	(0.022)
Concrete, no storage	-1.64**	0.12
	(0.71)	(1.17)
Concrete, storage	-1.32*	1.30
	(0.72)	(1.26)

Slate roof	-1.51***	-0.31
	(0.41)	(0.47)
Tile floor	1.67***	-0.15
	(0.31)	(0.42)
Number of rooms	0.16***	-0.045
	(0.050)	(0.057)
1(Multi HH)	-0.22	-0.073
	(0.51)	(0.90)
Num. other HH	0.26***	0.33
	(0.095)	(0.24)
Household size	0.068**	0.15***
	(0.029)	(0.058)
Adult share	4.20	14.1
	(6.22)	(9.83)
Children share	0.93	11.5
	(6.17)	(9.28)
Women share	-0.59	-0.85
	(0.82)	(1.48)
Room used (%)	0.58	-0.60
	(0.76)	(1.03)
1(Own Motorcycle)	-0.18	-1.15
	(0.46)	(0.72)
1(Own Fan)	0.24	0.31
	(0.40)	(0.53)
1(Own Refrigerator)	1.36***	0.097
	(0.31)	(0.40)
1(Own Car)	0.42	0.69
	(0.32)	(0.48)
Own house	-0.28	0.0049
	(0.35)	(0.56)
Num. earners	-0.25**	-0.43**
	(0.097)	(0.20)
Num. other earners	-0.10	-0.054
	(0.18)	(0.19)
1(Other earners)	-0.28	-0.41
	(0.43)	(0.53)
Adult earners (%)	0.65	1.62
	(0.72)	(1.31)
Constant	15.2**	5.95
	(6.43)	(10.4)
Observations	2,941	350
R-squared	0.197	0.179
H0: Boundary coefficient (p-value)	0	0.24
H0: Common slopes (Chow)		0

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 15: Differences in auction outcomes across the two formats

VARIABLES	(1) Winning bid	(2) 1(Ties)	(3) 1(Round winning bid)	(4) 1(Winner sniping)	(5) First bid (min.)
1(Open)	25.96[a]	0.165[a]	0.480[a]	0.426[a]	18.89[a]
	(0.0900)	(0.0286)	(0.0110)	(0.0109)	(0.435)
1(Sealed-bid)	25.72[a]	0.256[a]	0.573[a]	0.141[a]	15.63[a]
	(0.0906)	(0.0295)	(0.0107)	(0.00755)	(0.398)
Observations	4,189	2,892	4,189	4,189	4,189
R-squared	0.975	0.202	0.531	0.354	0.452
Mean dep. variable	25.84	0.189	0.527	0.281	17.24

Robust standard errors in parentheses
[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$

Robust standard errors in parentheses. Significance levels: [a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$. These regressions do not include additional control variables.

Table 16: Relationship between bidders' propensity to tie and participation decision (whithout shrinkage correction)

VARIABLES	(1) Sealed	(2) Sealed	(3) Open
Tie FE x Distance<2 Km		0.23[a]	
		(0.059)	
Tie FE	-0.054	-0.064	-0.027
	(0.042)	(0.041)	(0.042)
Observations	13,020	13,020	13,281
R-squared	0.036	0.041	0.030
Mean variable	0.31	0.31	0.31

Robust standard errors in parentheses
[a] $p<0.01$, [b] $p<0.05$, [c] $p<0.1$