Technology and Tax Capacity: Evidence from Local Governments in Ghana*

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Abstract

This paper studies the role of technology in local-government tax collection capacity in the developing world. We first conduct a new census of all local governments in Ghana to document a strong association between technology use and property tax billing, collection and enforcement. We then randomize the use of a new revenue collection technology within one large municipal government. Revenue collectors using the new technology delivered 27 percent more bills and collected 103 percent more tax revenues than control collectors. Collectors using the new technology learned faster about which households in their assigned areas were willing and able to make payments. We reconcile these experimental findings in a simple Beckerian time-use model in which technology allows revenue collectors to better allocate their time towards households that are the most likely to comply with taxpaying duties. The model's predictions are consistent with experimental evidence showing that treatment collectors are more likely to target households with greater liquidity, income, awareness of taxpaying duties, and satisfaction with local public goods provision.

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1 Introduction

A common feature of lower-income countries is a government that collects little tax revenue and provides few public goods. The literature on state capacity argues that the inability to collect taxes is at the heart of why low-income countries are as poor as they are (e.g. Besley, Ilzetzki, and Persson, 2013; Dincecco and Katz, 2016; Mayshar, Moav, and Pascali, 2022). This literature suggests that the path to development may begin with investing in the capacity to collect taxes to finance productivity-enhancing public goods.

This paper studies the role of technology in improving government tax capacity. The setting is local governments in Ghana, which are in charge of collecting property taxes but collect very little in practice. As we detail below, the technology in question consists of a geospatial database of properties embedded into an electronic tablet with GPS capabilities. Similar technologies have been implemented in a number of other developing countries in recent years with a goal of increasing tax revenues (Fish and Prichard, 2017). However, technology investments may ultimately have limited impact if they do not address the most important constraints on local tax capacity; moreover, the implementation of technology in the field may fail due to logistical and technical challenges or subversion by officials. To our knowledge, our paper is the first to randomize the presence of a new technology for tax collection to causally study its impacts.[1]

We set the stage by establishing facts about local tax capacity, based on a new census we conducted in every local government in Ghana. The census data highlight how poor infrastructure constrains tax collection practices. In a typical district fewer than half of property tax bills are actually delivered. Limited delivery stems from the fact that only around one in four properties has a physical address, and a minority of streets have names. As a result, location information on bills is imprecise and revenue collectors struggle to navigate in the field. Household compliance is low due to citizens' limited awareness of taxpaying duties, low satisfaction with public services, and limited enforcement. The majority of tax payments are paid in cash directly to revenue collectors, creating opportunities for "leakages." Our census reveals that a minority of local governments have adopted revenue management software and electronic databases of properties, and these governments have significantly better outcomes at every stage in the tax collection process. In particular, they deliver more bills, have higher payment rates and collect revenues with lower cost than governments without technology.

[1] Several prior studies have leveraged policy reforms to create non-experimental variation in technology usage, focusing on technologies which digitize third-party transactions between taxpayers, including Eissa and Zeitlin (2014); Brockmeyer and Somarriba (2022) and Fan, Liu, Qian, and Wen (2021); see Okunogbe and Santoro (2021) for a review of other related studies.

The tight empirical link between technology use and tax collection outcomes at the local-government level naturally invites questions about the direction of causality. To address these issues, we partnered with one large municipal government in Ghana and a private technology firm to randomize the use of technology within the government's jurisdiction. In particular, we randomized the use of a new revenue collection software and geospatial database of properties at the level of a revenue collector. In the experiment, both treatment and control collectors were given a stack of around 135 bills of similar value in a randomly assigned area and tasked with collecting as much revenue as possible in six weeks. The treatment group was given an electronic tablet that uses the geospatial data and improves navigation and locating properties. Otherwise the two groups of collectors, and their assigned areas, were observationally similar.

Revenue collectors using new technology delivered 27 percent more bills than the control collectors by the end of the study. We view this result as reflecting the navigational advantage that the technology provides in locating taxpayers more efficiently in an environment with scant property addressing. The time series of cumulative bills delivered exhibits a concave pattern over time, as collectors shift emphasis from delivering bills to following up with the households that already received a bill in order to collect payment from them. Revenue collections were 103 percent higher among the collectors assigned to the technology group, on average, implying a treatment effect on revenue collections around four times as large as the effect on bills delivered. Moreover, we find that the treatment effect on collections grows over time, leading to a rising average amount collected per bill delivered throughout the experiment.

We explore several potential hypotheses for why the treatment effect on collections is so much larger than the treatment effect on bill deliveries. One story is that households in treatment areas change attitudes toward payment after being visited by collectors with a modern technology. Yet households in treatment and control areas surveyed right after the experiment report statistically similar levels of perceived integrity and ability to enforce tax payments among local government officials. A second hypothesis is that the technology helps reduce leakages, e.g. in the form of payments made by households but diverted by revenue collectors before reaching the local government's coffers. However, several types of household survey questions about the preponderance of bribe payments point to more – rather than less – bribe activity in treatment areas than in control areas.

Our preferred explanation, which is new to this literature, is that technology allows collectors to directly gather knowledge about which households are most likely to make tax payments, and to better target those households in their collection efforts. By reducing navigational challenges, technology frees up scarce time for collectors which they use to learn, through repeat visits or longer visits, about the hard-to-observe household characteristics that are most relevant in determining a household's propensity to pay. Using surveys of collector behavior and strategies, we show that treatment collectors report fewer navigational challenges and better knowledge over time about which households in their assigned areas are willing and able to pay property taxes. In addition, we show that treatment collectors switch more over time into collection strategies focused on households with greater liquidity, income, awareness of taxpaying duties, and satisfaction with local public goods. Importantly, none of these household characteristics would have been known to the collectors at the start of the study period, highlighting the importance of technology for acquiring information about the 'soft' characteristics of taxpayers that would not be readily apparent on a tax bill or in a property database.[2]

We formalize this mechanism by embedding time-savings and learning in a dynamic Beckerian time use model in which forward-looking revenue collectors maximize collections subject to a time constraint each period. Households have a high or low payment probability, and the type is initially unknown to the collectors. Treatment collectors have higher probabilities of delivering a bill, which captures technology's navigational advantage in locating households. Treatment collectors also have a higher probability of learning a household's type, which captures how treatment collectors leverage the technology to learn more about household types. The probability of collecting a tax payment from a household of each type is identical across treatment and control collectors.

We calibrate the model to match the treatment effects on bill deliveries and on collector focus on hard-to-observe household characteristics. The calibrated model reproduces the concave time series pattern of treatment effects on bill deliveries and the convex effect on collections. The model's implied treatment effect on collections is roughly twice as large as its treatment effect on deliveries. Counterfactual simulations reveal that without faster learning about household types in the treatment group, the treatment effect on bill deliveries and collections would be similar in magnitude. Thus, our model shows that the differential learning and targeting mechanism explains roughly half the gap between delivery and collection effects observed in our experiment, making it about equally important as the direct effect of reduced navigational challenges in delivering bills.

Improved learning through technology has important distributional impacts. Due to increased knowledge and subsequent targeting of higher-income households in treatment areas, the tax system becomes more progressive: we find that tax payments as

[2]Our finding that technology impacts collector strategies is related to other experiments with tax collectors, including on performance-based postings and financial incentives (Khan, Khwaja, and Olken, 2015, 2019) and group-work assignments (Bergeron, Bessone, Kabeya, Tourek, and Weigel, 2021).

a share of taxes due increases in the top quartiles of the income-asset distribution but remains unchanged in the bottom quartile. However, technology appears to be a double-edged sword, as the treatment effect on bribes is concentrated in the bottom quartiles.

Our experimental findings shed novel light on the promises and pitfalls of using technology to build tax capacity.[3] Our results support theories of government arguing that technology investments lead to growth in government size, including due to efficiency improvements (Brennan and Buchanan, 1980; Kau and Rubin, 1981; Becker and Mulligan, 2003). At the same time, our bribe results suggest that early expansions of government size may be accompanied by increased corruption (as in Daunton, 2001; Carpenter, 2020; Cui, 2022). The technology we study improved tax outcomes by alleviating constraints on collection which arose from incomplete property addressing. The United Nations estimates that 4 billion people live in places without physical addresses (web link); in this context, our paper provides some of the first evidence about how technology may help overcome constraints on public service delivery stemming from incomplete property addressing infrastructure.

Our results suggest that the positive effects on tax outcomes are only partly due to the presence itself of technology. By reducing navigational challenges, technology freed up time for collectors in the field which they used to directly build 'soft' information about taxpayers' propensity to pay. Our findings therefore relate to papers which show how *pre-existing* information, mainly from third-parties including employers and financial institutions, can be leveraged to improve collection (Kleven, Knudsen, Kreiner, Pedersen, and Saez, 2011; Pomeranz, 2015; Naritomi, 2019; Balan, Bergeron, Tourek, and Weigel, 2022; Londoño-Vélez and Ávila-Mahecha, 2021). Most prior studies place third-party 'hard' information at the center of governments' informational capacity (Gordon and Li, 2009; Kleven, Kreiner, and Saez, 2016). Our work shows how, when such hard information sources are largely non-existent, the state can still strengthen its informational capacity by *directly* building 'soft' information on taxpayers. The importance of 'soft' information for tax capacity is most relevant in developing countries where third-party information often remains limited (Almunia, Hjort, Knebelmann, and Tian, 2022; Jensen, 2022; Waseem, 2022).[4]

[3]Experimental evidence on technology exists in other governance areas, including social transfers (Muralidharan, Niehaus, and Sukhtankar, 2016) and monitoring (Callen, Gulzar, Hasanain, Khan, and Rezaee, 2020; Dal Bo, Finan, Li, and Schechter, 2021; Vannutelli, 2022). Studies in public finance have indirectly highlighted technology's value by providing taxpayers with incentives or information made available due to its presence (Carillo, Pomeranz, and Singhal, 2017; Okunogbe and Pouliquen, 2022).

[4]Our work relates to recent studies on property taxation in developing countries, including those cited in footnote 2 and Best, Gerard, Kresch, and Naritomi (2020) and Brockmeyer, Estefan, Suárez Serrato, and Ramírez (2020). For a historical analysis of the US property tax, see Dray, Landais, and Stantcheva (2022).

2 Census of Tax Collection Capacity in Local Government

There is limited systematic evidence about the process of tax collection by local governments in the developing world. To better understand this process, and the constraints on collection, we conducted a census of all local governments in Ghana in 2017, focusing on taxation. In this section we summarize the main findings from this census.

2.1 Census of Local Government Tax Capacity

We conducted the census of local governments in fall 2017 in collaboration with several national ministries and all the local governments in Ghana's 216 districts (one local government per district). The aim of the census was to collect data on every relevant dimension of tax collection in each local government. Three sets of respondents were interviewed: local officials; locally elected assembly members; and, citizens. Within the first set – which is the most extensive – survey responses were collected from every official that participated in the tax collection process. These included the chief executive (the political head), the coordinating director (the bureaucratic head), the finance officer, the budget officer, the physical planning officer, the revenue accountants, and the revenue collectors. Survey modules for officials and assembly members captured information on the tax collection process and demographics and experience. Surveys of the citizens measured tax morale, knowledge about local taxes and demand for public goods.

The census contains 5,375 citizen responses (approximately 25 per district) and 2,785 local government officials and assembly members (13 per district). In addition to the survey data, we digitized and harmonized administrative records to measure all sources of local tax collection and all types of local public expenditure across the 216 districts.

2.2 Local Governments have Limited Tax Collection and Information

Our census data allows us to document facts on local tax capacity and its constraints, which are reported in Table 1. As can be seen in Panel A, the average local taxes collected per person is only 4.2 Ghanaian currency GHC ($0.67), with a median of 2.6 GHC. This is a small amount relatively to per capita income in Ghana, and a disappointingly low amount in the eyes of the Ghanian Government (Government of Ghana, 2014).

It is useful to consider that tax collections are determined both by the probability of bill delivery (*the delivery margin*) and the amount paid conditional on delivery (*the payment margin*). On the delivery margin, we find that in the average local government only 43 percent of property tax bills are delivered. The delivery margin is thus an important determinant of low tax collection. Many studies in public finance and development abstract from bill delivery, and focus instead on the payment margin. Officials in our survey indeed report challenges on the payment margin. In the typical district, the likelihood of a property owner paying a bill after receiving it is just 30.2 percent.

Government officials cite limited information as a key constraint on tax collection. Indeed, in Panel A of Figure 1, the absence of data on residential and commercial properties is the most frequently cited constraint on tax collection amongst chief executives, other local bureaucrats, and assembly members. In relation to the delivery margin, absence of data on property owners and challenges in locating them are cited as two of the three most important constraints on bill delivery (Panel B, Figure 1). The lack of information starts with the simple absence of precise street addressing: Panel B of Table 1 shows that, in the average district, only 26.7 percent of properties have an official address. The property tax registry inherits this limited address information, which leads the location on many property tax bills to be imprecise. Figure A1 provides an illustration of an actual tax bill in Madina (the local government where our experiment takes place). The only information on the location of the property is "Opposite Presec School" (a secondary boarding school). Across all of Ghana's districts, 74 percent of the revenue collectors we surveyed report that it is common not to be able to locate the property and/or the owner (Panel B, Table 1).

By constraining tax collector activities, limited information contributes to a high cost of collecting taxes (Panel C of Table 1). We proxy for this cost with the average monthly salary of revenue collectors as a percent of average monthly collections. Note that this is likely to be an under-estimate of the total cost, which may include other indirect expenditures such as for vehicles, fuel, and office staff time. Nevertheless, in the typical local government, the cost of collection is an astonishing *64.1 percent*. In other words, for every 100 Ghanaian Cedi in taxes collected, the local government retains only 35.9 Cedis after its tax collectors are paid. By contrast, the U.S. Internal Revenue Service estimates that it retains 99.7 out of 100 dollars collected (web link).

Finally, three other constraints on tax capacity are important to highlight in this study's context. First, only 17.1 percent of properties have official valuations in the average district. In the absence of official valuations, local governments are forced to tax properties according to a presumptive schedule, where the tax liability is based on easily observable proxies, such as number of floors, proximity to the city center, or the type of business, in the case of a bill to a business.[5] Second, in the average local government, an

[5] To feasibly implement market valuation methods requires continuously updated property and market information, including from third-parties such as banks and mortgage providers. Market valuation property taxes are more common in developed countries, while presumptive tax schedules are more common in developing countries with limited information and administrative constraints.

estimated 72.1 percent of property tax payments are made in cash directly to collectors, rather than by check or via electronic transfers directly to the local government finance office. Cash payments provide collectors with discretion to capture some of the household taxes and reduce the payments to the local government. Third, local governments face significant constraints to enforcing taxes due. Court action (whereby the delinquent property can be confiscated), or the threat of such action, is in practice the main enforcement tool that effectively has monetary consequences for tax delinquents. Yet only 22 percent of local governments report taking any tax defaulters to court in the previous year. Survey responses indicate that the reasons for limited court action lie outside the tax administration's immediate scope, and are due to legal constraints or political costs.

2.3 Technology and Taxation Outcomes

Some of the districts in the census report using computers, software and databases to help them distribute bills and collect revenues. We summarize the use of technology in each district by whether the local government has either a digital database of properties or a revenue software. Using this definition, technology is only adopted by 17 percent of local governments in the country (Panel B, Table 1). Of these, 12 percent have both technology components, while 5 percent has only one of the two. Conditional on adopting, the average district has been using technology for nearly a decade (8.75 years).

Adoption of technology is at the discretion of each local government, and the variation in adoption across the country reflects individual governments' choices. Appendix Table A1 provides cross-district correlates of adoption choices. We find that local governments are more likely to adopt technology when their district has a larger share of properties with official street addresses and property valuations and when legal capacity is stronger. Adoption is also positively correlated with district population size and its urban share. These results may suggest that technology investment is complementary to other characteristics that permit higher tax collection (Besley and Persson, 2009).

These patterns of selection contextualize the impacts of technology adoption on tax capacity. While we provide experimental evidence on these impacts within one local government in Section 3 onward, here we leverage the variation in adoption across the country to investigate the cross-district association between technology and tax outcomes at the level of entire local governments. In this exercise, the key identification concern is that adoption of the technology may be correlated with other district characteristics that also determine tax collection. We make some headway on this concern. First, we include the district covariates that are found to statistically predict adoption (Table A1). Second, we include the (district-specific) share of geographically adjacent districts that have adopted technology, to capture the influence of neighboring policies on local governments' decisions. Third, we include ten region fixed effects to narrow the comparison between adopters and non-adopters within each region.

The results are presented in Table 2. Technology is associated with improved outcomes at each step of the collection process: tax collection per capita (Panel A); share of bills delivered (Panel B); taxes paid per bill delivered (Panel C); and cost of collection (Panel D). When extensive controls are included (column 5), technology adoption is associated with a 78 percent increase in taxes collected. With these same controls, technology adoption is associated with a 21 percent increase in the share of bills delivered and a 37 percent increase in taxes paid per bill delivered. Finally, by improving both the delivery and payment margins, technology adoption is associated with a 13 percent decrease in the cost of collection (as a percent of taxes collected, Panel D).

3 Experimental Evidence

The census results of the previous section showed a strong association between technology use and tax outcomes in the cross-section of local governments in Ghana. This association suggests a potentially important role for technology in alleviating some constraints on tax capacity. Yet there is also evidence that districts which are more urban and have better administrative infrastructure are more likely to adopt technology in the first place. Moreover, there are other stated constraints on tax collections that may or may not be relaxed through technology use, such as political will to collect or legal constraints on enforcement. In this section we describe an experiment that we conducted with one large local government in urban Ghana. The goal of the experiment is to causally estimate the impacts of technology on tax outcomes and understand the mechanisms behind how technology affects taxation at different stages of the collection process.

3.1 Setting

We conducted the experiment in 2021 in La Nkwantanang Madina Municipal Assembly (henceforth, Madina). Madina is part of the Greater Accra region, and is more affluent and urban than the average district. We collaborated with the municipal government of Madina and a private technology firm called Melchia Investments which had developed a new technology aimed at increasing property tax revenues. The technology features the two components described in Section 2.3: a geospatial database of properties and a revenue software that integrates this database and assists in bill delivery and enforcement. The database of properties was created by combining high-resolution aerial photographs with digital registry maps.[6] At the "last mile" of the taxation process, the technology consists of a tablet that assists collectors who work in the field to deliver bills and collect payments. The tablet provides navigational assistance to help the collector go from an initial point to the location of a designated property (Figure A1). As we detail below, what we vary across treatment and control groups is the presence of the tablet.

During a fiscal year, the local government assigns collectors to designated geographical areas for approximately six weeks at a time (a 'campaign'). The designated areas are called 'collection units' and are defined with geographical boundaries that create a cluster of physically adjacent properties (Figure A2). During each six-week campaign, collectors are responsible for delivering bills and collecting payments from assigned property taxpayers in their collection unit. After each campaign, the collector is assigned to a new collection unit. Each area of Madina is only covered once during a fiscal year, due to the large number of properties relative to the limited number of collectors. Property owners are legally required to pay within four weeks of receiving the tax bill. Pay stations do exist, but in practice virtually all payments are made directly to the collector.

Our experiment was specifically embedded in the six-week campaign between March 15^{th} and April 25^{th} in 2021. Before the campaign, collectors received training from both municipal officers and employees of the technology firm. The main training sessions, common to all collectors, described the rules for property tax collection in Madina and the protocols to follow during interactions with property owners. In addition, the collectors assigned to the treatment group received training in how to use the handheld tablets. The compensation scheme (chosen by the municipal government and technology firm) was constant across treatment and control groups. Each collector received an 8 percent commission rate on taxes collected from their assigned bills. Collectors also received a daily transportation allowance and base salary.

3.2 Experimental Design

We trained 56 collectors and randomly assigned 28 to the treatment group and 28 to the control group. Of the 56 collectors, 39 had previously worked with the firm and 17 were hired shortly before the experiment. Of the 39 collectors with previous experience, 11 were designated as 'high performing' by the private firm. Collectors worked individually in their assigned collection unit, where they were assigned to approximately 135 bills each. Each collector had a supervisor randomly assigned to them during the campaign. Supervisors were in charge of monitoring the revenue collectors and assist-

[6]Casaburi and Troiano (2016) study the impacts of an enforcement program in Italy which detected property tax evasion by overlaying aerial photographs and property registry data.

ing them with challenges in the field.[7] All supervisors were randomly assigned to be in charge of both treatment and control collectors.

At the beginning of the experiment, all collectors in the treatment group were given the tablet for use during the six-week tax campaign. As described above, the database of properties was embedded into the tablet in order to help collectors navigate in the field and locate properties. Other than the tablet, the treatment group was not provided with any additional advantages. At the beginning of the campaign both groups were provided with their set of physical bills (see Figure A1 for an example). Apart from the electronic map, the information provided to collectors was thus constant across groups.

Randomization and Balance Our randomization proceeded in two steps. First, we randomly assigned each collector to a collection unit. Second, we randomly assigned the collector-collection unit pair to the treatment or control group. We stratified on the share of properties in the collection unit that were businesses (rather than residential). To avoid chance imbalances, we ran the full randomization 100 times and selected the run with the minimum t-statistic from balance checks on six variables (as in Banerjee, Chassang, Montero, and Snowberg, 2020). Two of these variables were specific to collectors: a dummy for previous work experience with the firm, and a dummy for high-performance rating (by the firm). The other four variables were specific to the collection unit: total bills to deliver; total taxes (current due and arrears); average current amount due per bill; and average previous pay status per bill (unpaid, partially paid, fully paid).

Table A3 summarizes a series of balance checks. In Panel A, we consider a set of characteristics at the tax bill level, based on administrative registry data. In Panel B we consider characteristics at the collector-unit level. None of the variables are statistically significantly different between groups at the 10 percent level or lower. For example, control and treatment collectors have statistically insignificant differences in the number of bills assigned to them, the average bill amount and the fraction of bills that are residential (rather than for a business). The fraction of collectors with previous experience in Madina, or that received a high performance rating, also have statistically insignificant differences across the two groups. In Panel C, we compare characteristics of households in the treatment and control areas, finding statistically insignificant differences in indices of income, liquidity and taxpayer awareness. At the bottom of each panel, we report the F-test from the null hypothesis that the difference in characteristics across variables are

[7] One potential concern is that the supervisors provide more assistance to the control group, due to greater navigational challenges, or to the treatment group, in order to improve the perceived performance of the technology. However, we find no differences by treatment status in the amount of supervisor support or supervisor monitoring reported by collectors (Appendix Table A2).

all zero. We fail to reject the null at the tax bill level ($F = 0.71, p = 0.66$); the collector-unit level ($F = 0.16, p = 0.95$), and the household level ($F = 1.07, p = 0.38$).

3.3 Experimental Data and Estimation

In this section, we describe the data sources that we make use of in our analyses and our estimation. We use administrative data at the property level, covering 7,560 residential and business properties, which contain information on owner names, property location, current tax due and arrears. This data set served to create the collection units for all collectors and to issue all the bills that were to be delivered during the tax campaign.

Our research team collected daily data from each collector on the number of bills delivered and the amount of revenue collected. These data allow us to study the activity of revenue collectors in the treatment and control groups at a high frequency. Non-compliance with reporting was low overall (and uncorrelated with treatment), though our small sample of 56 collectors raises concerns about the role of idiosyncratic measurement error at the daily level. For this reason, our main results winsorize the administrative outcomes at the 95^{th} percentile, separately by group and day.

In addition to the daily data, enumerators working for the research team conducted three rounds of surveys with all 56 collectors – at the beginning, middle, and end of the tax campaign. The first round was conducted during the initial week of the campaign; the mid-line during the third and fourth weeks; and, the end-line at the end of the sixth week. Topics covered include challenges in the field, strategies used for bill delivery and collection, and self-assessed knowledge about households, among other topics.[8]

Finally, the enumerators administered end-line surveys with 4,353 randomly selected households in April and May of 2021. A random sample of equal size was drawn from each of the 56 collection units. Whenever an initially selected property could not be located or contacted, the enumerator would randomly pick an adjacent property within the same collection unit. The end-line survey covered household characteristics, interactions with and views of collectors, taxation, and beliefs about enforcement and governance.

Given the random treatment assignment, we use OLS to estimate the causal impacts of technology. The econometric specification varies slightly depending on the unit of observation. For outcomes that vary at the day and collector level, we estimate:

$$y_{cd} = \beta_d \cdot \mathbf{1}(Tech)_c + \theta_d + \Omega \cdot X_c + \epsilon_{cd}, \tag{1}$$

[8] Attrition in the collector surveys is 17 percent but is uncorrelated with treatment. For both the collector surveys and the daily collector data, the results in the paper are based on the full sample; in both cases, estimates based on the balanced panel data-sets are nearly identical (results available upon request).

where y_{cd} is the outcome for collector-collection unit c on day d, θ_d are campaign-day fixed effects, and X_c contains time-invariant controls. In the main analysis, X_c only includes strata fixed effects for the share of businesses in total properties. In robustness checks, we include additional controls for previous work experience in Madina, a dummy for high quality collector rating, total number of bills to deliver, and the average tax due per bill. The dummy $\mathbf{1}(Tech)_c$ takes a value of 1 for all collector-units randomly assigned to the technology treatment. The treatment coefficient, β_d, is indexed by day because we estimate dynamic treatment effects by interacting the treatment dummy with the individual campaign-day fixed effects. In a robustness check, we leverage the panel-nature of the daily collector data and include fixed effects for each collector-collection unit pair in equation (1). In this case, the identifying variation is the treatment effect that varies within a collector-unit over time, relative to the initial impact on day 1, β_1 (our chosen omitted category). Standard errors are clustered at the collector-unit level.

For outcomes at the household level, we estimate:

$$y_{hc} = \beta \cdot \mathbf{1}(Tech)_c + \Omega \cdot X_{hc} + \epsilon_{hc}, \tag{2}$$

where h indexes households and c collector-units. Standard errors are clustered by collector-unit. X_{hc} always includes strata fixed effects. In robustness checks, we also include the controls at the collector-unit level in (1), as well as previous pay status and property category at the household level. Previous pay status measures if the property tax bill in the past year was fully paid, partly paid or not paid at all.

3.4 Experimental Effects on Tax Outcomes

We begin by studying the impacts of technology on bill delivery and tax collection using the collector daily reports. In Figure 2, we show the impacts on bills delivered. Panel A shows the averages by group and day, while Panel B reports the daily treatment coefficients β_d (equation 1). The treatment group delivers more bills than the control group. This difference initially builds up and peaks by the 24^{th} day, where treatment collectors have delivered 34 more bills than the control group (a 58 percent increase). The gap narrows in the second half of the campaign, where the stock of bills delivered in the treatment group steadies while control collectors continue to hand out bills. The confidence interval around the treatment coefficients is meaningfully wide, likely owing to the limited sample size and number of clusters; notwithstanding, the effect is statistically significant at the 5 percent level in all campaign-days beyond the 10^{th} day. At the end of the campaign, the treatment collectors have delivered 21.5 more bills on average, representing a 27 percent increase over the 80.7 bills in the control group.

In Figure 3, we find that technology causes a large increase in total taxes collected. There are no differences in tax performance during the first week, in which most collectors focus on bill delivery. However, from the second week onward, the treatment group collects at a higher rate; the treatment effect is statistically significant at the 5 percent level on all subsequent days and grows over time. At the end of the campaign, the treatment group has collected an additional 856 GHC on average, representing a 103 percent increase over the 829 GHC collected on average in the control group.

We can infer from these results that the treatment group collects more taxes per bill delivered. Appendix Figure A3 shows that this outcome grows over time; at the end of the campaign, the treatment group has collected 118 percent more taxes per bill delivered than the control group. This result implies that the tax collection impact is not only driven mechanically by the increase in bills delivered. The higher collection rate from each delivered bill motivates our investigation of mechanisms in Section 4.

Robustness In Figures A4 and A5, we explore the robustness of our experimental estimates from equation (1) for bills delivered and taxes collected. First, we find that the estimates are similar when using non-winsorized outcomes.[9] Second, the results are also similar, but more precisely estimated, upon including additional covariates. Third, we include collector-unit fixed effects, which implies that estimating β_d in equation (1) relies on the existence of a time-varying component in the treatment effect. In other words, β_d will reflect the treatment effect based on changes within collector-unit over time (relative to the initial impact β_1 on day 1). The presence of a dynamic treatment effect within collector is consistent with our mechanism evidence on learning in the field over the course of the tax campaign (Section 4.3).[10] Tellingly, the estimated impacts at the end of the campaign are comparable with and without the collector-unit fixed effects.

Another important concern is whether the context of the COVID-19 pandemic impacted the results. We conducted a pilot experiment in early 2019 in the same location, using the same technology and the same research protocol (though with a smaller sample of collectors). In that pilot we found similar effects as in the main experiment (Appendix Figure A7). Qualitatively, both the pilot and main experiment produce an effect on bill delivery that is larger in the middle-periods of the intervention rather than at the

[9]Winsorizing is partly motivated by the small sample size of collectors. Figure A6 shows that the results are almost identical across all sub-samples which leave out one collector at a time. This alleviates concerns that the average effects are unduly influenced by outlier performances of any individual collector.

[10]The fixed effect technically captures variation within each collector-collection unit. However, we interpret it as reflecting a treatment effect over time within collector, since we found no evidence suggesting there are time-varying effects within collection units unrelated to changes in collectors' behavior.

end. On the quantitative side, at the end of the interventions, the impact on bills delivered was 32 percent in the pilot versus 27 percent in the main experiment; the impact on taxes collected was 79 percent in the pilot versus 103 percent in the main experiment. This suggests that the results of the main experiment were not somehow an artifact of abnormal conditions during the pandemic.

Complementary evidence from household surveys Independent evidence about the effects of the technology on tax outcomes are available from our household surveys. Table 3 reports the treatment effects on key tax outcomes based on estimating equation (2). Households in the treatment group are more likely to report having been visited by a tax collector, get more total visits from tax collectors, and are more likely to have a bill delivered. The impacts on visit probability and total visits are statistically significant, whereas the impact on receiving a bill is positive but insignificant.[11] One potential explanation is households make excuses for their lack of payment (just 16 percent of these households report actually making any tax payment). A second is that the lack of bill delivery in spite of successful visits reflects collusive bribes (Section 4.2). In terms of magnitudes, the impact of technology on bill delivery is smaller in the household surveys than in the daily collector reports, though we cannot reject the null hypothesis that the two effects are the same in percentage terms (p-value 0.30).

Households in treatment areas are more likely to report making a tax payment and report higher payments than in control areas. Treatment areas also exhibit higher reported payments conditional on bill delivery. While the magnitudes of the effects on collections also differ between the household surveys and the collector reports, we fail to reject the null hypothesis that the effects are similar across sources (p-value 0.27).[12]

4 Mechanisms Behind Experimental Effects on Taxes

The technology was designed largely with the goal of improving the bill delivery margin. In the experiment, the treatment effect on bill deliveries was 27 percent, consistent with this goal. If the technology had *only* worked through the delivery margin, then the

[11]In Appendix Table A4, we show that the household-level results are robust to the removal of all controls and to the inclusion of more extensive controls, specifically the variables in Panel C of Table A3.

[12]We can also compare magnitudes by estimating equation (2) but using end-line administrative bill-level data. This bill-level data is unique at the household level and underpins the collector report data. The percentage impacts of technology on bill delivery and amount paid (both statistically significant at 5 percent) are moderately larger in the administrative data than in the household survey, but we cannot reject the null hypothesis of equal magnitudes across sources (p-values of 0.28 and 0.29, respectively). These additional results are available upon request.

experiment would have showed a similarly sized effect on revenue collections (as our model demonstrates in Section 5 below). Yet the experiment showed a treatment effect on collections of 103 percent, or four times the size of the treatment effect on deliveries. In other words the technology had a disproportionately large effect on the payment margin. But how did the technology allow collectors to improve so much on the payment margin relative to the delivery margin?

In this section, we investigate three potential mechanisms for why the technology had such a large impact on collections relative to bill deliveries. The first is that the presence of technology improves citizens' tax morale or strengthens perceived tax enforcement capacity. The second is that the technology reduces the potential for leakages by collectors. The third is that the technology makes it easier for collectors to directly learn about and target the households that have higher propensity to pay. We argue that evidence points most strongly to the third channel.

4.1 Tax Morale and Perceived Enforcement Capabilities

The first mechanism we consider is that technology improved households' tax morale or increased households' perceived enforcement capabilities of local government. Tax morale is broadly defined as the non-pecuniary motivations for tax compliance (Luttmer and Singhal, 2014). For instance, the presence of technology may improve households' views that the government is making efforts to collect taxes in more efficient and equitable ways, or to improve service delivery. Household perceptions of government enforcement capabilities may change if seeing a revenue collector with a new technology raises their expected pecuniary costs of non-compliance.

We use our household survey to create three indices for tax morale: government efforts to collect taxes in equitable and efficient ways; satisfaction with government services; and government governance capacity and integrity. We also create an index for information-enforcement, which tracks households' perceptions of government informational capacity and enforcement strength. Each index is based on several individual questions, which are detailed in Data Appendix B.2.

In Table 4, we study the impact of technology on these indices, by estimating equation (2). We find null effects on all outcomes.[13] In Table A5, we find null effects on 12 of the 13 individual underlying questions used to build the indices.[14] For example, there are

[13]Prior studies have also found that stronger tax collection effectiveness increases tax payments and bribes but does not impact households' morale or beliefs (Khan et al., 2015; Balan et al., 2022).

[14]Out of the 13 individual outcomes, the only one that is statistically impacted shows a decrease in the perception that everyone pays their fair share of taxes. If anything, this effect should lower morale.

null effects on enforcement-related questions such as ″Next time the tax collectors come to collect, what percent of households do you think will pay their taxes?″ and ″Imagine someone refuses to pay taxes – how likely do you think it is that the local government will pursue and enforce sanctions?″ There are also null effects on questions about satisfaction with government, including ″In your opinion, what has been the overall quality of services offered by the local tax department of Madina?″ and ″Overall, how would you rate the competency of the local government of Madina?″ In Appendix Figure A8, we investigate the possibility that the average null effects mask heterogeneity along the asset-income distribution. For example, it is possible that the presence of technology stimulates tax morale but only amongst more well-off households that are more likely to have paid taxes in the past. We find null effects across the income-asset distribution.[15]

4.2 Bribes

The second mechanism we consider is that technology may have improved the payment margin by reducing bribe activity. Bribes can come in the form of a "collusive bribe," where the household and collector agree on a payment made to the collector in exchange for a cessation of follow-up visits. They can also take the form of a "coercive bribe," in which the collector pockets tax payments made by the household in combination with a threat of retaliation against whistle-blowing.[16]

Technology can reduce these two types of bribe activities of collectors through better monitoring by supervisors, or easier reporting of bribe taking by households. Yet the effect of technology on bribes is ambiguous ex-ante. Technology may increase households' perception of collectors' enforcement capacity and raise collectors' bargaining power, which could increase bribe taking. Technology could also free up more time for the collectors to do all of their previous activities, including attempting to take bribes.[17]

To investigate how technology affects bribes, we estimate equation (2) with various outcome measures of bribe activity from the household survey (Data Appendix B.3). Importantly, due to the illegal and culturally sensitive nature of bribes, some of the measures came from indirect questions: for example, we ask if it is likely that collectors *in the household's area* are likely to ask for bribes. In Table 5, we find positive and statistically

[15] These null effects do not necessarily imply that technology investments cannot increase households' tax morale or perceived enforcement capacity. Such views may be shaped in the longer run, while our experiment captures short run impacts. We discuss long run effects of technology in Section 6.

[16] Other studies have found that coercive and collusive forms of private capture often co-exist within the same setting (Djankov and Sequeira, 2014; Okunogbe and Pouliquen, 2022).

[17] Other technologies, such as electronic filing of tax returns, may reduce private capture by limiting the extent of in-person interactions between officials and taxpayers (Okunogbe and Pouliquen, 2022).

significant effects of the treatment on bribes. While technology causes a meaningful increase in the likelihood of coercive or collusive bribes (column 1), the treatment effects on bribe amounts are smaller (columns 2-5). For example, technology causes a 1 percentage point increase in the amount of collusive bribes, expressed as a percent of the household's tax bill, and a 4 percentage point increase in the amount of coercive bribe, expressed as a percent of taxes collected. The treatment effect on collusive bribe amount in GHC (column 5) is approximately 4.5 times smaller than the treatment effect on tax amount paid (Table 3). Though caution is in order when interpreting the actual magnitudes, since these questions relate to a sensitive topic that is hard to measure directly.[18]

Overall, the fact that in all specifications we find positive, rather than negative, effects of the technology on bribe activity suggests that the technology's substantial impact on revenue collections does not work through a decrease in leakage by collectors. To the contrary: the experiment highlights how there is serious potential downside to technology in tax collection efforts that local governments should be aware of.

4.3 Learning and Differential Targeting

The third mechanism we consider is that collectors leverage the time savings from better navigation to directly build knowledge about households' propensity to make a tax payment. This greater knowledge about taxpayers then allows the collectors to better target their collection efforts to the households with higher propensity to pay. To our knowledge, this channel is new to the literature.

Three sets of observations motivate this mechanism. First, bill delivery in the field is characterized by significant navigational challenges that arise from imperfect addressing (Section 2.2 and Figure A1). As a result, 71 percent of control collectors at the beginning of the campaign reported finding it challenging to locate their assigned taxpayers (Panel B of Figure 4). Self-reported time-use data suggests that the average control collector would require 10.4 weeks to deliver all the assigned bills (while the campaign only last 6 weeks).[19] The time constraint on collectors' ability to deliver bills, let alone collect payments (which often requires repeat-visits), therefore appears to be binding.

Second, household propensity to pay is an important determinant of tax payment. This point was raised by numerous local government officials we interacted with. We use the household survey to proxy for willingness to pay with the household's awareness

[18] The results are robust to different specifications (Table A4) and measures of bribe (Figure A13).

[19] At the beginning of the campaign, control collectors report that the average weekly time devoted to work in the field is 19.5 hours, and the average time required to deliver a single bill is 1.5 hours. Thus, to deliver the average assigned 135 bills would in principle require 10.4 weeks: $(135 \times 1.5)/19.5 = 10.4$.

of taxation, and for ability to pay with income and liquidity (Appendix B.4). We find that the propensity to pay index (which combines the measures of awareness, income and liquidity) strongly predicts actual compliance outside of the experiment (Table A6).

Third, propensity to pay is heterogeneous across households and collectors have limited knowledge ex-ante about which households have higher propensity. Indeed, our survey data reveal that 71 percent of collectors at the beginning of the campaign report not having a good understanding of which households are more able and willing to pay (Panel A of Figure 5). Household propensity to pay is hard to know in this setting for several reasons. Ability to pay depends on income and liquidity, which are hard to observe and partly transitory. Moreover, propensity to pay is only weakly correlated with characteristics that are more easily observable to the collector, including the value of property taxes indicated on the tax bill.[20] Consistent with this, in Figure A9 we find that variation across properties in the value of the tax bill accounts for approximately 1 percent of the variation in household income and the index of propensity to pay.

Collector Behavior and Strategy To investigate this mechanism, we start by examining technology's impact on challenges in the field using the collector surveys. From the outset of the campaign, treatment collectors report less navigational challenges and less challenges in locating taxpayers (Figure 4). These gaps in reported challenges are statistically significant in all survey rounds, despite the small sample size. The gaps do decrease at the end of the campaign, suggesting that control collectors also improve their navigation over time. In Appendix Table A2, we find no strong evidence that other challenges in the field significantly differ between groups (e.g. resistance by property owners, wrong bill information, and lack of supervisor support). Due to improved navigation, treatment collectors spend 48 percent less time per bill delivered, but do not work less hours per week than the control group (Appendix Table A7).

What do treatment collectors spend their freed-up time on? We find they make more return-visits to property owners (Table 3, column 2). By conducting more return-visits, and possibly by extending the length of each visit, the collectors likely interact with households and learn about their propensity to pay. Consistent with this interpretation, the collector surveys show that treatment collectors increase their knowledge about households' propensity to pay over time. Panel A of Figure 5 shows that at the begin-

[20] This is because the property tax in Madina is calculated on a presumptive schedule (Section 2). In the presumptive tax, coarse proxies for capital value (e.g. number of floors and area-size) are used to calculate taxes owed – thereby weakening the link between property tax value and income or wealth.

ning of the campaign, there were no differences in collectors' knowledge.[21] Over time, a positive knowledge gap opens up (significant at 5 percent), as treatment collectors gather information about households' propensity to pay while doing their return-visits.[22]

The collector surveys reveal that the treatment group uses this additional information to target those households with higher propensity to pay. Mirroring the result on knowledge in Panel A, Panel B of Figure 5 shows that there were no differences in collection strategies at the beginning of the campaign experiment, but, over time, treatment collectors increasingly make use of the strategy to visit areas on specific days where property owners are more likely to be able to pay. Figure 6 shows that treatment collectors also increasingly make use of collection strategies that target property owners that are more willing to pay – by visiting households that have a stronger awareness of taxation (Panel A; p-value = 0.07) and that are more satisfied with public goods (Panel B; p-value = 0.08).

It is useful to divide collection strategies into two broad types: those that focus on hard-to-observe household characteristics, and those that focus on easy-to-observe characteristics. We define hard-to-observe characteristics as those that make up propensity to pay: ability to pay taxes (income and liquidity), awareness of taxation, and satisfaction with public goods. As argued above, these characteristics cannot be observed readily in the field nor can they be inferred via any information directly available to the collector (including on the tax bill). We define easy-to-observe characteristics as those that can be directly observed from the tax bill (tax bill amount and amount of previous payment - see Panel A of Figure A1) or easily observed in the field (greater proximity to the main road; government headquarters; collector's own house). Table 6 shows the treatment effects on the use of these two broad strategy types, by estimating equation (1) on the three rounds of collector surveys.[23] The table shows no differences in strategies at the beginning of the experiment. Over time, however, treatment collectors make disproportionately more use of the hard-to-observe strategies (significant at the 10 percent level, column 5), consistent with learning. In fact, the inclusion of collector-unit fixed effects makes the disproportionate reliance on hard-to-observe strategies more pronounced (and significant at the 5 percent level, column 6). Since these fixed effects isolate the part of the treatment impact

[21]Knowledge is a dummy variable which takes a value of 1 if the collector chooses the statement "I think I have a good understanding of which properties are more able and willing to pay" rather than the statement "I put a lot of effort to get my job done, but it remains unclear to me which exact properties are more likely or more willing to pay their property rates". See Data Appendix B.5 for more details.

[22]Part of the knowledge gap in the middle and final rounds is also due to a decrease in reported knowledge amongst control collectors, which could reflect updated accuracy-beliefs while in the field.

[23]For each characteristic, strategy use takes a value of 1 if the collector reports using 'all the time' or 'often' the collection strategy which focuses on this household characteristic, and 0 otherwise (Data Appendix B.5). Use of the hard-to-observe and easy-to-observe collection strategies are constructed as the average use over all characteristic strategies in each set.

that varies within collector over time (relative to the initial impact at the beginning of the experiment), this result is strongly consistent with learning and differential targeting over the course of the experimental period.

Which Household Types Get Targeted with the Technology? As a second piece of evidence related to this mechanism, we investigate how targeted households (those that make payment) differ from non-targeted households within a collection unit and, importantly, how technology causes this to differ between treatment and control areas.

The mechanism predicts positive selection under technology on proxies for propensity to pay. We estimate selection using the following specification on the household survey

$$y_{hc} = \theta \cdot \mathbf{1}(Pay)_h + \beta \cdot [\mathbf{1}(Pay)_h * \mathbf{1}(Tech)_c] + \Omega \cdot X_h + \mu_c + \epsilon_{hc} \tag{3}$$

y_{hc} is a fixed household/property characteristic and $\mathbf{1}(Pay)_h$ is a dummy for making any positive tax payment. Since $\mathbf{1}(Pay)_h$ is endogenous, θ indicates whether there is a statistical (non-identified) difference in a fixed characteristic between targeted (paying) and non-targeted (non-paying) households in the control group. The treatment coefficient β shows how the difference in characteristic between targeted and non-targeted households causally changes in treatment versus control areas; any non-zero β would indicate differential selection. We can include collection area fixed effects (μ_c) since we focus on differences in characteristics between households within collection areas.

We focus on the three fixed household characteristics of propensity to pay: income, liquidity, and taxation awareness. As argued above, these are hard-to-observe characteristics which local officials identified as determinants of compliance.[24] We also consider characteristics that are more easily observable: tax bill value, previous tax payment, and observable assets. The first two are directly observable on the tax bill (see the bill example in Figure A1). The third characteristic is derived from the household survey and measures assets that can more readily be observed outside the property (e.g. car, truck, electric generator). Targeting households with these observable characteristics may be useful, in particular for collectors with less knowledge about propensity to pay.

The results in Figure 7 show the level of selection in the control group (θ) and the

[24] The construction of these variables is described in detail in Data Appendix B.4. Even though these proxies are based on end-line household surveys, we think they are plausibly not impacted by the treatment. It is unlikely that technology-induced payment of taxes affects households' earnings choices within the six-week span of the tax campaign. The questions on liquidity refer to a 'typical' month rather than the specific past month during the campaign. Finally, no property owner from the areas of the experiment was neither summoned to court nor had their property confiscated during the tax campaign.

treatment group ($\theta + \beta$); differential selection (β) can visually be inferred as the difference in levels. In Panel A, we focus on the hard-to-observe characteristics. We find that targeted households in the treatment group have higher liquidity, income, and taxation awareness than non-targeted households (all significant at 5%) In contrast, targeted and non-targeted households in the control group are precisely estimated to have no differences in liquidity and income; targeted households have slightly more awareness than non-targeted, but the difference is not significant. As a result, the hard-to-observe propensity index (which combines awareness, income and liquidity) reveals strongly positive selection in the treatment group and almost null selection in the control group.[25] Panel B studies selection on more easily observable characteristics. There is little targeting on current tax amount due in both groups – suggesting it may not be a useful predictor of payment. We observe positive selection both on previous tax payment and on assets but of similar magnitude in treatment and control groups.

The strong differential selection between treatment and control on hard-to-observe characteristics (Panel A) thus contrasts with the absence of differential selection on easy-to-observe characteristics (Panel B). This contrasting selection result across hard versus easy to observe characteristics in Figure 7 mirrors the result on disproportionate use of hard-to-observe collection strategies by treatment collectors in Table 6 – though Figure 7 is based on household surveys while Table 6 is based on collector surveys.

Taken together, the results in this sub-section paint a picture consistent with the proposed mechanism: technology reduces navigational challenges and frees up scarce time; collectors use this extra time to learn about the hard-to-observe household characteristics of propensity to pay and subsequently target those with higher propensity.[26]

Finally, additional results suggest treatment collectors may also have learned about households' amenability to bribes. In Figure A11, we find that treatment households exposed to bribes have higher taxpayer awareness than those not exposed; specifically, they are more likely to have witnessed or heard about court actions and property con-

[25] An important concern is that these payment patterns reflect heterogeneous effects of technology on tax morale or perceived enforcement. However, Table A8 finds no differential impacts of technology on tax morale and perceived enforcement outcomes by income, liquidity or taxpayer awareness. Moreover, Figure A10 shows that the selection patterns on bill delivery are similar to the selection patterns on tax payment. Bill delivery may be a dimension of targeting if collectors learn during their very first encounter and selectively choose who to deliver to (Balan et al., 2022). Both of these results suggest that heterogeneous payment effects are unlikely to confound the targeting interpretation of the selection patterns in Figure 7.

[26] Our results are not consistent with a strategy where propensity to pay is in fact observable and collectors focus initially on those with highest propensity and then 'move down the curve'. Since the treatment collectors deliver more bills (Figure 2), this strategy would generate negative selection on proxies for propensity to pay such as income and liquidity (while we find positive selection in Figure 7). Moreover, this strategy would generate decreasing collection per bill delivered over time (while we find it increases).

fiscations by officials. This increased perception of effective enforcement may raise the credibility of collectors' threat of retribution in a setting of collusive or coercive bribes.

5 Model

The experimental results uncovered larger effects of technology on collections than on bill deliveries. We argued in the previous section that the data best support a mechanism that combines time-savings due to navigational improvement with the fact that collectors use the extra time to learn about taxpayer types. In this section, we formalize this mechanism by embedding time-savings and learning in a dynamic Beckerian time use model of collectors. We use the model to assess how much of the larger treatment effect on collections is plausibly due to learning, relative to the initial navigational advantage.[27]

5.1 Environment

The experiment lasts W weeks. Collectors are endowed with one unit of time each week and split time between delivering bills and trying to collect revenues. In week one each collector is endowed with a large number of bills. Each bill has a face value of one local currency unit. Neither the number of bills or variation in face value across bills play an important role in our experimental results, so we abstract of these in the model.

Collectors come in two types: treatment (T) and control (C). The two types differ exogenously in the number of bills they can distribute in a given amount of time. In one unit of time a treatment collector can distribute θ_T bills, and a control collector can distribute θ_C bills. We assume that $\theta_T \geq \theta_C$, which captures the greater efficiency in delivering bills in the treatment group. In relation to our empirical results, the assumption that $\theta_T \geq \theta_C$ is motivated by the technology's reduction in navigational challenges (Figure 4) and reduction in time spent to deliver a given bill (Table A7).

Households also come in two types: "high" and "low," referring to their probability of paying a bill. For simplicity we assume that high types have a positive probability of payment while low types have probability *zero* of making a payment after each visit. The household type is not known to the collectors until after they deliver a bill to that household; that is, collectors learn about household types only after bill delivery.

[27] A setting where collectors use the time-savings induced by technology to indiscriminately make return-visits at every property they delivered bills to could generate the larger treatment effect on collections than deliveries in Section 3. However, this indiscriminate time-use would not generate the results on collector knowledge and strategies in Section 4. The full set of observed results therefore motivate our choice to model both time-savings and learning and to investigate the quantitative importance of learning.

The treatment collectors have an advantage in learning about whether households are high types or not. For each bill delivered, treatment collectors have a probability η_T of discovering that the household is a high type, and a probability $1 - \eta_T$ of learning that the household is a low type. Control collectors have probabilities η_C and $1 - \eta_C$ of learning that the household is high type and low type. We assume that $\eta_T \geq \eta_C$, which captures the better opportunities for learning afforded in the treatment group.[28] In relation to our empirical results, the assumption that $\eta_T \geq \eta_C$ reflects the improved knowledge gathered by treatment collectors about households' propensity to pay (Figure 5) and their increased use of collection strategies that focus on hard-to-observe household characteristics related to propensity to pay (Figure 5 and Figure 6).

The collection technology is exactly the same for treatment and control collectors. Each week, collectors devote time, c, to collecting from households that have been delivered bills. We assume that collectors attempt to collect only from households they know to be high-type households, which makes sense given that low-types have a probability zero of paying. We assume that each unit of time has diminishing marginal value in collecting from each household in a given week. This could be because repeat visits in the same week reduce the household's willingness to comply, or because the constraints keeping the household from paying earlier in a week are still binding later in the week (e.g. the household is waiting for a paycheck).

We model diminishing returns to collection activity at the weekly level as follows. Spending c units of time per bill trying to collect from h bills yields the following probability of collection per bill: λc^{μ}, where $\lambda > 0$ and $0 < \mu < 1$. Hence, the total collections in the week are the following: $\lambda c^{\mu} h$. As a simple example, suppose the collector has identified measure $h = 5$ high-type bills. If they spend $c = 1$ on the full measure 5 of bills then they can collect from each of those bills with probability λ. They then have measure $5(1 - \lambda)$ bills left over in the next period.

The collector's choice variables each week are time spent distributing bills, b, and time spent on each bill trying to collect, c. Note that a collector would never spend a different amount of time on different bills because of the concavity of the collection probability in time spent trying to collect. Since $\mu < 1$, the highest returns are for the first units of time spent trying to collect from each bill. So optimality implies that all bills should get equal time devoted to collection efforts.

The Collector's Dynamic Problem The goal of a collector is to maximize tax rev-

[28]In a richer spatial model one could endogenize the increased learning that comes from the navigational advantage and time-savings of the technology. We abstract from spatial considerations, and other micro-founded channels of learning, for simplicity.

enues. Collectors have the following state variables each week: h, the number of bills that have been delivered to a household identified as a high type, and w, the week of the experiment. The collectors' choice variables for each week are b, the time spent trying to deliver bills, and c, the time spent trying to collect from each high-type bill. The time constraint for the collector is that $b + ch = 1$ in each week.

The dynamic trade-off for a collector is that spending more time trying to collect from households this week means spending less time delivering bills that can be collected from next week. Intuitively, this will mean that in the later weeks, collection is a larger priority, while in the earlier weeks, delivering bills is more important.

State variables evolve each week according to the collectors' time allocation choices. After spending b units of time delivering bills, the stock of high types learned about increases by $\theta_j \eta_j b$ for collector type $j \in \{C, T\}$. After spending c units of time per bill trying to collect, a fraction λc^{μ} get collected from, leaving $h(1 - \lambda c^{\mu})$ remaining high-type bills for the next week. So the law of motion for known high types with a bill delivered becomes $h' = \theta_j \eta_j b + h(1 - \lambda c^{\mu})$.

Let $V(h, w)$ be the present discounted value of having h high-type bills delivered by day w. The collector's dynamic problem is therefore:

$$V(h, w) = \max_{\{b,c\}} \left\{ \lambda c^{\mu} h + E\Big[V(h', w') \Big] \right\} \tag{4}$$

where $w' = w + 1$, subject to the time constraint, $b + ch = 1$, and the law of motion for high-type bills discovered, $h' = \theta_j \eta_j b + h(1 - \lambda c^{\mu})$.

In the last week, collectors spend the maximum time trying to collect. This means that $b = 0$ and c is the maximum amount of time spent on each bill that uses up the collector's full time endowment. If the collector has measure h high-type bills, then the collector can spend $c = 1/h$ units of time collecting from each bill. The result is $\lambda(1/h)^{\mu} h$ revenues collected, meaning that $V(h, W) = \lambda(1/h)^{\mu} h$.

The remaining periods can be solved by backwards iteration. The optimal dynamic program is to allocate time so that the marginal benefit of trying to collect this week equals the marginal benefit of delivering more bills to collect from next week. If a collector spends too much time collecting now, the benefit of collecting this week will be very low at the margin relative to the value of having more bills ready to collect from next week. If the collector spends too little time collecting this week, the marginal benefit of collecting now will be very high compared to the value of having more bills delivered.

5.2 Quantitative Predictions of Model

We now calibrate the model and use it to simulate the effects of counterfactual changes to the environment. We begin by setting the number of weeks to be $W = 6$ as in the experiment. We then set $\theta_C = 1$, which is a normalization on bill delivery efficiency in the control group. We set $\eta_C = 0.1$ meaning that control collectors have a 10 percent change of finding a high type after delivering a bill. We set the parameters of the collection function to be $\lambda = \mu = 0.5$. The former controls the average level of collections, and the latter controls the degree of curvature in collection efforts. Appendix Table A9 presents results for alternative parameterizations showing that our results are not particularly sensitive to these parameter choices.

The most important two parameters in our calibration are θ_T and η_T, which govern the treatment group's advantage in delivering bills and finding high-type households. Our strategy is to choose values of these two parameters to match two moments from our experiment: (i) the treatment effect on bill deliveries, and (ii) the treatment effect on collectors' focus on strategies that target hard-to-observe household characteristics. The former is 27 percent, as shown in Figure 2. The latter is 22 percent, as shown in column (6) of Panel A of Table 6, corresponding to the disproportionate reliance on collector strategies targeting hard-to-observe household characteristics relative to strategies targeting easy-to-observe characteristics. Matching these two moments requires setting $\theta_T = 1.38$ and $\eta_T = 0.13$.

Figure 8 plots the calibrated model's predictions for bills delivered, taxes collected, the stock of high-type bills delivered but not collected from, and the fraction of time spent on collections in each group. The model does well in reproducing the concave time pattern of bill deliveries (top left panel), and by construction gets the 27 percent treatment effect on deliveries correct. The model also gets the convex pattern of collections, with the largest treatment effects coming at the end of the experiment period, as in the data. The model's treatment effect on collections is 51 percent (top right panel), or about twice the treatment effect on deliveries.

To get more intuition about how the model works, the bottom panels of Figure 8 plot the stock of high-type bills delivered (but not collected from) and the time spent on collections each week. In the bottom left panel one can see that the treatment group accumulates a larger stock of bills delivered to known high-types, with a difference that peaks during during the middle and later weeks of the experiment. Equipped with the large stock of high-type bills delivered, the return from allocating time to collection increases relative to the return from allocating time to bill delivery. As a result, in the bottom right panel, one can see that the treatment group spends more time on collections than the control group, particularly in weeks four and five of the experiment. These model predictions are broadly consistent with the empirical observations that the treatment group is better aware of which households are willing and able to pay during the experiment (Figure 5, Panel A), and more focused on collection strategies targeting these households (Figures 5 and 6), particularly in the later parts of the experiment.

As a frame of reference, we compute a counterfactual simulation of the model in which we shut down the learning and differential targeting channel. In particular we set $\eta_T = \eta_C$, and leave all other parameters as in the benchmark calibration. Note this leaves in place the treatment group's advantage in delivering bills, but gives them no additional advantage in learning whether households are high types or not.

Figure 9 plots the model's predictions in this counterfactual simulation. Now the treatment effect on bill deliveries is modestly larger than before, at 34 percent. The treatment effect on collections is substantially smaller than before, at 26 percent. The bottom panels help illustrate why. The treatment group's stock of high-type bills is still larger than the control group in this counterfactual, but basically only because of the advantage in delivering bills to begin with. Relative to the setting with the additional learning advantage, the slower rate of discovery of high-type bills in the middle weeks of the campaign leads to a smaller increase in the relative benefit of allocating time to collection versus delivery. As a result, the treatment group spends only slightly more time each period on collection than the control group. The result is a treatment effect on collections that is similar in magnitude to the treatment effect on bills delivered.

In summary, when the model is calibrated to match the treatment effect on targeting hard-to-observe household characteristics that signal a high payment probability, the model predicts a treatment effect on collections that is about twice the treatment effect on deliveries. In a counterfactual simulation in which the treatment group has no such learning advantage, the treatment effect on collections and deliveries are roughly equal in magnitude. Since the treatment effect on collections was around four times larger than on deliveries in the experiment (Section 3.4), the model's learning channel seems to explain around half the gap in the magnitudes of the two treatment effects. More generally, we conclude that the learning channel is roughly equally important as the navigational direct effect of higher bill deliveries on revenue collections.[29]

[29] In Appendix C, we conduct a regression-based analysis which is complementary to the model analysis. We use data to proxy for the navigational advantage by measuring days since bill delivery at the property level. We find that after controlling for days since delivery in our equation for tax outcomes (equation 2), which can be interpreted as 'shutting down' the navigational advantage in the model, there remains a large treatment effect of technology on tax outcomes. Though based on a different research design, the regression results yield a conclusion that is consistent with the model results and that suggests learning is an important channel in determining the total treatment effect on collections.

6 Distributional Implications of Technology and Broader Relevance

One important focus of our study thus far is how technology leads to differential targeting of households that are more likely to make payment. One aspect of this targeting is that households with higher income are more likely under technology to receive a bill and make tax payments, while households with more assets are equally likely to be targeted with and without technology (Figure 7). These targeting results have implications for the distributional impacts of technology.

To see this, we create four quartiles of the joint income-asset distribution. This distribution is an aggregate index which captures information on both the household's income and assets (Data Appendix B.4). We estimate distributional effects in the household survey by allowing the treatment to vary across the income-asset quartiles (q):

$$y_{hqc} = \beta_q \cdot \mathbf{1}(Tech)_c \cdot \mathbf{1}[Quartile = q] + \Omega \cdot X_{hc} + \epsilon_{hc} \quad (5)$$

The results from estimating equation (5) on the likelihood of making a positive tax payment are presented in Panel A of Figure 10. Due to the targeting of higher income, we find that technology strongly improves the equity of the local tax system: treated households in the top two quartiles are 9.8 to 10.1 percentage points more likely to pay than control households, representing a 65 percent increase. In contrast, technology has a somewhat precise null effect on tax payments in the bottom income-asset quartile. In Appendix Figure A12, we show that technology raises taxes paid as a percent of taxes due in the top quartiles. Since technology does not plausibly impact household income, this result implies that technology improves the progressivity of the tax system (it makes taxes paid, as a share of household income, more positively correlated with income).

By estimating equation (5) for bribes, we find that technology has a positive impact on bribe likelihood which is concentrated among households with lower income-assets. This result is presented in Panel B of Figure 10 which, by visual comparison with Panel A, highlights that technology's impacts on tax and bribe payments affect different segments of households. These results parallel the conclusions of Khan et al. (2015) and Gauthier and Goyette (2014) that tax and bribe payments are substitutes. In Figure A13, we show that the percent increase in bribe amount is concentrated in the bottom quartiles – implying that technology makes the bribe system more regressive.[30]

Thus, technology has starkly contrasting incidence impacts on taxes and bribes: tax payments become more progressive and concentrated amongst well-off households,

[30] Previous work has also found that 'street-level' bribes affect poorer households to a larger extent (Fried et al., 2010; Khan et al., 2015; Peiffer and Rose, 2018).

while bribes become more regressive and concentrated amongst less well-off households.

Broader Relevance The experiment in our study focuses on the effects of technology in one large municipal government in Ghana over a six week horizon. How might the results extend to other settings and longer time horizons?

Our results show that technology positively impacted tax collection by alleviating constraints that arose largely from having incomplete property addressing. Technology likely has smaller effects in settings with developed addressing systems. The United Nations estimates that approximately 4 billion people live in places without physical addresses, and most of these are in the developing world. This gives reason to think that technology will have an impact on property tax collections in other developing nations more broadly. The impacts of technology will likely be smaller in settings where other policies help alleviate the challenges associated with collecting property taxes, such as hiring more collectors or extending the duration of each tax campaign. Yet each of these alternatives are expensive, suggesting that technology may still be valuable from a policy perspective, to the extent that it can help economize on manpower costs.

Finally, this technology permitted the gathering of soft information on taxpayers' propensity to pay, which is most relevant in settings with limited coverage of hard information (such as third-party reports on income) and enforcement. This technology may be less relevant at higher levels of development, where governments are characterized by broad third-party coverage and enforcement (Kleven et al., 2016; Jensen, 2022).

One important question left unanswered is whether technology, such as the one in this study, would have a larger or smaller effect on tax collections at greater time horizons. If the knowledge gleaned about specific taxpayers' propensity to pay is permanent, then the returns to learning induced by technology would diminish over time. To the extent that knowledge about taxpayers is transitory, though, such as for liquidity or income shocks, then the longer-run effects of technology may also be large. The longer-run effects would likely be lower if governments implement other policies over time that alleviate collectors' time constraints or expand third-party coverage. At the same time, while we found no short-run impacts on households' tax morale or enforcement beliefs, the sustained use of technology may positively affect these views over the longer run and increase compliance.[31] In our cross-sectional census data, we found that local govern-

[31] The increase in bribes under technology, if persistent in the longer-run, may however counter these positive tax morale impacts. Reflecting this ambiguity, 88 percent of treatment households report a preference for the technology-based collection system over the manual system but treated households also report a stronger and statistically significant dis-interest in engaging with the state – concentrated amongst those that were subject to increased bribes (results available upon request)

ments which have had technology in place for an average of 8.75 years were associated with a 78 percent increase in tax collection (Section 2 and Table 2). Compared to the short-run causal tax increase of 103 percent we estimate over one tax campaign, these numbers suggest somewhat smaller returns to technology at greater time horizons.[32]

7 Conclusions

This paper has studied the role of technology in improving tax capacity. We focus on local governments in Ghana, which are in charge of property taxes but in practice collect very little. Both cross-sectional census data and experimental evidence point to a close connection between use of technology and positive outcomes at every stage of the tax collection process. In our experiment, we found that technology had a direct impact on deliveries, as intended. But then it allowed collectors to directly gather information on taxpayers' propensity to pay and, as a result, change their collection strategies to focus on those most likely to pay. This novel channel highlights the important ways in which government officials change their behavior in the presence of a new technology, and how this behavioral change is a key component of the large treatment effect on tax collections.

Our findings contribute to the literature on informational capacity and state 'legibility' – the breadth and depth of government's knowledge about its citizens and their activities (Scott, 1998; Lee and Zhang, 2017). Prior work shows that pre-existing information can improve collection, including from employers, financial institutions and local chiefs. We relate to these studies by showing how governments can directly build 'soft' information on taxpayers' propensity to pay through feasible policy investments. Directly building 'soft' information is most likely to strengthen state legibility in developing countries where 'hard' information, including from third-parties, is constrained.

Use of technology for local taxation is limited but growing in Africa and other areas of the world (Knebelmann, 2022). More work is needed to understand the impacts and barriers to tax collection technologies in diverse settings and over the longer run. More work is also required to rigorously establish the extent to which technology in practice leads to changes in public expenditures, since one of the ultimate goals of technology investments in taxation is to fund improved provisions of useful public goods.

[32] Relative to the tablet's running costs, the technology in our experiment was cost-effective and delivered a 96 percent increase in taxes collected net of cost (Appendix Table A10). However, cost as a percent of taxes collected did not markedly decrease in the treatment group relative to control. By contrast, the cross-sectional regressions show a large reduction in cost associated with technology adoption over nearly a decade (Panel D of Table 2) – possibly suggesting that efficiency gains materialize over the longer run.

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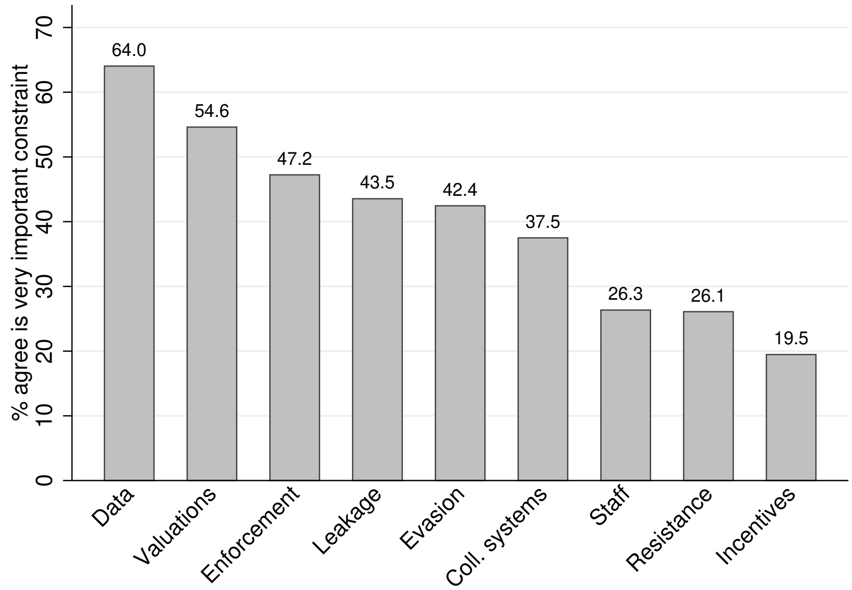
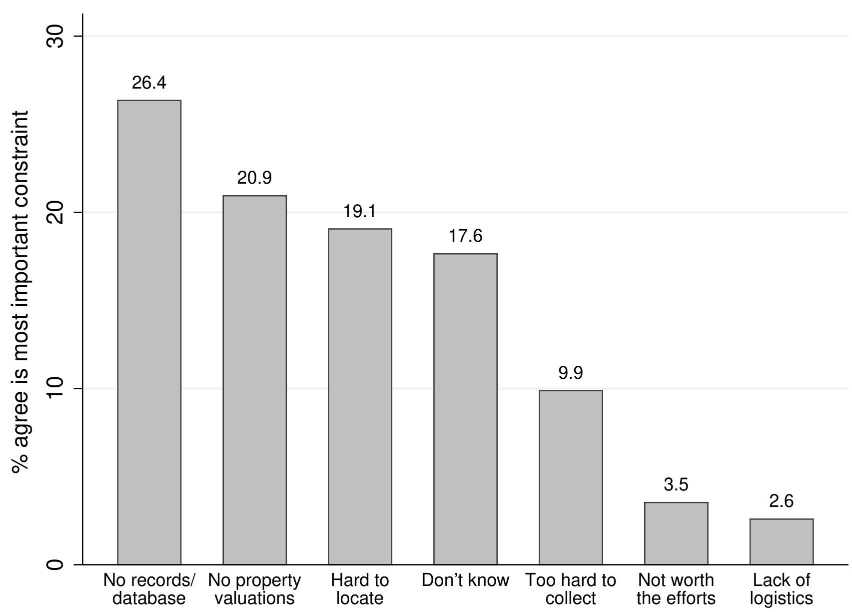
Figure 1: Constraints on Tax Collection and Bill Delivery

(a) Perceived Importance of Different Constraints on Tax Collection



(b) Most Important Perceived Constraint on Bill Delivery

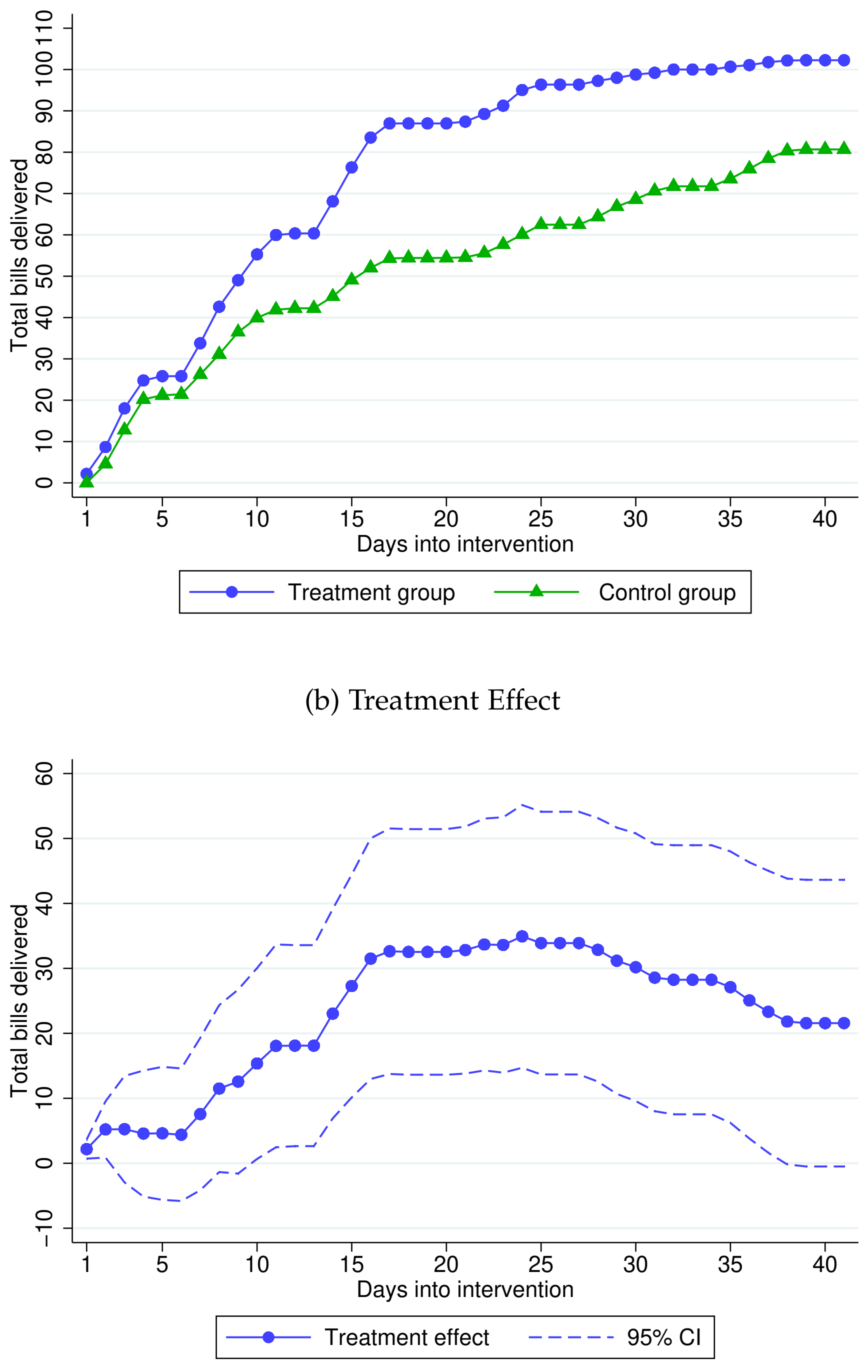


Notes: These panels show the perceived constraints on tax collection and bill delivery as reported by local government officials and politicians. In Panel A, the bars show the percent of all respondents that consider a particular constraint to be 'most important', on a five-choice scale from 'least important' to 'most important'. In Panel B, the bars show the percent of all respondents who consider a particular constraint to be the most important constraint (mutually exclusive choices). Responses are pooled across all respondents in all 216 local governments.

Figure 2: Impact of Technology on Bills Delivered

(a) Bills Delivered per Collector By Group

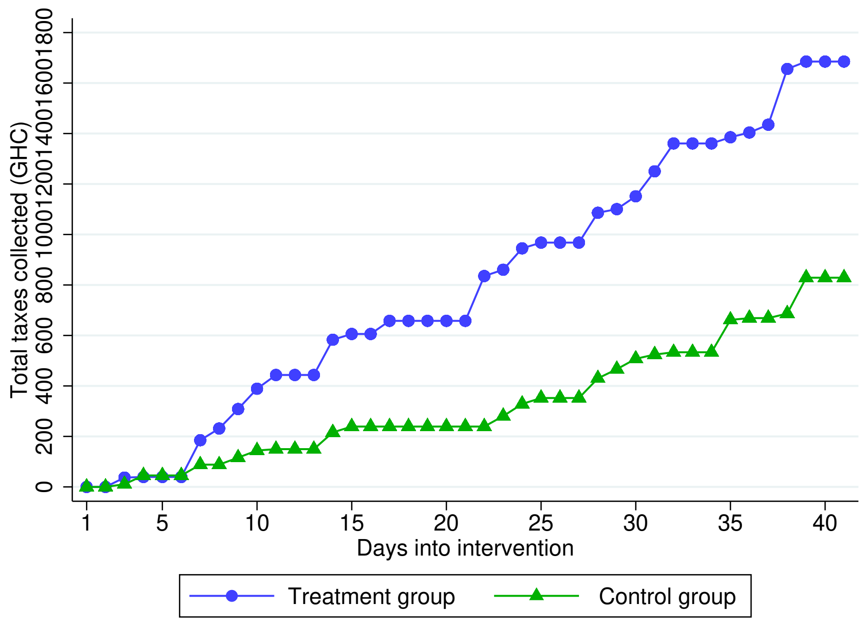
(b) Treatment Effect



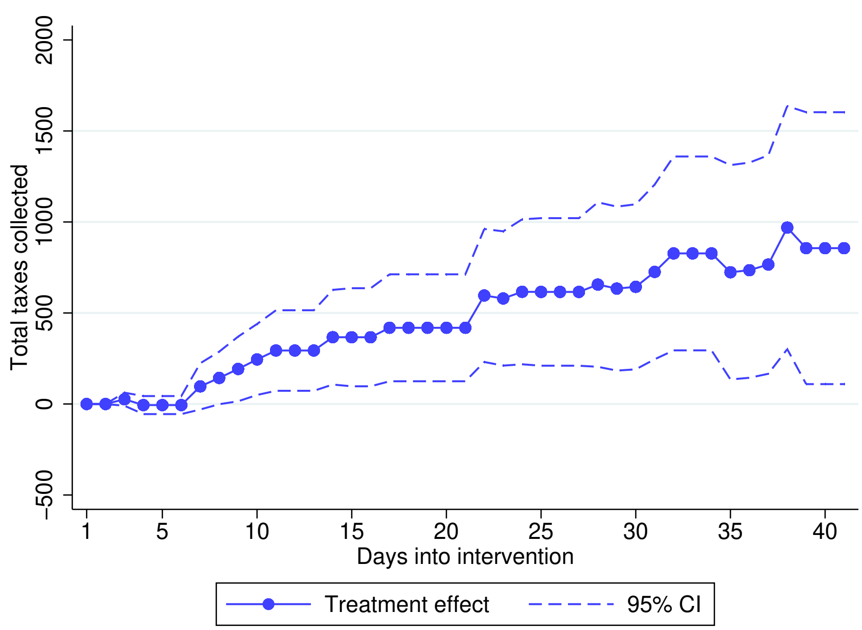
Notes: These panels show the impact of technology on the number of property tax bills delivered. Panel A shows the average number of bills delivered by group and by day of the intervention. Panel B displays the treatment effect coefficients on technology, separately by day, based on estimating equation (1). The analysis is based on the daily collector data, described in Section 3.3.

Figure 3: Impact of Technology on Taxes Collected

(a) Taxes Collected per Collector by Group



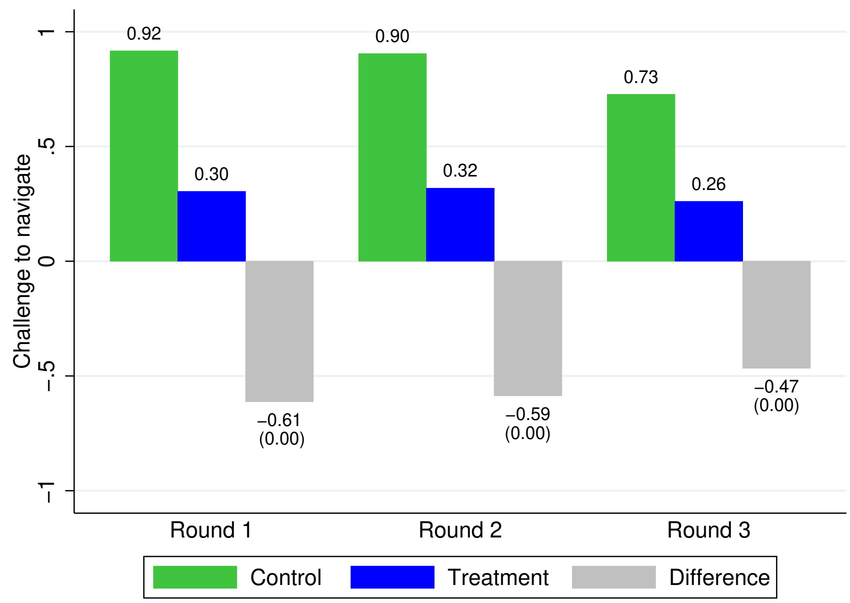
(b) Treatment Effect



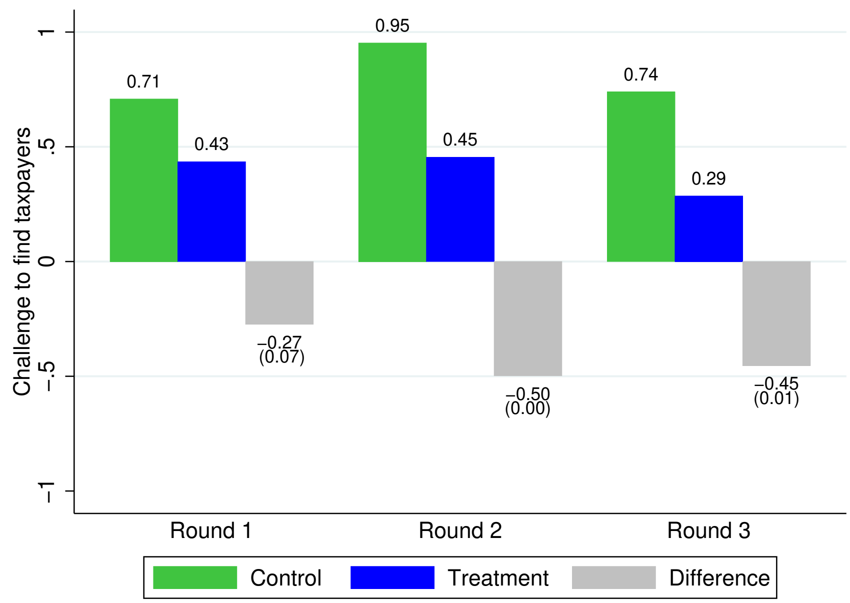
Notes: These panels show the impact of technology on the amount of property taxes collected. Panel A shows the average total amount of taxes collected by group (treatment, control) and by day of the intervention. Panel B displays the treatment effect coefficients on technology, separately by day, based on estimating equation (1). The analysis is based on the daily collector data, described in Section 3.3.

Figure 4: Impact of Technology on Search Challenges in the Field

(a) Challenging to Navigate in the Field?



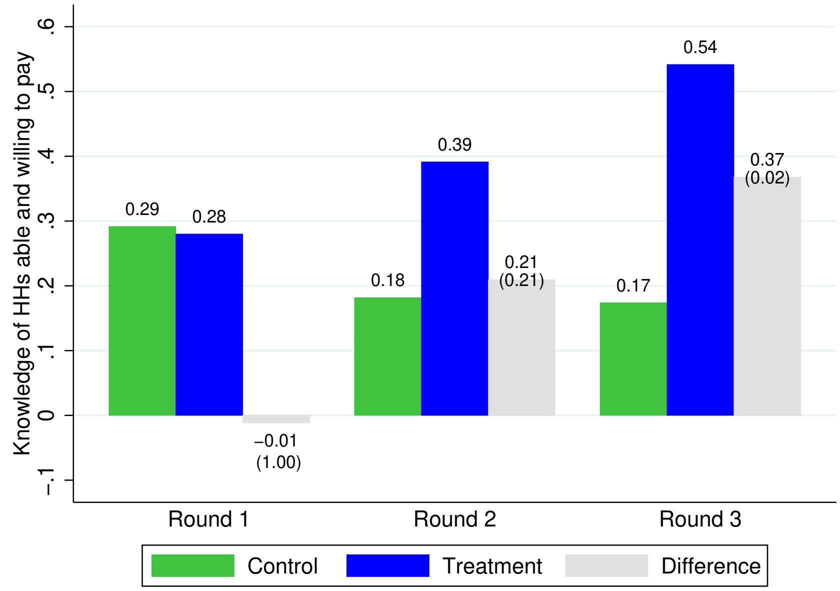
(b) Challenging to Locate Taxpayers?



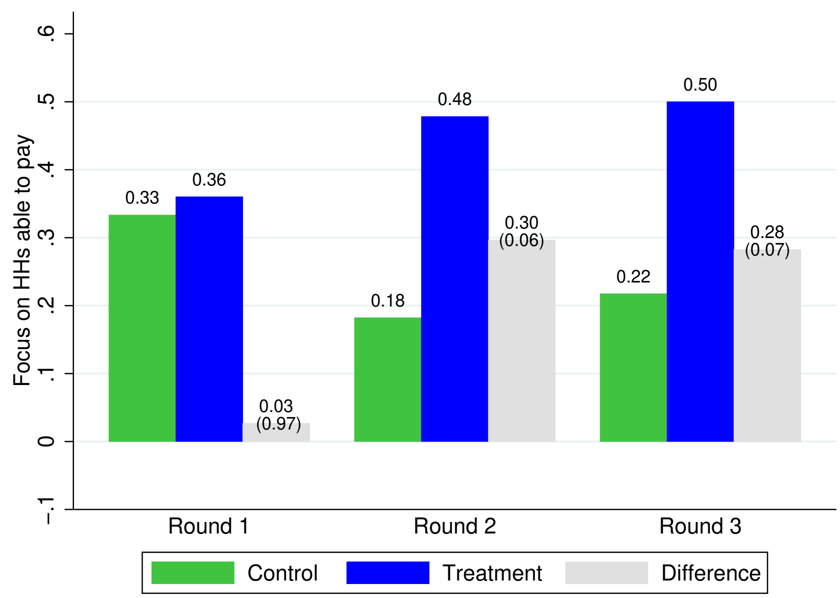
Notes: In Panel A, the outcome is a dummy variable which takes a value of 1 if the collector finds it challenging or very challenging to navigate in the field (and 0 otherwise). In Panel B, the outcome is a dummy variable which takes a value of 1 if the collector finds it challenging or very challenging to locate assigned taxpayers (and 0 otherwise). The grey bar measures the difference in outcome between treatment and control; the number in parentheses is the randomization inference-based p-value on the statistical significance of the difference. For a description of the challenge measures, see Section 4.3 and Data Appendix B.5. The analysis is based on the collector surveys, described in Section 3.3.

Figure 5: Collector Knowledge of and Focus on Households that are Able to Pay

(a) Knowledgeable about Which Households are Able and Willing to Pay?



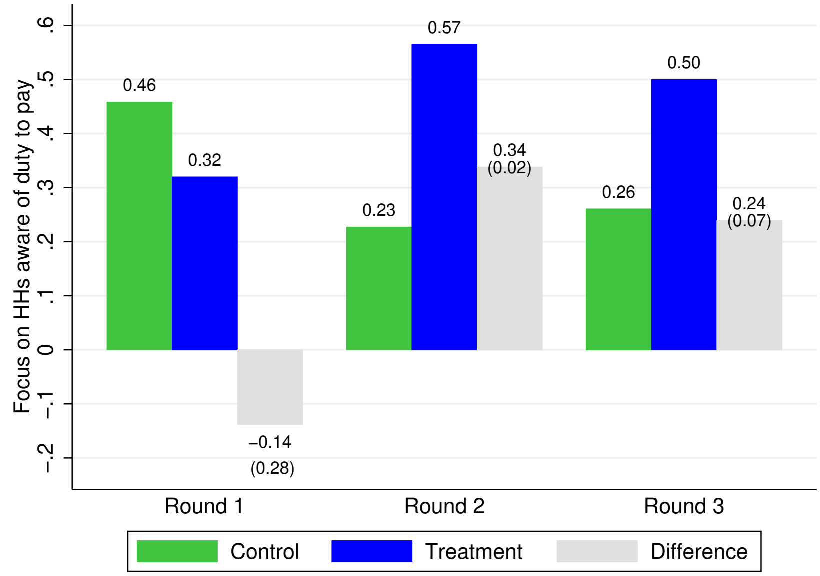
(b) Focus on Households that are Able to Pay?



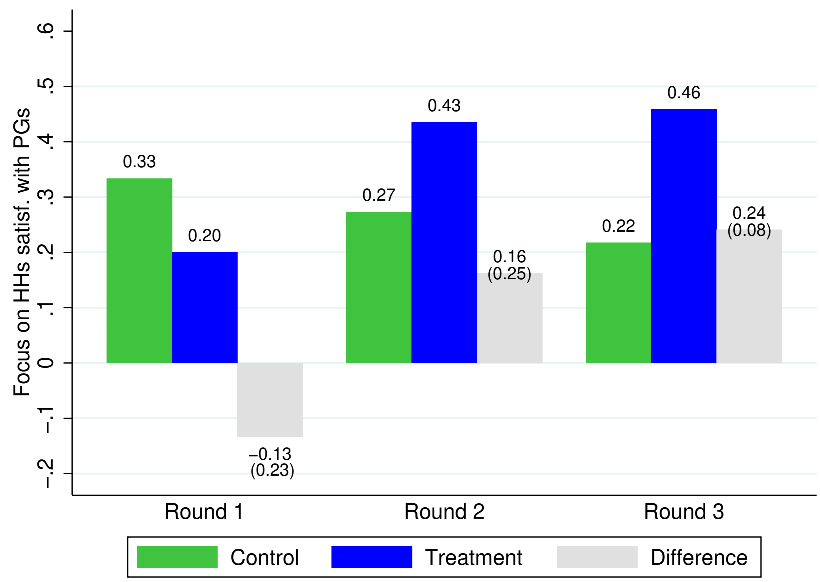
Notes: In Panel A, the outcome takes a value of 1 if the collector reports having a good understanding of which properties are more able and willing to pay (and 0 otherwise). In Panel B, the outcome is a dummy variable which takes a value of 1 if the collector uses all the time or often the collection strategy to focus on properties on specific days where property owners are more likely to be able to pay (and 0 otherwise). The grey bar measures the difference in outcome between the treatment and control groups; the number in parentheses is the randomization inference-based p-value on the statistical significance of the difference. For a detailed description of the knowledge and strategy measures, see Data Appendix B.5. The analysis is based on the collector surveys, described in Section 3.3.

Figure 6: Collector Focus on Those Aware of Tax Duties and Satisfied with Public Goods

(a) Focus on Households that are Aware of Tax Payment Duty?



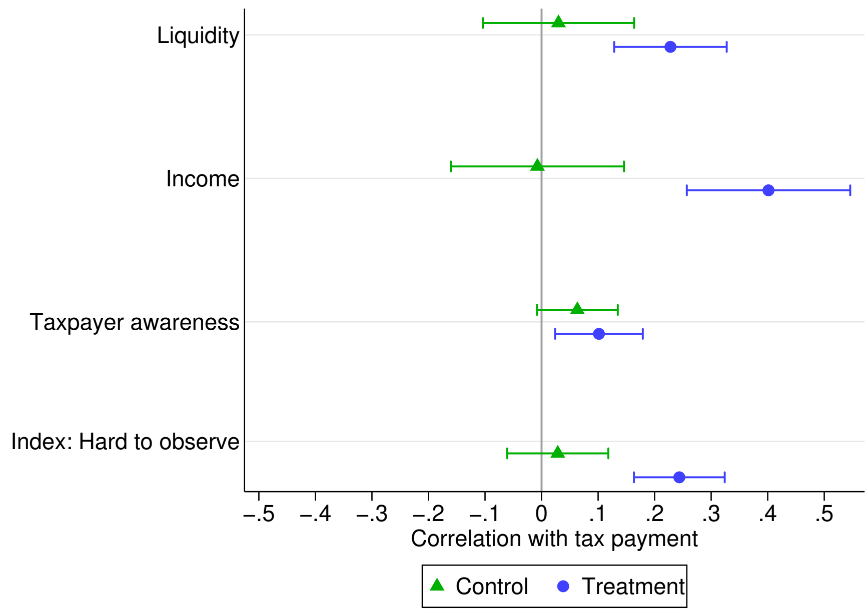
(b) Focus on Households that are Satisfied with Public Goods?



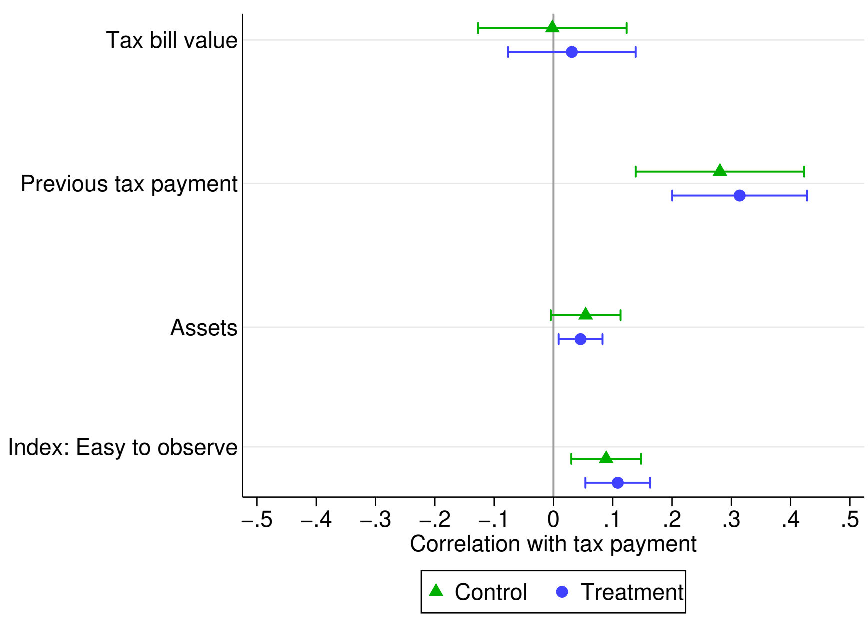
Notes: In Panel A, the outcome takes a value of 1 if the collector uses all the time or often the collection strategy to focus on properties where the collector knows the owners are aware of their duty to pay property taxes (and 0 otherwise). In Panel B, the outcome takes a value of 1 if the collector uses all the time or often the collection strategy to focus on properties where the collector knows the owners are more likely to pay because of satisfaction with delivery of public services (and 0 otherwise). The grey bar measures the difference in reliance on these strategies between the treatment and control groups; the number in parentheses is the randomization inference-based p-value on the statistical significance of the difference. For a detailed description of the strategy measures, see Data Appendix B.5. The analysis is based on the collector surveys, described in Section 3.3.

Figure 7: Characteristics of Households that Made a Tax Payment by Treatment Status

(a) Hard-to-Observe Characteristics

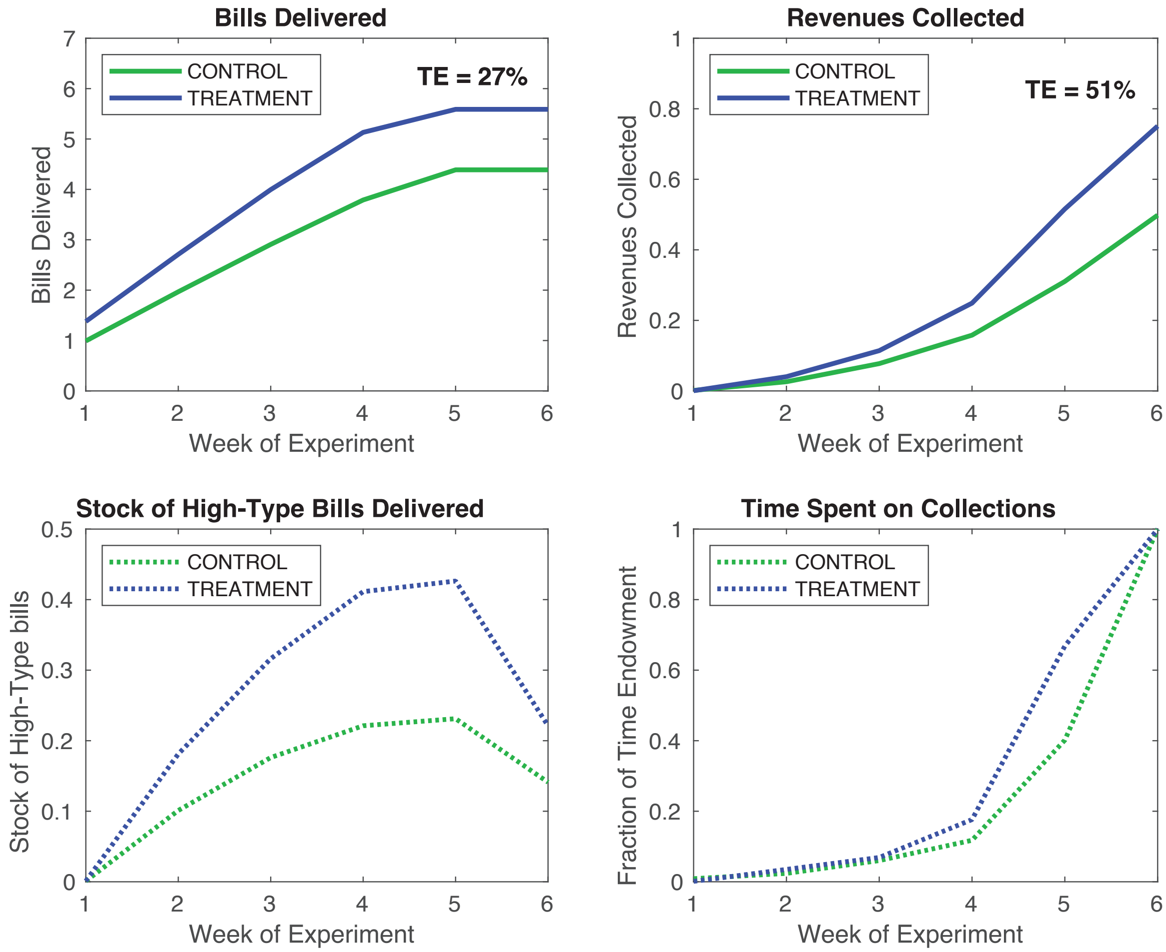


(b) Easy-to-Observe Characteristics



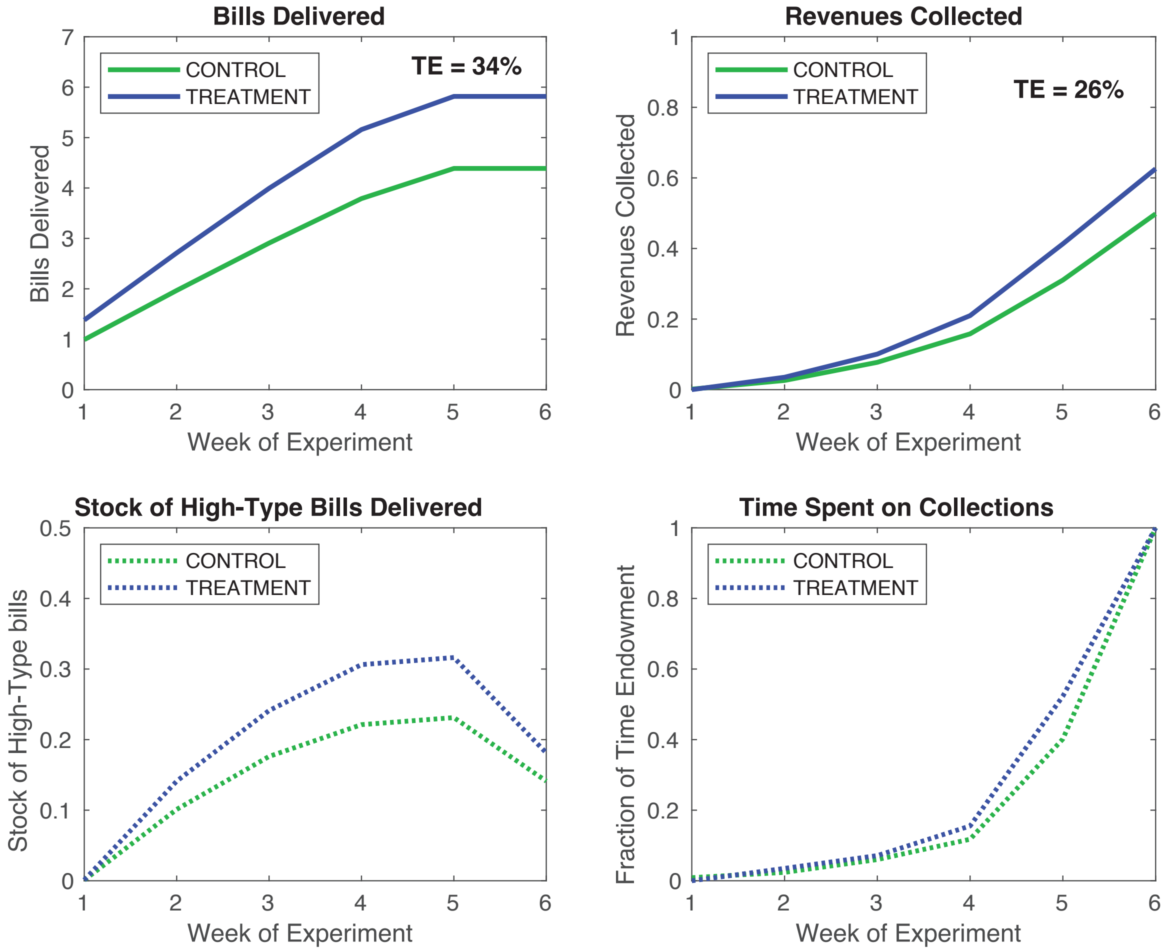
Notes: These figures show targeting of property owner characteristics for tax payment, based on estimating equation (3). Characteristics vary by row and the bottom row of each graph is an index which is the unweighted average of the characteristics. The characteristics in Panel A are harder to observe, while the characteristics in Panel B are easier to observe (see Section 4.3 for further explanation). Data Appendix B.4 provides details on the characteristics and the indices.

Figure 8: Predictions of Benchmark Model



Notes: This figure shows the predictions of the benchmark model for the control and treatment groups. The upper panels plot the model's predictions for bills delivered and revenues collected over the course of the experiment. The bottom panels plot the stock of high-type bills that have been delivered (but not collected from) and the fraction of time spent on collections (rather than bill delivery).

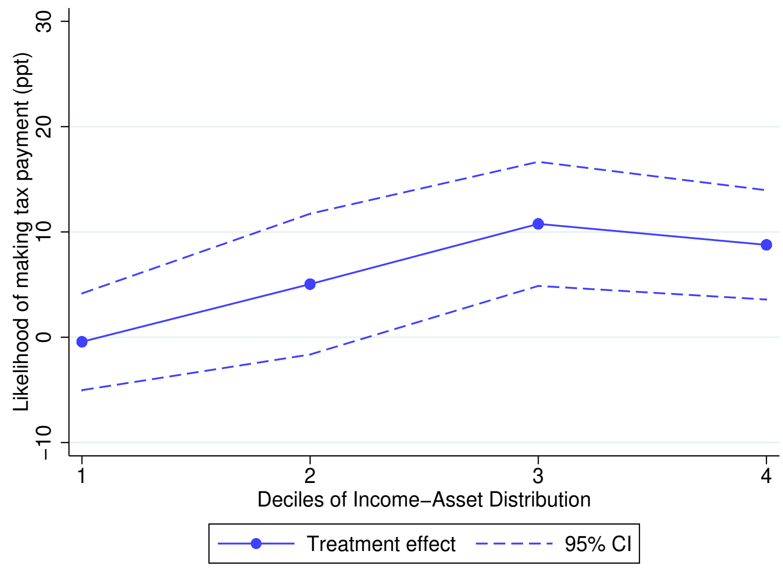
Figure 9: Predictions of Model with No Learning Advantage from Technology



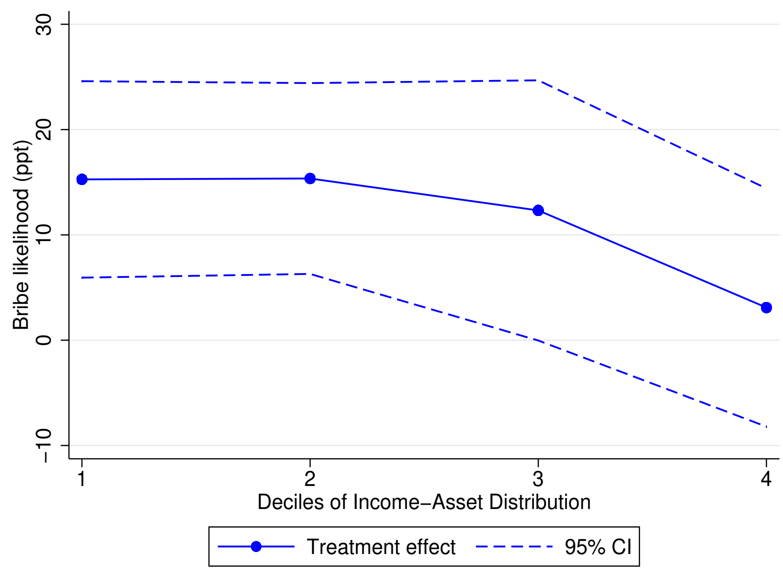
Notes: This figure shows the predictions of the model when the learning probability is set to be the same in the treatment and control groups. The upper panels plot the model's predictions for bills delivered and revenues collected over the course of the experiment. The bottom panels plot the stock of high-type bills delivered (but not collected from) and the fraction of time spent on collections (rather than bill delivery).

Figure 10: Distributional Effects of Technology on Taxes and Bribes

(a) Treatment Effect on Tax Payment



(b) Treatment Effect on Bribe



Notes: These panels show the impact of technology on the likelihood of making any positive tax payment (Panel A) and on the likelihood of bribes (Panel B). The bribe dummy takes a value of 1 if the household estimates that the tax collector will ask for any positive amount of unofficial payment during interactions with property owners (collusive bribe); or, if the household estimates that the collector will keep for themselves any positive amount of money collected from property owners (coercive bribe). The bribe variable takes a value of 0 only if the estimated amounts of collusive bribe and coercive bribe are both equal be 0. Both panels display the treatment effect coefficient on technology, separately by quartile of the income-asset distribution, based on estimating equation (5). The income-asset distribution is calculated as the unweighted average, by household, of the income index and the assets index. For more detail on the index measures and the bribe and tax payment measures, see Data Appendix B.3-B.4.

Table 1: Characteristics of Local Tax Capacity in Ghana

	Mean	Median
Panel A: Tax outcomes		
Taxes collected per capita (GHC)	4.2	2.6
Share of bills delivered (%)	43.0	43.3
Taxes collected per bill delivered (GHC)	11.5	6.7
Share of bills that are paid (%)	30.2	29.3
Panel B: Information and technology		
Share of properties with address (%)	26.7	20.0
1(Common not to locate property/owner)	0.74	1
1(Technology: database or software)	0.17	0
Panel C: Other capacity dimensions		
Share of properties with valuation (%)	17.1	0
Share of tax payments made in cash (%)	72.1	76.6
Cost of collection (% taxes collected)	64.1	47.5
1(Take tax defaulters to court)	0.22	0
Number of local governments	216	216

Notes: All variables are calculated at the district level (N=216), using unweighted averages. In Panel A, the variables measure tax outcomes: total local taxes collected per capita; the share of bills that are actually delivered to property owners; total taxes collected per bill delivered; the share of bills delivered which are paid. In Panel B, the variables relate to information constraints and use of technology: the share of properties which have a physical address; a dummy variable which equals 1 if it is common for a collector not to be able to locate an assigned property or their owner (and 0 otherwise); a dummy equal to 1 if the local government has an electronic database of properties or a tax revenue management software (and 0 otherwise). In Panel C, the variables relate to additional constraints on tax capacity: the share of properties with official valuation; the share of tax payments that are made in cash to the collector; the cost of collecting taxes, as a share of total taxes collected; the likelihood that a local government takes tax defaulters to court. For a detailed description of all variables, see Data Appendix B.1.

Table 2: Associations with Technology at the Local Government Level

	(1)	(2)	(3)	(4)	(5)
Panel A: Taxes collected per Capita					
1(Technology)	6.32***	3.71***	4.06***	3.08**	3.24***
	(1.62)	(0.88)	(0.60)	(1.16)	(0.94)
Mean outcome variable	4.15	4.15	4.15	4.15	4.15
Panel B: Share of Bills Delivered (%)					
1(Technology)	0.26***	0.08**	0.18***	0.14***	0.09**
	(0.06)	(0.03)	(0.04)	(0.03)	(0.03)
Mean outcome variable	0.43	0.43	0.43	0.43	0.43
Panel C: Taxes per Bill Delivered					
1(Technology)	6.9*	5.1**	4.8**	3.1***	4.2***
	(3.6)	(2.0)	(1.8)	(0.9)	(1.1)
Mean outcome variable	11.5	11.5	11.5	11.5	11.5
Panel D: Cost of collection (% taxes collected)					
1(Technology)	-12.09**	-11.14**	-8.74*	-8.83*	-8.54*
	(4.67)	(4.22)	(4.22)	(4.42)	(4.35)
Mean outcome variable	64.1	64.1	64.1	64.1	64.1
District controls		x			x
Share neighbors with tech			x		x
Region FE				x	x
Observations	216	216	216	216	216
Clusters	10	10	10	10	10

Notes: The regression model is a cross-sectional regression of all 216 districts in Ghana, with one local government per district. The variable **1**(Technology) is a dummy variable taking a value of 1 if the local government either has an electronic database of properties or a revenue management software that assists with bill printing, payment recording, and follow-up enforcement. Across panels, the outcome is: local taxes collected per capita (Panel A); the share of bills that are delivered (Panel B); local taxes collected per bill delivered (Panel C); the cost of collecting taxes as a share of total taxes collected (Panel D). Across columns, the specifications are: no controls in column (1); district controls (log per capita income, log population, urban share of population, share of properties with valuations, share of properties on official addresses, legal capacity, officials' years of work experience) in column (2); the share of each district's geographically adjacent neighbor governments with technology in column (3); region fixed effects in column (4); all three sets of controls in column (5). Standard errors are clustered at the region level. See Data Appendix B.1 for more detail on the variables.

Table 3: Impacts of Technology on Visits, Compliance and Revenues

	Any visit by tax collector (1)	Total visits (in %) (2)	Bill delivered by tax collector (3)	Any positive tax payment (4)	Total payment amount (in GHC) (5)	Payment amount per bill delivered (6)
Technology	0.087**	0.094*	0.054	0.043**	25.9**	47.3**
	(0.033)	(0.050)	(0.036)	(0.021)	(10.9)	(19.6)
Household controls	X	X	X	X	X	X
Collector-unit controls	X	X	X	X	X	X
Strata FE	X	X	X	X	X	X
Mean in CG	0.55	0.67	0.51	0.16	41.0	80.9
Observations	4334	4334	4334	4334	4334	2276
Clusters	56	56	56	56	56	56

Notes: This table presents the impacts of technology on main tax outcomes of interest. All coefficients are based on estimating equation (2), and using the household sample (Section 3.3). Across columns, the outcome is: a dummy for any visit received by a tax collector; the total number of visits (expressed in %, using the inverse hyperbolic sine transformation); a dummy for bill delivered; a dummy for any tax payment made; total tax amount paid (in GHC); total tax paid, restricted to households that received a bill. For a description of household controls and collector-unit controls, please refer to Section 3. The robustness of these results to the removal of control variables, or the inclusion of more extensive controls, is presented in Appendix Table A4.

Table 4: Impacts of Technology on Citizen Beliefs and Tax Morale

	Satisfaction with government services (1)	Integrity of government (2)	Tax equity & efficiency efforts by government (3)	Enforcement information capacity of government (4)
Technology	-0.00771	0.0629	-0.0143	-0.0536
	(0.0701)	(0.0728)	(0.0604)	(0.0572)
Household controls	X	X	X	X
Collector-unit controls	X	X	X	X
Strata FE	X	X	X	X
Mean in CG	0.05	-0.04	-0.03	0.00
Observations	4324	4326	4326	4326
Clusters	56	56	56	56

Notes: This table presents the impacts of technology on beliefs and tax morale. All coefficients are based on estimating equation (2), and using the household sample (Section 3.3). The outcome in each column is a (standardized) index variable, which averages over multiple (standardized) household survey questions. For the description of each underlying question that is used in each index, please see Data Appendix B.2. Across columns, the outcome index measures: the extent of satisfaction with government's delivery of services (column 1); the perceived integrity and competency of the local government (column 2); the local government's efforts to collect taxes in an equitable and efficient manner (column 3); the perceived enforcement capacity of the government and the informational knowledge that the government possesses about its citizens (column 4). For a description of household controls and collector-unit controls, please refer to Section 3.

Table 5: Impacts of Technology on Bribe Activity

	Any bribe (coercive or collusive) (1)	Total bribe amount (in %) (2)	Collusive bribe amount (% of tax due) (3)	Coercive bribe amount (% of payment) (4)	Collusive bribe amount (in GHC) (5)
Technology	0.12***	0.03**	0.01**	0.04*	6.16**
	(0.04)	(0.01)	(0.00)	(0.02)	(3.07)
Household controls	X	X	X	X	X
Collector-unit controls	X	X	X	X	X
Strata FE	X	X	X	X	X
Mean in CG	0.14	0.11	0.02	0.19	11.6
Observations	4334	4334	4334	4331	4334
Clusters	56	56	56	56	56

Notes: This table presents the impacts of technology on measures of bribe activity by collectors. All coefficients are based on estimating equation (2), and using the household survey (Section 3.3). In column 1, the outcome is a dummy which takes a value of 1 if the household estimates that the tax collector will ask for any positive amount of unofficial payment during visits to property owners (collusive bribe); or, if the household estimates that the collector will keep for themselves any positive amount of money collected from property owners (coercive bribe). The bribe dummy takes a value of 0 only if the estimated amounts of collusive bribe and coercive bribe are both equal be 0. In column 2, the outcome is the total bribe amount, in percent. At the household level, it is the average of the coercive bribe amount, expressed as a percent of a hypothetical 1000 GHC collected by the tax collector, and the collusive bribe amount, expressed as a percent of the household's true tax liability. In column 3, the outcome is the collusive bribe amount, expressed as a percent of the household's true tax liability. In column 4, the outcome is the coercive bribe amount, expressed as a percent of a hypothetical 1000 GHC collected by the tax collector. In column 5, the outcome is the collusive bribe amount in GHC that the household estimates will be asked by the tax official as unofficial payment during visits to households. The bribe variables are described in detail in Data Appendix B.3. For a description of household controls and collector-unit controls, please refer to Section 3. The robustness of these results to the removal of control variables, or the inclusion of more extensive controls, is presented in Appendix Table A4.

Table 6: Impact of Technology on Collector Strategies in the Field

	Focus on collections, hard-to-observe household characteristics		Focus on collections, easy-to-observe household characteristics		Difference in strategies: Hard versus easy to observe	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Average effect						
Technology	0.141**	0.357**	0.087*	0.133	0.053	0.223**
	(0.066)	(0.136)	(0.046)	(0.092)	(0.039)	(0.102)
	[0.032]	[0.000]	[0.076]	[0.089]	[0.190]	[0.001]
Panel B: Dynamic effect						
Technology $\times$ Round 1	-0.082	–	0.007	–	-0.089	–
	(0.103)	–	(0.068)	–	(0.077)	–
Technology $\times$ Round 2	0.264**	0.364**	0.123	0.137	0.143**	0.227**
	(0.125)	(0.153)	(0.091)	(0.102)	(0.058)	(0.095)
Technology $\times$ Round 3	0.253**	0.349**	0.138	0.130	0.117*	0.219**
	(0.117)	(0.151)	(0.088)	(0.106)	(0.061)	(0.093)
Collector-unit controls	X		X		X	
Survey round FE	X	X	X	X	X	X
Collector-unit FE		X		X		X
Mean in CG	0.280	0.280	0.239	0.239	0.041	0.041
Observations	141	141	141	141	141	141

Notes: This table presents the impacts of technology on collector strategies. In columns (1)-(2), the outcome is the likelihood that a collector makes uses all the time or often of collection strategies which focus on hard-to-observe household characteristics (liquidity, income, taxpayer awareness, satisfaction with public goods). In columns (3)-(4), the outcome is the likelihood that a collector makes use often or all the time of collection strategies which focus on more easily observable household characteristics (value of tax bill, past tax payment, geographical location). In column (5)-(6), the outcome is the difference between the reliance on hard-to-observe versus easy-to-observe strategies. For a detailed description of these collector strategies, see Data Appendix B.5. All regressions use the panel of three collector survey rounds (at the beginning, middle and end of the campaign), and include survey round fixed effects. Odd columns include collector-unit controls. Even columns include collector-unit fixed effects, in which case the omitted treatment category is round 1. Panel A reports the average effect of technology, while Panel B reports the round-by-round treatment effect (based on interacting round fixed effects with the technology variable). Standard errors clustered at the collector-unit are reported in parentheses. In Panel A, the randomization inference based p-value is reported in brackets.

Appendix
Technology and Tax Capacity: Evidence from Ghana

A Additional Figures and Tables

Table A1: Associations with Technology Adoption

	1(Technology exists) (1)	(2)
Total population	0.114***	0.084**
	(0.025)	(0.027)
Income per capita	0.073**	0.009
	(0.027)	(0.021)
Urban share of population	0.096***	0.048**
	(0.024)	(0.020)
Share of properties with address	0.112*	0.088*
	(0.053)	(0.044)
Share of properties with valuation	0.174***	0.130***
	(0.029)	(0.026)
Legal capacity to enforce taxes	0.084*	0.053**
	(0.042)	(0.022)
Tax-delinquents taken to court	-.001	-.001
	(0.016)	(0.011)
Officials' years of work experience	0.058**	0.058*
	(0.021)	(0.030)
Officials' years of education	0.014	-0.007
	(0.025)	(0.016)
Trust in officials	0.004	-0.002
	(0.013)	(0.013)
Citizen tax awareness	-0.030	-0.026
	(0.015)	(0.026)
Citizen compliance attitude	-0.006	0.013
	(0.016)	(0.010)
Region FE		X
Observations	216	216
Clusters	10	10

Notes: Each cell represents the β coefficient from a separate cross-district regression, based on the model $\mathbf{1}(Technology)_{dr} = \beta \cdot X_d + \mu_r + \epsilon_{dr}$ where $1(Technology)_{dr}$ is a dummy equal to 1 if the local government in district d in region r uses technology for tax collection (see Section 2). X_d is the district characteristic which varies between rows; across columns, region fixed effects (μ_r) are included. All district characteristics are standardized, for ease of comparison across rows. Standard errors are clustered at the regional level. For a description of all the district characteristics, see Data Appendix B.1.

Table A2: Challenges Reported in the Field by Collectors

	Unable to locate properties owners (1)	Wrong information printed on bills (2)	Resistance from property to accept bill (3)	Supervisors don't monitor activities in the field (4)	Supervisors unavailable for support if needed (5)
Technology	-1.040***	-0.266*	-0.100	-0.154	0.181
	(0.130)	(0.145)	(0.124)	(0.164)	(0.153)
	[0.00]	[0.07]	[0.43]	[0.35]	[0.26]
Collector-unit controls	X	X	X	X	X
Survey round FE	X	X	X	X	X
Mean in CG	0.51	0.13	0.04	0.07	-0.09
Observations	136	135	135	139	140

Notes: This table presents the impacts of technology on the extent of challenges encountered by collectors in the field. All regressions pool the collector survey responses across the survey rounds, and include survey round fixed effects. All regressions also include the collector-unit controls described in Section 3. The outcomes measure the extent to which collectors agree (on a scale from 1 to 5) that a particular challenge characterizes their weekly work in the field: inability to locate property owners; wrong information (address or tax amount due) printed on bills; resistance from property owners (mistrust of collector or refusal to pay); absence of monitoring by supervisors; unavailability of supervisors to support in the field. The outcomes are standardized based on the set of underlying questions that characterize each challenge. Robust standard errors are reported in parentheses; the randomization inference-based p-value is reported in brackets. For a detailed description of the outcomes, see Data Appendix B.5

Table A3: Randomization Balance

	N	Control mean	Treatment coefficient
	(1)	(2)	(3)
Panel A: Tax bill characteristics			
Current tax amount	7560	322.8	-9.0
			(16.4)
Total tax amount	7560	692.5	-5.5
			(29.1)
Previous pay status	7560	1.2	0.0
			(0.0)
Previous tax payment	7560	59.7	-6.6
			(9.4)
Residential	7560	0.5	0.0
			(0.0)
Property quality	7560	0.5	0.0
			(0.1)
F-test joint significance [F, p]			[0.7,0.66]
Panel B: Collector-unit characteristics			
Experience in Madina	56	0.7	-0.1
			(0.1)
Performance rating	56	0.2	-0.1
			(0.1)
Total bills to deliver	56	135.2	1.7
			(4.7)
Average amount per tax bill	56	322.6	-7.4
			(16.5)
F-test joint significance [F, p]			[0.2,0.95]
Panel C: Household characteristics			
Income index	4353	-0.014	0.003
			(0.106)
Liquidity index	4353	0.051	-0.177
			(0.119)
Taxpayer awareness index	4353	0.011	-0.01
			(0.039)
F-test joint significance [F, p]			[1.07,0.38]

Notes: This table presents balance checks of the randomization assignment for characteristics at the bill level (Panel A), the collector-unit level (Panel B), and the household level (Panel C). Details on the variables used in this table are provided in Section 3.3. The treatment coefficient in column (3) is the coefficient on technology in a cross-sectional regression with strata fixed effects. Standard errors are clustered at the collection unit level. At the bottom of each panel, the F-test on the joint significance of all characteristics is reported along with the p-value.

Table A4: Robustness Checks for Technology Impacts on Tax and Bribe outcomes

	Any visit by tax collector (1)	Total visits (%) (2)	Bill delivered (3)	Any positive tax payment (4)	Total payment amount (in GHC) (5)	Any bribe (coercive or collusive) (6)	Total bribe amount (in %) (7)	Coercive bribe amount (in %) (8)	Collusive bribe amount (in %) (9)
Panel A: No Controls									
Technology	0.082**	0.085*	0.049	0.039**	24.93**	0.120***	0.027**	0.012**	0.042*
	(0.034)	(0.04)	(0.036)	(0.017)	(10.89)	(0.038)	(0.012)	(0.005)	(0.023)
Panel B: Extensive Controls									
Technology	0.086**	0.087*	0.055	0.047**	27.21**	0.113***	0.025**	0.014**	0.036*
	(0.032)	(0.049)	(0.034)	(0.020)	(11.18)	(0.037)	(0.010)	(0.005)	(0.019)
Strata FE	X	X	X	X	X	X	X	X	X
Mean in CG	0.55	0.67	0.51	0.16	40.95	0.14	0.11	0.02	0.19
Observations	4353	4353	4353	4353	4353	4353	4353	4353	4350
Clusters	56	56	56	56	56	56	56	56	56

Notes: This table presents technology impacts on the same set of outcomes as in Table 3 and Table 5. The estimation model is the same, except that: in Panel A, all household and collector controls are removed; in Panel B, additional controls are added. The additional controls in Panel B are the set of 6 fixed characteristics used in the targeting analysis – see Section 4.3 and Figure 7. For a description of the bribe variables, see Data Appendix B.3.

Table A5: Beliefs about Enforcement and Tax Morale

	Technology coefficient ($\hat{\beta}$) (1)	Mean in CG (2)	N (3)
Panel A: Enforcement and Information			
Share of HHs that comply with taxes	0.80	60.32	4330
	(2.38)		
Likelihood non-complier will end up paying	-0.07	3.08	4330
	(0.07)		
Likelihood Gov't has info about my tax status	-0.13	2.95	4330
	(0.13)		
Likelihood Gov't has info about my job	0.03	2.52	4330
	(0.09)		
Panel B: Gov't Efforts to Improve Tax Collection			
Agree efforts to collect taxes efficiently	0.01	3.58	4330
	(0.07)		
Agree efforts to ensure fair share paid	-0.18***	3.42	4330
	(0.07)		
Agree efforts to collect for useful purposes	0.08	3.04	4330
	(0.11)		
Panel C: Government Capacity and Competency			
% of taxes wastefully spent	-3.48	55.81	4330
	(4.64)		
Agree Gov't has capacity to improve roads	0.04	3.94	4330
	(0.11)		
Overall Gov't competency rating	0.07	2.41	4330
	(0.07)		
Panel D: Satisfaction with Gov't Services			
Quality of tax collector services	-0.003	2.31	4330
	(0.05)		
Quality of tax authority services	-0.02	2.31	4330
	(0.05)		
Quality of overall Gov't services	-0.01	2.20	4330
	(0.05)		

Notes: This table presents technology impacts on beliefs and tax morale. Each row presents the technology treatment coefficient (in column 1) from estimating equation (2) on different outcomes (which are described to the left). Standard errors are clustered at the collection-unit. Column (2) presents the mean of the outcome variable in control areas, while column (3) shows the sample size. For a description of all the outcomes, see Data Appendix B.2. All regressions include household and collector controls (Section 3).

Table A6: Proxy for Propensity to Pay is a Predictor of Tax Payment

	(1)	(2)	(3)	(4)
Panel A: Outcome is tax payment status				
Propensity to pay index	0.056**			
	(0.022)			
Income index		0.026**		
		(0.012)		
Taxpayer awareness index			0.016	
			(0.020)	
Liquidity index				0.029**
				(0.012)
Panel B: Outcome is total taxes paid				
Propensity to pay index	20.64***			
	(7.000)			
Income index		14.73***		
		(4.774)		
Taxpayer awareness index			1.980	
			(5.849)	
Liquidity index				5.360
				(3.718)
Outcome mean: Panel A	1.255	1.255	1.255	1.255
Outcome mean: Panel B	60.99	60.99	60.99	60.99
Control tax liability	X	X	X	X
Control block FEs	X	X	X	X
Observations	4353	4353	4353	4353
Clusters	56	56	56	56

Notes: This table shows that the characteristics of propensity to pay are robust predictors of tax payment outside of the experimental setting. In Panel A, the outcome is the tax payment status in the year prior to the experiment, which can take a value of 1 (=no payment), 2 (=partial payment), 3 (=full payment). In Panel B, the outcome is the total amount of taxes paid in GHC, in the year prior to the experiment. Across columns, the outcome is regressed on different explanatory variables: the propensity index in column 1; the income index in column 2; the taxpayer awareness index in column 3; the liquidity index in column 4. The propensity index is the household-level unweighted average of the income, liquidity and awareness indices. For a discussion of the propensity to pay index, please see Section 4.3. For a detailed description of all the indices, please see Data Appendix B.4. All regressions include the level of property tax liability due as a control as well as block fixed effects (approximately 7-8 properties per block). Standard errors are clustered at the collection-unit level.

Table A7: Impact of Technology on Collector Performance Measures

	# of unsuccessful visits per successful visit (1)	Total hours worked per week (2)	Average # of hours spent to deliver one bill (3)	Satisfaction & happiness on the job (4)
Technology	-1.222	-2.382	-0.798***	0.117
	(1.024)	(1.412)	(0.207)	(0.150)
	[0.23]	[0.11]	[0.00]	[0.42]
Collector-unit controls	X	X	X	X
Survey round FE	X	X	X	X
Mean in CG	7.67	18.84	1.66	-0.07
Observations	141	141	111	139

Notes: This table presents impacts of technology on collector performance measures. All regressions pool the collector survey responses across the survey rounds, and include survey round fixed effects. All regressions also include the collector-unit controls described in Section 3. Across columns, the outcome is: number of unsuccessful visits per property for every successful visit; hours worked per week; hours worked per bill delivered; and, satisfaction and happiness in the job. The last outcome is a standardized variable, based on responses to three underlying questions: how productive the week was for the collector; how content the collector is while working; and, how satisfied the collector is with their job. Robust standard errors are reported in parenthesis; the randomization inference-based p-value is reported in brackets. For a detailed description of the outcomes, see Data Appendix B.5.

Table A8: Heterogeneity in Beliefs about Enforcement and Tax Morale

	Technology coefficient (β)	Heterogeneity coefficient ($\beta \times H$)
Outcome: Enforcement and Information Capacity Index		
Heterogeneity H: Liquidity index	-0.050	-0.016
	(0.056)	(0.053)
Heterogeneity H: Income index	-0.051	0.002
	(0.057)	(0.042)
Heterogeneity H: Taxpayer awareness index	-0.050	-0.021
	(0.056)	(0.057)
F-test joint significance of interaction terms [F, p]	[0.09, 0.96]	
Outcome: Efforts to Improve Tax Collection Index		
Heterogeneity H: Liquidity index	-0.016	0.048
	(0.059)	(0.055)
Heterogeneity H: Income index	-0.010	0.059
	(0.060)	(0.039)
Heterogeneity H: Taxpayer awareness index	-0.012	0.068
	(0.061)	(0.069)
F-test joint significance of interaction terms [F, p]	[1.27, 0.29]	
Outcome: Satisfaction with Gov't Services Index		
Heterogeneity H: Liquidity index	-0.018	-0.042
	(0.069)	(0.059)
Heterogeneity H: Income index	-0.009	0.011
	(0.069)	(0.032)
Heterogeneity H: Taxpayer awareness index	-0.007	0.041
	(0.070)	(0.064)
F-test joint significance of interaction terms [F, p]	[0.45,0.72]	

Notes: This table presents heterogeneous technology impacts on beliefs and tax morale. Each row presents the technology treatment coefficient and the interaction coefficient, from estimating equation 2 augmented with the interaction between technology and the heterogeneity dimension H. Rows differ in the interaction (liquidity, income or taxpayer awareness), and panels differ in the outcome. The F-test at the bottom of each panel tests the joint significance of the three interaction coefficients for a given outcome. The outcomes are the same as in Table 4 (also described in Data Appendix B.2). The heterogeneity dimensions are the indices used in Panel A of Figure 7 (also described in Data Appendix B.4).

Table A9: Model Sensitivity Analysis

	Treatment Effect on Collections		
	Calibrated Model	No Learning	Ratio
Benchmark calibration	51	26	1.9
Higher base delivery efficiency (θ_C=1.5)	50	26	1.9
Higher frequency of high type (η_C=0.2)	52	27	1.9
Lower curvature in collections (μ=0.4)	52	25	2.0
Lower efficiency in collections (λ=0.4)	51	26	1.9

Notes: This table reports the treatment effects on collections in the calibrated model and in the counterfactual equilibrium of the model when there is no collector learning ($\eta_T = \eta_C$). In the top row, the benchmark calibration sets $\theta_C = 1$, $\eta_C = 0.1$, $\mu = 0.5$, $\lambda = 0.5$, sets $\theta_T = 1.38$ in order to match the 27 percent treatment effect on bills delivered (Section 3.4), and sets $\eta_T = 0.13$ to match the 22 percent increase in the disproportionate reliance on collector strategies targeting hard-to-observe versus easy-to-observe household characteristics (Section 4.3). In each subsequent row, the calibrated model matches the treatment effect on bill deliveries of 27 percent, and keeps all other parameters other than the change indicated as in the benchmark calibration.

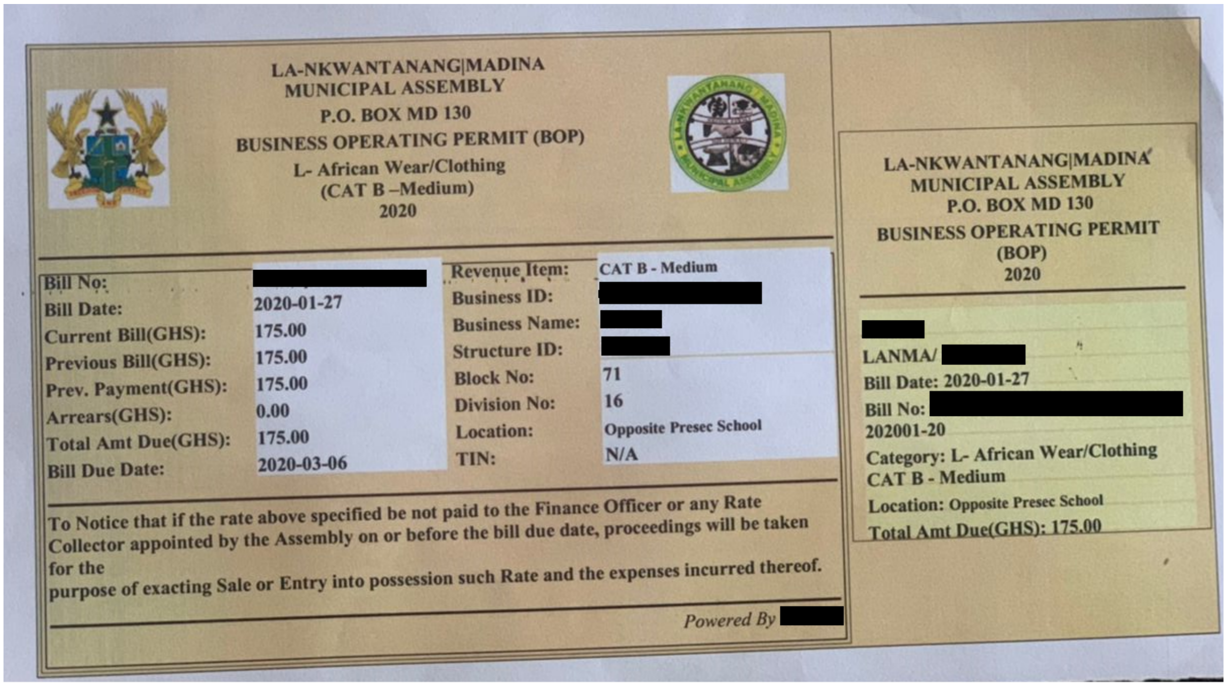
Table A10: Cost-Benefit Analysis per Collector

			Control	Treatment
Cost items	Unit price	Total units		
Daily allowance	10	42	420	420
Commission rate	8%	42	66.3	134.8
Tablet rental	10	42	0	420
Network connection	40	1	0	40
Total cost			486.3	1014.8
Totals				
Total taxes collected			829	1685
Total taxes net of cost			342.7	670.2

Notes: This table presents a cost-benefit analysis for the running costs of the average collector in the treatment and control groups during the 42 days of the tax experiment campaign. Some cost items are common to all collectors. Each collector receives 10 GHC in daily allowance. Moreover, each collector in both groups receives an 8% commission for taxes collected – which corresponds to 66.3 GHC ($0.08 \times 828 = 66.3$) for the average collector in the control group and 134.8 GHC ($0.08 \times 1685 = 134.8$) for the average collector in the treatment group (based on Figure 3). Some cost items are specific to the treatment group. In particular, the private firm pays a 10 GHC daily rental price to the tablet provider; moreover, the tablet requires network connection. The top panel reports the total costs for the average collector over the 6-week campaign. In the bottom panel are reported the average taxes collected at the end of the campaign, as well as the taxes collected net of total cost. It is important to note that the cost items in the treatment group refer to the running cost of using the tablet on a daily basis – they do not account for any cost of building the geo-spatial database which serves as the input to the tablet (see Section 3).

Figure A1: Illustrations of Tax Bill and Tablet

(a) Example of Business Property Tax Bill


LA-NKWANTANANG|MADINA
MUNICIPAL ASSEMBLY
P.O. BOX MD 130
BUSINESS OPERATING PERMIT (BOP)
L- African Wear/Clothing
(CAT B –Medium)
2020

Bill No:	[redacted]	Revenue Item:	CAT B - Medium
Bill Date:	2020-01-27	Business ID:	[redacted]
Current Bill(GHS):	175.00	Business Name:	[redacted]
Previous Bill(GHS):	175.00	Structure ID:	[redacted]
Prev. Payment(GHS):	175.00	Block No:	71
Arrears(GHS):	0.00	Division No:	16
Total Amt Due(GHS):	175.00	Location:	Opposite Presec School
Bill Due Date:	2020-03-06	TIN:	N/A

To Notice that if the rate above specified be not paid to the Finance Officer or any Rate Collector appointed by the Assembly on or before the bill due date, proceedings will be taken for the purpose of exacting Sale or Entry into possession such Rate and the expenses incurred thereof.

Powered By [redacted]

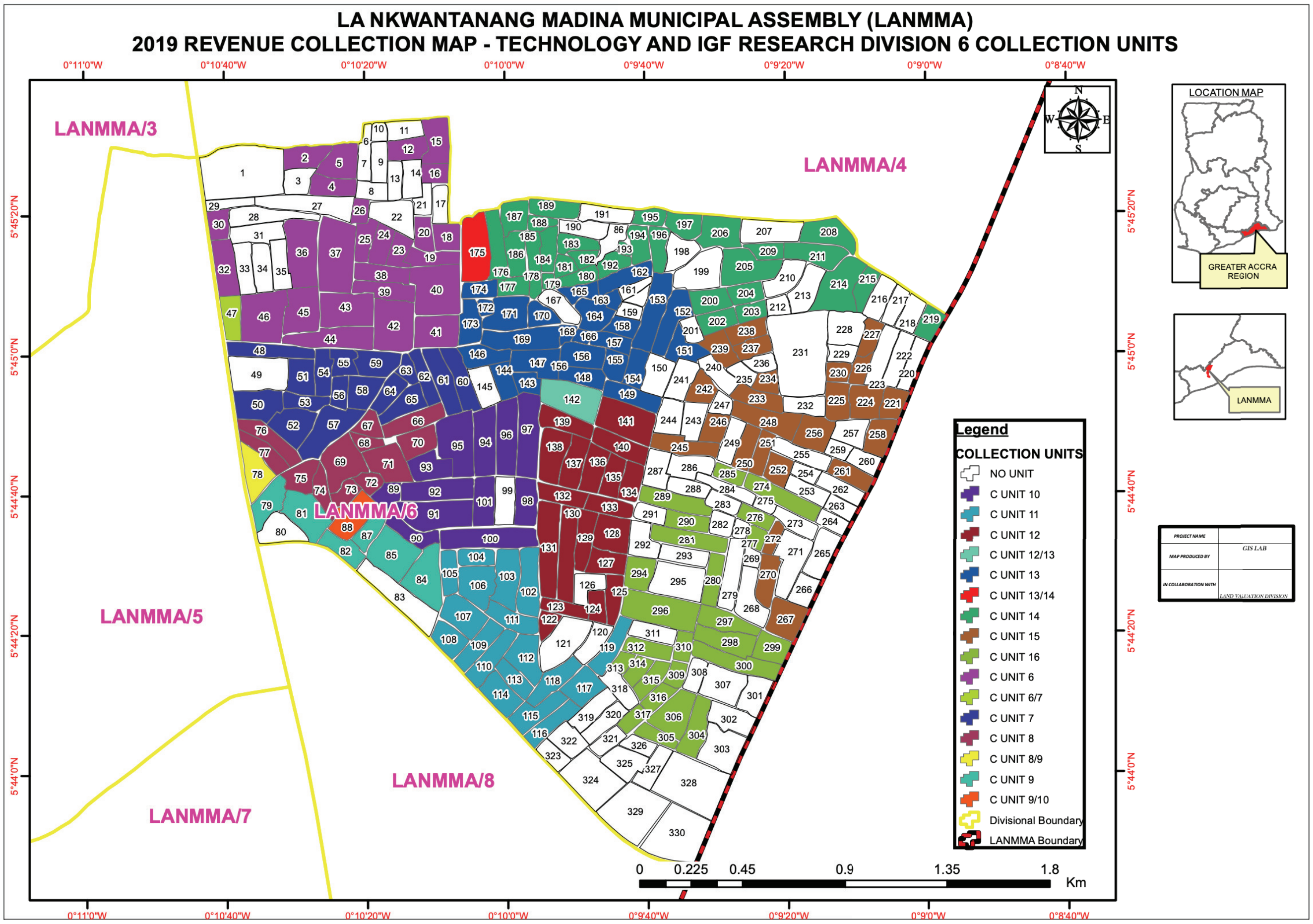
LA-NKWANTANANG|MADINA
MUNICIPAL ASSEMBLY
P.O. BOX MD 130
BUSINESS OPERATING PERMIT
(BOP)
2020

[redacted]
LANMA/ [redacted]
Bill Date: 2020-01-27
Bill No: [redacted]
202001-20
Category: L- African Wear/Clothing
CAT B - Medium
Location: Opposite Presec School
Total Amt Due(GHS): 175.00

(b) Navigational Assistance Provided by Tablet

Notes: Panel A illustrates a typical business property tax bill used by the local government of Madina (where the experiment takes place). Panel B illustrates the navigational assistance provided in the tablet that is used by treatment collectors but not control collectors.

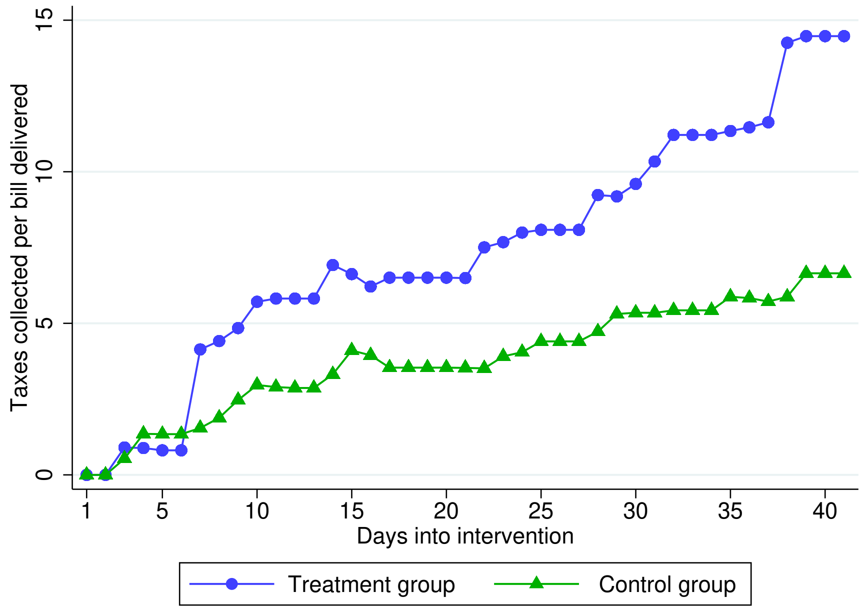
Figure A2: Illustration of Tax Collection Units



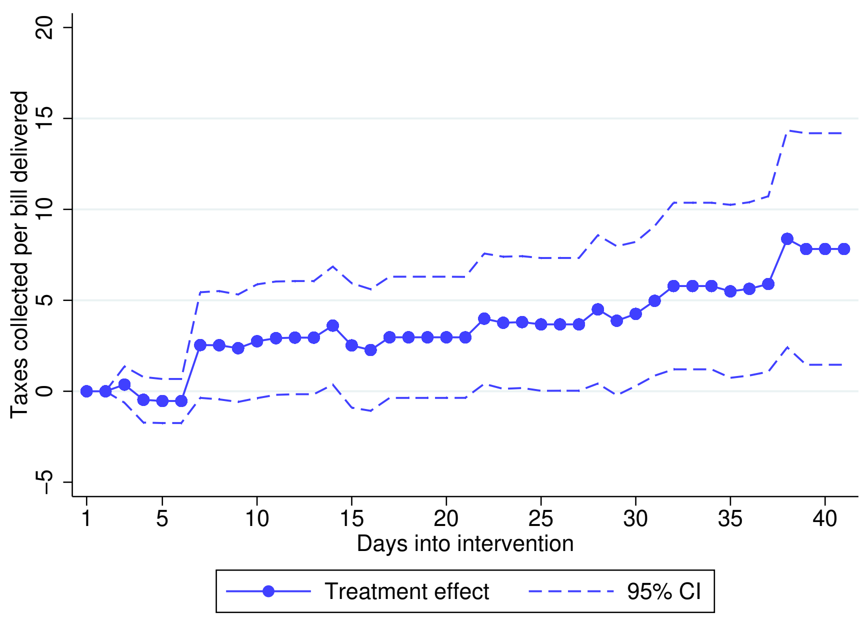
Notes: This graph provides an illustration of some of the collection units that exist in the district of Madina. Due to confidentiality, these collection units are not necessarily included in the experimental sample.

Figure A3: Impacts of Technology on Taxes Collected per Bill Delivered

(a) Taxes Collected per Bill Delivered by Group



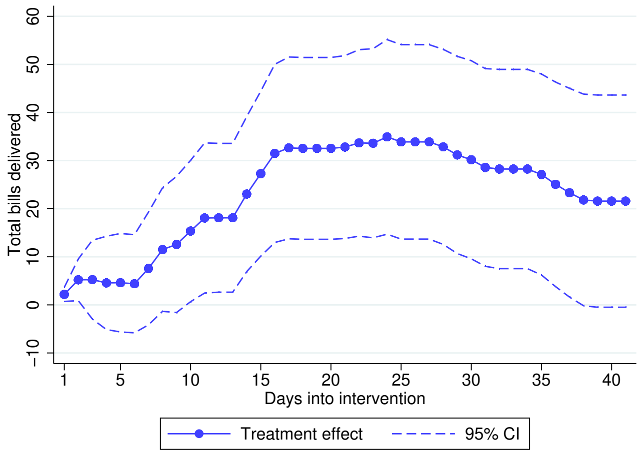
(b) Treatment Effect



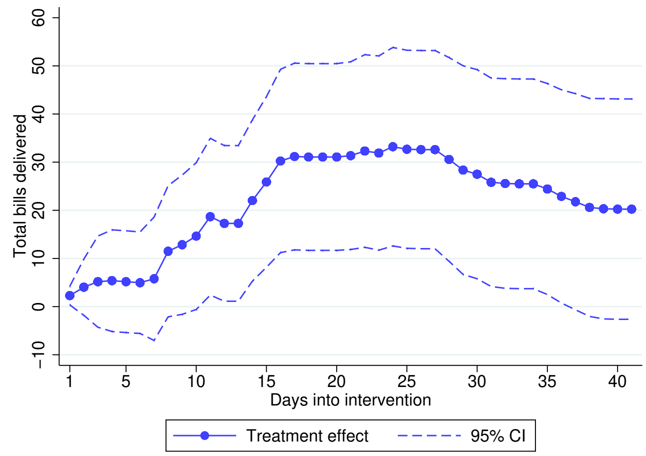
Notes: These panels show the impact of technology on the amount of taxes collected per bill delivered. Panel A shows the average amount of taxes collected per bill delivered by group (treatment, control) and by day of the intervention. Panel B displays the treatment effect coefficients on technology, separately by day, based on estimating equation (1). The analysis is based on the daily collector data, described in Section 3.3.

Figure A4: Robustness for Impact on Bills Delivered

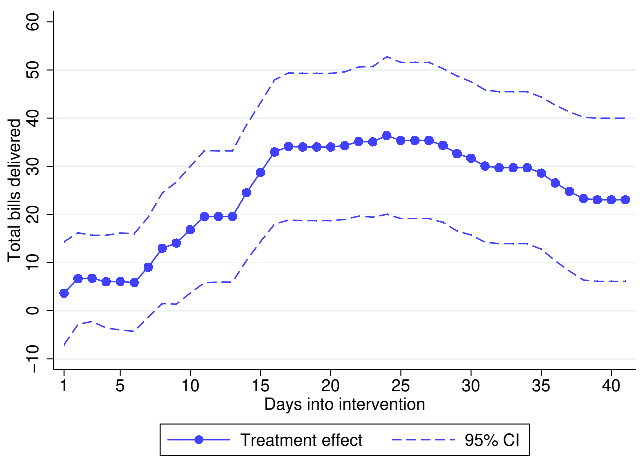
(a) Benchmark



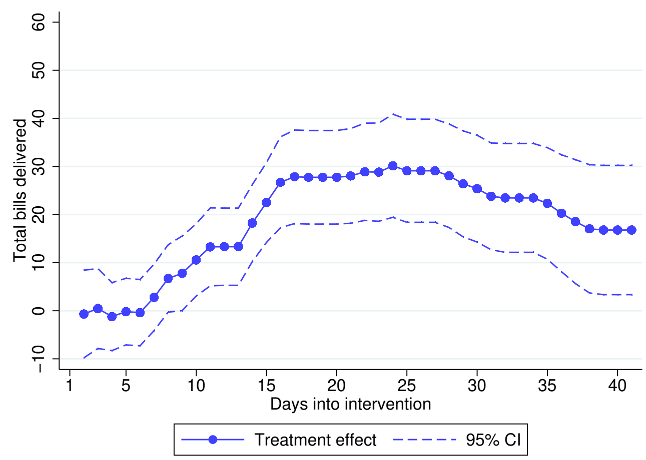
(b) Non-Winsorized Outcome



(c) Inclusion of Covariates

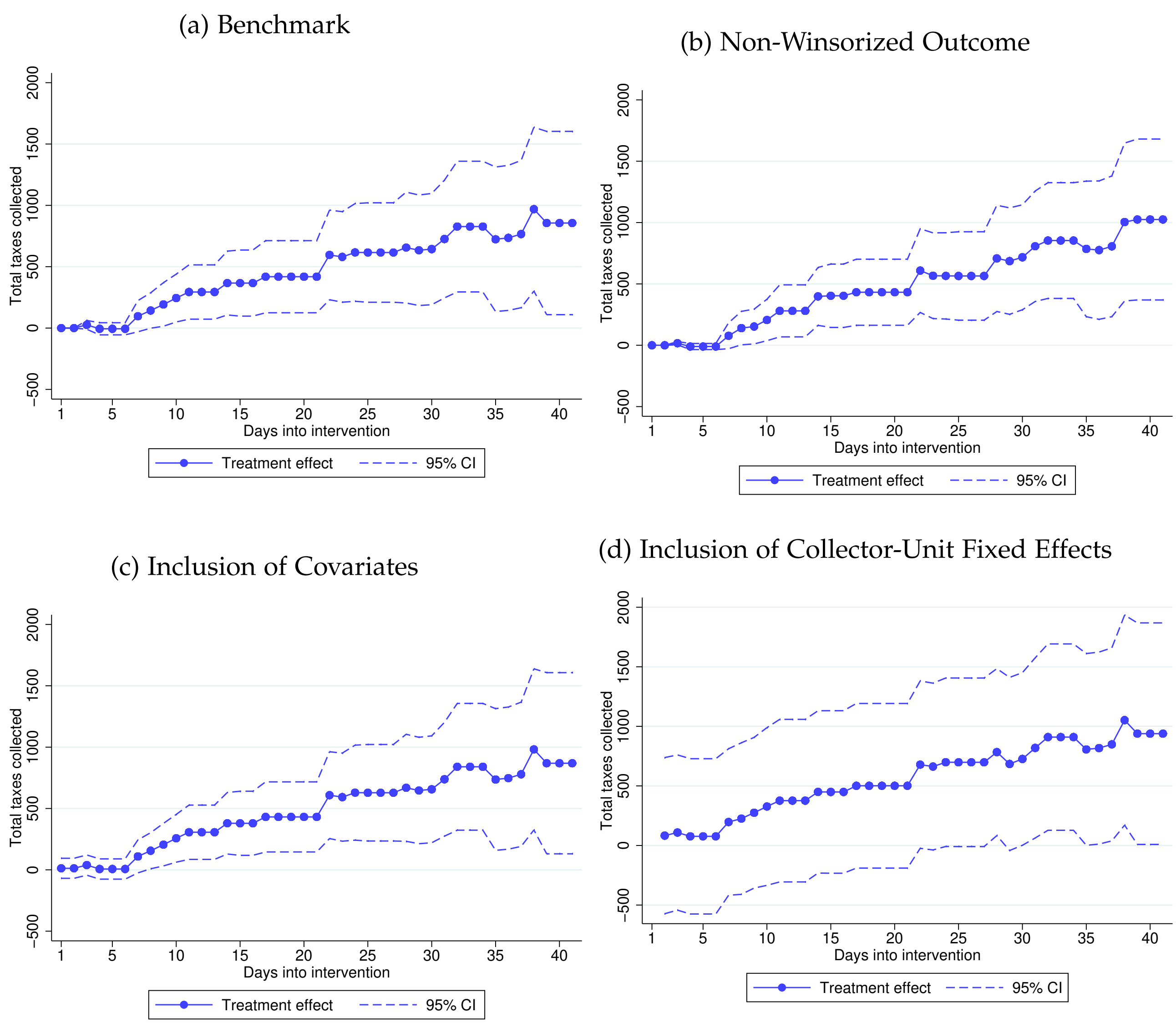


(d) Inclusion of Collector-Unit Fixed Effects



Notes: These panels show robustness for the impact of technology on the number of property tax bills delivered. Panel A replicates the benchmark result from Figure 2, based on estimating equation (1). In Panel B, the benchmark is changed by using the non-winsorized outcome. In Panel C, the benchmark is changed by including control variables: a dummy for whether the collector has previously worked in Madina; a dummy for whether the collector is assessed to be high performing; the total number of bills assigned to the collector; and, the average tax bill value per bill assigned. In Panel D, the benchmark estimation is augmented with collector-unit fixed effects – in this case we omit β_1, the treatment category in day 1 (see equation 1). The analysis is based on the daily collector data, described in Section 3.3.

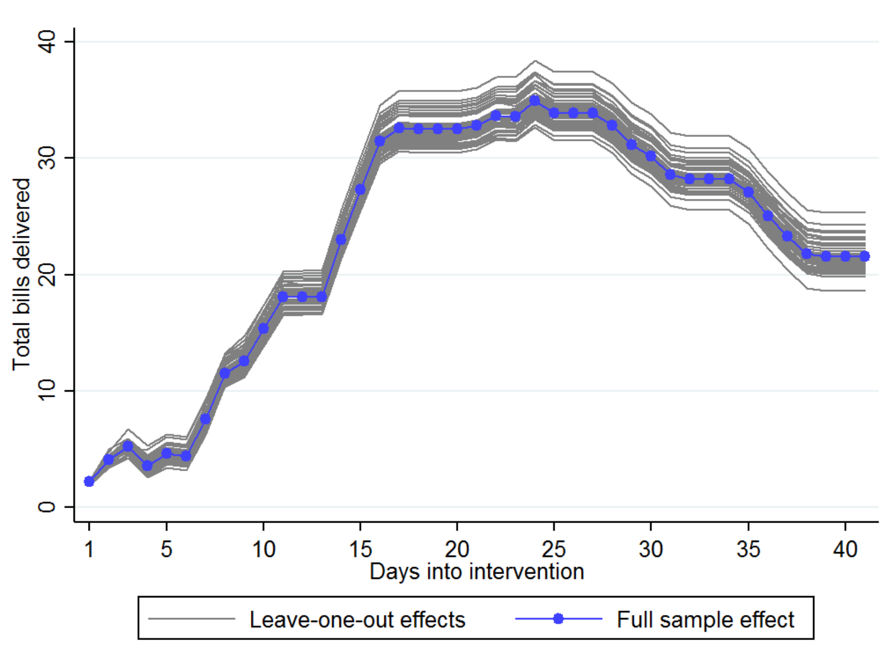
Figure A5: Robustness for Impact on Taxes Collected



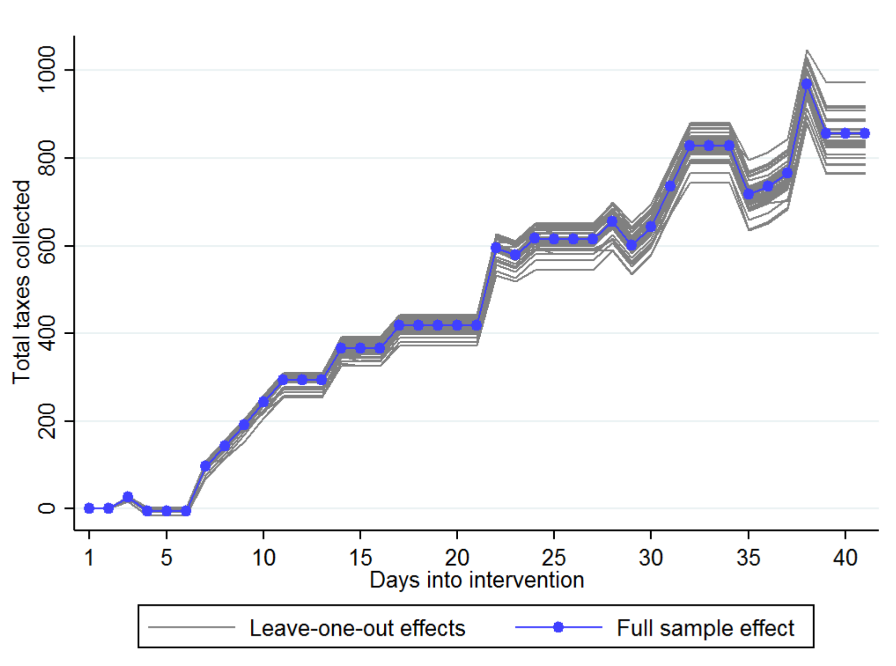
Notes: These panels show robustness for the impact of technology on total taxes collected. Panel A replicates the benchmark result from Figure 3, based on estimating equation (1). In Panel B, the benchmark is changed by using the non-winsorized outcome. In Panel C, the benchmark is changed by including control variables: a dummy for whether the collector has previously worked in Madina; a dummy for whether the collector is assessed to be high performing; the total number of bills assigned to the collector; and, the average tax bill value per bill assigned. In Panel D, the benchmark estimation is augmented with collector-unit fixed effects – in this case we omit β_1, the treatment category on day 1 (see equation 1). The analysis is based on the daily collector data, described in Section 3.3.

Figure A6: Robustness of Impacts to Leave-one-out Sample Restrictions

(a) Bills Delivered



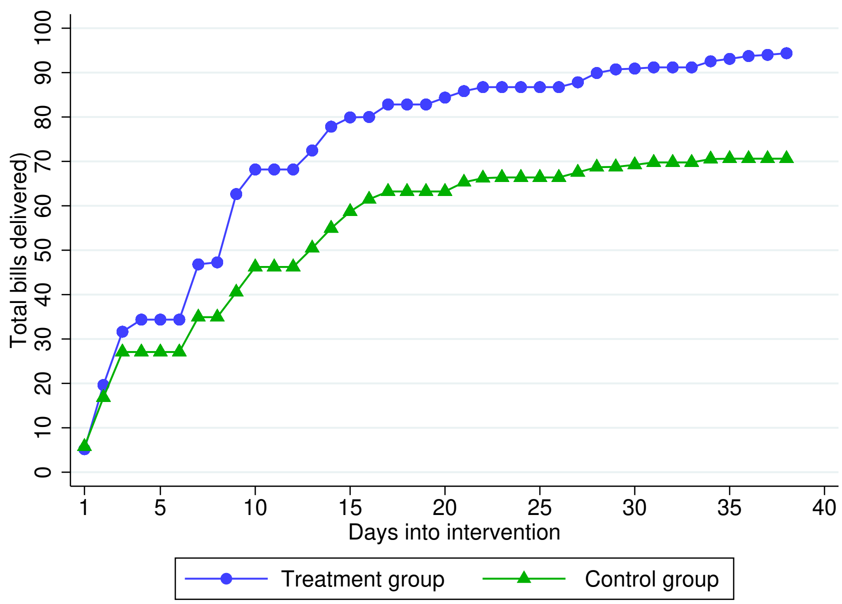
(b) Taxes Collected



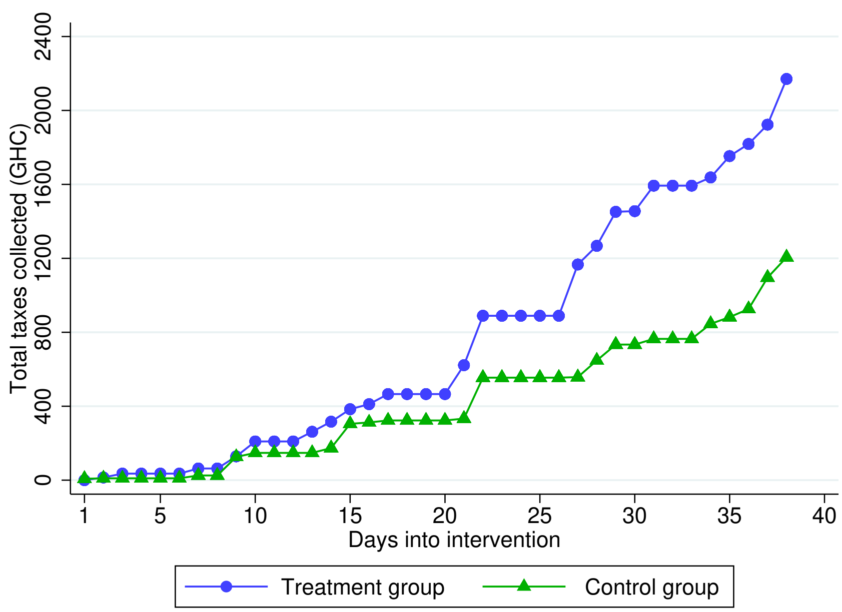
Notes: These panels show the robustness of technology impacts on total bills delivered (Panel A) and total taxes collected (Panel B). In both panels, the blue dotted line represents the dynamic treatment effect estimated in the full sample (Panel B of Figure 2 and Figure 3, respectively). Each dark-gray line represents the dynamic treatment effects from estimating the same econometric model, but in individual sub-samples which remove one collector at a time.

Figure A7: Results from Pilot Experiment

(a) Average Number of Bills Delivered



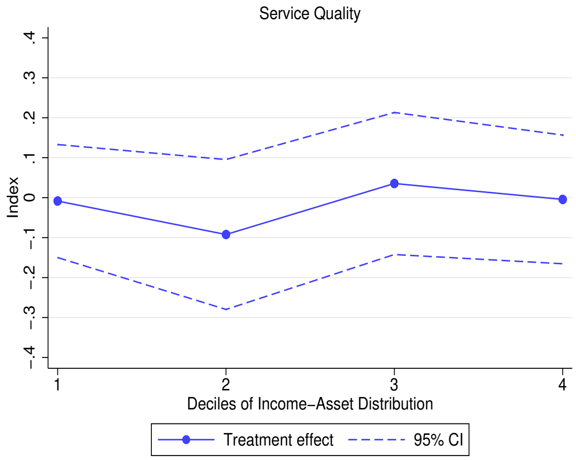
(b) Average Total Taxes Collected



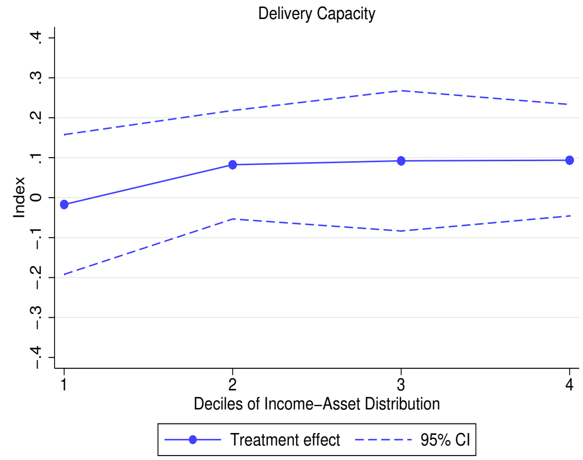
Notes: These panels show the impacts of technology on bills delivered and taxes collected based on the pilot experiment conducted in early 2019. The pilot was implemented in the same location as the main experiment, using the same technology, and following the same protocol for randomization and data-collection (see Section 3 for details). The pilot involved only 24 collectors and lasted 5 weeks, while the main experiment involves 56 collectors and lasts 6 weeks. Panel A (B) is constructed in the same way as Panel A of Figure 2 (Panel A of Figure 3). The treatment collectors had delivered 32% more bills at the end of the pilot experiment (compared to 27% at the end of the main experiment) and collected 79% more taxes (103%).

Figure A8: Distributional Effects on Beliefs about Government Capacity and Tax Morale

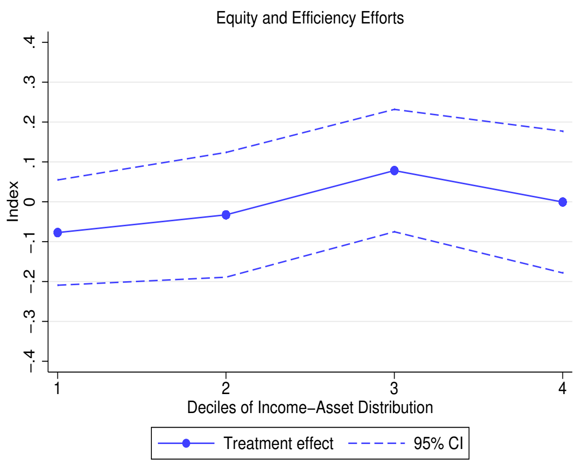
(a) Quality of Government Services



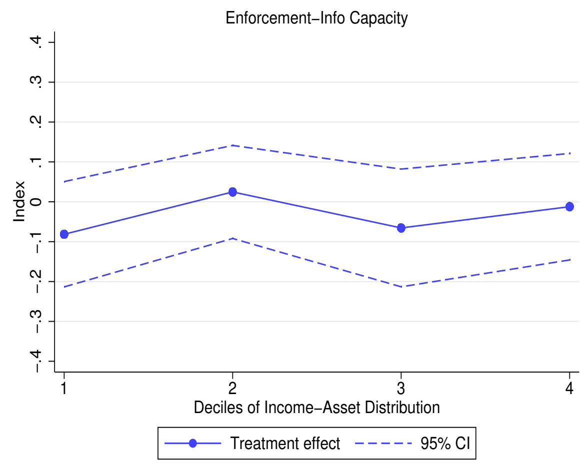
(b) Government Delivery Capacity



(c) Equity and Efficiency of Tax System



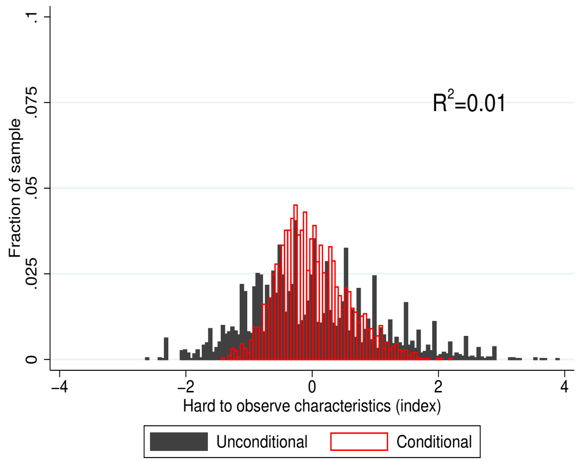
(d) Government Enforcement Capacity



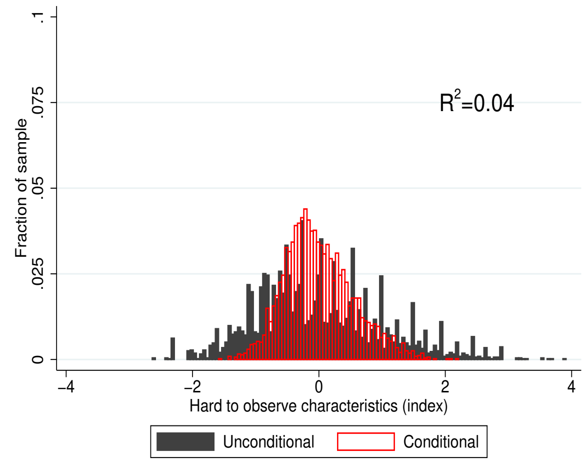
Notes: These panels investigate distributional impacts of technology on household beliefs about government capacity and tax morale. The four panels study four indices: satisfaction with the quality of government services (Panel A); capacity and integrity of local government (Panel B); government efforts to improve the efficiency and equity of the collection process (Panel C); the enforcement and information capacity of the local government (Panel D). These indices are the outcomes in Table 4. Each panel displays the treatment effect coefficients on technology, separately by quartile of the income-asset distribution, based on estimating equation (5). The income-asset distribution is calculated as the unweighted average, by household, of the income index and the assets index. For a detailed description of the different indices, see Data Appendix B.2-B.4.

Figure A9: Correlation between propensity to pay and property characteristics

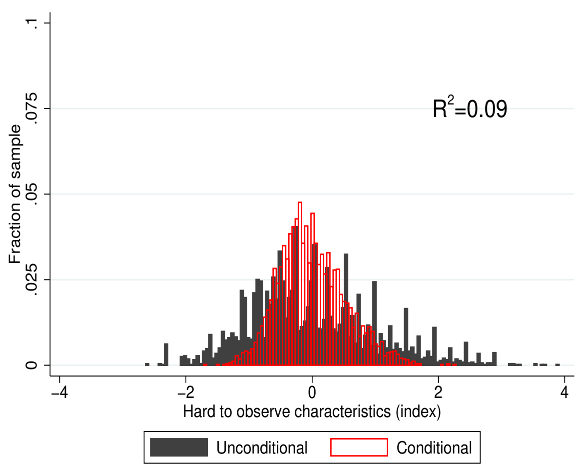
(a) Value of Tax Bill



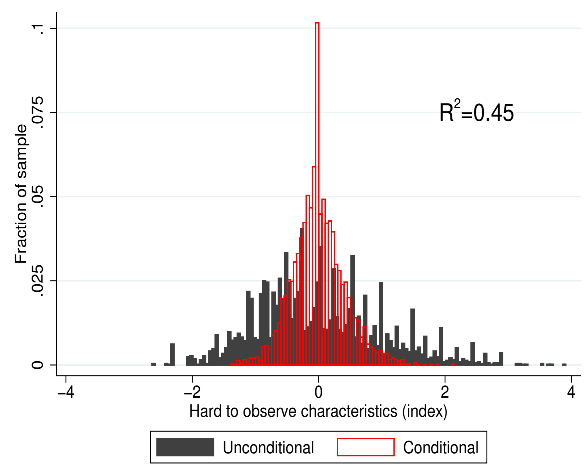
(b) Easily Observable Chars. (Index)



(c) Narrow Property Categories



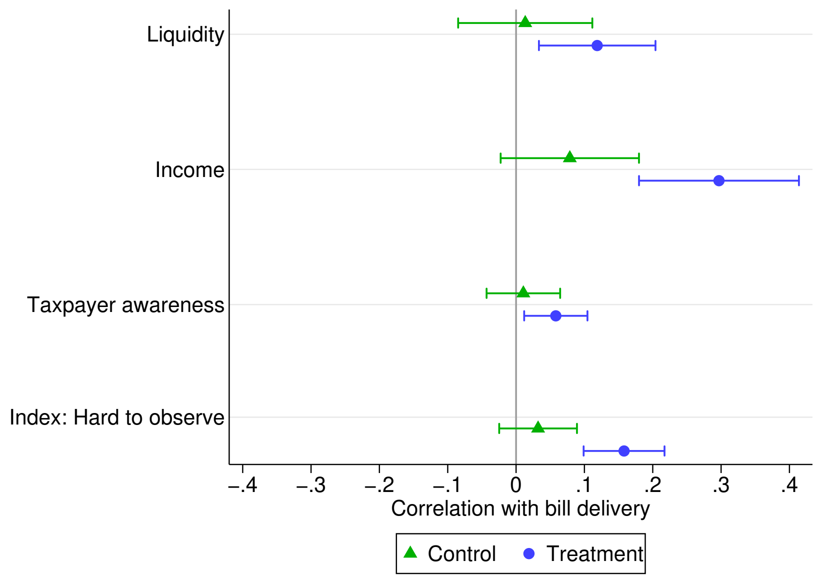
(d) Granular Location (Block Fixed Effects)



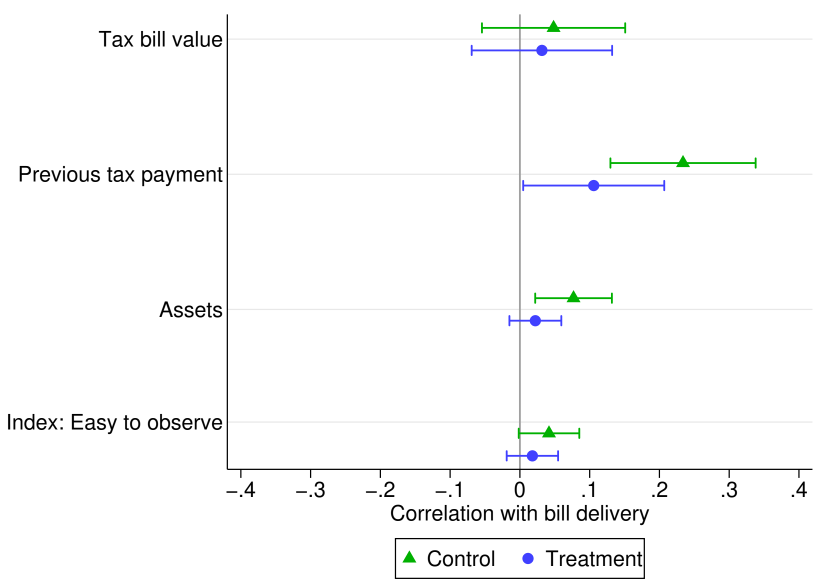
Notes: These panels show the distribution of the propensity index, which measures the household's propensity to pay based on income, liquidity and taxpayer awareness. In each panel, the grey-colored histogram shows the unconditional distribution of the propensity to pay index; the red-colored histogram shows the conditional distribution of the index, after controlling for specific characteristics. In the top-right corner of each graph is reported the R^2 of the regression of the unconditional index on the specific characteristic. Across panels, the included characteristic is: value of tax bill (Panel A); index for easily observable characteristics (Panel B); categories of property quality; block fixed effects (Panel D). Details on the construction of the propensity to pay index and the easily-observable index are provided in Section 4.3 and in Figure 7. For additional details on the indices and all the other variables used in this graph, see Data Appendix B.4. The block is a geographical cluster which contains 7 to 8 properties on average.

Figure A10: Characteristics of Households that Received a Bill by Treatment Status

(a) Hard-to-Observe Characteristics



(b) Easy-to-Observe Characteristics

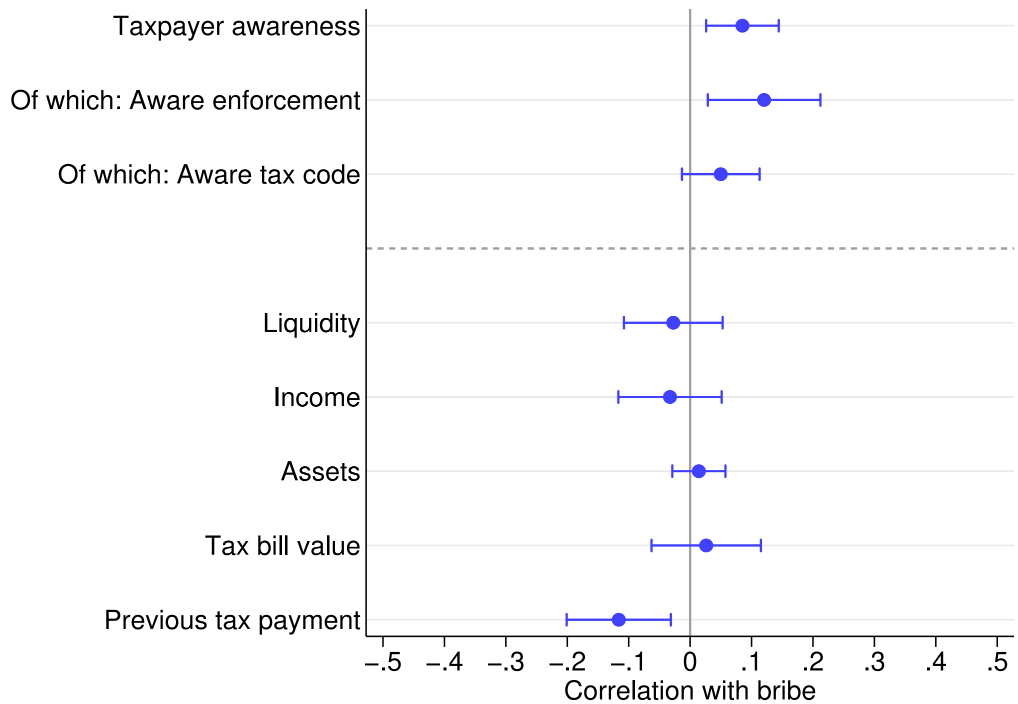


Notes: These panels show the selection on bill delivery for fixed household characteristics. The characteristics are the same as in Figure 7. The econometric model is the same as equation (3), except that the dummy for tax payment is replaced with a dummy for bill delivery. Formally, we estimate

$$y_{hc} = \theta \cdot \mathbf{1}(Billdelivered)_h + \beta \cdot [\mathbf{1}(Billdelivered)_h * \mathbf{1}(Tech)_c] + \Omega \cdot X_h + \mu_c + \epsilon_{hc}$$

For a detailed description of the household characteristics and the indices, see Data Appendix B.4.

Figure A11: Characteristics of Households Targeted for Bribes in the Treatment Group



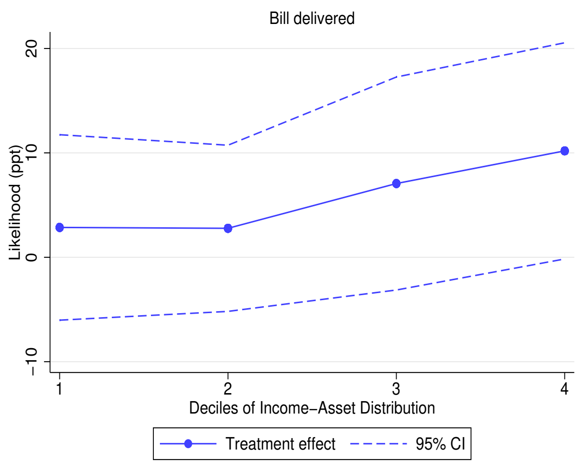
Notes: This panel shows the selection on bribe incidence for fixed household characteristics. The econometric model is the same as equation (3), except that the dummy for tax payment is replaced with a dummy for any bribe incidence (same as in Panel B of Figure 10). Moreover, the analysis is limited to treatment areas, where there was an overall increase in bribe incidence (Table 5). Formally, we estimate

$$y_{hc} = \theta \cdot \mathbf{1}(Bribe)_h + \Omega \cdot X_h + \mu_c + \epsilon_{hc}$$

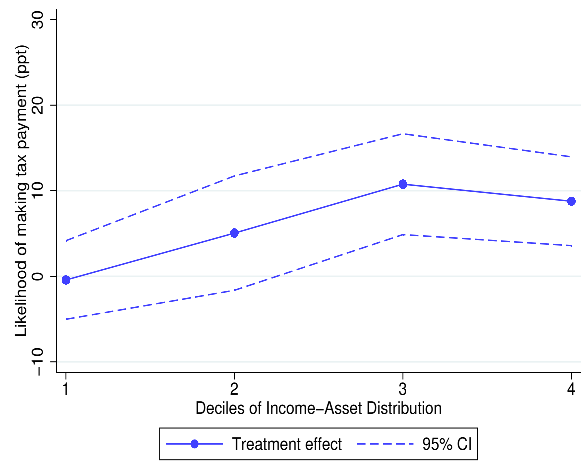
The fixed household characteristics are the same as those described in Figure 7 and Figure A10. In addition to those characteristics, the top panel reports two additional characteristics which measure awareness about enforcement and awareness about the tax code. For a detailed description of the variables, see Data Appendix B.3-B.4.

Figure A12: Robustness of Distributional Impacts to Additional Tax Measures

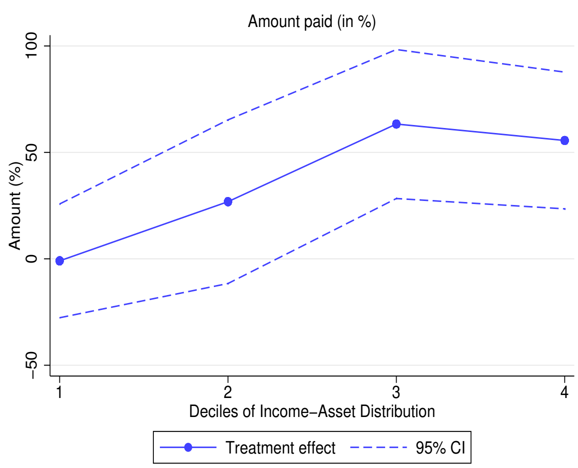
(a) **1**(Bill Delivered)



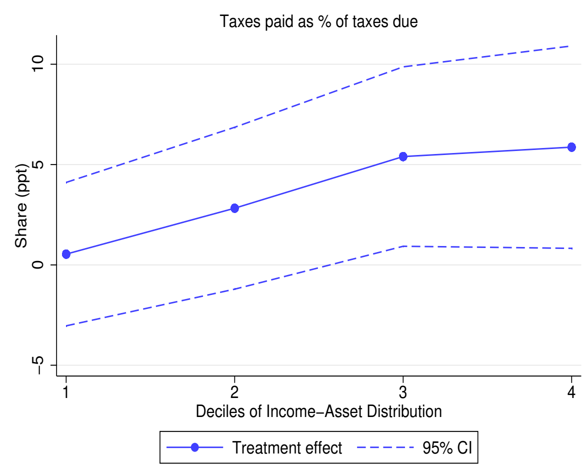
(b) **1**(Any Taxes Paid)



(c) Total Amount Paid (%)



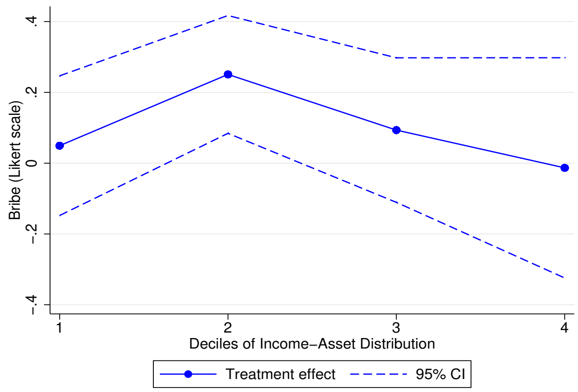
(d) Total Taxes Paid (% of Taxes Due)



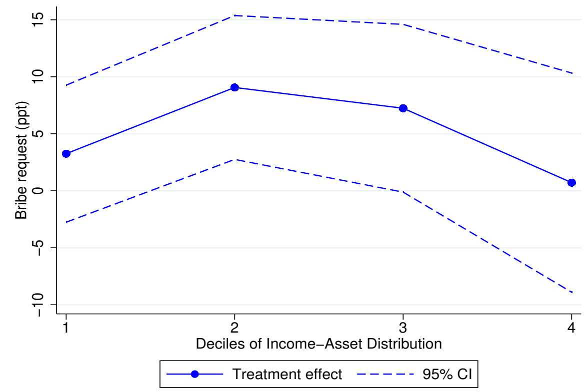
Notes: These panels show robustness for the distributional impact of technology on tax outcomes. The econometric model is the same as Figure 10, but the outcome varies across panels: a dummy for a bill delivered (Panel A); a dummy for any taxes paid (Panel B); amount of taxes paid, expressed as a percent using the inverse hyperbolic sine (Panel C); and, the amount of taxes paid, expressed as a percent of taxes due (Panel D).

Figure A13: Robustness of Distributional Impacts to Additional Bribe Measures

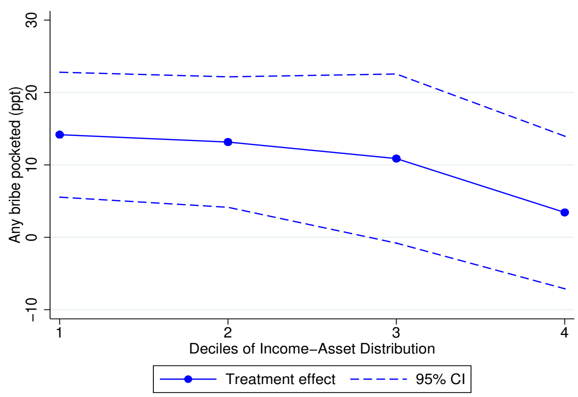
(a) Collusive Bribe (Likert Scale)



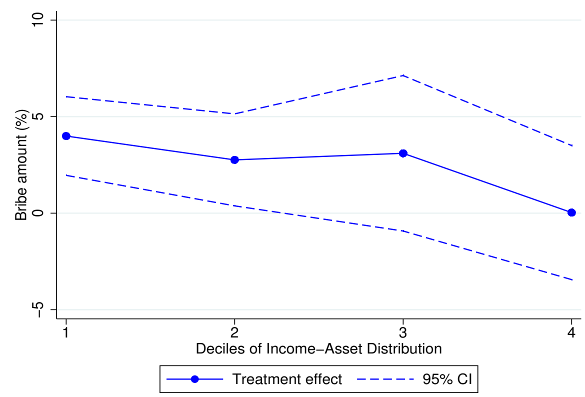
(b) **1**(Any Collusive Bribe)



(c) **1**(Any Coercive Bribe)



(d) Total Bribe Amount (%)



Notes: The econometric model is the same as in Figure 10, but the outcome varies across panels. In Panel A, the outcome is the likelihood (on a scale from 1 to 5, where 1 is 'very unlikely' and 5 is 'very likely') estimated by the household that a local collector will solicit any unofficial payment while conducting visits with property owners. In Panel B, the outcome is a dummy variable taking a value of 1 if the answer to the question in Panel A is 'maybe', 'somewhat likely' or 'very likely', and 0 if the answer is 'not very likely' or 'very unlikely'. In Panel C, the outcome is a dummy variable which takes a value of 1 if the household estimates that the local tax collector will pocket any strictly positive amount out of a hypothetical 1000 GHC collected from property owners. In Panel D, the outcome is the total bribe amount, in percent. This is calculated at the household level as the average of the coercive bribe amount, expressed as a percent of a hypothetical 1000 GHC collected by the tax collector, and the collusive bribe amount, expressed as a percent of the household's true tax liability. For additional description of the outcomes, see Data Appendix B.3.

B Data Appendix

This section provides additional details on the variables considered in this paper.

B.1 Variables from Census of Local Governments

- *Share of bills delivered (%)* This variable is the answer to the question "Considering all the properties in your district, approximately what percent were sent a bill this year?" The answer ranges from 0% to 100%.
- *Taxes collected per bill delivered (GHC)* This variable divides the total taxes collected per capita (in Ghanaian Cedi) by the variable *share of bills delivered*.
- *Share of bills that are paid (%)* This variable is based on the answer to the question "Cumulatively, what share of bills are paid by the end of the year?". This answer is asked separately for business property taxes and for resident property taxes. We construct the district-level variable as the unweighted average over the responses for businesses and residents.
- *Share of properties with address (%)* This variable is the answer to the question "Approximately what percent of the properties in your assembly have an official address assigned to them?". The answer ranges from 0% to 100%.
- *Common to not locate property* This variable takes a value of 1 (0) if the respondent answers 'Yes' ('No') to the question "When delivering bills, it is common that you cannot locate the property/business for the bill to be delivered?"
- *Common to not locate owner* This variable takes a value of 1 (0) if the respondent answers 'Yes' ('No') to the question "When delivering bills, it is common that you locate the property/business but cannot locate the owner?"
- *Share of properties with valuation (%)* This variable is the answer to the question "Approximately what percent of the properties in the district are currently assessed by the Lands Valuation Board?". The answer ranges from 0% to 100%.
- *Share of tax payments made in cash (%)* This variable is the answer to the question "Approximately what percent of property rates are paid in cash?". The answer ranges from 0% to 100%.

- *Cost of collection (% of taxes collected)*. This variable is based on two questions asked to collectors in the census. The first question asks the collector what is their salary in a typical month. The second question asks the collector what is total revenue collected in a typical month. The variable is the ratio of salary to revenue collected, expressed as a a percent.

- *Officials with post-secondary education*. This variable is a dummy variable equal to 1 (0) if the local official has completed any form of post-secondary education (has completed secondary education or less). In turn, we calculate the unweighted share of officials with post-secondary education in each district.

- *Officials' average years of work experience*. This variable is the answer to the question "For how many years and months have you worked in local government?". Note that this variable includes working in the local official's current district as well as other districts in the past. In turn, we calculate the unweighted average years of work experience in each district.

- *Legal capacity to enforce taxes*. This variable is a dummy variable which takes a value of 1 if the local assembly has gazetted the fee fixing resolution for the fiscal year 2017-2018, and zero otherwise.

- *Take tax defaulters to court*. This variable is a dummy variable equal to 1 (0) if the respondent answers 'Yes' ('No') to the question "Does the assembly normally take ratepayers/business owners to court for non-payment of property rates".

- *Main reason for no court: Legal*. This variable is a dummy variable equal to 1 if the respondent answers 'Legal constraints' in answer to the question "Why does your district not take more ratepayers/business property owners to court for non-payment?" and zero otherwise. The other possible answers are 'Not worth it'; 'Politically sensitive'; and, 'Yet to implement/prefer non-enforcement'.

- *Main reason for no court: Political*. This variable is a dummy variable equal to 1 if the respondent answers 'Politically sensitive' in answer to the question "Why does your district not take more ratepayers/business property owners to court for non-payment?" and zero otherwise. The other possible answers are 'Not worth it'; 'Legal constraints'; and, 'Yet to implement/prefer non-enforcement'.

- *Citizen tax awareness*. This variable is a dummy variable equal to 1 if the respondent answers 'Yes' to the question "Have you heard about the fee fixing resolution?" and 0 if the respondent answers 'No'.

B.2 Variables from Household Survey Related to Tax Morale and Enforcement

- *Satisfaction with government services index* This is an index variable, which is based on the average responses of households to three questions related to satisfaction with services. Possible responses are 'very satisfied', 'somewhat satisfied', 'neutral', somewhat unsatisfied', and 'very unsatisfied'. For each of the three questions, the answer is reverse coded such that higher values imply more satisfaction and all answers are standardized. The index variable is the unweighted average across the three standardized satisfaction questions outlined below

    1. "In your personal dealings with tax collectors in Madina, how satisfied are you with the outcomes?"
    2. "What has been your level of satisfaction with the overall quality of services offered by the local tax department of Madina"
    3. "What has been your level of satisfaction with the overall quality of services offered by the local government of Madina?"

- *Integrity of government index* This is an index variable, which is created as the unweighted average over the standardized responses to the different questions outlined below. Questions are reverse coded where relevant such that higher answers always indicate more positive view on integrity and competency of the local government

    1. "In your opinion, approximately what percent of the collections by the Madina Assembly will be put to good use for the benefit of the community?"
    2. "If the Madina Assembly wants to improve all the roads, it will do this efficiently and without problems". There are five answers, ranging from 'strongly agree' to 'strongly disagree'.
    3. "If the Madina Assembly wants to improve access to water for most citizens, it will be able to do so efficiently and without problems". There are five answers, ranging from 'strongly agree' to 'strongly disagree'.
    4. "If the Madina Assembly needed to improve waste management, it would be able to do so efficiently and without problems". There are five possible answers, ranging from 'strongly agree' to 'strongly disagree'.
    5. "Overall, how would you rate the Madina Assembly?". There are four possible answers, ranging from 'very competent' to 'not competent at all'.

- *Tax equity and efficiency efforts by government index* This is an index variable, based on the respondent's strength of agreement with three statements. Possible answers to each question are 'agree strongly', 'agree somewhat', 'neither agree nor disagree', 'disagree somewhat', 'strongly disagree'. Answers are reverse coded such that higher values reflect stronger agreement, and standardized. The index is the average across the respondent's agreement with the statements below

  1. "Madina is making efforts to collect taxes in an efficient way"
  2. "Madina is making efforts to ensure everyone in their community pays their fair share of taxes"
  3. "Madina is making efforts to collect taxes that will be useful for local development of the community"

- *Enforcement and information capacity of the government index* This is an index variable, which is created as the unweighted average over the standardized responses to the different questions outlined below. Questions are reverse coded where relevant such that higher answers always indicate stronger perceptions of enforcement and informational capacity

  1. "What share of households and businesses in the Madina Assembly do you think usually pay their taxes?" Answers range from 0% to 100%
  2. "Imagine a tax collector comes to your neighborhood, and someone refuses to pay. How likely do you think that the local government will pursue and enforce sanctions?". There are four answers, ranging from 'very likely' to 'very unlikely'.
  3. "Do you think the local government knows the precise address of your residence?". There are four answers, ranging from 'very likely' to 'very unlikely'.
  4. "Do you think the local government knows which of your neighbors did not pay property or business tax in 2020?". There are four answers, ranging from 'very likely' to 'very unlikely'.
  5. "Do you think the local government knows what you do for a living?". There are four answers, ranging from 'very likely' to 'very unlikely'.

B.3 Variables from Household Survey Related to Bribes

- *Any bribe (coercive or collusive)* This variable is based on two dummy variables. The first dummy variable takes a value of 1 if the household estimates that tax collectors will ask for any strictly positive unofficial payments when they are working in the field, and zero otherwise. This variable proxies for the likelihood of collusive bribes. The exact question is: ″Do you think it is likely that a local revenue collector will offer to take an unofficial payment from property owners/businesses in order to not make any return visits to their property?″ The possible answers were: ″very likely″; ″somewhat likely″; ″maybe″; ″not very likely″; ″very unlikely″. If a respondent answered ″very likely″, ″somewhat likely″ or ″maybe″, then the follow up question was: ″what is the amount in GHC that is typically asked for?″. We replace this answer with zero if the respondent's first answer was ″not very likely″ or ″very unlikely″, and use this modified answer to construct the coercive bribe dummy. The second dummy variable takes a value of 1 if the household reports that the tax collector will pocket any positive amount out of a hypothetical 1000 Ghanaian Cedi collected from households (coercive bribe). The exact question is: ″Suppose a collector comes to a typical neighborhood in Madina and collects 1000 Ghanaian Cedi. How much of this money do you think the collector will submit to LANMA's tax finance office account? And, how much will they put in their pockets?″. The variable used in the analysis takes a value of 1 if either the coercive dummy or the collusive dummy is equal to 1, and takes a value of 0 otherwise.

- *Any bribe (coercive)* This variable is a dummy variable which takes a value of 1 if the household reports that the tax collector will pocket any positive amount out of a hypothetical 1000 Ghanaian Cedi collected from households. The exact question is: ″Suppose a collector comes to a typical neighborhood in Madina and collects 1000 Ghanaian Cedi. How much of this money do you think the collector will submit to LANMA's tax finance office account? And, how much will they put in their pockets?″.

- *Any bribe (collusive)* This variable is a dummy variable which takes a value of 1 if the household estimates that tax collectors will ask for any strictly positive unofficial payments when they are working in the field, and zero otherwise. The exact question is: ″Do you think it is likely that a local revenue collector will offer to take an unofficial payment from property owners/businesses in order to not make any return visits to their property?″ The possible answers were: ″very likely″; ″somewhat likely″; ″maybe″; ″not very likely″; ″very unlikely″. If a respondent answered ″very likely″, ″somewhat likely″ or ″maybe″, then the follow up question was: ″what is the amount in GHC that is typically asked for?″. We replace this answer with zero if the respondent's first answer was ″not very likely″ or ″very unlikely", and use this modified answer to construct the collusive bribe dummy.

- *Collusive bribe (Likert scale)* This variable is the answer to the question "Do you think it is likely that a local revenue collector will offer to take an unofficial payment from property owners/businesses in order not make any return visits to their property/business?". The 5 possible answers range from 'very unlikely' to 'very likely'. We assign numerical values from 1 to 5 which increase in the likelihood.

- *Total bribe amount (in %)* This variable is constructed at the household level as the unweighted average of the variable *'Collusive bribe amount (% of tax due)'* and the variable *'Coercive bribe amount (% of payment collected)'*. Both of these variables are described below.

- *Collusive bribe amount (% of tax due)* The collusive amount is the amount that the household estimates will be asked by the tax collector as unofficial payment while conducting visits to the household, expressed as a percent of the household's actual property tax due. The exact question is: "Do you think it is likely that a local revenue collector will offer to take an unofficial payment from property owners/businesses in order to not make any return visits to their property?" The possible answers were: "very likely"; "somewhat likely"; "maybe"; "not very likely"; "very unlikely". If a respondent answered "very likely", "somewhat likely" or "maybe", then the follow up question was: "what is the amount in GHC that is typically asked for?". We replace this answer with zero if the respondent's first answer was "not very likely" or "very unlikely", and express this modified answer relative to the value of household's actual amount of property tax due.

- *Coercive bribe amount (% of payment collected)* The coercive amount is the percent that the household estimates will be pocketed by the tax collector out of a hypothetical 1000 Ghanaian Cedi that the official has collected as payments from households while working in the field. The exact question is: "Suppose a collector comes to a typical neighborhood in Madina and collects 1000 Ghanaian Cedi. How much of this money do you think the collector will submit to LANMA's tax finance office account? And, how much will they put in their pockets?" We use the answer to the latter question to construct this variable.

- *Collusive bribe amount (in Ghanaian Cedi)* The collusive amount is the amount that the household estimates will be asked by the official as unofficial payment while conducting visits to the household. The exact question is: "Do you think it is likely that a local revenue collector will offer to take an unofficial payment from property owners/businesses in order to not make any return visits to their property?" The possible answers were: "very likely"; "somewhat likely"; "maybe"; "not very likely"; "very unlikely". If a respondent answered "very likely", "somewhat likely" or "maybe", then the follow up question was: "what is the amount that is typically asked for?". We replace this answer with zero if the respondent's first answer was "not very likely" or "very unlikely", and use this modified answer as the variable.

B.4 Variables from Household Survey Related to Learning and Targeting

- *Liquidity* This variable is created as the unweighted average over two household survey questions, which are outlined below. The survey questions are reverse coded such that higher values reflect lower liquidity constraints. Answers to both survey questions are standardized, and the liquidity index is in turn the unweighted average over these two standardized survey variables. The two variables are
  1. "Think of a typical month. On how many days did you find yourself short of cash for basic expenditures for your house?". The answer can range from 0 to 30 days
  2. "In a typical month, imagine that one day you learn you need to pay an additional 300 Cedi fee in order to remain in your house. Could you find this money in the next 4 days?". The possible answers are 'Yes, with a little difficulty'; 'Yes, with great difficulty'; 'Very unlikely'; 'I could never pay this fee'
- *Income* This variable is based on the answer to the household question "What was the household's total earnings this past month?". The answer is given in Ghanaian Cedi. The income index is the standardized answer.
- *Taxpayer awareness* This variable is the unweighted average of six dummy variables which each take a value of 1 if the person answers 'Yes' to the individual questions outlined below, and take a value of 0 if the respondent answers 'No'. In turn, the unweighted average across the six variables is standardized to create the awareness index.
  1. "Do you know of someone who received a letter from their MMDA summoning them to appear in court for non-payment of property rates"

2. ″Do you know of someone who was actually taken to court for non-payment of property rates?″
3. Have you heard of any instance where a property owner had their property confiscated for non-payment of property rates?″
4. ″As best as you can remember, did you receive any text message earlier this year from your MMDA about paying the property rate?″
5. ″As far as you know, do the MMDAs have the legal authority to collect property rates?″
6. ″Have you heard of the fee-fixing resolution?″

- *Taxpayer awareness – Enforcement* This variable is the unweighted average of three dummy variables which each take a value of 1 if the person answers ′Yes′ to the individual questions outlined below, and take a value of 0 if the respondent answers ′No′. In turn, the unweighted average across the three variables is standardized to create the index variable.

  1. ″Do you know of someone who received a letter from their MMDA summoning them to appear in court for non-payment of property rates″
  2. ″Do you know of someone who was actually taken to court for non-payment of property rates?″
  3. Have you heard of any instance where a property owner had their property confiscated for non-payment of property rates?″

- *Taxpayer awareness – Tax code* This variable is the unweighted average of three dummy variables which each take a value of 1 if the person answers ′Yes′ to the individual questions outlined below, and take a value of 0 if the respondent answers ′No′. In turn, the unweighted average across the three variables is standardized to create the index variable.

  1. ″As best as you can remember, did you receive any text message earlier this year from your MMDA about paying the property rate?″
  2. ″As far as you know, do the MMDA′s have the legal authority to collect property rates?″
  3. ″Have you heard of the fee-fixing resolution?″

- *Propensity to pay index/hard to observe index* This variable is the unweighted average of the three index variables *Liquidity*, *Income* and *Taxpayer awareness*

- *Tax bill value* This variable is based on the administrative data and measures the total amount of taxes that are owed. The total amount owed is the sum of the current year's property taxes and outstanding arrears due to less than full payment of the past year's property taxes. The variable is standardized.

- *Previous tax payment* This variable is based on the administrative data and measures the payment status from the previous fiscal year. It takes a value of 1/2/3 if the past year's property taxes were not paid at all/partially paid/fully paid. The variable is standardized.

- *Assets* This variable is the sum over how many of the following assets the household currently possesses: motorbike; car or truck; television; electric generator; sewing machine; radio. In turn, the variable is standardized.

- *Easy to observe index* This variable is the unweighted average of the three standardized variables *tax bill value*, *previous tax payment* and *assets*.

B.5 Variables from Collector Surveys

- *Challenge to navigate in the field* This variable is a dummy variable which takes a value of 1 if the respondent 'strongly agrees' or 'agrees' with the statement "Finding my way around my collection unit was a challenge for me this week"; the dummy variable takes a value of 0 if the respondent answers 'neither agree nor disagree', 'disagree' or 'strongly disagree.

- *Challenge to locate taxpayers* This variable is a dummy variable which takes a value of 1 if the respondent 'strongly agrees' or 'agrees' with the statement "Locating bill recipients was challenging for me this week"; the dummy variable takes a value of 0 if the respondent answers 'neither agree nor disagree', 'disagree' or 'strongly disagree.

- *Knowledge about households which are willing and able to pay* This variable takes a value of 1 if the respondents chooses statement A "I think I have a good understanding of which properties are more able and willing to pay and am able to focus my efforts on them" rather than statement B "I put a lot of effort to get my job done, but it remains unclear to me which exact properties are more likely or willing to pay their property rates". The variable takes a value of 0 if the respondent picks statement B. Respondents had to pick the statement which "you would say best characterizes your work in the field over the past weeks".

- *Focus on households that are able to pay* This variable takes a value of 1 if the respondent uses ′all the time′ or ′often′ the collection strategy ″Go to areas on specific days where I know property owners are more likely to be able to pay″; the variable takes a value of 0 if the respondent uses this strategy ′only from time to time′, ′not much′ or ′never′.

- *Focus on households that are aware of tax payment duty* This variable takes a value of 1 if the respondent uses ′all the time′ or ′often′ the collection strategy ″Go to areas where I know most taxpayers are aware of their duty to pay property rates″; the variable takes a value of 0 if the respondents uses this strategy ′only from time to time′, ′not much′ or ′never′.

- *Focus on households that are satisfied with public goods* This variable takes a value of 1 if the respondent uses ′all the time′ or ′often′ the collection strategy ″Go to areas where I know owners are more satisfied with the delivery of public services and are more likely to pay″; the variable takes a value of 0 if the respondents uses this strategy ′only from time to time′, ′not much′ or ′never′.

- *Focus on collections with hard-to-observe household characteristics* This variable measures the frequency with which collectors make use of the three strategies that target hard-to-observe household characteristics: *focus on households that are aware of tax payment duty*, *focus on households that are able to pay*, and *focus on households that are satisfied with public goods*. The variable is the average across those three strategy use variables, and takes a value between 0 and 1.

- *Focus on collections with easy-to-observe household characteristics* This variable measures the frequency with which collectors make use of six strategies that target easy-to-observe household characteristics. For each strategy, outlined below, we measure use with a value of 1 if that collection strategy is used ′often′ or ′all the time′ and 0 if it is used ′only from time to time′, ′not much′ or ′never′. In turn, the variable is the average use across these six strategies, and takes a value between 0 and 1. The six strategies considered are

    1. ″Go to areas where I know most taxpayers have paid property rates in the past year″
    2. ″Go to areas where I know there are many properties with high property rates″

3. ”Go to areas where I know there are many property rate payers that have not yet paid this year’s rates”
4. ”Go to areas which are close to the main road/center of activity”
5. ”Go to areas which are close to my home”
6. ”Go to areas which are closer to the Madina headquarters”

- *Difference in strategies: Hard versus easy to observe* This variable is the difference between the variable *’Focus on collections with hard-to-observe household characteristics’* and the variable *’Focus on collections with easy-to-observe household characteristics’*

- *Unable to locate properties and owners* This variable measures the collectors’ extent of agreement with two statements: ”Finding my way around my collection unit was challenging”; ”Locating bill recipients was challenging”. For each statement, the respondent can answer ’strongly disagree’, ’disagree’, ’neither agree nor disagree’, ’agree’, ’strongly agree’. We assign numerical values from 1 to 5, with larger values indicating stronger agreement. The answer to each statement is standardized, and the variable is the average over the two standardized answers.

- *Wrong information printed on bills* This variable measures the collectors’ extent of agreement with the two statements: ”Some of the bills I tried to deliver this week had the wrong addresses”; ”Some of the bills I tried to deliver this week had the wrong amounts”. For each statement, the respondent can answer ’strongly disagree’, ’disagree’, ’neither agree nor disagree’, ’agree’, ’strongly agree’. We assign numerical values from 1 to 5, with larger values indicating stronger agreement. The answer to each statement is standardized, and the variable is the average over the two standardized answers.

- *Resistance from property to accept bill* This variable measures the collectors’ extent of agreement with three statements: ”Collection was challenging this week because bill recipients preferred not to pay in cash”; ”Collection was challenging this week because bill recipients preferred mobile payments, but I was not able to accept mobile payments”; ”Collection was challenging this week because bill recipients said that they did not trust me to collect their payment”. For each statement, the respondent can answer ’strongly disagree’, ’disagree’, ’neither agree nor disagree’, ’agree’, ’strongly agree’. We assign numerical values from 1 to 5, with larger values indicating stronger agreement. The answer to each statement is standardized, and the variable is the average over the three standardized answers.

- *Supervisors do not monitor field activities* This variable measures the extent to which collectors perceive that their supervisors are not monitoring their work. Specifically, we ask the collector's extent of agreement with the statement: "My supervisors spent a lot of time monitoring my work this week". For each statement, the respondent can answer 'strongly disagree', 'disagree', 'neither agree nor disagree', 'agree', 'strongly agree'. We assign numerical values from 1 to 5, with larger values indicating stronger *disagreement*. Values are standardized to be comparable with other outcomes.

- *Supervisors do not check mistakes made in the field* This variable measures the extent to which collectors perceive that their supervisors are not checking mistakes made by collectors in the field. Specifically, we ask the collector's extent of agreement with the statement: "My supervisors checked on me regularly this week to make sure I was not making mistakes". For each statement, the respondent can answer 'strongly disagree', 'disagree', 'neither agree nor disagree', 'agree', 'strongly agree'. We assign numerical values from 1 to 5, with larger values indicating stronger *disagreement*. Values are standardized to be comparable with other outcomes.

- *Supervisors are unavailable for support* This variable measures the extent to which collectors perceive that their supervisors are not available to support the collectors in the field. Specifically, we ask the collector's extent of agreement with the statement: "My supervisors were available to help me this week when I needed them". For each statement, the respondent can answer 'strongly disagree', 'disagree', 'neither agree nor disagree', 'agree', 'strongly agree'. We assign numerical values from 1 to 5, with larger values indicating stronger *disagreement*. Values are standardized to be comparable with other outcomes.

- # *Unsuccessful visits per successful visit* This variable is the answer to the question "There are many challenges to getting things done in the field. Looking back at this past week, let us think about the unsuccessful visits you made to properties. A successful visit is a visit to a property where you were able to complete the task you had planned. For every successful visit, how many unsuccessful visits would you say that there were, for the typical property?"

- *Total hours worked per week* This variable is the product of the following two questions: "How many days did you work this week?"; and, "During the days where you did work this week, what would you say is approximately the number of hours you worked?".

- *Average # hours spent to deliver one bill* This variable is the ratio of total bills delivered per week (self-reported by the collector) divided by the variable *total hours worked per week*.

- *Satisfaction and happiness on job* This variable measures the collectors' extent of agreement with three statements: "Overall, this was a productive week for me"; "Overall, I was content while working this week"; "Overall, I am satisfied with my job". For each statement, the respondent can answer 'strongly disagree', 'disagree', 'neither agree nor disagree', 'agree', 'strongly agree'. We assign numerical values from 1 to 5, with larger values indicating stronger agreement. The answer to each statement is standardized, and the variable is the average over the three standardized answers.

C Additional Analysis: Days Since Bill Delivery

Motivation Our results have shown that tax collectors face time-constraints when trying to deliver their bills, and technology allowed treatment collectors to better navigate and, in turn, more quickly find property owners to deliver bills. The extra time on hand provided by the navigational advantage could be used by treatment collectors to conduct repeat visits indiscriminately to all properties they delivered a bill to. As modelled in Section 5, since the likelihood that a property owner makes a positive payment is increasing in the number of visits, this navigational time-advantage could lead to a positive treatment effect on tax collection. In this appendix section, we provide a regression-based analysis of the extent to which the experimental treatment effect on tax collection is accounted for by this navigational time-advantage.

The idea is to leverage additional data to measure the time since bill delivery at the property level in our sample and use this variable as a proxy for the treatment group's navigational advantage. In turn, we can include this (imperfect) proxy in the estimating equation for our main tax outcomes (equation 2) to inspect how much of a treatment effect there remains on technology *after controlling for the navigational advantage*. If there is a remaining effect, then it suggests that, conditional on the initial navigational advantage, other channels such as learning and targeting play a role in determining the full treatment impact on tax outcomes.

This exercise is closely related to the quantitative model-investigation in Secton 5. In the model, treatment collectors were endowed with a navigational advantage ($\theta_T > \theta_C$) and a learning advantage ($\eta_T > \eta_C$). The learning advantage reflects the idea that, rather than use any extra time on hand to indiscriminately make return-visits to all properties where a bill was delivered, treatment collectors use the extra time to learn about households' propensity to pay and in turn selectively target their collection efforts on those households with higher payment propensity. Our experimental results provided support for the existence of learning and targeting (Section 4.3). Interpreted through the lens of the model, controlling for time since delivery conceptually amounts to 'shutting down' the navigational advantage (i.e., setting $\theta_T = \theta_C$); any remaining treatment effect on technology would then be attributed to the learning advantage.

Data and measurement To implement this exercise requires data at the bill-level on both tax payment and the (ideally exact) date of bill delivery. We attempted to collect delivery dates by asking tax collectors to maintain a diary during the tax campaign. We compiled the diaries at the end of the campaign which should, in principle, record the date of delivery for each bill that the collector was assigned to. In practice, the data quality of these diary entries is limited, for several reasons. First, conducting continuous quality-checks on diary entries during the tax campaign itself was challenging. Second, upon compiling the diaries at the end of the campaign, we learned that some collectors had been filling out entries at the end of each campaign week – introducing measurement error around the exact date of delivery for a particular bill. Third, while providing aggregate daily information on the number of bills delivered was part of the established process prior to the experiment (Section 3.3), the requirement to maintain a diary was introduced during our experiment and was new to the collectors. We observe incomplete diary entries for some bills (e.g. where the bill was claimed to be delivered, but the information on delivery date is missing), and it is possible that collectors paid less attention to maintaining the diary than to submitting aggregate daily information to their supervisors. For these reasons, we view the results based on aggregate delivery date as more precise (Figure 2), and consider the results from this section as secondary.

Relating days since bill delivery to tax performance With these caveats in mind, Figure A14 plots the density distribution of days since bill-delivery separately for the treatment and control groups. We focus on the sample of bills for which we also have household data, but results are similar based on the full experimental sample. We measure days since bill delivery as the number of days between the official end-date of the tax campaign and the date of delivery based on the diaries. Thus, a larger number indicates that the collector had more days available to conduct follow-up visits and collect payments before the end of the campaign. Consistent with the dynamics of bill-delivery based on aggregate collector-level data (Figure 2), this figure shows that treatment collectors delivered more bills in the early days of the tax campaign – and consequently have more days available to conduct follow-up visits. We can reject with confidence that the density distributions of the two groups are equal (Kolmogorov-Smirnov D-statistic= 0.095 with p-value= 0.001).

In the model in Section 5, tax performance is an increasing function of days since delivery. Leveraging the fact that we observe tax outcomes and delivery dates at the bill level, in Figure A15 we plot tax performance as a function of days since delivery: the likelihood of making a tax payment in panel A, and the total amount paid in panel B. It is important to note that these are descriptive associations, since both the characteristics of the property that receives a bill and the date of bill delivery are endogenous. To visualize the associations, we create five days-since-delivery bins of equal size (quintiles), and calculate the average tax outcomes separately by quintile and treatment-control groups.

Consistent with our model, the control group pattern shows that the likelihood of making a tax payment is increasing in the days since delivery. However, the profile in the treatment group is distinctly different – maintaining a positive slope, but being shifted upward everywhere relative to the control group profile. If the treatment effect on tax outcomes was entirely due to the navigational time-advantage, then the relationship between days since delivery and tax performance in Figure A15 should be identical in the treatment group and the control group. In this case, the positive treatment effect on tax outcomes would simply come from the fact that the treatment group has more days since delivery (Figure A14), which allows them to make more indiscriminate return-visits to all properties they delivered a bill to. The difference in profiles suggests that treatment collectors have more time on hand than control collectors but, rather than apply it indiscriminately, they make use of this extra time in targeted ways to improve their tax performance (such as through learning).

To formally test for statistical differences across profiles, we use the household sample to estimate

$$y_{hqc} = \beta_q \cdot \mathbf{1}(Tech)_c + \pi_q + \epsilon_{hqc}, \tag{6}$$

where y_{hqc} is the tax outcome of household h in quintile q and collection unit c, and π_q are fixed effects for the five quintiles of days-since-delivery. Standard errors are clustered at the collection unit. β_q is indexed with q because the treatment dummy is interacted with the quintile group fixed effects. In the top-left corners of each panel, we report the F-statistic which tests the joint significance of the five β_q coefficients. For both the likelihood of tax payment (F-statistic= 7.78, p-value= 0.007) and total tax payment (F-statistic= 3.30, p-value= 0.011), we can reject that the two profiles are the same.

Impacts of technology conditional on days since delivery The statistical difference in profiles suggests that the navigational time-advantage may not be the only mechanism which drives the experimental results on tax outcomes. To complete this investigation, we augment our main estimation equation for tax outcomes (equation 2) with the measure of days since delivery, $dayssince_h$:

$$y_{hc} = \beta \cdot \mathbf{1}(Tech)_c + \mu \cdot dayssince_h + \iota_h + \Omega \cdot X_{hc} + \epsilon_{hc}, \tag{7}$$

where y_{hc} is the tax outcome of household h in collector-unit c. We assume a linear relationship between the outcome and days-since-delivery; the results are robust to more flexible functional forms. We cluster at the level of the collector-unit. We use the full household sample, but $dayssince_h$ is only defined for the households that were delivered a bill. To maintain the full sample, we assign an arbitrary value (-400) to $dayssince_h$ to all households with no bill delivered, and include a fixed effect, ι_h, which flags these values. Maintaining the full sample improves the precision of coefficients Ω on household and collector-unit characteristics X_{hc}; results are qualitatively similar if we restrict the sample to households with bills delivered.

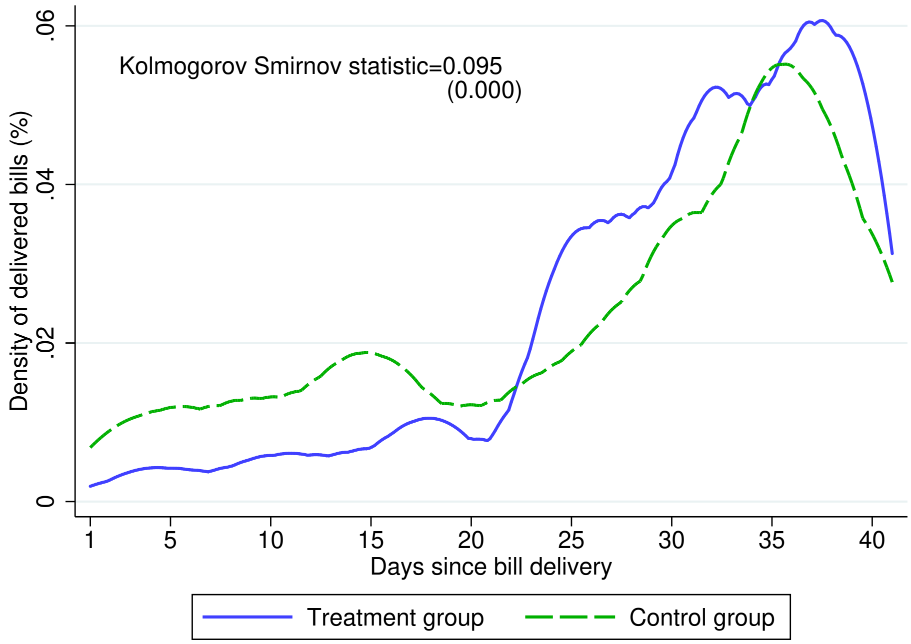
The purpose of estimating equation (7) is to gauge how much of an effect of technology there remains, once the mediating channel of navigational advantage is controlled for by including $dayssince_h$. As described above, this exercise is related to the model in Section 5: conceptually, the variable $dayssince_h$ measures (imperfectly) the navigational advantage that is captured in the model by assuming $\theta_T > \theta_C$. If we interpret equation (7) through the lens of the model, controlling for $dayssince_h$ amounts to 'shutting down' the navigational advantage channel (setting $\theta_T = \theta_C$) and inspecting how much of a treatment effect there remains. In the model, the remaining treatment effect β on technology would be attributed to learning and targeting.

It is important to note that the interpretation of equation (7) is challenged by the issue that the variable $dayssince_h$ is endogenous – including to the treatment. Potential biases should be kept in mind when interpreting the results, presented in Table A11; additional work on this exercise could include finding an instrument for days since delivery, to simultaneously estimate the causal effects of $dayssince_h$ and $\mathbf{1}(Tech)_c$.

In the first two columns of Table A11, we observe that controlling for days since delivery reduces the treatment coefficient on total visits by almost 50% and the coefficient loses its statistical significance at conventional levels. The coefficient on days-since-delivery is positive and strongly significant. This suggests that the treatment effect on total visits is strongly mediated by technology's navigational advantage to deliver bills faster. In columns (3) and (4), we see that controlling for days-since-delivery does reduce the treatment effect on likelihood of tax payment, but only by 14% and the treatment coefficient on technology remains statistically significant. In other words, navigational advantage does appear to account for some part of technology's tax impact, but there is a sizeable remaining impact possibly due to learning and targeting. These regression results are consistent with the results from the calibrated model in Section 5. For total tax payment (columns 5 and 6), the inclusion of days-since-delivery reduces the treatment effect by 10.5% and the technology coefficient remains significant. Similar results are obtained in the sample which conditions on a bill being delivered (columns 7 and 8).

The analyses in this section remain limited due to identification and data concerns, but the various pieces of evidence do suggest an important role for mechanisms such as learning above and beyond the initial navigational advantage.

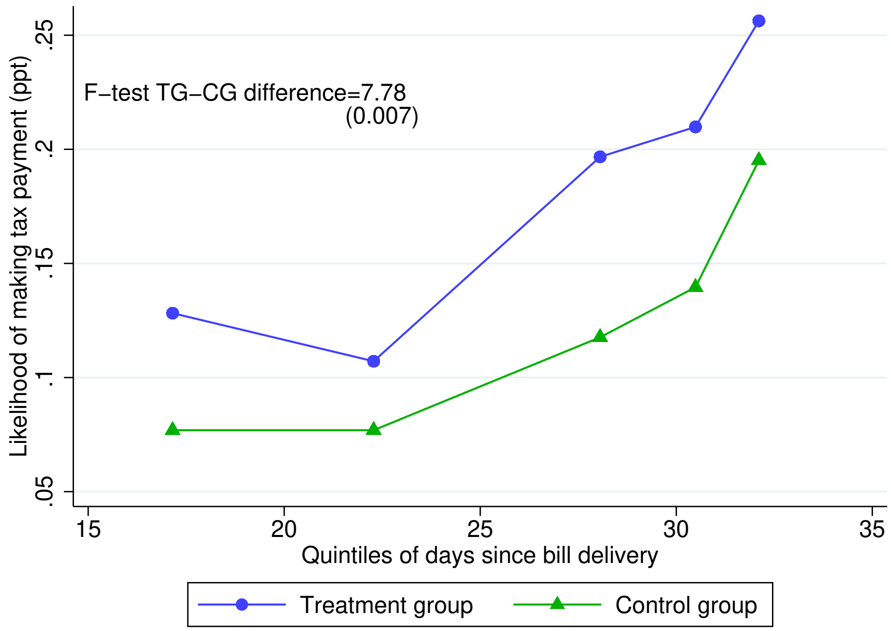
Figure A14: Distribution of Days Since Bill Delivery



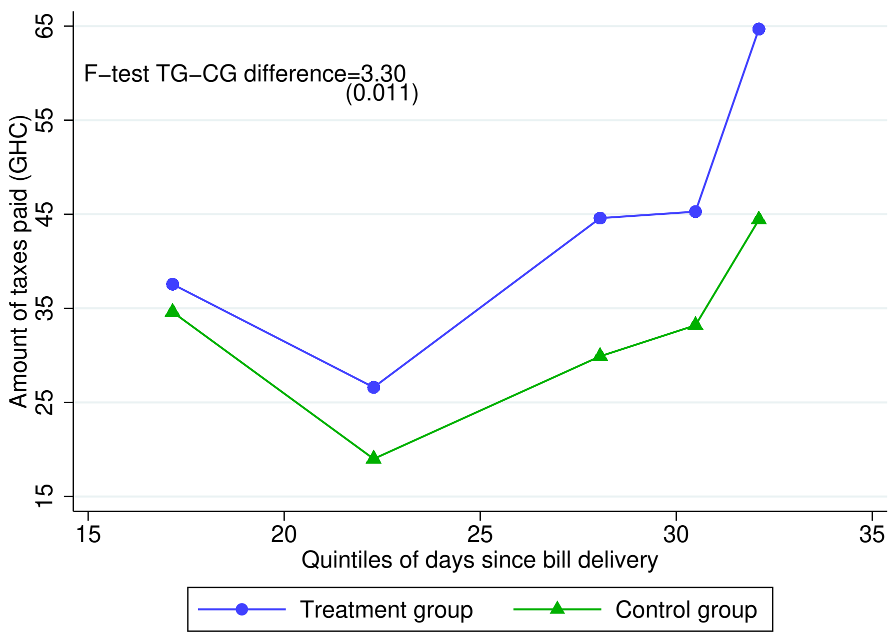
Notes: This figure shows the density distribution of bills delivered by days since bill delivery date, separately for the treatment group and the control group. We measure days since delivery as the number of days between the official end-date of the tax campaign and the date of delivery based on the collector diaries. The statistic reported in the top-left corner is the Kolmogorov-Smirnov D-statistic which tests that the treatment and control distributions are equal. The p-value for the D-statistic is reported in parentheses.

Figure A15: Tax Outcomes as a Function of Days Since Bill Delivery

(a) Likelihood of Making Positive Tax Payment



(b) Taxes Collected



Notes: These panels show the associations between days since bill delivery and, respectively, likelihood of making a positive tax payment (panel A) and total taxes paid (panel B). The distribution of days since bill delivery (Figure A14) is separated into five quintiles (five bins of equal size), and the average value of the tax outcome is calculated separately by quintile and group (treatment and control). The F-statistic reported in the top left-corner is the statistic which tests the hypothesis that the gaps between treatment and control are jointly zero in all five quintiles. This F-statistic is based on estimating equation (6).

Table A11: Main Impacts While Controlling for Days Since Bill Delivery

	Total visits (in %)		Any positive tax payment		Total tax payment (in GHC)		Total tax payment (in GHC) per bill delivered	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Technology	0.094*	0.049	0.043**	0.037*	25.9**	23.2**	47.3**	48.3**
	(0.050)	(0.050)	(0.021)	(0.020)	(10.9)	(10.1)	(19.6)	(18.2)
Days since bill delivery		0.014***		0.005***		0.507		0.351
		(0.004)		(0.001)		(7.359)		(1.238)
Household controls	X	X	X	X	X	X	X	X
Collector-unit controls	X	X	X	X	X	X	X	X
Strata FE	X	X	X	X	X	X	X	X
Mean in CG	0.67	0.67	0.16	0.16	41.0	41.0	80.9	80.9
Observations	4334	4334	4334	4334	4334	4334	2276	2276
Clusters	56	56	56	56	56	56	56	56

Notes: The regression model and outcomes in this table are the same as in Table 3, with the only addition that we include in even-numbered columns the variable which measures days since bill delivery. Specifically, this variable measures the number of days between the official end-date of the tax campaign and the date of bill delivery based on the collector diaries (see Section C for details.) For a description of the regression model, please refer to Table 3 and Section 3.