

Supplementary Data and Appendix For Online Publication

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A1 Additional Tables and Figures

Table A1: Components of the Tax Campaign and Its Evaluation

Activity	Actor	Timing	Observations	Neighborhoods
Tax Campaign				
Property register	Collectors	May-Dec 2018	19,600	180
Tax collection	Collectors	May-Dec 2018	19,600	180
Evaluation				
Baseline citizen survey	Enumerators	Jul-Dec 2017	1,404	180
Midline citizen survey	Enumerators	Jun 2018-Feb 2019	16,346	180
Baseline collector survey	Enumerators	April-May 2018	34	N/A

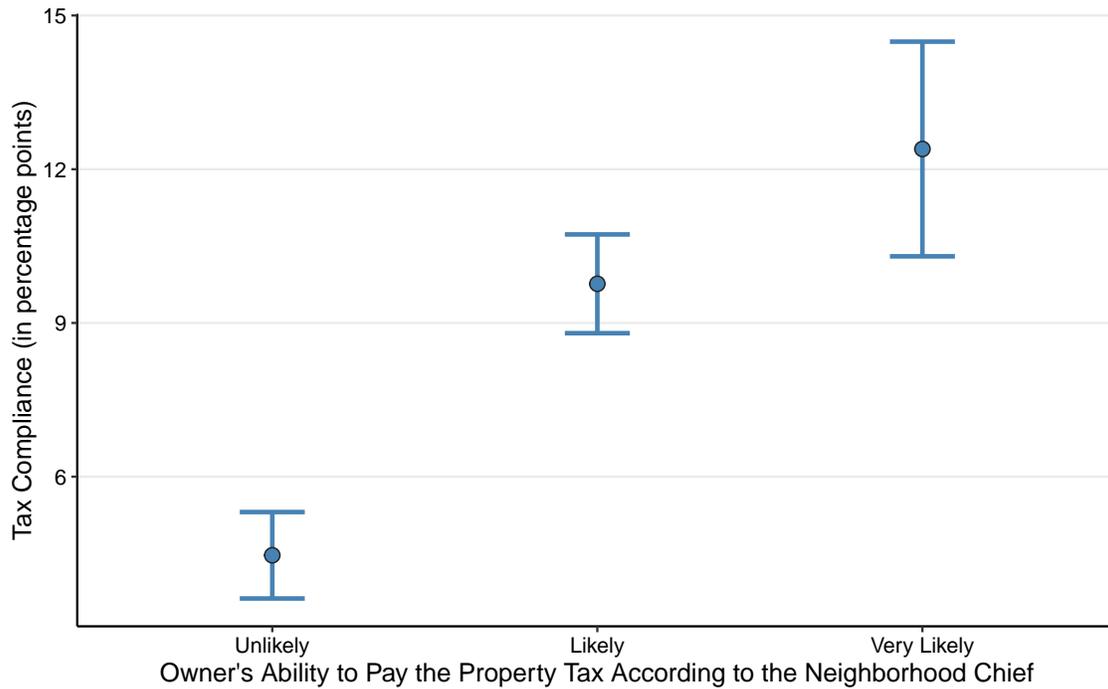
Notes: This table reports the actors, the timing, the number of observations (properties) and the number of clusters (neighborhoods) associated with each tax campaign activity. The property register has more observations per neighborhood than the midline survey because the former includes information on all compounds, including (exempt) government buildings, churches, and empty lots, while the midline survey was only conducted with privately owned plots liable for the property tax. The primary tax outcomes result from merging official property tax records with data from the property register. The mechanics of the tax campaign and data sources are discussed, respectively, in Sections 2 and 4.

Table A2: Balance

	Sample (1)	Observations (2)	Mean (L-L pairs) (3)	L-H pairs (4)	H-H pairs (5)
<u>Panel A: Property Characteristics</u>					
Distance to State Buildings (in km)	Registration	19,354	0.829	-0.009 (0.107)	0.165 (0.125)
Distance to Health Institutions (in km)	Registration	19,354	0.349	0.014 (0.036)	-0.008 (0.035)
Distance to Education Institutions (in km)	Registration	19,354	0.356	0.059* (0.033)	-0.003 (0.029)
Distance to Roads (in km)	Registration	18,849	0.442	-0.028 (0.061)	-0.058 (0.066)
Distance to Eroded Areas (in km)	Registration	18,849	0.123	0.001 (0.015)	-0.019 (0.018)
Walls Quality	Midline	16,131	1.123	0.054 (0.036)	0.024 (0.038)
Roof Quality	Midline	16,346	0.976	-0.017** (0.008)	-0.009 (0.011)
Fence Quality	Midline	14,857	1.362	0.054 (0.078)	-0.055 (0.099)
Property value (in USD)	Registration	19,587	1171.490	387.369 (321.349)	-29.377 (314.303)
<i>F</i> Statistic, <i>p</i> -value				1.417, 0.186	1.423, 0.192
<u>Panel B: Property Owner Characteristics</u>					
Gender	Midline	9,396	0.804	0.005 (0.016)	0.004 (0.018)
Age	Midline	8,270	51.789	0.676 (0.859)	-0.359 (1.048)
Employed Indicator	Midline	10,295	0.789	0.018 (0.018)	0.007 (0.021)
Salaried Indicator	Midline	10,295	0.269	-0.006 (0.016)	0.003 (0.016)
Work for Government Indicator	Midline	10,295	0.164	-0.05 (0.013)	0.010 (0.015)
Relative Work for Government Indicator	Midline	11,448	0.224	0.008 (0.017)	0.037* (0.021)
<i>F</i> Statistic, <i>p</i> -value				1.046, 0.398	0.405, 0.874
<u>Panel C: Property Owner Characteristics</u>					
Main Tribe Indicator	Baseline	1,404	0.722	0.056* (0.032)	0.006 (0.039)
Years of Education	Baseline	1,399	10.714	-0.040 (0.356)	-0.111 (0.414)
Has Electricity	Baseline	1,404	0.108	0.041** (0.021)	0.051* (0.026)
Log Monthly Income (in CF)	Baseline	1,245	10.999	0.031 (0.080)	0.101 (0.083)
Trust Chief	Baseline	1,399	3.128	0.020 (0.090)	-0.080 (0.104)
Trust National Government	Baseline	1,342	2.651	-0.181* (0.097)	-0.126 (0.110)
Trust Provincial Government	Baseline	1,348	2.503	-0.146 (0.104)	-0.040 (0.121)
Trust Tax Ministry	Baseline	1,337	2.405	-0.075 (0.093)	-0.090 (0.123)
<i>F</i> Statistic, <i>p</i> -value				1.299, 0.249	1.619, 0.132
<u>Panel D: Neighborhood Characteristics</u>					
Tax Compliance in 2016	Baseline	180	0.061	-0.011 (0.017)	0.013 (0.025)
Tax Revenue Per Property Owner in 2016	Baseline	180	170.711	98.057 (159.501)	518.404 (487.404)
Affected by Conflict in 2017	Baseline	180	0.000	0.031* (0.018)	0.053 (0.037)
<i>F</i> Statistic, <i>p</i> -value				0.511, 0.676	1.079, 0.359
<u>Panel E: Attrition</u>					
Registration to Midline	Registration	19,587	0.149	0.024 (0.064)	0.014 (0.064)

Notes: This table reports coefficients from balance tests conducted by regressing baseline and midline characteristics of properties (Panel A), property owners (Panels B and C), and neighborhoods (Panel D) on an indicator for the type of the collector pair (low-high or LH, high-high or HH, with low-low or LL as the omitted category). Panel E shows differences in attrition from registration to midline surveying. Standard errors are clustered at the neighborhood level ($* = p < 0.1$, $** = p < 0.05$, $*** = p < 0.01$). All balance checks are conducted in the primary analysis sample of 180 neighborhoods, which excludes the logistics pilot, pure control, and local taxation neighborhoods in Balan et al. (2022) and exempted properties. The results are summarized in Section 3.2. The variables are described in detail in Section A14.

Figure A1: Neighborhood Chief Estimates of Household Type v. Tax Compliance



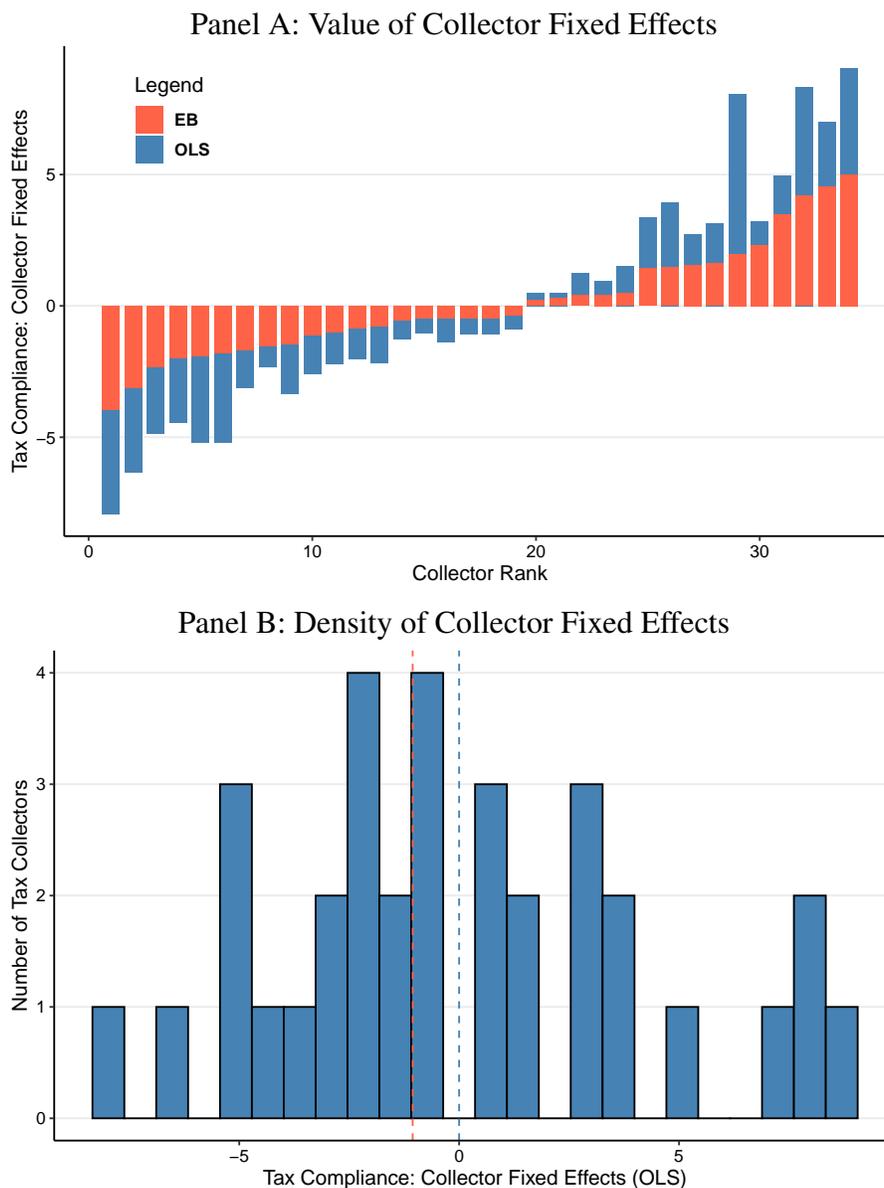
Notes: This figure shows property tax compliance by owner’s ability to pay the property tax according to the neighborhood chief. Neighborhood chiefs report whether each property owner is “unlikely,” “likely,” or “very likely” to be able to pay the property tax. The sample comes from the 80 randomly assigned neighborhoods in the analysis sample. We discuss these results in Section 6.1.

Table A3: Correlates of high-type households

	Coef. (1)	SE (2)	p-value (3)	Mean (4)	Observations (5)	Sample (6)
<u>Panel A: Property Characteristics</u>						
Distance to State Buildings (in km)	0.003	0.014	0.819	0.832	6,903	Registration
Distance to Health Institutions (in km)	0.011*	0.007	0.090	0.402	6,903	Registration
Distance to Education Institutions (in km)	-0.002	0.006	0.750	0.425	6,903	Registration
Distance to Roads (in km)	-0.004	0.011	0.706	0.429	6,901	Registration
Distance to Eroded Areas (in km)	-0.001	0.003	0.774	0.120	6,901	Registration
Walls Quality	0.009	0.005	0.106	0.965	5,737	Midline
Roof Quality	0.034***	0.010	0.000	1.147	5,737	Midline
Fence Quality	0.000	0.016	0.992	1.374	5,177	Midline
Property value (in USD)	276.721***	59.648	0.000	1325.137	6,903	Registration
<u>Panel B: Property Owner Characteristics</u>						
Employed Indicator	0.061***	0.015	0.000	0.800	3,681	Midline
Salaried Indicator	0.061***	0.015	0.000	0.253	3,681	Midline
Work for Government Indicator	0.026**	0.013	0.047	0.163	3,681	Midline
Relative Work for Government Indicator	0.039***	0.014	0.006	0.241	4,103	Midline
<u>Panel C: Property Owner Characteristics</u>						
Gender	-0.036	0.046	0.430	1.367	542	Baseline
Age	-2.624*	1.515	0.084	47.674	542	Baseline
Main Tribe Indicator	0.033	0.041	0.426	0.765	542	Baseline
Years of Education	0.620	0.405	0.127	10.496	542	Baseline
Has Electricity	0.051*	0.029	0.080	0.130	542	Baseline
Log Monthly Income (in CF)	0.154	0.251	0.538	10.621	540	Baseline
Trust Chief	-0.056	0.095	0.555	3.216	540	Baseline
Trust National Government	0.055	0.122	0.649	2.524	526	Baseline
Trust Provincial Government	0.030	0.120	0.806	2.426	525	Baseline
Trust Tax Ministry	-0.068	0.117	0.564	2.320	516	Baseline

Notes: This table reports the relationship between household type (low or high) and property or property owner's characteristics. More specifically, we regress each property or property owner's characteristic on an indicator for the household being high type. Columns 1–6 report the regression coefficient, robust standard errors and the associated p-values ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$), mean of the characteristic, number of non-missing observations, and the survey the data comes from (registration, midline or baseline). The characteristics are described in detail in Section A14. We discuss these results in Section 6.1.

Figure A2: Collector Fixed Effects Estimates



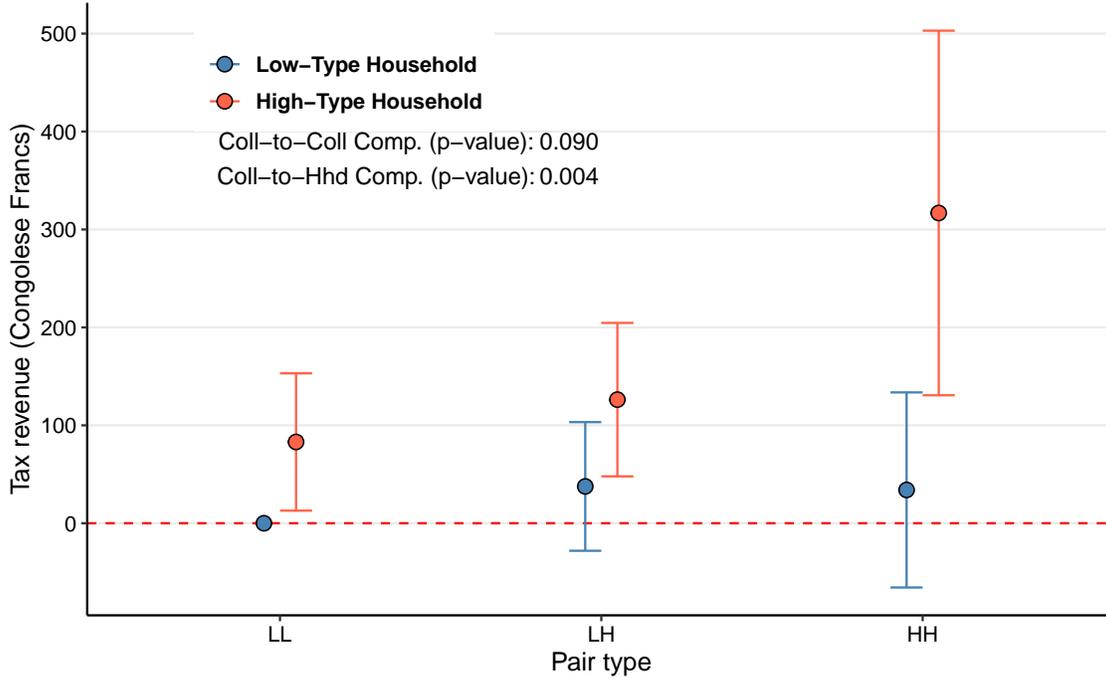
Notes: This figure shows the value and density of the tax collector fixed effects. Panel A reports the value of each collector’s fixed effect (y-axis). Collector fixed effect ($\hat{\alpha}_c$) are obtained by running the OLS regression (6) with tax compliance as the outcome and are shown in blue. We also report the Empirical Bayes estimate ($\hat{\alpha}_c^{EB}$) for each collector in red. Collectors are ranked in terms of their Empirical Bayes estimate (x-axis). Panel B reports a histogram of the collector fixed effects obtained by running the OLS regression (6) with tax compliance as the outcome. A blue dotted line represents the average collector fixed effect value, while a red one represents the median value. We discuss these results in Section 6.

Table A4: Correlates of high-type collectors

	Coef. (1)	SE (2)	p-value (3)	Mean (4)	Observations (6)	Sample (7)
<u>Panel A: Demographics</u>						
Female	0.000	0.083	1.000	0.059	34	Baseline
Age	4.342	2.713	0.120	30.424	33	Baseline
Main Tribe	0.176	0.140	0.215	0.206	34	Baseline
Level of Education	0.507**	0.197	0.015	3.636	33	Baseline
Math Score	0.853**	0.337	0.017	-0.091	33	Baseline
Literacy (Tshiluba)	0.449	0.312	0.160	0.054	33	Baseline
Literacy (French)	0.303	0.308	0.334	0.067	33	Baseline
Monthly Income	61.388*	32.635	0.069	109.844	33	Baseline
Possessions	0.684	0.417	0.111	1.727	33	Baseline
Works Other Job	-0.040	0.169	0.813	0.667	33	Baseline
Born in Kananga	-0.154	0.177	0.389	0.545	33	Baseline
<u>Panel B: Trust in the Government</u>						
Trust Nat. Gov.	0.059	0.337	0.863	2.971	34	Baseline
Trust Prov. Gov.	0.235	0.306	0.448	3.000	34	Baseline
Trust Tax Min.	0.294	0.256	0.258	3.500	34	Baseline
Index	0.247	0.273	0.372	0.128	34	Baseline
<u>Panel C: Perceived Performance of Government</u>						
Prov. Gov. Capacity	-0.294*	0.164	0.082	0.382	34	Baseline
Prov. Gov. Responsiveness	0.000	0.310	1.000	1.765	34	Baseline
Prov. Gov. Performance	0.412	0.449	0.366	4.559	34	Baseline
Prov. Gov. Use of Funds	-0.056	0.093	0.553	0.665	33	Baseline
Index	-0.169	0.347	0.628	0.135	34	Baseline
<u>Panel D: Government Connections</u>						
Job through Connections	0.036	0.168	0.833	0.267	30	Baseline
Relative work for Prov. Gov.	-0.257*	0.149	0.093	0.242	33	Baseline
Relative work for Tax Ministry	-0.136	0.153	0.381	0.242	33	Baseline
Index	-0.422	0.344	0.229	-0.022	33	Baseline
<u>Panel E: Tax Morale</u>						
Taxes are Important	0.294*	0.158	0.073	2.794	34	Baseline
Work of Tax Min. is Important	0.000	0.173	1.000	3.765	34	Baseline
Paid Taxes in the Past	-0.083	0.223	0.713	0.381	21	Baseline
Index	0.220	0.287	0.449	0.094	34	Baseline
<u>Panel F: Redistributive Preferences</u>						
Imp. of Progressive Taxes	0.176	0.169	0.304	1.618	34	Baseline
Imp. of Progressive Prop. Taxes	-0.118	0.158	0.463	1.176	34	Baseline
Imp. to Tax Employed	0.353	0.248	0.164	3.353	34	Baseline
Imp. to Tax Owners	0.294	0.343	0.398	3.088	34	Baseline
Imp. to Tax Owners w. title	0.235	0.185	0.212	3.353	34	Baseline
Index	0.371	0.364	0.315	-0.294	34	Baseline

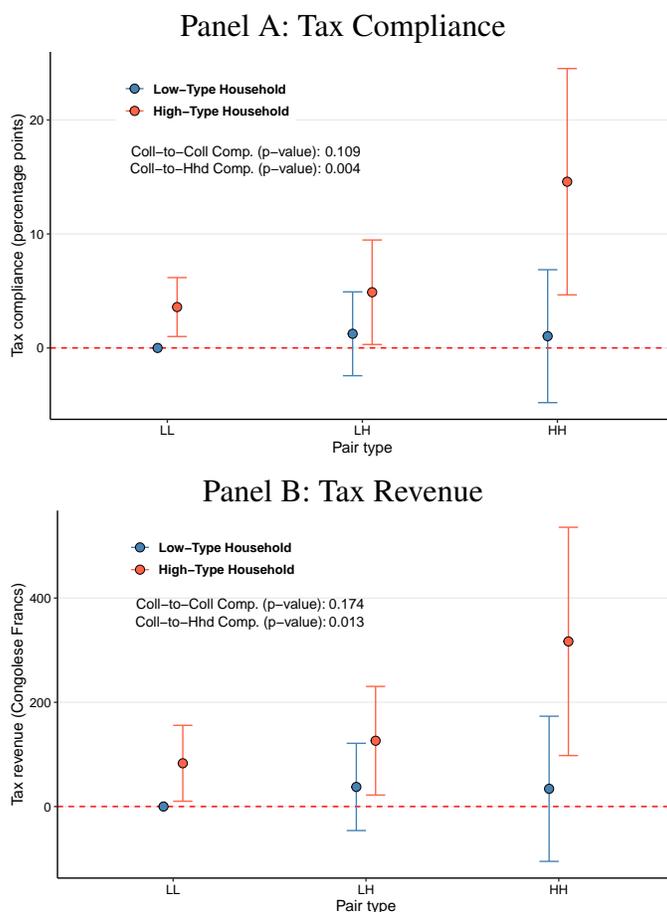
Notes: This table reports the relationship between characteristics and the type (low or high) of the tax collector. More specifically, we regress each collector's characteristic on an indicator for the collector being high type. Columns 1–6 report the regression coefficient, robust standard errors and the associated p-values ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$), mean of the characteristic among collectors, and number of non-missing observations. The variables come from a baseline surveys with tax collectors described in Section 4. We discuss these results in Section 6.2.

Figure A3: Tax Revenue By Collector and Household Types



Notes: This figure shows the estimates of the average tax revenue per property owner (in Congolese Francs) when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures the tax revenue per property owner for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from equation (7) with tax revenue per owner as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. The figure also reports p-values associated with tests for the average tax compliance function exhibiting increasing differences in collector type and in collector and household type. We report the p-value associated with a test that tax revenue, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.1.

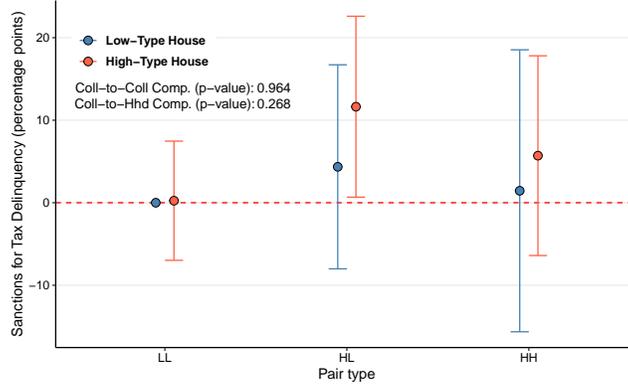
Figure A4: Tax Compliance and Tax Revenue By Collector and Household Types — Bootstrapped Standard Errors



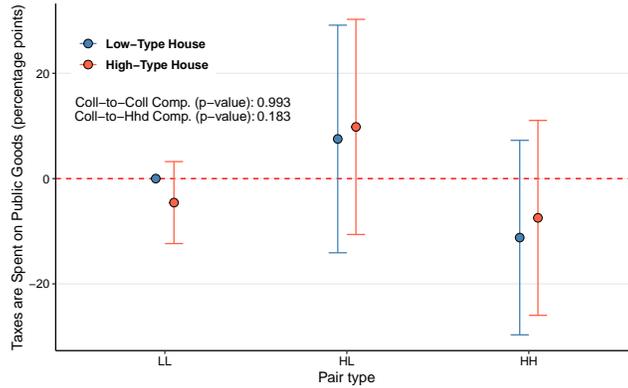
Notes: This figure shows the estimates of the average tax compliance (Panel A) and tax revenue per owner (Panel B) when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures tax compliance probability (Panel A) and tax revenue per owner (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from Equation (7) with tax compliance (Panel A) or tax revenue (Panel B) as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates corresponding to clustered standard errors that use Bayesian bootstrap re-sampling (100 samples) at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.1.

Figure A5: Citizens' Perception of Enforcement and Use of Tax Revenue by Collector and Household Types

Panel A: Self-Reported Probability of Sanctions for Delinquency

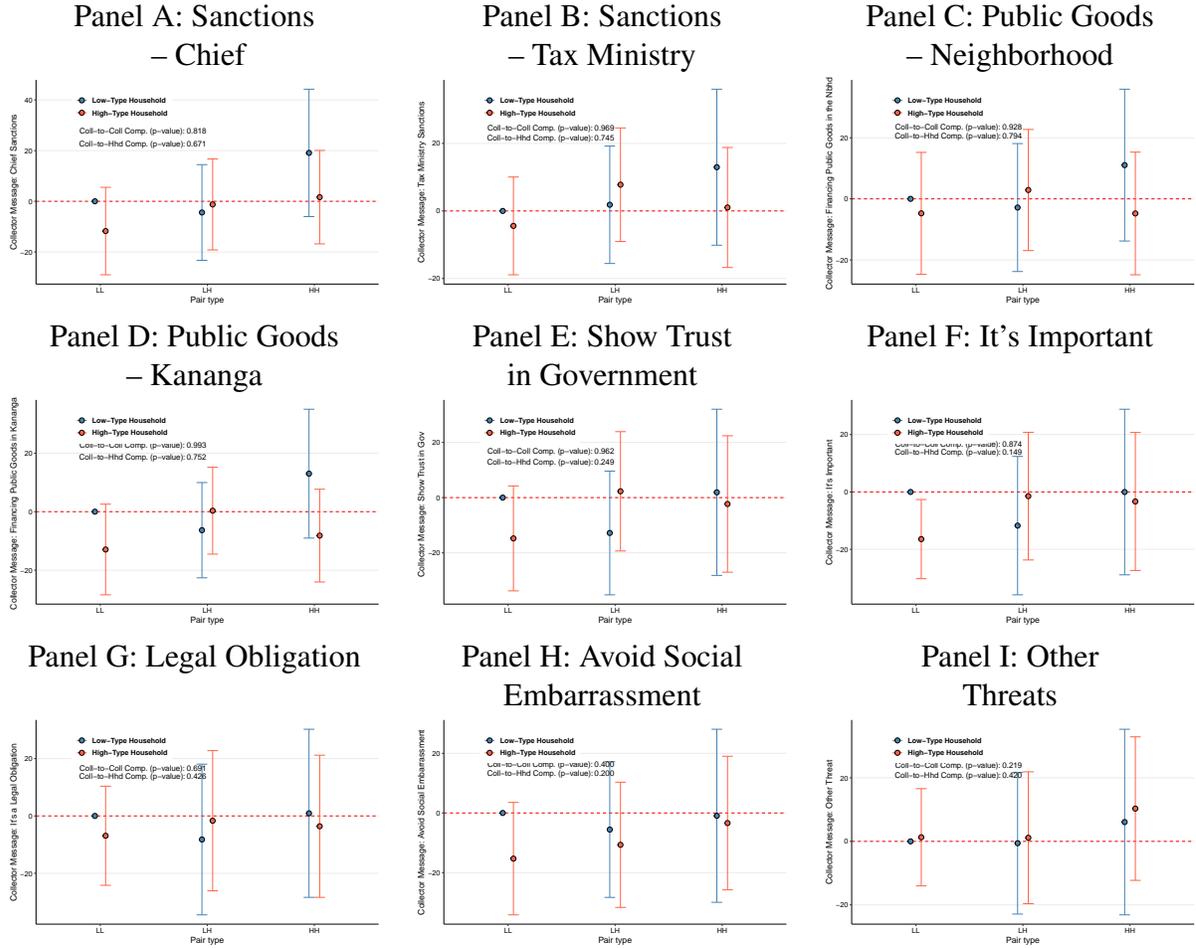


Panel B: Self-Reported Probability that Taxes are Spent on Public Goods



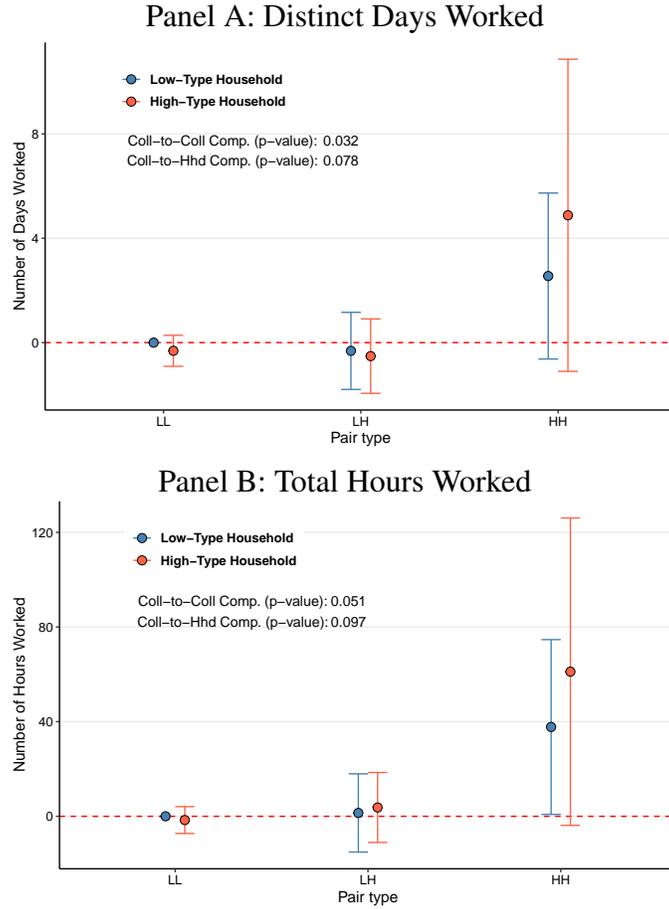
Notes: This figure shows the estimates of the average perception of enforcement and spending of tax revenues on public goods measured when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures the perceived probability of sanctions for tax delinquency (Panel A) and the perceived probability that tax revenues are spent on public goods (Panel B) measured in the midline survey and for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from equation (7) with perception of enforcement or that tax revenues are spent on public goods as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. Each outcome is multiplied by 100 so the coefficients can be interpreted as percentage point changes. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

Figure A6: Collectors' Strategies by Collector and Household Types



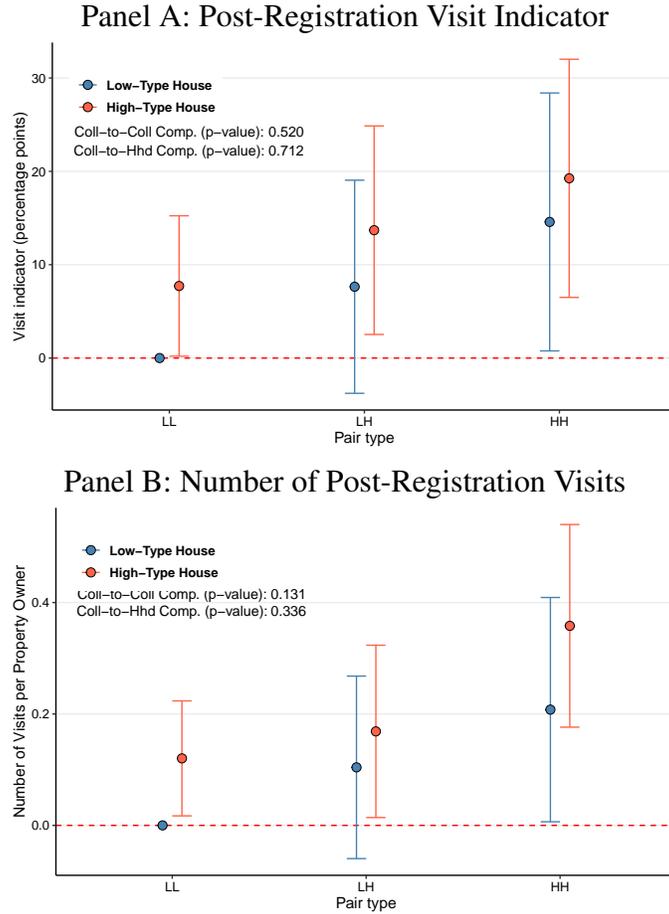
Notes: This figure shows the estimates of the different possible messages used by collectors when soliciting payment when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures the messages used by collectors when demanding payment measured in the endline survey and for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from equation (7) with the collectors' message as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. Each outcome is an indicator for whether the collector used the message, multiplied by 100 so the coefficients can be interpreted as percentage point changes. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

Figure A7: Days and Hours Collectors Worked by Collector and Household Types



Notes: This figure shows the estimates of distinct days worked by the tax collectors (Panel A) and the total number of hours worked by the tax collectors (Panel B) for different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis uses the dated chalk marks midline survey data and the tax receipt data to captures numbers of days worked (Panel A) and number of hours worked (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from Equation (7) with tax visits as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

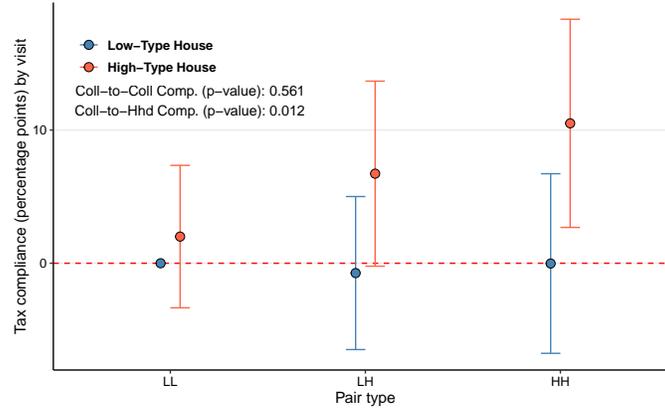
Figure A8: Tax Visits by Collector and Household Types



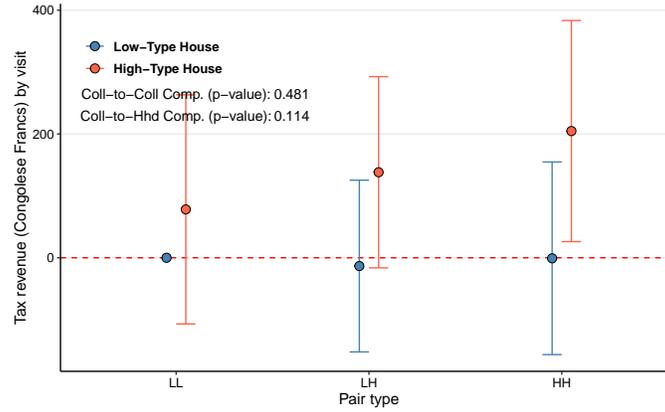
Notes: This figure shows the estimates of post-registration extensive margin visits (Panel A) and intensive margin number of visits (Panel B) when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures extensive margin tax visits (Panel A) and intensive margin number of tax visits (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from Equation (7) with tax visits as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

Figure A9: Productivity of Tax Visits by Collector and Household Types

Panel A: Tax Compliance per Post-Registration Visit

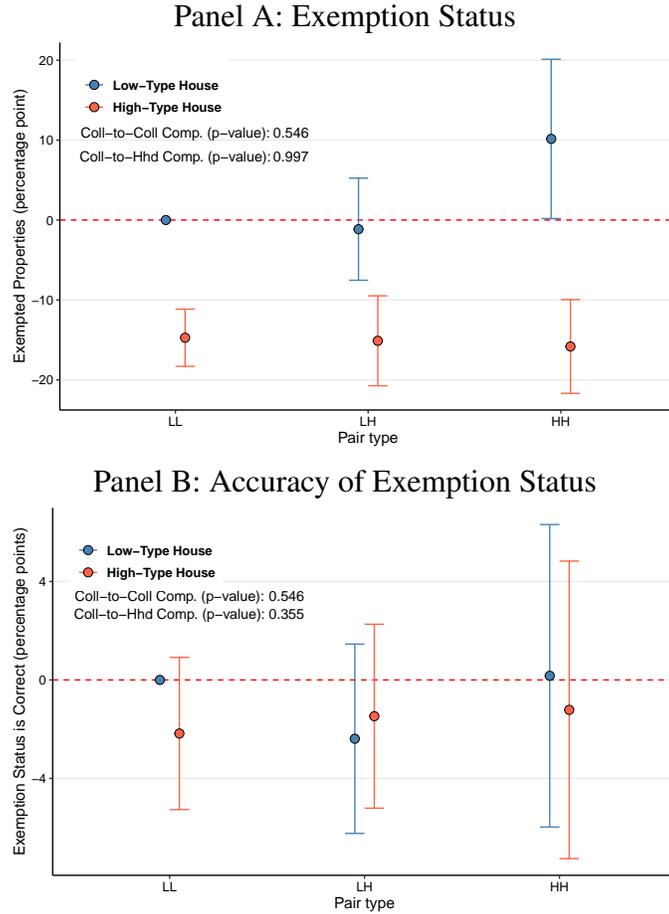


Panel B: Tax Revenue per Post-Registration Visit



Notes: This figure shows the estimates of tax compliance per post-registration visits (Panel A) and tax revenue per post-registration visits (Panel B) when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures tax compliance (in percentage points) per tax visit (Panel A) tax revenue (in Congolese Francs) per tax visit (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from Equation (7) with tax compliance or revenue per visit as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

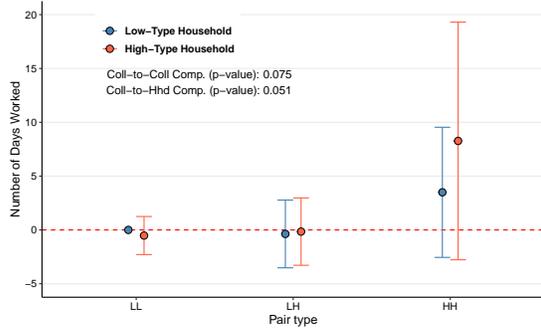
Figure A10: Exemption by Collector and Household Types



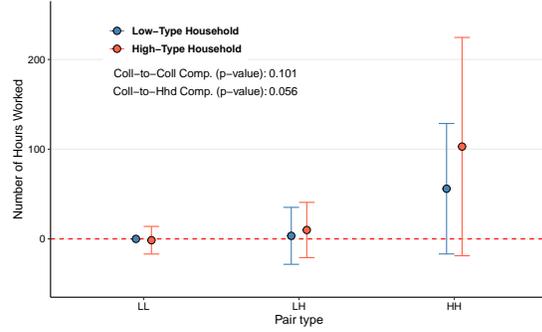
Notes: This figure shows the estimates of the property’s tax exemption status at registration (Panel A) and whether this exemption status was deemed accurate by the enumerator during the registration survey (Panel B) when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households’ type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures the exemption status of the household (Panel A) and whether this exemption status was judged accurate by the enumerator (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from Equation (7) with tax exemption status (Panel A) or the accuracy of this exemption status (Panel B) as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

Figure A11: Days and Hours Collectors Worked by Collector Types, Household Types, and Employment Rates

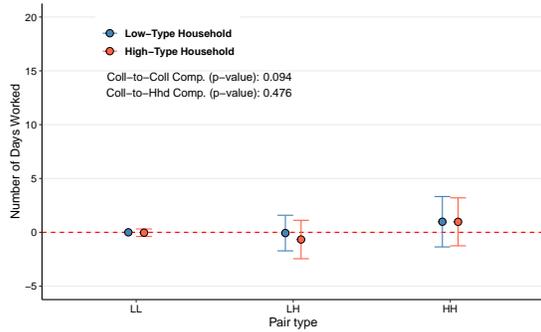
Panel A: Distinct Days Collectors Worked Above Median Employment Rate Nbhd



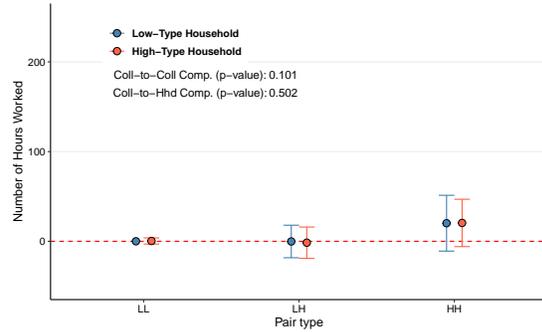
Panel B: Total Hours Collectors Worked Above Median Employment Rate Nbhd



Panel C: Distinct Days Collectors Worked Below Median Employment Rate Nbhd

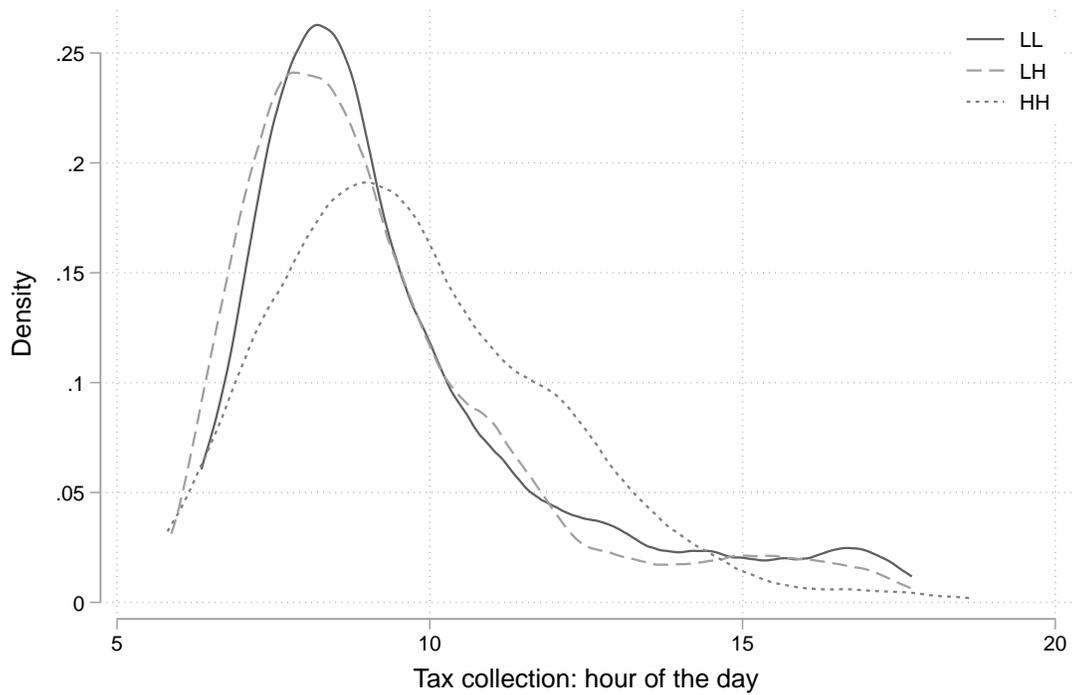


Panel D: Total Hours Collectors Worked Below Median Employment Rate Nbhd



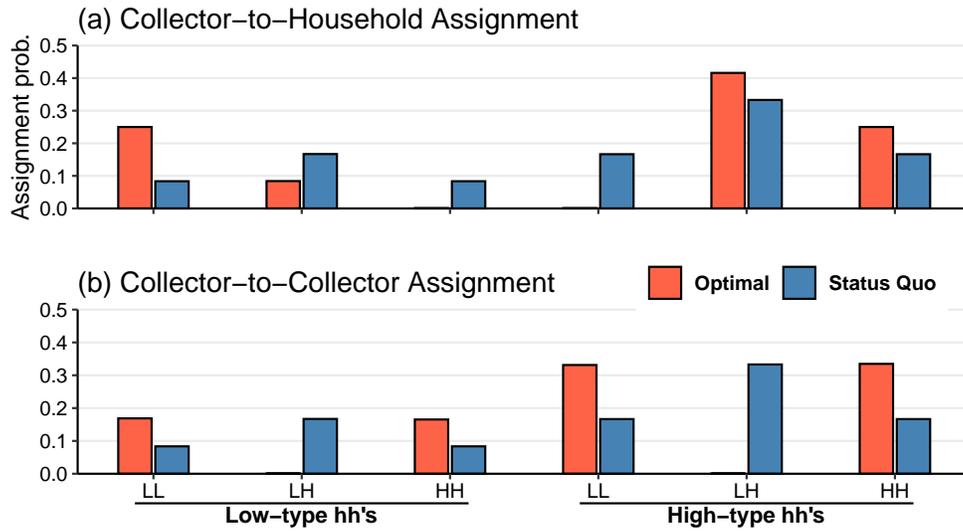
Notes: This figure shows the estimates of distinct days worked by the tax collectors (Panel A and C) and the total number of hours worked by the tax collectors (Panel B and D) for different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The estimation is reported for neighborhoods characterized by an above median level of employment (Panel A and B) and a below median level of employment (Panel C and D). The x-axis shows the three different types of collectors' pair: LL, LH, HH. The y-axis uses the dated chalk marks midline survey data and the tax receipt data tax to captures numbers of days worked (Panel A) and number of hours worked (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from Equation (7) with tax visits as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 7.2.

Figure A12: Time of Tax Collection by Collector Types



Notes: This figure shows the distribution of tax collection time within the day for different types of collector pairs (low-low or LL, low-high or LH, high-high or HH). Information on the precise date and time (including hour, minute, second) at which each tax collection took place comes from the tax receipt data. We discuss these results in Section 7.2.

Figure A13: Collector-to-Household and Collector-to-Collector Optimal Assignments



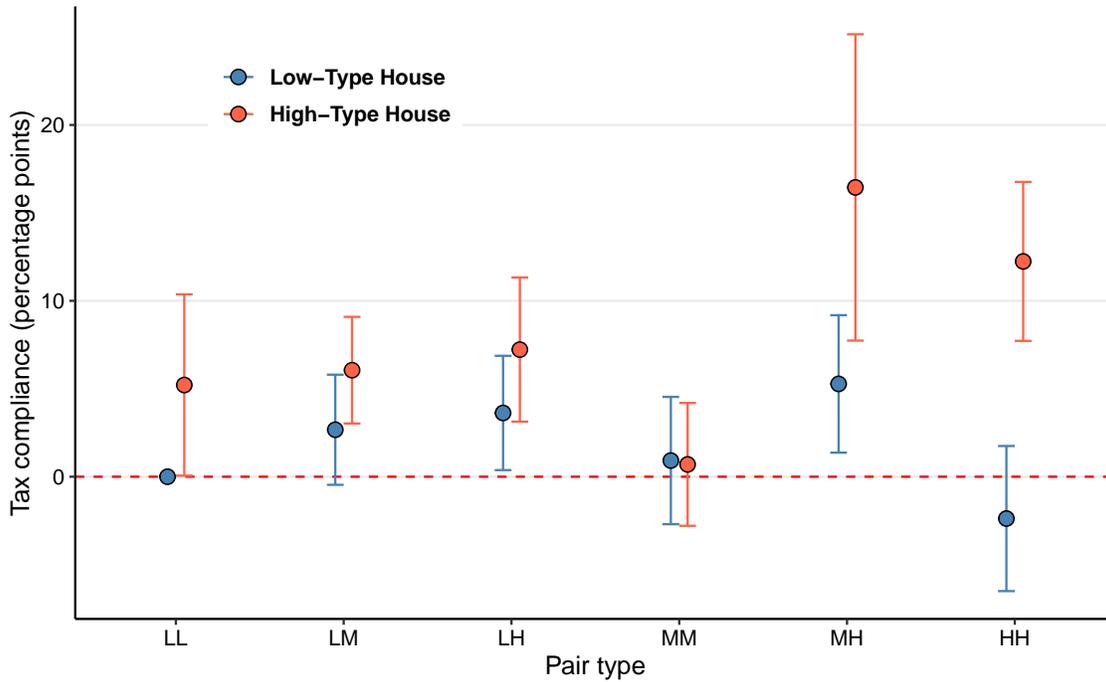
Notes: This figure shows the assignment function from two alternative counterfactual optimal assignment mechanisms in comparison to the status quo assignment. Panel A shows the collector-to-household-only counterfactual optimal assignment. Panel B shows the collector-to-collector-only counterfactual optimal assignment. In both graphs, each bar represents the probability of each match type under the optimal (red) and status quo (blue) assignment functions. The first 6 bars show the assignment functions with matches involving low-type households. The 6 subsequent bars show the assignment functions with matches involving high-type households. We discuss these results in Section 8.1.

Table A5: Effects of the Optimal Assignment: Compliance and Revenues – Standard Vs Bootstrapped Standard Errors

	Household Types: Household Propensity to Pay			
	Collector Types: Fixed Effects Model			
	Standard Errors: Clustered at Neighborhood-Level		Standard Errors: Bayesian Bootstrap	
	Tax Compliance (in percentage points) (1)	Tax Revenue (in Congolese Francs) (2)	Tax Compliance (in percentage points) (3)	Tax Revenue (in Congolese Francs) (4)
Optimal Assignment	2.941** (1.239) [0.024]	54.471* (30.52) [0.074]	2.941* (1.682) [0.080]	54.471 (37.872) [0.150]
Collector-to-Collector Only	1.294 (0.947) [0.172]	21.444 (21.675) [0.322]	1.294 (1.308) [0.323]	21.444 (30.373) [0.480]
Collector-to-Household Only	0.837*** (0.312) [0.007]	17.156** (8.520) [0.044]	0.837** (0.384) [0.029]	17.156* (9.929) [0.084]
Mean	8.000	206.213	8.000	206.213
Observations (Holdout Sample)	11,732	11,732	11,732	11,732
Observations (Analysis Sample)	6,904	6,904	6,904	6,904

Notes: This table shows the impact of the counterfactual optimal assignment policy in comparison to the status quo (random) assignment. Columns 1 and 3 show results for probability of compliance, i.e., a dummy indicating whether households paid the property tax (multiplied by 100). The point estimates should be interpreted as percentage point changes. Columns 2 and 4 show results for average tax revenue per household in Congolese Francs. All columns present results when collector types are estimated using a fixed effects model as described in Section 6.2. Each row shows counterfactual results for a different optimal assignment. The first row presents results when optimizing on both the collector-to-household and the collector-to-collector dimension. The second and third rows show results when only optimizing the collector-to-household and the collector-to-collector dimension of the assignment, respectively. We report conventional clustered standard errors at the neighborhood level in Columns 1 and 2. In Columns 3 and 4, we instead report standard errors from Bayesian bootstrap re-sampling at the neighborhood level (100 samples) in parenthesis while the corresponding p-values are presented in brackets ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$). The average tax compliance (Columns 1 and 3) and tax revenue (Columns 2 and 4) is reported at the bottom of the table. We also report the size of the holdout and analysis sample. We discuss these results in Section 6.4 and 8.1.

Figure A14: Tax Compliance By Collector and Household Types– Three Types of Collectors



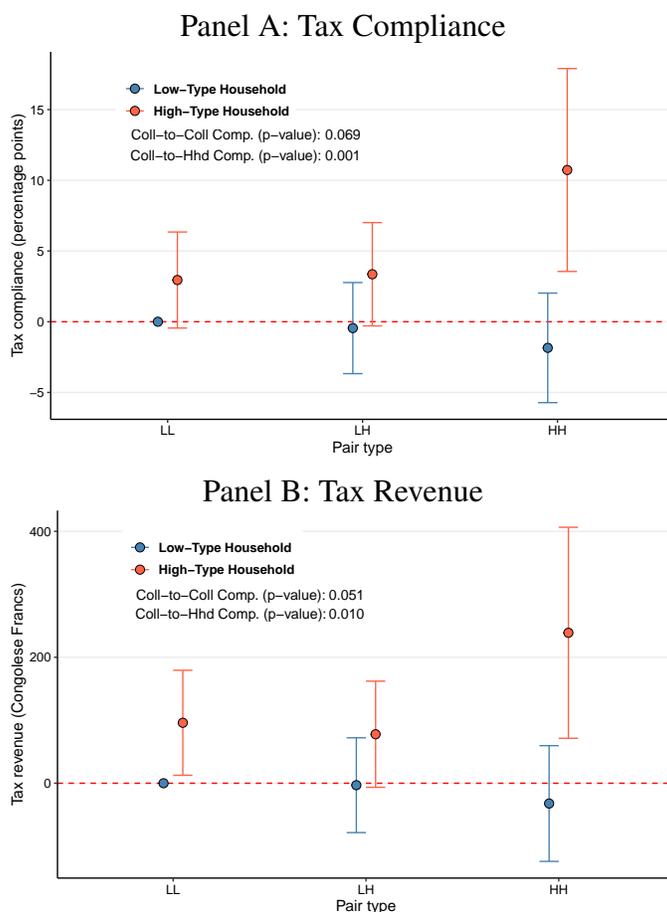
Notes: This figure shows the estimates of average tax compliance when assigned to different types of collector pairs (low-low or LL, low-medium or LM, low-high or LH, medium-medium or MM, medium-high or MH, high-high or HH) by households' type (low or high). The x-axis shows the six different types of collector pairs: LL, LM, LH, MM, MH, HH. The y-axis captures tax compliance probability for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from equation (7) with tax compliance as the outcome and when including eleven dummies: (H, H, h) , (H, H, l) , (M, H, h) , (M, H, l) , (M, M, h) , (M, M, l) , (L, H, h) , (L, H, l) , (L, M, h) , (L, M, l) , and (L, L, h) (the excluded category is (L, L, l)) reflecting matches of households of type $V = l, h$ and collectors of type $A = L, M, H$. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We discuss these results in Section 8.2.

Table A6: Effects of the Optimal Assignment on Tax Compliance and Revenues – Three Types of Collectors

	Household Types: Household Propensity to Pay			
	Collector Types: Fixed Effects Model		Collector Types: Coll. Chars. Model	
	Tax Compliance (in percentage points) (1)	Tax Revenue (in Congolese Francs) (2)	Tax Compliance (in percentage points) (3)	Tax Revenue (in Congolese Francs) (4)
Optimal Assignment	4.411** (2.062) [0.032]	62.212 (48.797) [0.202]	3.296 (2.135) [0.123]	49.675 (44.713) [0.267]
Collector-to-Collector Only	3.105** (1.542) [0.044]	73.921* (39.767) [0.063]	1.592 (1.741) [0.360]	36.288 (37.677) [0.335]
Collector-to-Household Only	1.345*** (0.335) [0.000]	38.887*** (9.731) [0.000]	1.271*** (0.354) [0.000]	30.219*** (8.498) [0.000]
Mean	8.000	206.213	8.000	206.213
Observations (Holdout Sample)	11,732	11,732	11,732	11,732
Observations (Analysis Sample)	6,904	6,904	6,904	6,904

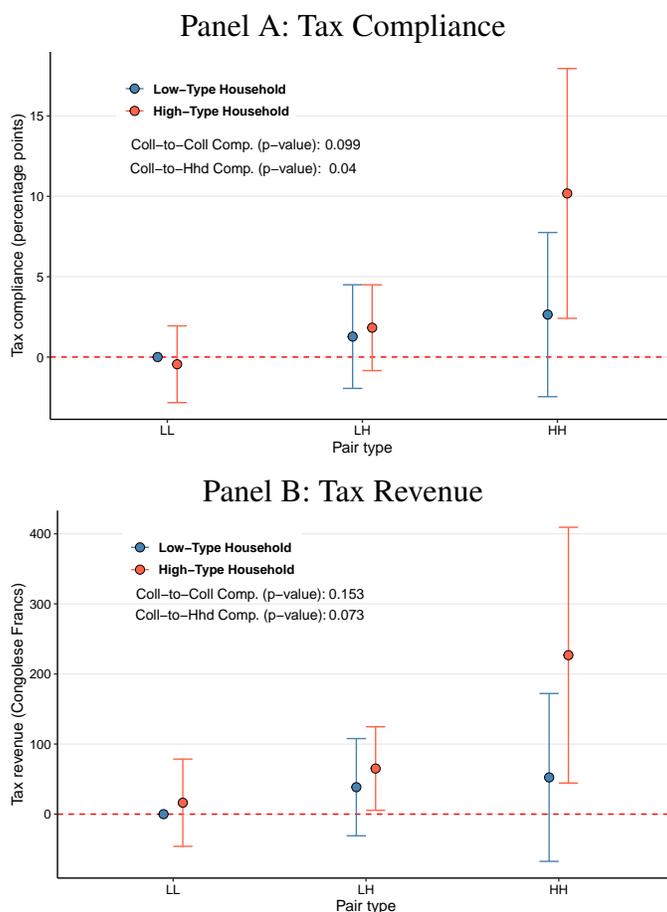
Notes: This table shows the impact of the counterfactual optimal assignment policy with three types of tax collectors (low or L, medium or M, high or H), relative to the status quo (random) assignment. Columns 1 and 3 show results for probability of compliance, i.e., a dummy indicating whether households paid the property taxes (multiplied by 100). The point estimates should be interpreted as percentage point changes. Columns 2 and 4 show results for average tax revenue per household in Congolese Francs. Columns 1–2 present results when collectors’ types are estimated using a fixed effects model as described in Section 6.2. Columns 3–4 show results when collectors’ types are estimated from tax collectors’ characteristics as described in Section 8.2. Each row represents a counterfactual for a different optimal assignment. The first row presents results when optimizing on both the collector-to-household and the collector-to-collector dimension. The second and third rows show results when only optimizing the collector-to-collector and the collector-to-household dimension of the assignment, respectively. Standard errors are clustered at the neighborhood level and presented in parenthesis while the corresponding p-values are presented in brackets ($* = p < 0.1$, $** = p < 0.05$, $*** = p < 0.01$). The average tax compliance (Columns 1 and 3) and tax revenue (Columns 2 and 4) is reported at the bottom of the table. We also report the size of the holdout and analysis sample. We discuss these results in Section 8.2.

Figure A15: Tax Compliance and Revenue By Collector and Household Types – Collectors’ Type: Collector Characteristics Model



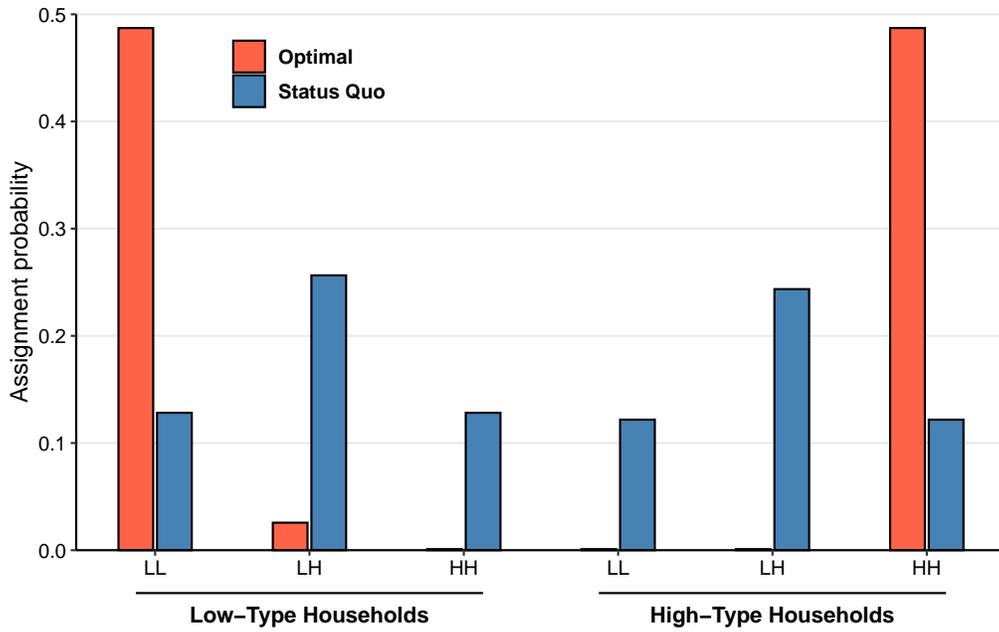
Notes: This figure shows the estimates of average tax compliance when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households’ type (low or high). Collectors’ types are estimated from tax collectors’ characteristics as described in Section 8.2. The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures the tax compliance probability (Panel A) or tax revenue (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from equation (7) with tax compliance as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 8.2.

Figure A16: Tax Compliance and Revenue By Collector and Household Types – Households’ Type: Households Characteristics Model



Notes: This figure shows the estimates of average tax compliance when assigned to different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households’ type (low or high). Collectors’ types are estimated from the fixed effects model described in Section 6.2 and household types are estimated using household characteristics as described in Section 8.2. The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis captures the tax compliance probability (Panel A) or tax revenue (Panel B) for different types of collector pairs and households. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The point estimates are estimated from equation (7) with tax compliance as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test that each outcome, denoted Y , exhibits increasing differences in collector type for high-type households (we test $H_1: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] > 0$ against $H_0: [Y(H, H, h) - Y(L, H, h)] - [Y(H, L, h) - Y(L, L, h)] \leq 0$) and increasing differences in collector and household type (we test $H_1: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] > 0$ against $H_0: [Y(H, H, h) - Y(L, L, h)] - [Y(H, H, l) - Y(L, L, l)] \leq 0$). We discuss these results in Section 8.2.

Figure A17: Optimal Vs. Status Quo Assignments – Households’ Type: Households Characteristics Model



Notes: This figure shows the optimal and the status quo assignment functions. Each bar represents the probability of each match type under the optimal (red) and status quo (blue) assignment functions. The first 6 bars show the assignment functions with matches involving low-type households. The 6 subsequent bars show the assignment functions with matches involving high-type households. We discuss these results in Section 8.2.

Table A7: Effects of the Optimal Assignment on Compliance and Revenues – Household Types: Households Characteristics Model

	Collector Types: Fixed Effects Model			
	Household Types: Household Propensity to Pay		Household Types: Household Chars. Model	
	Tax Compliance (in percentage points) (1)	Tax Revenue (in Congolese Francs) (2)	Tax Compliance (in percentage points) (3)	Tax Revenue (in Congolese Francs) (4)
Optimal Assignment	2.941** (1.239) [0.024]	54.471* (30.52) [0.074]	2.759* (1.504) [0.067]	50.417 (34.836) [0.148]
Collector-to-Collector Only	1.294 (0.947) [0.172]	21.444 (21.675) [0.322]	0.773 (0.770) [0.315]	11.085 (17.251) [0.520]
Collector-to-Household Only	0.837*** (0.312) [0.007]	17.156** (8.520) [0.044]	1.000* (0.572) [0.080]	19.828 (13.622) [0.146]
Mean	8.000	206.213	8.000	206.213
Observations (Holdout Sample)	11,732	11,732	11,732	11,732
Observations (Analysis Sample)	6,904	6,904	7,866	7,866

Notes: This table shows the impact of the counterfactual optimal assignment policy in comparison to the status quo (random) assignment. Columns 1 and 3 show results for probability of compliance, i.e., a dummy indicating whether households paid the property taxes (multiplied by 100). The point estimates should be interpreted as percentage point changes. Columns 2 and 4 show results for average tax revenue per household in Congolese Francs. All columns present results when collectors' types are estimated using a fixed effects model as described in Section 6.2. In Columns 1–2, household types are defined using chiefs' estimates of household type as described in Section 6.1. The results are therefore identical to Columns 1–2 of Table 1. In Columns 3–4, household types are estimated using household characteristics as described in Section 8.2. Each row represents a counterfactual for a different optimal assignment. The first row presents results when optimizing on both the collector-to-household and the collector-to-collector dimension. The second and third rows show results when only optimizing the collector-to-collector and the collector-to-household dimension of the assignment, respectively. Standard errors are clustered at the neighborhood level and presented in parenthesis while the corresponding p-values are presented in brackets ($* = p < 0.1$, $** = p < 0.05$, $*** = p < 0.01$). The average tax compliance (Columns 1 and 3) and tax revenue (Columns 2 and 4) is reported at the bottom of the table. We also report the size of the holdout and analysis sample. We discuss these results in Section 8.1 and 8.2.

Table A8: Effects of the Optimal Assignment on Tax Compliance and Revenue – Objective: Tax Revenue Maximization

	Household Types: Household Propensity to Pay			
	Objective: Tax Revenue Maximization		Objective: Tax Revenue Net of Bribes Maximization	
	Tax Revenue	Bribe Payments	Tax Revenue	Bribe Payments
	(in Congolese Francs)	(in Congolese Francs)	(in Congolese Francs)	(in Congolese Francs)
	(1)	(2)	(3)	(4)
Optimal Assignment	61.014** (26.179) [0.020]	14.902 (12.447) [0.231]	37.256 (29.925) [0.213]	-0.404 (4.783) [0.933]
Collector-to-Collector Only	36.530* (21.871) [0.095]	5.734 (7.101) [0.419]	38.225* (23.195) [0.099]	4.197 (5.747) [0.465]
Collector-to-Household Only	15.631* (8.208) [0.057]	2.206 (3.188) [0.489]	18.669* (10.138) [0.066]	5.596** (2.757) [0.042]
Mean	206.213	30.431	206.213	30.431
Observations (Holdout Sample)	11,732	11,732	7,694	7,694
Observations (Analysis Sample)	6,904	4,691	6,904	4,691

Notes: This table shows the impact of the counterfactual optimal assignment policy, in the case where the government aims at maximizing tax revenue or tax revenue net of bribes, relative to the status quo (random) assignment. Columns 1 and 3 show results for average tax revenue per household in Congolese Francs. Columns 2 and 4 show results for average bribe payments per household in Congolese Francs, drawn from midline surveys. All columns present results when collector types are estimated using a fixed effects model as described in Section 6.2 and household types are defined using chiefs' estimates of household type as described in Section 6.1. Each row represents a counterfactual for a different optimal assignment. The first row presents results when optimizing on both the collector-to-household and the collector-to-collector dimension. The second and third rows show results when only optimizing the collector-to-collector and the collector-to-household dimension of the assignment, respectively. Standard errors are clustered at the neighborhood level and presented in parenthesis while the corresponding p-values are presented in brackets ($* = p < 0.1$, $** = p < 0.05$, $*** = p < 0.01$). The average tax revenue (Columns 1 and 3) and bribe amount (Columns 2 and 4) is reported at the bottom of the table. We also report the size of the holdout and analysis sample. We discuss these results in Section 8.2.

Table A9: Effects of the Neighborhood-Level Optimal Assignment: Compliance and Revenues

	Neighborhood Type: Share of High-Type Households		Neighborhood Type: Number of High-Type Households	
	Tax Compliance (in percentage points) (1)	Tax Revenue (in Congolese Francs) (2)	Tax Compliance (in percentage points) (3)	Tax Revenue (in Congolese Francs) (4)
Optimal Assignment	1.764* (1.023) [0.085]	30.667 (23.572) [0.193]	2.906** (1.472) [0.048]	56.181* (34.232) [0.100]
Collector-to-Collector Only	1.159 (0.915) [0.205]	18.606 (20.901) [0.373]	2.802* (1.465) [0.056]	54.250 (33.994) [0.111]
Collector-to-Household Only	0.260*** (0.099) [0.009]	5.315** (2.531) [0.036]	1.408*** (0.532) [0.008]	30.146** (12.749) [0.018]
Mean	8.000	206.213	8.000	206.213
Observations (Holdout Sample)	11,732	11,732	11,732	11,732
Observations (Analysis Sample)	6,904	6,904	6,904	6,904

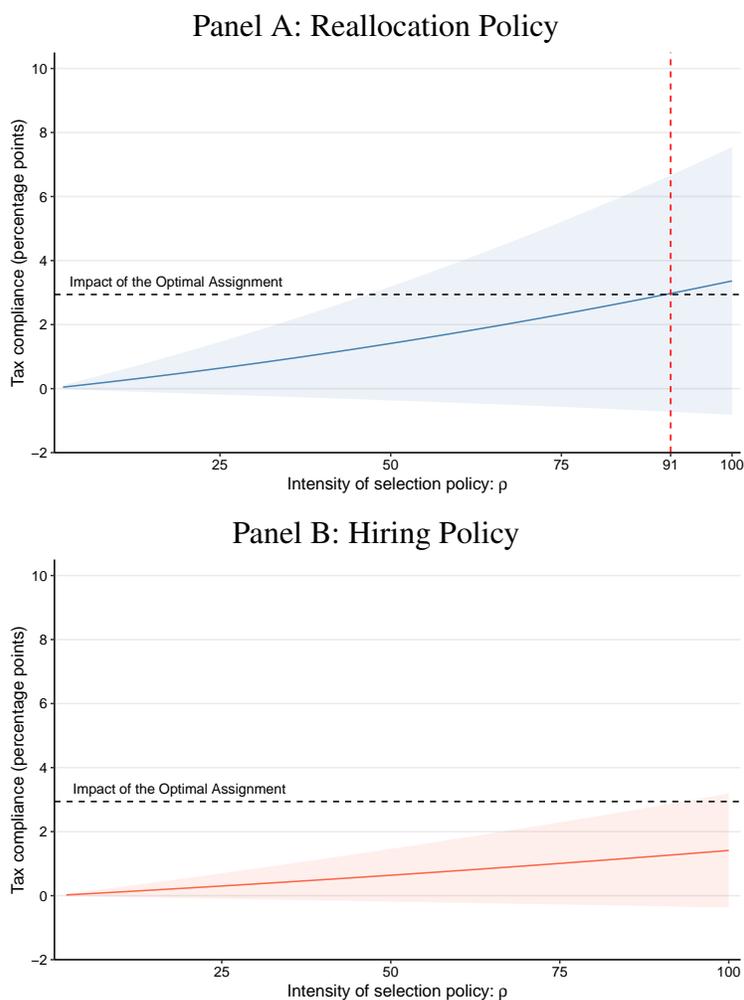
Notes: This table shows the impact of the neighborhood-level counterfactual optimal assignment policy in comparison to the status quo (random) assignment. Columns 1–2 assume that the government defines neighborhoods type based on the share of high and low type households. Columns 3–4 instead assume that the government defines neighborhood type based on the number of high and low type households. The coefficients in Columns 1 and 3 show the impact on tax compliance, i.e., a dummy indicating whether households paid the property taxes (multiplied by 100). The point estimates should be interpreted as percentage point changes. Columns 2 and 4 show results for average tax revenue per household in Congolese Francs. All the results use collector types estimated using a fixed effects model as described in Section 6.2 and property types are estimated as described in Section 6.1. Each row represents a counterfactual for a different optimal assignment. The first row presents results when optimizing on both the collector-to-household and the collector-to-collector dimension. The second and third rows show results when only optimizing the collector-to-collector and the collector-to-household dimension of the assignment, respectively. Standard errors are clustered at the neighborhood level and presented in parenthesis while the corresponding p-values are presented in brackets ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$). The average tax compliance (Columns 1 and 3) and tax revenue (Columns 2 and 4) is reported at the bottom of the table. We also report the size of the holdout and analysis sample. We discuss these results in Section 8.2.

Table A10: Effects of the Optimal Assignment on Tax Compliance and Revenue – Robustness: Inference on Winners

	Objective: Compliance Maximization		Objective: Revenue Maximization	
	Tax Compliance (in percentage points) (1)	Tax Revenue (in Congolese Francs) (2)	Tax Compliance (in percentage points) (3)	Tax Revenue (in Congolese Francs) (4)
Benchmark Estimator	2.941 [0.394–5.488]	54.471 [-5.361–114.302]	3.172 [0.773–5.570]	61.014 [9.703–112.325]
Conditional Estimator	2.897 [0.311–5.027]	51.229 [-18.562–103.222]	3.160 [0.890–5.138]	60.554 [10.653–103.063]
Hybrid Estimator	2.890 [0.324–5.053]	51.296 [-16.452–104.095]	3.162 [0.884–5.163]	60.592 [10.560–103.629]
Mean	8.000	206.213	8.000	206.213
Observations (Holdout Sample)	11,732	11,732	11,732	11,732
Observations (Analysis Sample)	6,904	6,904	6,904	6,904

Notes: This table provides estimates and 90% confidence intervals for the impact of the counterfactual optimal policy after accounting for possible over-fitting concerns associated with the “winner’s curse” problem (Andrews et al., 2021). We adapt Andrews et al. (2021) to our context, a non-discrete optimal assignment policy space, in several steps. First, the solution must lie at the intersection of three hyper-planes defined by the two linearly independent constraints in Problem 1 and the requirement that the distribution probabilities sum up to 1. Second, the Fundamental Theorem of Linear Programming (Dantzig, 1951) — which states that if an optimal solution exists, there exists an optimal solution consisting of extreme points on the policy space — allows us to select three points in this 3 dimensional space. We focus on the three solutions in the (finite) set of extreme points that are linearly independent and that yield the highest value when applied to the objective function. Row 1 provides our baseline estimates from Table 1 and Table A8. Rows 2 and 3 provide the conditional and hybrid estimators suggested by Andrews et al. (2021). Columns 1-2 examine the case in which the government seeks to maximize tax compliance, while Columns 3-4 examines the revenue maximization case. The average tax compliance (Columns 1 and 3) and tax revenue (Columns 2 and 4) is reported at the bottom of the table. We also report the size of the holdout and analysis sample. We discuss these results in Section 8.2.

Figure A18: Effects of Selection Policies when Collector Types are Estimated using Collectors' Characteristics



Notes: This figure shows the impact of the selection policies on the probability of tax compliance (y-axis). Selection policies involve reassigning $\rho\%$ (x-axis) of the assignments that a low-ability collector would receive under the status quo assignment to other collectors. Panel A shows the estimated effects of the *reallocation policy*, where the workload is re-assigned to existing high-ability collectors in the sample. Panel B shows the estimated effects of the *hiring policy*, where the workload is reassigned to newly hired collectors with types drawn uniformly from $\{L,H\}$. In both Panels, collector types are estimated from tax collectors' characteristics as described in Section 8.2. The shaded areas represent 95% confidence intervals. The dashed horizontal line indicates the counterfactual impact of the optimal assignment policy on tax compliance when collector types are estimated from tax collectors' characteristics as reported in Column 3 of Table 1. We discuss these results in Section 9.1.

Table A11: Effect of Collectors' Wage Increases

	Tax Compliance	Tax Revenue	Visit Indicator	Nb of Visits	Bribe Indicator	Bribe Amount
log. Wage	0.037** (0.015)	54.126** (25.113)	0.046 (0.030)	0.104** (0.049)	0.010 (0.007)	9.281 (8.017)
Mean	0.074	153.609	.415	0.546	0.016	1288.265
Elasticity	0.492	0.352	0.110	0.190	0.643	0.461
Observations	18,775	18,775	12,525	12,383	12,544	196
Tax Rate FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines treatment effects of the collectors' piece-rate wage on tax compliance, tax revenues, tax visits, and bribe payments. It reports the results of regressions of the log of the piece-rate wage on tax compliance (Columns 1), tax revenue (Columns 2), a post-registration visit indicator (Column 3), the number of post-registration visits (Column 4), an indicator for any bribe payment (Column 5), and the amount of bribe paid (Column 6). We discuss these results in Section 9.2.

Table A12: Effect of Enforcement Messages

	Tax Compliance			Tax Revenue (in CF)		
	(1)	(2)	(3)	(4)	(5)	(6)
Central Enforcement	0.014 (0.009)	0.016* (0.009)		32.837* (18.610)	36.510** (18.453)	
Local Enforcement	0.014 (0.009)	0.016* (0.009)		31.244* (18.723)	35.545* (18.783)	
Pooled Enforcement			0.016** (0.007)			36.038** (15.589)
Observations	2665	2665	2665	2665	2665	2665
Mean	0.029	0.029	0.029	57.671	57.671	57.671
FE: neighborhood	No	Yes	Yes	No	Yes	Yes

Notes: This table examines treatment effects of randomized tax letter enforcement messages on compliance and revenues. It reports estimates from a regression of tax compliance (Columns 1–3) and tax revenue (Columns 4–6) on treatment dummies for households assigned to enforcement messages on tax letters distributed during property registration. [Bergeron et al. \(2021\)](#) describe these tax letters and the message randomization. The excluded category is the control message in all regressions. Columns 2–3 and 5–6 introduce randomization stratum (neighborhood) fixed effects. Columns 3 and 6 pool households assigned to the *central enforcement* message and the *local enforcement* message. The data are restricted to the sample of 2,665 properties subject to randomized messages on tax letters, which were introduced toward the end of the tax campaign. We discuss these results in Section 9.2.

A2 Properties of the Optimal Assignment Function

A2.1 Uniqueness

The optimal assignment problem is a linear program. As a consequence its solutions are constrained to be in a convex set, implying that it has at least one solution (Luenberger, 1984). However, there might be more than one solution to the optimal assignment problem.¹ We follow Bhattacharya (2009) and assume uniqueness of the optimal assignment.

Assumption 1. *There exists a unique f^* that solves the Optimal Assignment Problem*

A2.2 Asymptotic Distribution Properties

The importance of the uniqueness assumption lies in the asymptotic properties of the optimal assignment and the ARE estimator (Bhattacharya, 2009). Two key results apply under the uniqueness assumption. First, our estimator is consistent for the optimal assignment function (f^* in Problem 1). Second, our estimator of the impact of the optimal assignment ARE is consistent.

These results are obtained if β identifies the average compliance function up to a constant. This can be obtained by assuming that the assignment is conditionally exogenous:

Assumption 2. $Y_h(c_1, c_2) \perp D_h(c_1, c_2) | X_{h,c_1,c_2,t}$

Where $D_h(c_1, c_2)$ is an indicator for match h, c_1, c_2 and $X_{h,c_1,c_2,t}$ is a vector of observable household and collector characteristics and time dummies. Assumption 2 requires that, conditional on observable characteristics, the status quo assignment is independent of potential compliance $Y_h(c_1, c_2)$.² In general matching problems, this assumption is enough to show that the ARE is identified (Graham et al., 2020b). Empirical evidence consistent with Assumption 2 are shown in Table A2 and described in Section 3.

Proposition 1 summarises the main properties of our key estimators.

Proposition 1. *Assume that $\sqrt{n}(\hat{\beta} - \beta) \xrightarrow{d} \mathcal{N}(0, \Sigma)$ and Assumptions 1–2 hold. Then:*

1. \hat{f}^* is consistent to f^* .
2. \widehat{ARE} is consistent to ARE.
3. $\sqrt{n}(\widehat{ARE} - ARE) \xrightarrow{d} \mathcal{N}(0, (f^* - f^{SQ})' \Sigma (f^* - f^{SQ}))$

¹For example, if Y is separable in a_1, a_2 , and v , all feasible assignment functions yield the same average compliance, and the solution is not unique.

²If the assignment were to depend on some unobservable characteristics, we would not be able to identify the expected compliance for counterfactual matches (i.e., those we do not observe in the data). This is critical given that the optimal assignment function requires consistently estimating the expected output for pairs of collectors and households that we do not observe in the data conditional exclusively on their observable types.

The third result states that the sampling error of \hat{f}^* is asymptotically irrelevant for the estimation of ARE, which relies on $\hat{f}^* \xrightarrow{p} f^*$ at a faster rate than \sqrt{n} (Bhattacharya, 2009).

Proof:

1. It is exactly the same as proof of Bhattacharya (2009)'s Proposition 1.

2. We denote vectors in bold and scalars in normal font. $ARE = \mathbf{Y}(\mathbf{f}^* - \mathbf{f}^{SQ})$. Under Assumptions 2 and 3, $\beta + k\mathbf{1} = \mathbf{Y}$, with k a constant and $\mathbf{1}$ a vector of 1's. Thus,

$$\begin{aligned} ARE &= \mathbf{Y}(\mathbf{f}^* - \mathbf{f}^{SQ}) \\ &= (\beta + k\mathbf{1})(\mathbf{f}^* - \mathbf{f}^{SQ}) \\ &= \beta(\mathbf{f}^* - \mathbf{f}^{SQ}) + k\mathbf{1}\mathbf{f}^* - k\mathbf{1}\mathbf{f}^{SQ} \end{aligned}$$

Since \mathbf{f}^* and \mathbf{f}^{SQ} are probability mass functions, they sum to 1 and $k\mathbf{1}(\mathbf{f}^* - \mathbf{f}^{SQ}) = 0$. Thus, $ARE = \beta(\mathbf{f}^* - \mathbf{f}^{SQ})$. As a result, showing that $\widehat{ARE} \xrightarrow{p} ARE$ is equivalent to showing that

$$\widehat{\beta}(\widehat{\mathbf{f}}^* - \mathbf{f}^{SQ}) \xrightarrow{p} \beta(\mathbf{f}^* - \mathbf{f}^{SQ})$$

which results from $\widehat{\mathbf{f}}^* \xrightarrow{p} \mathbf{f}^*$ (Proposition 1), $\widehat{\beta}$ converging in probability to β (by assumption), and the fact that the limit of the multiplications of two objects is the multiplication of the limit (in probability) of these two objects.

3. The proof is a particular case (assuming uniqueness of the solution of Problem 1) of Bhattacharya (2009). We show the proof for this simpler case and we drop the bold notation for vectors since there is no ambiguity here and by definition

$$\sqrt{n} \left(\widehat{ARE} - ARE \right) = \sqrt{n} \left(\widehat{\beta}\widehat{\mathbf{f}}^* - \beta\mathbf{f}^* \right) - \sqrt{n} \left(\widehat{\beta}\widehat{\mathbf{f}}^{SQ} - \beta\mathbf{f}^{SQ} \right)$$

The first term can be written as

$$\sqrt{n} \left(\widehat{\beta}\widehat{\mathbf{f}}^* - \beta\mathbf{f}^* \right) = \mathbf{f}^* \sqrt{n} \left(\widehat{\beta} - \beta \right) 1_{[\widehat{\mathbf{f}}^* = \mathbf{f}^*]} + \sqrt{n} \left(\widehat{\beta} - \beta \right) \widehat{\mathbf{f}}^* 1_{[\widehat{\mathbf{f}}^* \neq \mathbf{f}^*]} + \sqrt{n}\beta \left(\widehat{\mathbf{f}}^* - \mathbf{f}^* \right) 1_{[\widehat{\mathbf{f}}^* \neq \mathbf{f}^*]}$$

where $\sqrt{n} \left(\widehat{\beta} - \beta \right) \widehat{\mathbf{f}}^* 1_{[\widehat{\mathbf{f}}^* \neq \mathbf{f}^*]}$, is $o_p(1)$ (i.e., converges in probability to zero) since $\widehat{\mathbf{f}}^*$ is bounded (it is a probability mass function), and $\left(\widehat{\beta} - \beta \right) \widehat{\mathbf{f}}^*$ and $\sqrt{n} 1_{[\widehat{\mathbf{f}}^* \neq \mathbf{f}^*]}$ are $o_p(1)$ (see Corollary 1 in Bhattacharya (2009)). Similarly, $\sqrt{n}\beta \left(\widehat{\mathbf{f}}^* - \mathbf{f}^* \right) 1_{[\widehat{\mathbf{f}}^* \neq \mathbf{f}^*]}$ is also $o_p(1)$ since $\widehat{\mathbf{f}}^* - \mathbf{f}^*$ is bounded (both are probability mass functions), β is not a random vector (and is finite), and $\beta \left(\widehat{\mathbf{f}}^* - \mathbf{f}^* \right)$ and $\sqrt{n} 1_{[\widehat{\mathbf{f}}^* \neq \mathbf{f}^*]}$ are $o_p(1)$ (see Corollary 1 in Bhattacharya (2009)). Ignoring $o_p(1)$ terms, we thus have

$$\sqrt{n} \left(\widehat{\beta}\widehat{\mathbf{f}}^* - \beta\mathbf{f}^* \right) = \mathbf{f}^* \sqrt{n} \left(\widehat{\beta} - \beta \right) 1_{[\widehat{\mathbf{f}}^* = \mathbf{f}^*]}$$

By Item 1 of Proposition 1, $1_{[\widehat{\mathbf{f}}^* = \mathbf{f}^*]}$ converges in probability to 1 and can be ignored when

deriving the asymptotic distribution. Therefore, $\sqrt{n} \left(\widehat{\beta} \widehat{f}^* - \beta f^* \right) \xrightarrow{d} \mathcal{N}(0, (f^*)' \Sigma f^*)$.

The second term can be written as

$$\sqrt{n} \left(\widehat{\beta} f^{SQ} - \beta f^{SQ} \right) = f^{SQ} \sqrt{n} \left(\widehat{\beta} - \beta \right)$$

and by definition $\sqrt{n} \left(\widehat{\beta} - \beta \right) \xrightarrow{d} \mathcal{N}(0, \Sigma)$, so $\sqrt{n} \left(\widehat{\beta} f^{SQ} - \beta f^{SQ} \right) \xrightarrow{d} \mathcal{N}(0, (f^{SQ})' \Sigma f^{SQ})$.

Combining these two results, we have $\sqrt{n} \left(\widehat{ARE} - ARE \right) = \sqrt{n} \left(\widehat{\beta} \widehat{f}^* - \beta f^* \right) - \sqrt{n} \left(\widehat{\beta} \widehat{f}^{SQ} - \beta f^{SQ} \right)$, so $\sqrt{n} \left(\widehat{ARE} - ARE \right) \xrightarrow{d} \mathcal{N}(0, (f^* - f^{SQ})' \Sigma (f^* - f^{SQ}))$ \square .

A3 Optimal Number of Collector Types

We rely on unsupervised machine learning methods to shed light on the optimal number of collector types in our context. Specifically, we apply several clustering validation methods to identify the optimal number of collector types for k-means clustering (Lloyd, 1982). We use these methods in a collector-level dataset containing the average (*i*) tax compliance (i.e., the fraction of owners who paid the property tax), (*ii*) tax revenue (i.e., the average amount of property taxes paid per owner), (*iii*) extensive margin tax visits (i.e., the fraction of property owners visited), and (*iv*) intensive margin tax visits (i.e., the number of tax visits per property owner). For each collector, measures (*i*)–(*iv*) are computed across all neighborhoods assigned to a collector during the 2018 property tax campaign.

One of the most popular cluster optimization methods is the “elbow method” (Thorndike, 1953). It involves running k-means clustering and calculating the sum of squared errors (SSE) for a range of values of k. The SSE can be defined as:

$$SSE = \sum_{j=1}^k \sum_{i \in C_j} (x(i) - \bar{x}_j)^2$$

where $x(i) - \bar{x}_j$ is the distance between point i and \bar{x}_j , the predicted center of point i ’s cluster, C_j . The SSE measures the sum of the squared distances between each observation and the predicted cluster center. The optimal number of clusters is given by the “elbow” of the relationship between the SSE and the number of clusters k. The optimal number of collector types — i.e., the “elbow” for the collector-level data — appears to be equal to three for tax compliance and revenue (Figure A19, Panel A1) and two for extensive and intensive margin tax visits (Figure A19, Panel A2).

The “silhouette method” (Rousseeuw, 1987) involves running k-means clustering and calculating the silhouette coefficient for a range of values of k. The silhouette coefficient of observation i is defined as:

$$S(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

where $b(i)$ is the smallest average distance of point i to all points in any cluster and $a(i)$ is the average distance of i from all other points in its cluster. The silhouette value of point i measures how similar point i is to its own cluster relative to other clusters. The silhouette coefficient of the dataset is the average of the silhouette coefficient of the individual points in the data. The optimal number of clusters according to the silhouette method is then given by the global maximum of the silhouette coefficient. According to the silhouette method, the optimal number of collector types is equal to two when focusing on tax compliance and revenue (Figure A19, Panel B1) or intensive and extensive margin tax visits (Figure A19, Panel B2).

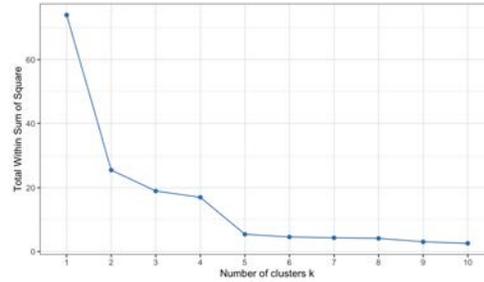
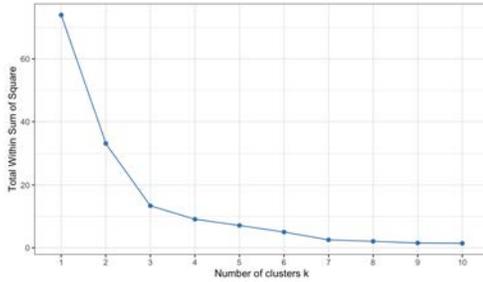
Additionally, we compute the optimal number of clusters for 30 indices that aim at identifying the optimal number of clusters for k-means clustering using the *NbClust* R package. Charrad et al. (2014) provides the list of 30 indices used by the *NbClust* package. Across these indices, the number of collector types that appears to be most frequently optimal is two for both for tax (Figure A19, Panel C1) and visits (Figure A19, Panel C2) outcomes.

Figure A19: Optimal Number of Collector Types

Panel A: Elbow Method

A1: Tax Outcomes

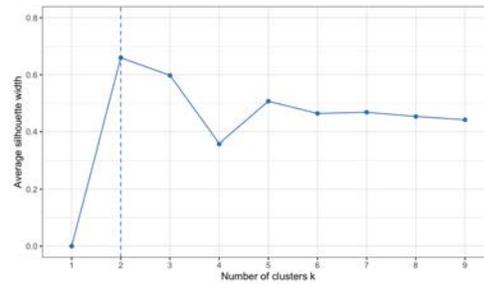
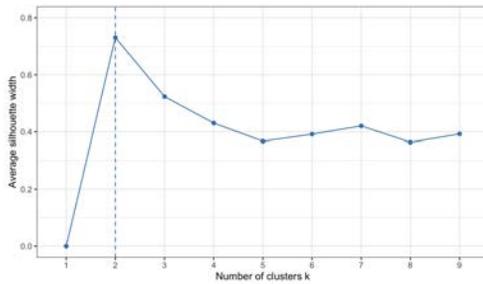
A2: Visit Outcomes



Panel B: Silhouette Method

B1: Tax Outcomes

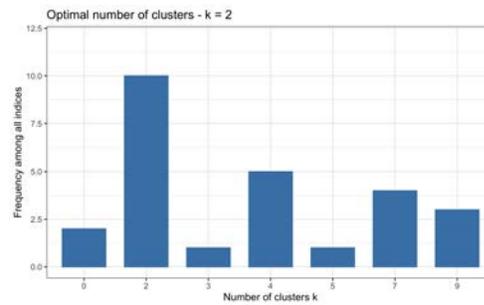
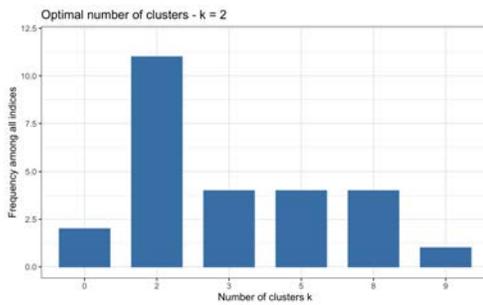
B2: Visit Outcomes



Panel C: 30 Methods

C1: Tax Outcomes

C2: Visit Outcomes



Notes: This figure reports the optimal number of collector types for k-means clustering using several methods. Panel A presents the results of the “elbow method” by reporting the sum of squared errors (y-axis) for different number of types (x-axis). Panel B presents the results of the “silhouette method” by showing the silhouette coefficient (y-axis) for different number of types (x-axis). Panel C presents the optimal number of types according to the 30 methods used by the *NbClust* package (Charrad et al., 2014). It also specifies the optimal number of types that arose with the highest frequency across the 30 methods. Panels A1, B1, and C1 present results when considering average tax compliance and revenue by collector as the outcome. Panels A2, B2, and C2 present results when considering extensive and intensive margin average tax visits as the outcome. We discuss these results in Section 6.2.

A4 Monte Carlo Simulations

This section uses Monte Carlo simulations to evaluate to what extent potential misspecifications of the econometric model in equation (6) affect the accuracy of the categorization of tax collectors as high or low type when using the approach described in Section 6.2.

For each Monte Carlo simulation, we report results for 1,000 simulated datasets. Each simulated dataset mimics our tax data structure. First, we assume that 34 tax collectors are involved in the tax campaign. We also assume that we know each collector’s “true type” and that there 17 low-type and 17 high-type collectors. Second, we assume that tax collectors are randomly assigned to a new teammate and randomly assigned to work in two neighborhoods every month. We also assume that this monthly reassignment happens over six months (the duration of the tax campaign), thus resulting in 204 neighborhoods per simulated dataset. We evaluate several families of distributions to simulate neighborhood-level tax compliance from: Normal, Uniform, Exponential, Logistic, Beta, Log-Normal, and Gamma. According to distribution tests (see Figure A20 for the Cullen and Frey (1999) plot, also known as the Pearson plot), the distribution of tax compliance at the neighborhood level might belong to the Beta, Gamma, or Log-Normal distribution, and we perform separate Monte Carlo simulations for these three families of distribution.

We first consider simulations that assume that the average tax compliance function exhibits non-linearities in collector type (i.e., the econometric model in equation (6) is misspecified). In our context the average compliance function exhibits complementarities in collector types (Figure 1) and we can therefore draw from the distribution — within a given family distributions (Beta, Gamma, Log-Normal) — that fits the neighborhood-level tax compliance data best for each type of collector pair ($L-L$, $L-H$, $H-H$), which we identify using moment matching estimation. We then construct a household-level simulated dataset by assuming that each neighborhood comprises 127 households (the average number of households per neighborhood in the data) and by creating an individual-level tax compliance indicator such that for each neighborhood, the average tax compliance matches the compliance in the neighborhood-level simulation.

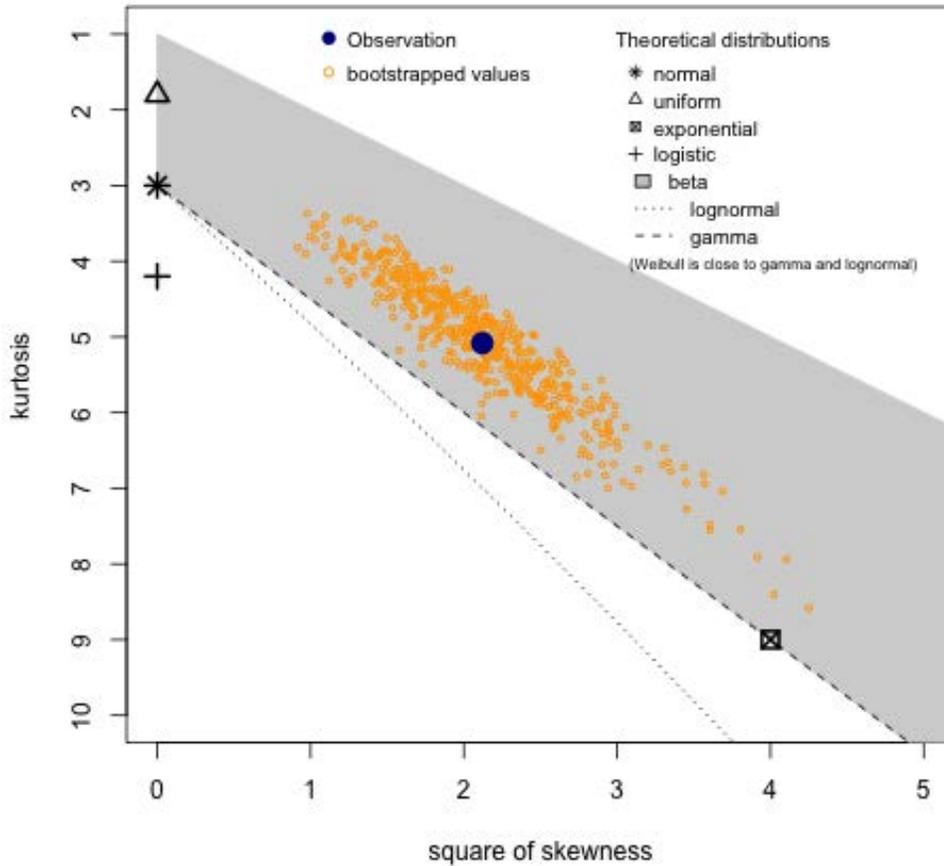
We then turn to simulations that assume that the average tax compliance function is linear in collector type (i.e., the econometric model in equation (6) is not misspecified). For $L-L$ and $H-H$ collector pairs, we simulate the neighborhood-level tax compliance from the distribution — within a given family of distribution (Beta, Gamma, Log-Normal) — that fits the neighborhood-level tax compliance data best for each type of collector pair ($L-L$, $L-H$, $H-H$), which we identify using moment matching estimation. To obtain linearity in collector type, we simulate the neighborhood-level tax compliance for $L-H$ collector by identifying and sampling from the distribution — within a given family of distribution (Beta, Gamma, Log-Normal) — that has a mean equal to the mid-point between the average tax compliance for $L-L$ and $H-H$ pairs and a variance equal to the sample variance in tax compliance across $L-H$ pairs. We then follow the procedure described above to construct a household-level simulated dataset from the neighborhood-level simulated dataset.

For each simulation, we estimate the $\hat{\alpha}_c$ coefficients in equation (6) and estimate the type of each collector using the rank of the $\hat{\alpha}_c$ coefficients, denoted $r_c = \text{rank}(\hat{\alpha}_c) / N_c$. The

17 collectors characterized by $r_c < 0.5$ (i.e., ranked below median) are deemed low-type, while the 17 collectors characterized by $r_c > 0.5$ (i.e., ranked above median) are deemed high-type. For each collector we can then compare their estimated type with their true type. More specifically, we report the percentage of collectors that are misclassified (i.e., whose estimated type differs from their true type) across the 1,000 simulated datasets constituting each Monte Carlo simulation.

We present the results in Table A13. Column 1 shows the percentage of collector misclassifications when assuming that the average tax compliance function exhibits complementarities in collector type (i.e., the econometric model in equation (6) is misspecified) when simulating data for each type of collector pairs using Beta (Panel A), Gamma (Panel B), or Log-Normal (Panel C) distributions. We find that the percentage of collectors that are misclassified is 18.771% when simulating data using Beta distributions, 18.518% when using Gamma distributions, and 18.040% when using Log-Normal distributions. Column 2 reports the percentage of collector misclassifications when we assume that the average tax compliance function is linear in collector type (i.e., the econometric model in equation (6) is not misspecified). We find that the percentage of collectors that are misclassified is 18.106% when simulating data for each type of collector pair using Beta distributions, 18.059% when using Gamma distributions, and 17.507% when using Log-Normal distributions. The results show that the percentage of collectors that are misclassified is always higher when the average tax compliance function exhibits complementarities in collector type than when it is linear. However, the corresponding difference in the percentage of collectors that are misclassified, reported in Column 3 of Table A13, is small: 0.665% when simulating data using Beta distributions, 0.459% when using Gamma distributions, and 0.533% when using Log-Normal distributions. The Monte Carlo simulation results thus provide reassuring evidence that potential misspecifications of the econometric model in equation (6) are unlikely to have large effects on the estimated collector types and on the estimated average tax compliance function and impact of implementing the optimal assignment.

Figure A20: Distribution Fitting – Skewness and Kurtosis Plot



Notes: This figure reports a skewness-kurtosis graph (Cullen and Frey, 1999) to help choose the distribution that fits the neighborhood-level tax compliance data best. The skewness and kurtosis of the neighborhood-level tax compliance data are represented by the blue circle while the orange hollow circles represent the skewness and kurtosis of 500 bootstrap samples of the neighborhood-level tax compliance data, drawn with replacement. The figure also shows the skewness and kurtosis of several candidate distributions: normal, uniform, exponential, logistic, beta, lognormal, gamma. Some of the distributions (uniform, normal, logistic, and exponential) have only one possible value for the skewness and kurtosis, while others (lognormal, gamma, and beta) have areas of possible values, presented as lines or areas. We discuss the results in Section 6.2.

Table A13: Monte Carlo Simulations

Outcome:	Percentage of Type misclassification (i.e., estimated type differs from true type)		
	Average tax compliance function exhibits complementarities in collector type (equation (6) is misspecified)	Average tax compliance function is linear in collector type (equation (6) is not misspecified)	Difference
	(1)	(2)	(3)
<i>Panel A: Beta Distribution Fit</i>			
Misclassification (in%)	18.771 % [18.356 %–19.186%]	18.106% [17.697%–18.515%]	0.665%
<i>Panel B: Gamma Distribution Fit</i>			
Misclassification (in%)	18.518% [18.105%–18.931%]	18.059% [17.650%–18.468%]	0.459%
<i>Panel C: Log-Normal Distribution Fit</i>			
Misclassification (in%)	18.040% [17.605–18.475]	17.507% [17.077–17.937]	0.533%

Notes: This table reports the Monte Carlo simulations results. For each Monte Carlo simulation, we report results for 1,000 simulated datasets. Each simulated dataset mimics our tax data: 34 tax collectors are randomly assigned to a new teammate and work in two randomly chosen neighborhoods every month throughout the six-month tax campaign. We assume that we know the collectors’ “true type”: 17 collectors are low-types and 17 are high-types. We simulate the neighborhood-level tax compliance data from several families of distributions: Beta distributions (Panel A), Gamma distributions (Panel B), and Log-Normal distributions (Panel C). Column 1 assumes that the average tax compliance function is non-linear in collector type (i.e., equation (6) is misspecified). In our context, the average tax compliance function exhibits complementarities in collector types and we can therefore draw from the distribution — within a given family of distribution (Beta, Gamma, Log-Normal) — that fits the neighborhood-level tax compliance data best for each type of collector pair ($L-L$, $L-H$, $H-H$), which we identify using moment matching estimation. Column 2 assumes that the average tax compliance function is linear in collector type (i.e., equation (6) is not misspecified). For $L-L$ and $H-H$ collector pairs, we simulated the neighborhood-level tax compliance from the distribution — within a given family of distribution (Beta, Gamma, Log-Normal) — that fits the neighborhood-level tax compliance data best for each type of collector pair. To obtain linearity in collector type, we simulate the neighborhood-level tax compliance for $L-H$ collector pairs by identifying and sampling from the distribution — within a given family of distribution (Beta, Gamma, Log-Normal) — that has a mean equal to the mid-point between the average tax compliance for $L-L$ and $H-H$ pairs and a variance equal to the sample variance for $L-H$ pairs. For each simulation, we estimate the $\hat{\alpha}_c$ coefficients using equation (6) and obtain the estimated collector types using their rank $r_c = \text{rank}(\hat{\alpha}_c/N_c)$. Collectors with $r_c > 0.5$ are deemed high-type, while collectors with $r_c < 0.5$ are deemed low-type. We report the percentage of collector that are misclassified, i.e., the percentage of tax collectors whose estimated type differs from their true type across the 1,000 simulations. We also report the corresponding 95 percent confidence intervals. Finally, Column 3 reports the difference in the percentage of misclassification between Columns 1 and Column 2. We discuss these results in Section 6.2.

A5 Estimation of the Average Tax Compliance Function

When estimating the average compliance function using Equation (7), the coefficients of interest are the $\beta(a_1, a_2, v)$ coefficients. Absent the campaign month dummies, these coefficients define the average tax compliance function $Y(a_1, a_2, v)$. When campaign month dummies are included, $\beta(a_1, a_2, v)$ should be interpreted as a convex combination of $Y(a_1, a_2, v, t) - Y(L, L, l, t)$, where $Y(\cdot)$ is a function of the campaign month t (Abadie and Cattaneo, 2018).³ To avoid this complication in the notation, we make the additional assumption that the average compliance function is separable in campaign month.

Assumption 3. *The average compliance function $Y(a_1, a_2, v, t) = Y(a_1, a_2, v) + \lambda(t)$, where the latter term is an arbitrary function of time.*

A6 Additional Mechanism Tests

This section builds on the discussion of skill and effort mechanisms in Section 7.2 by exploring several additional possible mechanisms that could explain that the average compliance function exhibits complementarities in collector and collector-household type.

Homophily. A possible explanation for complementarities in collector types is performance gains due H - H pairs' homophily. Tax collection could for example be enhanced for H - H pairs if high-type collectors have an easier time communicating due to they shared background. For homophily to explain complementarities in collector type, we would need to observe that (i) similarity between collectors in certain traits is associated with higher tax compliance, and (ii) benefits from homophily are more pronounced among H - H pairs.⁴

Regarding (i), we find relatively few traits for which similarity between tax collectors is associated with higher tax compliance. The only trait where homophily is associated with higher compliance is redistributive preferences (Table A14).⁵ Turning to (ii), we find little evidence that the relationship between collector similarity and tax collection is more pronounced for H - H pairs (relative to L - H and L - L pairs). Similarity in redistributive preferences, or other traits do not appear to differentially boost compliance for H - H pairs (Table A15).⁶ Overall, these results suggest that homophily is unlikely to explain the complementarity in collector and collector-household type documented in Section 7.1.

Social Incentives. A related but distinct explanation for complementarities in collector type stems from social incentives: i.e., being paired with a friend or person from the same social network might boost effort and lead to higher tax compliance differentially among high-type collectors (Ashraf and Bandiera, 2018). Social incentives could generate complementarities in collector type if pairing friends together in H - H pairs triggers “contagious

³Since the vector of coefficients β is only identified up to a constant, we define $\beta(L, L, l) = 0$.

⁴We restrict our analysis to high-type households since complementarities in collector types are only present among high-type households (Figure 1).

⁵By contrast, similarity in traits typically associated with homophily — gender, age, and education (Lang, 1986) — are not associated with higher team performance (Table A14, Panel A).

⁶The only exception is gender, for which similarity between teammates is correlated with larger increases in compliance for H - H pairs. However, less than 6% of collectors are female and thus the gains to gender similarity in collection are unlikely to explain the complementarities in collector type we observe.

enthusiasm,” while pairing friends together in *H-L* or *L-L* pairs triggers an averaging of productivity (conformity) or even generates “contagious malaise” (Bandiera et al., 2010).⁷

Although we do not directly observe social links, we examine several proxies, including whether collectors live in the same neighborhood of Kananga,⁸ started collecting taxes in the same campaign month,⁹ or share religious denomination.¹⁰ There is marginally significant evidence that *H-H* pairs conduct more tax visits when the collectors are from the same neighborhood but this does not translate into higher compliance (Table A16, Columns 1–2). Being in the same cohort appears to differentially suppress effort for *L-L* (marginally significant), but no clear differences emerge between *H-L* and *H-H* pairs (Columns 3–4). Finally, there is some evidence that church links boost effort and compliance among *H-L* pairs compared to *L-L* pairs, but this does not appear to be the case among *H-H* pairs (Columns 5–6).¹¹ Thus, while social incentives might matter for tax collection, they are unlikely to explain the complementarities in collector and collector-household type documented in Section 7.1.

Differential exemptions. Another potential explanation is that *L-L* and *L-H* pairs exempt more properties, which then translates into lower levels of tax payments. To investigate this issue, we add exempted properties to the data and estimate tax exemption status by collector and household type (Figure A10). Tax exemption does not appear to exhibit increasing differences in collector or collector-household type and is thus unlikely to explain the complementarities shown in section 7.1.

⁷Again, because complementarities in collector types are only present among high-type households (Figure 1), we restrict our analysis to high-type households.

⁸Which we proxy by the distance between the location of the collectors’ homes.

⁹Most collectors began at the start of the tax campaign, but some joined in later months.

¹⁰Churches are an important nexus of social activity in Kananga, and while we do not observe the precise church in which collectors pray, we do know their religious denomination (e.g., Catholic, Protestant, Pentecostal, etc.).

¹¹As we show in Table A14, for other potential proxies for social links (age, tribe, education, and income), similarity in these traits is not associated with higher tax collection performance for *H-H* collector pairs relative to *L-H* and *L-L* pairs when assigned to high-type households (Table A15).

Table A14: Tax Compliance by Similarity in Collector Characteristics

<i>Outcome: Tax Compliance</i>	Col. Similarity			Mean Char. (4)	Obs. (5)
	Coef. (1)	SE (2)	p-value (3)		
<u>Panel A: Demographics</u>					
Female	0.010	0.007	0.163	0.068	4,598
Age	0.014	0.017	0.434	30.527	4,480
Main Tribe	-0.020	0.017	0.251	0.223	4,598
Years of Education	-0.013	0.014	0.362	3.622	4,480
Math Score	0.009	0.011	0.405	-0.111	4,480
Literacy (Tshiluba)	-0.038**	0.016	0.023	0.018	4,480
Literacy (French)	0.005	0.017	0.750	-0.004	4,480
Monthly Income	-0.005	0.018	0.796	172.640	4,598
Possessions	0.002	0.011	0.888	1.731	4,480
Born in Kananga	-0.003	0.013	0.808	0.560	4,598
<u>Panel B: Trust in the Government</u>					
Trust Nat. Gov.	-0.008	0.012	0.514	2.895	4,598
Trust Prov. Gov.	0.007	0.009	0.450	2.920	4,598
Trust Tax Min.	-0.011	0.015	0.487	3.486	4,598
Index	0.009	0.014	0.499	0.065	4,598
<u>Panel C: Perceived Performance of Government</u>					
Prov. Gov. Capacity	0.001	0.013	0.925	0.414	4,598
Prov. Gov. Responsiveness	0.015	0.017	0.389	1.614	4,598
Prov. Gov. Performance	0.000	0.009	0.970	4.476	4,598
Prov. Gov. use of Funds	0.013	0.019	0.499	614.686	4,598
Index	-0.005	0.010	0.618	0.063	4,598
<u>Panel D: Government Connections</u>					
Job through Connections	-0.033***	0.012	0.007	0.285	3,934
Relative work for Prov. Gov.	0.003	0.010	0.237	0.006	4,598
Relative work for Tax Ministry	-0.010	0.013	0.467	0.285	4,598
Index	-0.012	0.013	0.329	0.034	4,480
<u>Panel E: Tax Morale</u>					
Taxes are Important	0.007	0.022	0.745	2.806	4,598
Work of Tax Min. is Important	0.005	0.016	0.757	3.796	4,598
Paid Taxes in the Past	0.002	0.010	0.868	2.095	4,598
Index	0.004	0.017	0.835	0.124	4,598
<u>Panel F: Redistributive Preferences</u>					
Imp. of Progressive Taxes	0.016	0.011	0.167	1.622	4,598
Imp. of Progressive Prop. Taxes	0.021**	0.008	1.179	0.004	4,598
Imp. to Tax Employed	-0.005	0.014	0.696	3.316	4,598
Imp. to Tax Owners	0.010	0.016	0.552	3.099	4,598
Imp. to Tax Owners w. title	-0.011	0.010	0.290	3.334	4,598
Index	0.032***	0.009	0.000	-0.292	4,598

Notes: This table reports the relationship between tax compliance and similarity in individual collectors' characteristics. We regress an indicator for tax compliance on the absolute value of a standardized measure of the difference between each collectors' characteristic reverse-coded to be increasing in similarity, controlling for the value of each individual collector's characteristic within the team. The sample used is only high-type households in the analysis sample. We focus on high-type households since complementarities in collector types are only present among high-type households (Figure 1). Columns 1–3 report the correlation coefficient, standard errors (clustered at the neighborhood level) and the corresponding p-values on the similarity measure ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$). Columns 4–5 reports the mean collector characteristics (the average within teams) and number of non-missing observations, respectively. Monthly income (Panel A) is in 1000's of Congolese Francs. We focus on high-type households since complementarities in collector types are only present among high-type households (Figure 1). The variables come from surveys with tax collectors described in Section 4. We discuss these results in Section 7.2.

Table A15: Tax Compliance by Pair Type and Proxies for Social Links By Collector Types

<i>Outcome: Tax Compliance</i>	Measure of Similarity in Collector Characteristics								
	Female (1)	Age (2)	Main Tribe (3)	Born in Kananga (4)	Years Edu. (5)	Mon. Income (6)	Govt Conn. Index (7)	Possess. (8)	Redist. Views Index (9)
Similarity X <i>H-H</i> Pair (I)	0.085*** (0.015)	-0.075 (0.055)	-0.057* (0.034)	0.022 (0.033)	0.034 (0.039)	-0.022 (0.037)	-0.064** (0.025)	-0.032 (0.038)	-0.002 (0.034)
Similarity X <i>L-H</i> Pair (II)	0.037*** (0.010)	-0.021 (0.019)	-0.026 (0.016)	0.021 (0.020)	0.005 (0.017)	0.015 (0.019)	0.002 (0.015)	0.003 (0.014)	0.014 (0.015)
Similarity (III)	-0.019** (0.007)	0.019 (0.015)	0.007 (0.010)	-0.010 (0.014)	-0.006 (0.009)	-0.026** (0.009)	0.003 (0.007)	-0.012* (0.007)	0.010 (0.008)
<i>H-H</i> Pair	0.121** (0.036)	0.093* (0.050)	0.122*** (0.034)	0.117** (0.036)	0.110*** (0.027)	0.100** (0.033)	0.117*** (0.030)	0.145*** (0.042)	0.118** (0.042)
<i>L-H</i> Pair	0.017 (0.017)	0.020 (0.019)	0.013 (0.017)	0.004 (0.021)	0.017 (0.020)	0.014 (0.017)	0.011 (0.018)	0.017 (0.017)	0.007 (0.018)
p-value Test: (I)=(II)	0.002	0.325	0.370	0.981	0.476	0.342	0.019	0.387	0.636
p-value Test: (I)=(III)	<0.001	0.124	0.096	0.441	0.333	0.925	0.022	0.630	.746
<i>L-L</i> Pair Mean	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072	0.072
Observations	4,598	4,480	4,598	4,598	4,480	4,598	4,480	4,480	4,598

Notes: This table reports the relationship between tax compliance and similarity in individual collectors' characteristics interacted with pair type. We regress an indicator for tax compliance on pair types interacted with the absolute value of a standardized measure of the difference between collectors' characteristics, reverse-coded to be increasing in similarity, for proxies of social links. Column titles list the measure of similarity used as a regressor and in interaction terms with pair type indicators. All regressions cluster standard errors at the neighborhood level ($* = p < 0.1$, $** = p < 0.05$, $*** = p < 0.01$). The sample used is only high-type households in the analysis sample. We focus on high-type households since complementarities in collector types are only present among high-type households (Figure 1). Test (I)=(II) reports the p-value from the test that correlation coefficients for Similarity X *H-H* Pair and Similarity X *L-H* Pair are equal. Test (I)=(III) reports the p-value from the test that correlation coefficients for Similarity X *H-H* Pair and Similarity are equal. The *L-L* Pair Mean reports average tax compliance within neighborhoods assigned *L-L* pairs. The variables come from surveys with tax collectors described in Section 4. We discuss these results in Section 7.2.

Table A16: Social Incentives: Collector Home Location, Cohort, and Church by Collector Type

	Measure of Similarity in Collector Characteristics					
	Collector Homes (proximity)		Collector Cohort (same)		Collector Church (same)	
	Compliance (1)	Visited (2)	Compliance (3)	Visited (4)	Compliance (5)	Visited (6)
Similarity X <i>H-H</i> Pair (I)	0.023 (0.028)	0.072* (0.042)	0.073 (0.088)	0.198 (0.158)	0.075 (0.108)	0.068 (0.206)
Similarity X <i>L-H</i> Pair (II)	0.014 (0.010)	0.027 (0.038)	-0.003 (0.043)	0.139 (0.106)	0.134** (0.043)	0.266** (0.082)
Similarity (III)	-0.010 (0.008)	-0.012 (0.029)	0.001 (0.028)	-0.136* (0.081)	-0.055*** (0.015)	-0.086 (0.055)
<i>H-H</i> Pair	-0.038 (0.230)	-0.413 (0.314)	0.073 (0.073)	0.083 (0.140)	0.112** (0.045)	0.133** (0.064)
<i>L-H</i> Pair	-0.069 (0.066)	-0.141 (0.265)	0.013 (0.020)	0.031 (0.068)	-0.011 (0.018)	-0.006 (0.068)
p-value Test: (I)=(II)	0.754	0.247	0.400	0.700	0.607	0.343
p-value Test: (I)=(III)	0.282	0.208	0.475	0.118	0.249	0.500
<i>L-L</i> Pair Mean	0.072	0.357	0.072	0.357	0.072	0.357
Observations	3,415	2,261	4,598	3,116	4,598	3,116

Notes: This table examines if social links among collectors are differentially associated with performance among high-type collectors and high-type households. It considers three proxies for social links: the distance between collectors' home locations in kilometers (Columns 1–2); whether collectors began working on the campaign in the same month (Columns 3–4); and whether collectors belong to the same church (Columns 5–6). In each column, we regress the outcome — tax compliance or visits — on pair types interacted with these measures of social links. The outcome is tax compliance in odd columns and receipt of post-registration visits from collectors in even columns. All regressions cluster standard errors at the neighborhood level ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$). The sample used is only high-type households in the analysis sample. We focus on high-type households since complementarities in collector types are only present among high-type households (Figure 1). Test (I)=(II) reports the p-value from the test that correlation coefficients for Similarity X *H-H* Pair and Similarity X *L-H* Pair are equal. Test (I)=(III) reports the p-value from the test that correlation coefficients for Similarity X *H-H* Pair and Similarity are equal. The *L-L* Pair Mean reports average tax compliance within neighborhoods assigned *L-L* pairs. The variables come from surveys with tax collectors described in Section 4. We discuss these results in Section 7.2.

A7 Number of Collector Types and Impact of the Optimal Assignment

This section uses our theoretical framework to explore the relationship between the number of collector types and the impact of implementing the optimal assignment policy, as summarized in Section 8.2.¹² We prove that increasing the number of collector types from K to $2K$ would magnify the effect on tax compliance from implementing the optimal assignment.

Setup

For analytical tractability, we assume a continuum of collectors of mass 1. We assume that a collector m has ability q_m , distributed uniformly in $[0, 1]$. Collectors work in pairs and the expected tax compliance of a household assigned to collectors m and n is given by:

$$y : [0, 1] \times [0, 1] \rightarrow [0, 1] \quad (13)$$

We refer to the expected tax compliance when assigned to tax collectors of ability q_m and q_n as the production function. The production function is symmetrical ($y(q_m, q_n) = y(q_n, q_m) \forall q_m, q_n$) and increasing in each of its components

Because we lack the data to estimate the production function for each level of tax collector ability, we divide the collectors into a finite number of types. We find the optimal assignment and analyze its effects on tax compliance (relative to the status quo assignment) using these collector types.

We first define a partition of collectors into K types as the list of k sets given by:

$$Q_k^K = \left[\frac{k-1}{K}, \frac{k}{K} \right] \quad \forall k \in \{1, \dots, K\} \quad (14)$$

We then define the production function over types as

$$Y^K(Q_m^K, Q_n^K) = K^2 \int_{m-1/K}^{m/K} \int_{n-1/K}^{n/K} y(q_m, q_n) dq_m dq_n \quad (15)$$

An assignment function $m(Q_m^K, Q_n^K)$ is the probability that a pair of type (Q_m^K, Q_n^K) is assigned to a household. It has the following properties:

1. **Symmetry:** $m(Q_m^K, Q_n^K) = m(Q_n^K, Q_m^K)$.
2. $0 \leq m(Q_m^K, Q_n^K) \leq 1 \forall Q_m^K, Q_n^K$.
3. $\sum_{i=1}^K m(Q_i^K, Q_m^K) + m(Q_m^K, Q_i^K) = 2/K \cdot \forall Q_m^K$
4. $\sum_{i=1}^K \sum_{j=1}^K m(Q_i^K, Q_j^K) = 1$.

¹²We ignore the assignment of collectors to households since it is irrelevant for our argument.

When collectors are partitioned into K types, the optimal assignment function solves the problem

$$m^*(K) = \arg \max_m \sum_{i=1}^K \sum_{j=1}^K m(Q_i^K, Q_j^K) \quad (16)$$

and the expected tax compliance under the optimal assignment if we partition the collectors into K types is given by

$$Y^*(K) = \sum_{i=1}^K \sum_{j=1}^K Y^K(Q_i^K, Q_j^K) \cdot m^*(Q_i^K, Q_j^K) \quad (17)$$

Results

We would like to prove that the expected tax compliance under the optimal assignment is (weakly) increasing in the size of the type partition K . Our setup allows us to prove the case stated in the following proposition:

Proposition. If we double the number of types, the expected tax compliance under the optimal assignment is weakly increasing, i.e., for every $K > 0$, $Y^*(2K) \geq Y^*(K)$.

Proof

Consider the optimal assignment function with K types, $m^*(K)$. We show that we can find an assignment function when partitioning the type space into $2K$ types that yields the same expected tax compliance to the optimal assignment function $m^*(K)$.

First, we define the function $g : \mathcal{N} \rightarrow \mathcal{N}$ such that

$$g(n) = (n + 1) // 2$$

where $//$ is the integer division operator.

We then consider the following assignment function with $2K$ types:

$$m(Q_i^{2K}, Q_j^{2K}) = \frac{1}{4} m^*(Q_{g(i)}^K, Q_{g(j)}^K) \quad \forall 1 \leq i, j \leq 2K$$

The assignment function m thus finds the type associated with each of the types Q_i^{2K} and Q_j^{2K} if we had partitioned the type space into K instead of $2K$ types and attributes the same probability as the optimal assignment function would.

First, it is straightforward to show that m satisfies the properties of an assignment function. Below we demonstrate this for Property 4 above. The proofs for Properties 1–3 are also straightforward.

To see that Property 4 is satisfied, note that:

$$\begin{aligned}
& \sum_{i=1}^{2K} \sum_{j=1}^{2K} m(Q_i^{2K}, Q_j^{2K}) \\
&= \sum_{a=1}^K \sum_{b=1}^K m(Q_{2a-1}^{2K}, Q_{2b-1}^{2K}) + m(Q_{2a-1}^{2K}, Q_{2b}^{2K}) + m(Q_{2a}^{2K}, Q_{2b-1}^{2K}) + m(Q_{2a}^{2K}, Q_{2b}^{2K}) \\
&= 4 \cdot \sum_{a=1}^K \sum_{b=1}^K \frac{1}{4} \cdot m^*(Q_a^K, Q_b^K) \\
&= \sum_{a=1}^K \sum_{b=1}^K m^*(Q_a^K, Q_b^K) = 1 \quad \square
\end{aligned}$$

Second, we show that m yields the same expected tax compliance as m^* :

$$\begin{aligned}
& \sum_{i=1}^{2K} \sum_{j=1}^{2K} m(Q_i^{2K}, Q_j^{2K}) Y^{2K}(Q_i^{2K}, Q_j^{2K}) \\
&= \sum_{a=1}^K \sum_{b=1}^K m(Q_{2a-1}^{2K}, Q_{2b-1}^{2K}) Y^{2K}(Q_{2a-1}^{2K}, Q_{2b-1}^{2K}) + m(Q_{2a-1}^{2K}, Q_{2b}^{2K}) Y^{2K}(Q_{2a-1}^{2K}, Q_{2b}^{2K}) + \\
& \quad m(Q_{2a}^{2K}, Q_{2b-1}^{2K}) Y^{2K}(Q_{2a}^{2K}, Q_{2b-1}^{2K}) + m(Q_{2a}^{2K}, Q_{2b}^{2K}) Y^{2K}(Q_{2a}^{2K}, Q_{2b}^{2K}) \\
&= \sum_{a=1}^K \sum_{b=1}^K m^*(Q_a^K, Q_b^K) \left[Y^{2K}(Q_{2a-1}^{2K}, Q_{2b-1}^{2K}) + Y^{2K}(Q_{2a-1}^{2K}, Q_{2b}^{2K}) + Y^{2K}(Q_{2a}^{2K}, Q_{2b-1}^{2K}) \right. \\
& \quad \left. + Y^{2K}(Q_{2a}^{2K}, Q_{2b}^{2K}) \right] \\
&= \sum_{a=1}^K \sum_{b=1}^K m^*(Q_a^K, Q_b^K) Y^K(Q_a^K, Q_b^K) = Y^*(K)
\end{aligned}$$

where the last line is obtained by linearity of the integral.

In sum, we show that if we partition the type space in $2K$ types, we can find an assignment function that yields the same expected tax compliance as the best assignment function if we partition the type space into K types. Since this is not necessarily the optimal assignment in $2K$ space, we conclude that expected tax compliance $Y^*(2K)$ is at least as high as $Y^*(K)$. \square .

A8 Using Bonhomme (2021) ‘‘Heterogeneity, Sorting, and Complementarity’’ Methodology

In this section, we estimate a nonlinear model for tax collector team production using the econometric framework proposed by [Bonhomme \(2021\)](#). This method allows us to document heterogeneity in collector performance and complementarities between tax collectors when only team-level tax compliance is observed. Additionally, it does not involve estimating collector type in a first step and is thus unaffected by potential misspecifications in the esti-

mation of tax collector type (cf. Section 6.2). It does not rely on a split-sample approach and is therefore more powered to estimate the average tax compliance function and the optimal assignment with a higher number of tax collector types (cf. Section 8.2).

In order to estimate the nonlinear model in the presence of unobserved worker heterogeneity in a team setting, we follow [Bonhomme \(2021\)](#) and rely on a finite mixture model, where the distribution of the discrete tax collector type is modeled using a random-effects approach.¹³ To estimate the nonlinear random-effects model we again follow [Bonhomme \(2021\)](#) by using a mean-field variational method.¹⁴

Figures [A21](#) and [A22](#) document the patterns of heterogeneity and complementarity in the nonlinear model estimated for 2–6 collector types. For conciseness, we only comment on the results for 2 and 3 collector types (Figure [A21](#)). The type proportions are 46.67%, 53.33% for two types and 43.11%, 31.99%, 24.89% for three types,¹⁵ and the matrices below show the average tax compliance distribution (in percent) with two and three collector types and confirm that tax collectors have heterogeneous productivity levels:

$$\begin{pmatrix} 5.86 & 7.33 \\ 7.33 & 15.22 \end{pmatrix}$$

$$\begin{pmatrix} 7.84 & 5.69 & 7.95 \\ 5.69 & 4.64 & 14.26 \\ 7.95 & 14.26 & 29.28 \end{pmatrix}$$

The implications of the estimated model for heterogeneity and complementarity are shown graphically for two and three collector types in Figure [A21](#). Panel B suggests the presence of complementarity, since with two (three) collector types the return of two high types working together is 1.21 (2.76) standard deviations above the return of two low types working together. To assess how complementarities might affect the allocation of collectors, Panel C reports the allocation that maximizes total tax compliance while keeping the marginal distribution of collector types the same as under the status quo assignment. The results confirm that the positive assortative assignment by collector type would be optimal. Figure [A22](#) shows similar results for 4–6 collector types, although the results are noisier due to the small number of observations for each collector match type (Figure [A22](#), Panel A).¹⁶

Table [A17](#) reports the decomposition of the tax compliance variance for 2–6 collector types. In the nonlinear case, the total tax compliance variance (Table [A17](#), row 1) has four

¹³We use random effects because the estimates of collector types are not sufficiently precise to follow a grouped fixed-effects approach as in [Bonhomme et al. \(2019\)](#).

¹⁴The presence of unobserved collector heterogeneity in a network of collector pairs makes the estimation of a nonlinear random-effects model challenging since the same collector may participate in multiple pairs, and pairs contain multiple collectors. Variational estimators are widely used in networks and other complex data settings ([Bishop, 2006](#); [Blei et al., 2017](#)).

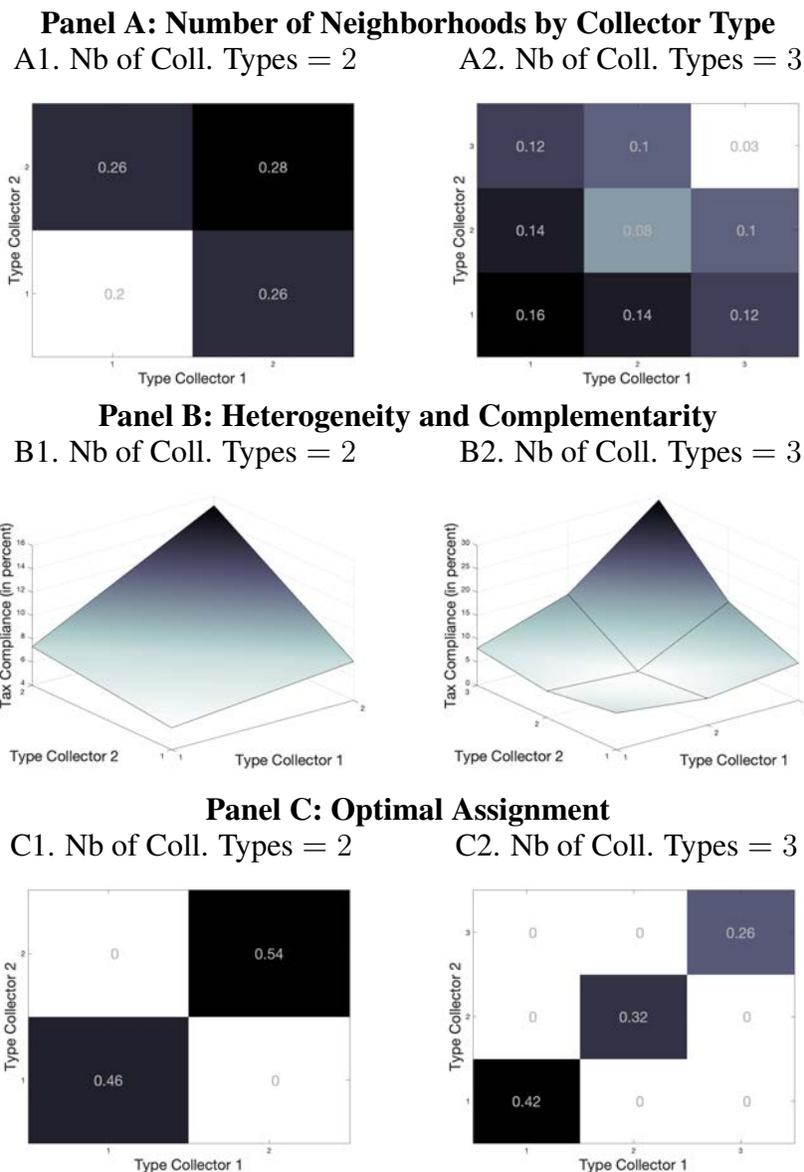
¹⁵The type proportions are 36.18%, 20.40%, 21.33%, 22.09% for four types, 30.76%, 21.13%, 5.56%, 23.08%, 19.47% for five types, and 11.69%, 22.14%, 21.70%, 8.32%, 14.28%, 21.87% for six types.

¹⁶With five (six) collector types, each type combination is estimated from 0.01–0.09 (0.01–0.07) of the total sample, i.e. from 2 to 16 (2 to 13) neighborhoods (Figure [A22](#), Panel A2–A3).

components, again following [Bonhomme \(2021\)](#). The “heterogeneity” component (Table [A17](#), row 2) reflects the variation in collector effects on output. The “sorting” component (Table [A17](#), row 3) reflects the variance contribution due to team composition not being random. As described in Section 3, tax collectors are randomly assigned to teams monthly and the sorting component is therefore equal to zero in our context. The “nonlinearities” component (Table [A17](#), row 4) reflects interaction effects between tax collectors, above and beyond the additive effects of tax collector types. The remainder of the variance is attributed to other factors (Table [A17](#), row 5).

The results presented in Table [A17](#) show that heterogeneity explains a large fraction of the total variance: between 20.86% and 33.80% depending on the number of collector types. Similarly, nonlinearities explain a substantial fraction of the variance in tax compliance: between 3.14% and 21.69% depending on the number of collector types. This is considerably higher than the share of the variance explained by complementarities in other contexts analyzed by [Bonhomme \(2021\)](#) such as complementarities between economic researchers (0.84%–2.41%) or inventors (3.42%–7.85%).

Figure A21: Nonlinear Model Estimates and Optimal Allocation of Tax Collectors

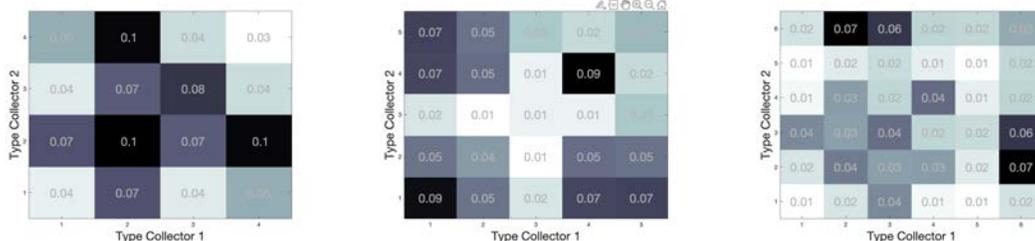


Notes: This figure reports estimates of the finite mixture model estimated using random effects following [Bonhomme \(2021\)](#). Panel A shows the proportion of each combination of types in the data. Panel B shows the average tax compliance (in percent) for different combinations of collector types. Panel C shows the proportion of collector types in the optimal allocation. The first figure of each panel (A1, B1, C1) shows the results with two collector types. The second figure of each panel (A2, B2, C2) shows the results with three collector types. We discuss these results in Section 8.2.

Figure A22: Nonlinear Model Estimates and Optimal Allocation of Tax Collectors

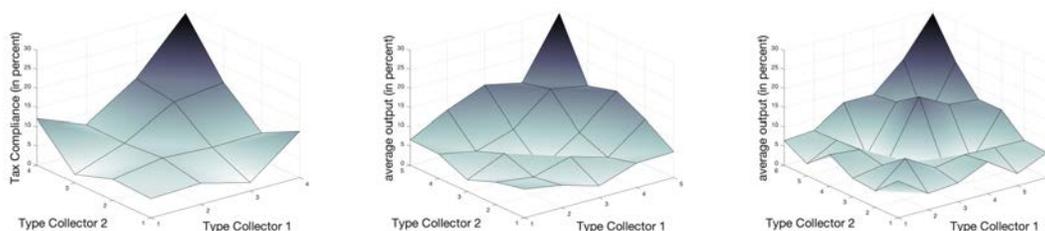
Panel A: Number of Neighborhoods by Collector Type

A1. Nb of Coll. Types = 4 A2. Nb of Coll. Types = 5 A3. Nb of Coll. Types = 6



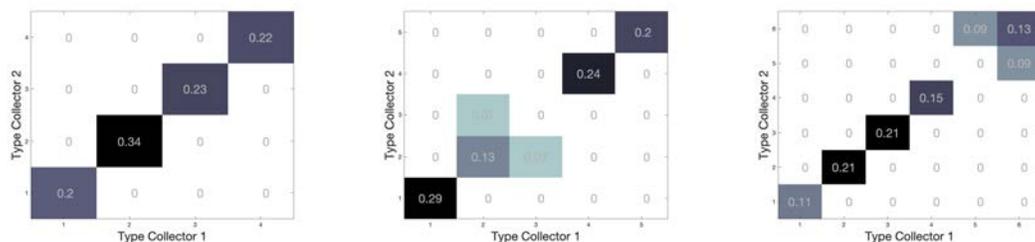
Panel B: Heterogeneity and Complementarity

B1. Nb of Coll. Types = 4 B2. Nb of Coll. Types = 5 B3. Nb of Coll. Types = 6



Panel C: Optimal Assignment

C1. Nb of Coll. Types = 4 C2. Nb of Coll. Types = 5 C3. Nb of Coll. Types = 6



Notes: This figure reports estimates of the finite mixture model estimated using random effects following [Bonhomme \(2021\)](#). Panel A shows the proportion of each combination of types in the data. Panel B shows the average tax compliance (in percent) for different combinations of collector types. Panel C shows the proportion of collector types in the optimal allocation. The first figure of each panel (A1, B1, C1) reports the results with four collector types. The second figure of each panel (A2, B2, C2) reports the results with five collector types. The third figure of each panel (A3, B3, C3) reports the results with five collector types. We discuss these results in Section 8.2.

Table A17: Variance Decomposition with Nonlinear Production Function in Tax Collector Type

	Collector Types = 2		Collector Types = 3		Collector Types = 4		Collector Types = 5		Collector Types = 6	
	Variance	%								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total variance	58.88		58.88		58.88		58.88		58.88	
Heterogeneity	12.29	20.86%	17.49	29.71%	17.97	30.52%	19.90	33.80%	18.77	31.87%
Sorting	0	0%	0	0%	0	0%	0	0%	0	0%
Nonlinearities	1.85	3.14%	6.32	10.73%	9.21	15.65%	8.51	14.45%	12.77	21.69%
Other factors	44.75	76.00%	35.07	59.56%	31.70	53.83%	30.48	51.76%	27.34	46.44%

Notes: This table reports estimates of variance components from a nonlinear model in collector type estimated following [Bonhomme \(2021\)](#). We report results for different number of collector types: two (Columns 1–2), three (Columns 3–4), four (Columns 5–6), five (Columns 7–8), six (Columns 9–10). Columns 1, 3, 5, 7, and 9 report the total variance (row 1) and its components: heterogeneity (row 2), sorting, which is always equal to zero given the random assignment of collectors to teammates (row 3), nonlinearities (row 4), and other components (row 5). Columns 2, 4, 6, 8, and 10 report the percentage of the total variance represented by each component. We discuss these results in Section 6.2 and 8.2.

A9 Neighborhood-Level Optimal Assignment

The neighborhood-level optimal assignment f^* can then be defined as:

$$\begin{aligned}
 f^* &\equiv \arg \max_f \sum_{n \in N} \sum_{a_1, a_2 \in \{L, H\}^2} f(a_1, a_2, n) \bar{Y}_n(a_1, a_2) \\
 &\sum_{a_1, a_2 \in \{L, H\}^2} f(a_1, a_2, n) = 1 \quad \forall n \in N \\
 &\sum_{n \in N} \left[2f(a, a, n) + \sum_{a' \neq a} (f(a', a, n) + f(a, a', n)) \right] = N^{nbh} \quad \forall a \in \{L, H\}
 \end{aligned}$$

As in Problem 1, the objective function is the expected tax compliance under assignment f , but we now consider the average tax compliance over all neighborhoods N :

$$\bar{Y}_n(a_1, a_2) = \frac{N_n(l) \hat{\beta}(a_1, a_2, l) + N_n(h) \hat{\beta}(a_1, a_2, h)}{N_n(l) + N_n(h)}$$

with $N_n(l)$ and $N_n(h)$ the number of low- and high-type households in neighborhood n .¹⁷

The constraints are analogous to those in Problem 1. The first constraint imposes that all neighborhoods are assigned to one pair of collector (i.e., the probability that a neighborhood is assigned to one pair of collectors equals one.) The second constraint imposes that tax collectors of each type are assigned to the same number of neighborhoods as under the status quo assignment.

¹⁷We exclude 6 neighborhoods with less than 10 observations from the analysis.

An alternative possible objective function to the expected tax compliance $\bar{Y}_n(a_1, a_2)$ is the expected number of tax payers, $N_n \bar{Y}_n(a_1, a_2)$:

$$N_n \bar{Y}_n(a_1, a_2) = N_n(l) \hat{\beta}(a_1, a_2, l) + N_n(h) \hat{\beta}(a_1, a_2, h)$$

which would imply the following objective function:

$$\sum_{n \in N} \sum_{a_1, a_2 \in \{L, H\}^2} N_n f(a_1, a_2, n) \bar{Y}_n(a_1, a_2)$$

and would allow the government to assign high-type pairs to neighborhoods with a large number of households, increasing the number of households assigned to high-type collectors in comparison to the status quo assignment.

Whether the outcome of interest is average compliance, $\bar{Y}_n(a_1, a_2)$, or the expected number of tax payers, $N_n \bar{Y}_n(a_1, a_2)$, the impact of the optimal assignment function, relative to the status quo assignment, is given by

$$\sum_{n \in N} \sum_{a_1, a_2 \in \{L, H\}^2} N_n \bar{Y}_n(a_1, a_2) \left[f^*(a_1, a_2, n) - f^{SQ}(a_1, a_2, n) \right]$$

where $f^{SQ}(a_1, a_2, n) = 1/4$ for all $a_1, a_2 \in \{L, H\}^2$.

A10 Endogenous Responses to Implementing the Optimal Policy

Throughout the analysis, we assume that the average tax compliance function would be unaffected by changes in the assignment function.¹⁸ This assumption is essential for the implementation of the optimal policy to have the effects documented in Sections 8.1-8.2. To see this, let's assume that the average compliance function depends on the assignment function f and is denoted $Y(a_1, a_2, v_h, f)$. Unless $Y(a_1, a_2, v_h, f^{SQ}) = Y(a_1, a_2, v_h, f^*)$, the tax compliance achieved under the status quo assignment function f^{SQ}

$$\sum_{a_1, a_2, v_h} f^*(a_1, a_2, v_h) Y(a_1, a_2, v_h, f^{SQ})$$

would differ from the tax compliance achieved under f^*

$$\sum_{a_1, a_2, v_h} f^*(a_1, a_2, v_h) Y(a_1, a_2, v_h, f^*)$$

In our context, changes in the assignment function could affect the average tax compliance function through changes in collectors' effort or in their opportunities for learning. We explore both possibilities below.

¹⁸This assumption is known as the stable unit treatment value assumption (SUTVA) in the impact evaluation literature.

A10.1 Endogenous Effort Provision

A10.1.1 Endogenous Effort due to Time Constraints

A first source of concern is that changing collectors' assignment could impact effort levels by match types, which would impact the average tax compliance function and result in $Y(a_1, a_2, v_h, f^{SQ}) \neq Y(a_1, a_2, v_h, f^*)$. Endogenous effort could affect the average tax compliance function if collectors target high-type households for tax visits and are time-constrained, i.e., are unable to do all the tax visits that would have a positive return during the month-long campaign period. Under these conditions, implementing the optimal assignment could lead to lower visit levels and lower tax compliance for (H, H, h) match types than observed under the random assignment.

To see this, consider the simplified case where there are four households in Kananga, two low-types (v^L) and two high-types (v^H). Additionally assume that there are two collector teams, a low-type team (a^{L-L}) and a high-type team (a^{H-H}), each assigned to two households. Finally, assume that collector teams are time-constrained and can only visit one of the two households they are assigned to. We assume that the probability of household h paying the property tax is $\Pr(y_h = 1) = e_{p,h} v_h a^p$, where $e_{p,h}$ indicates whether collector pair p visited household h after registration. Under the status quo assignment, each collector pair is assigned to a low-type and a high-type household. Since $v^H > v^L$, both collectors choose to visit the high-type household.¹⁹ Tax compliance under the status quo assignment would thus be $v^H a^{H-H} + v^H a^{L-L}$. Under the optimal assignment, high-type households would be assigned to the high-type team and low-type households would be assigned to the low-type team because $a^{H-H} > a^{L-L}$. Due to time-constraints, the high-type team would only visit one of the high-type households and the low-type team would only visit one of the low-type households and tax compliance would be $v^H a^{H-H} + v^L a^{L-L}$, which is strictly lower than the compliance achieved under the status quo assignment since $v^H > v^L$. By contrast, if collectors were not time-constrained, compliance under the optimal assignment would be $2v^H a^{H-H} + 2v^L a^{L-L}$ which would be strictly higher than the compliance achieved under the status quo assignment ($v^H + v^L$) $a^{H-H} + (v^H + v^L)a^{L-L}$ since $v^H > v^L$ and $a^{H-H} > a^{L-L}$.

We first investigate if in our context tax collectors target high-type households for tax visits. Examining heterogeneity in post-registration collector visits by household type, we do find evidence that collectors target high-type households for tax visits (Figure A8).²⁰ We then investigate whether tax collectors are time-constrained in our context. We first examine the distribution of tax payments over the month-long tax collection period in each neighborhood.²¹ If collectors were time-constrained, the marginal value of an additional visit should be larger than its marginal cost at the end of the month and we would expect a steady stream of tax payments until the end of the tax collection period. However, the data reveal that

¹⁹For example if they face financial or promotion incentives based on performance.

²⁰This is especially the case for $L-L$ teams, which are 8 percentage points more likely to visit high- than low-type households ($p = 0.045$). By contrast, $H-H$ teams are 5 percentage points more likely to visit high- than low-type households ($p = 0.17$).

²¹The month-long collection periods were staggered throughout the experiment and did not systematically coincide with calendar months.

tax payments across neighborhoods are on average close to zero on the last few days of the tax collection period (Figure A23, Panel A), suggesting that the marginal value of visits at the end of the tax collection period is on average very small.²² Second, if collectors were time-constrained, they should visit a lower fraction of households when assigned to a larger neighborhood.²³ However, we find no significant relationship between neighborhood size and proportion of households visited (Figure A23 Panel B).²⁴ Taken together, these results suggest that changes in collector effort by match type resulting from tax collectors' time constraints are unlikely to result in changes in the average tax compliance function when the assignment function changes.

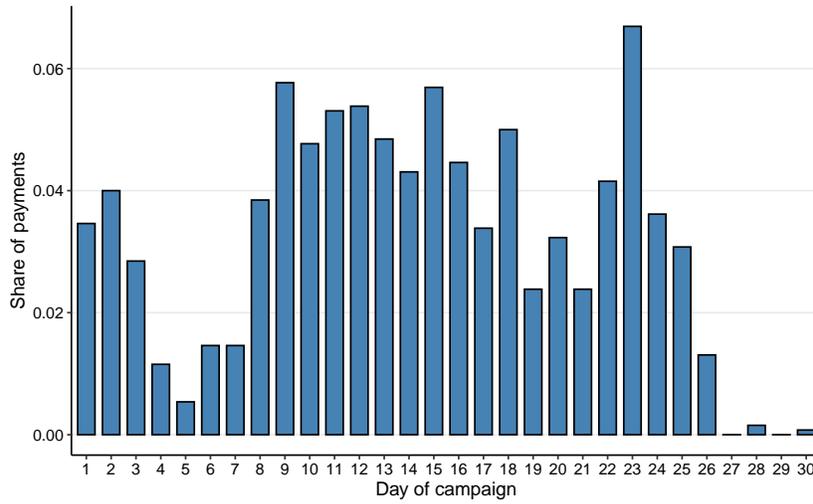
²²This is unlikely to be explained by collector fatigue given that their activity jumps sharply immediately following the assignment to new neighborhoods in the next campaign month.

²³Collector characteristics are orthogonal to neighborhood size due to the random assignment of collectors to neighborhoods.

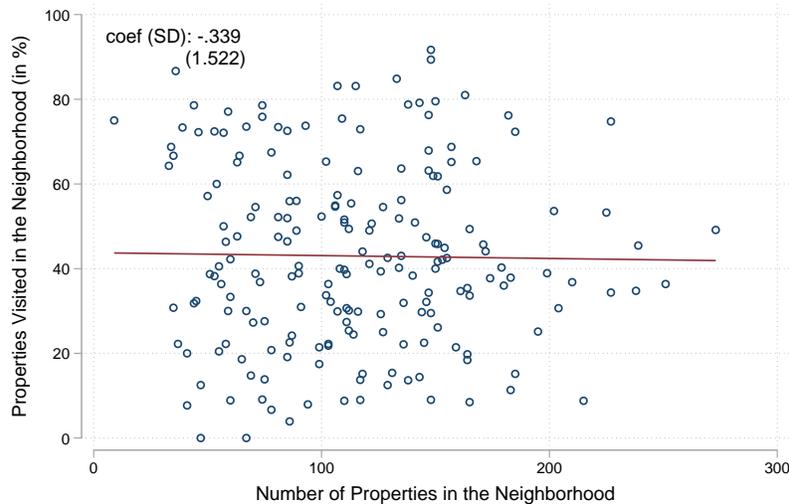
²⁴A one standard deviation increase in the number of households (50 households) in a neighborhood has a small and insignificant effect on the likelihood of being visited (0.3 percentage points, $p = 0.8$).

Figure A23: Tax Collectors' Time Constraints

Panel A: Distribution of Tax Payments over Time



Panel B: Visits as a Function of Neighborhood Size



Notes: This figure investigates whether tax collectors experienced various forms of time constraints when collecting taxes in Kananga. Panel A shows the distribution of tax payments across the days of the month-long tax collection period across all neighborhoods. Day 1 corresponds to the first day of the month-long tax collection period across all neighborhoods and day 30 to the last day of the month-long tax collection period across all neighborhoods. The month-long collection periods were staggered throughout the experiment and did not systematically coincide with calendar months. Panel B shows the relationship between the size of the neighborhoods (i.e., the number of properties) and the fraction of households visited by the tax collectors in the neighborhood. Panel B, also reports the coefficient and robust standard errors of a neighborhood-level regression of the percentage of properties visited after registration on the standardized number of properties. We discuss these results in Section 8.3

A10.1.2 Endogenous Effort due to Demoralization

Endogenous effort could also affect the average tax compliance function if assigning low-type collectors to low-type teammates and low-type households — as in the optimal assignment — demoralizes them and lead to lower effort and tax compliance for (L, L, l) match types than observed under random assignment.²⁵

We explore this possibility by analyzing whether the exogenous variation in collectors' assignments to low-type teammates and households during the 2018 campaign affected collectors' motivation measured at endline. Drawing on the psychology literature (Tremblay et al., 2009), the endline collector survey asked to what extent collectors were motivated in their work by (i) extrinsic motivation (i.e., due to financial compensation), (ii) intrinsic motivation (i.e., due to the fulfilling nature of the job), (iii) introjection (i.e., due to a positive self-image from the work), or (iv) goal orientation (i.e., due to the social importance of the work). We compute standardized indices for each motivation type based on the corresponding set of questions. We then estimate the correlation of collectors' endline motivation with the share of low-type teammates they were assigned to during the tax campaign (Table A18) and the share of low-type households they were assigned to during the campaign (Table A19). While we find that low-type collectors exhibited lower levels of motivation at endline (Table A18 and A19, Column 1), there is no evidence that being exogenously exposed to a higher fraction of low-type teammates or low-type households during the campaign undermined collectors' motivation (Table A18 and A19, Column 2) for low- or high-type collectors (Table A18 and A19, Column 3).²⁶ Overall, these results run counter to the low-type collector demoralization story.

We also investigate a more extreme form of demoralization, namely the possibility that low-type tax collectors could drop out of the campaign entirely under the optimal assignment (Table A20). We find no evidence that low-type collectors are more likely to drop out (Column 1) or that being exogenously exposed to a higher fraction of low-type teammates or low-type households during the campaign is associated with a higher probability of dropping out (Columns 2 and 4) for low- or high-type collectors (Columns 3 and 5).²⁷ Thus, according to available evidence, it appears unlikely that the assignment of low-type collectors to low-types teammates or households under the optimal assignment would trigger demoralization and reduce low-type collector pairs' effort levels compared to the random assignment.

Nonetheless, for completeness, we examine how the effect of the optimal policy would vary if low-type collectors were to become so demoralized under the optimal assignment that they drop out from the tax campaign. Specifically, we assume that low-type collectors cease their work on the tax campaign immediately (on day 1) and permanently, thereby contributing zero revenue to the state. Figure A24 investigates tax compliance under the optimal assign-

²⁵While we assume that collectors' financial incentives (piece-rate performance-based wages) would remain the same under the optimal assignment, it is possible that low-type collectors anticipate lower group productivity under the optimal assignment, which could lower their motivation.

²⁶If anything, low-type collectors' motivation levels appear to have been *less* impacted than high-type collectors by assignment to low-type teammates and households (Table A18 and A19, Column 3).

²⁷If anything, Column 3 of Table A20 suggests that low-type collectors are less likely to drop out from the tax campaign than high-type collectors when assigned to low-type teammates.

ment when a fraction of low-type collectors drop out relative to tax compliance under the status quo assignment. As expected, a higher fraction of low-type collectors dropping out is associated with a lower effect of implementing the optimal assignment on tax compliance. That said, the estimated effect remains positive and significant at the 5% level for dropout rates below 25% and at the 10% level for dropout rates below 50%.²⁸ Thus, our results suggest that the optimal assignment would outperform the status quo even for high rates of collector dropout. As a benchmark, only three tax collectors in our sample (8.82%) did not complete the full 2018 tax campaign.²⁹

²⁸For dropout rates above 50%, the estimated impact of the optimal assignment is still positive but not statistically different from zero at conventional significance levels.

²⁹Moreover, Figure A24 assumes that low-type collectors drop out on day 1 before they collect any revenue. However, in practice low-type collectors would likely work for a few months before becoming demoralized and dropping out. For the three collectors in our sample who dropped out of the 2018 tax campaign, two worked for two months and one worked for four months. If we assume that low-type collectors would work for a few months before dropping out, then Figure A19 underestimates the effect of the optimal assignment policy when a fraction of low-type collectors drop out.

Table A18: Collector Motivation by Teammates Type

	(1)	(2)	(3)
<u>Panel A: Extrinsic Motivation</u>			
Coll. Low-Type	-1.207*** (0.275)		-1.668** (0.562)
Frac. Low-Type Teammates		-0.214 (0.555)	-0.201 (0.584)
Coll. Low-Type X Frac. Low-Type Teammates			0.873 (0.998)
<u>Panel B: Intrinsic Motivation</u>			
Coll. Low-Type	-0.892** (0.311)		-1.571** (0.661)
Frac. Low-Type Teammates		-0.318 (0.561)	-0.617 (0.601)
Coll. Low-Type X Frac. Low-Type Teammates			1.335 (1.182)
<u>Panel C: Introjection</u>			
Coll. Low-Type	-0.787** (0.319)		-1.041 (0.803)
Frac. Low-Type Teammates		-0.172 (0.558)	-0.126 (0.767)
Coll. Low-Type X Frac. Low-Type Teammates			0.483 (1.293)
<u>Panel D: Goal Orientation</u>			
Coll. Low-Type	-0.714** (0.325)		-1.520* (0.757)
Frac. Low-Type Teammates		0.096 (0.528)	-0.333 (0.498)
Coll. Low-Type X Frac. Low-Type Teammates			1.522 (1.247)
Observations	34	34	34

Notes: This table shows the impact of each collector's own type (Column 1), of their teammates' types (Column 2), and their interaction (Column 3) on endline measures of collectors' extrinsic motivation (Panel A), intrinsic motivation (Panel B), introjection (Panel C), and goal orientation (Panel D) in collecting taxes during the 2018 property tax campaign. Each outcome variable is a standardized index for each motivation type. Column 1 reports the effect of collector's own type on motivation by regressing motivation on an indicator for the collector being low-type. Column 2 reports the effect of collectors' teammates type on motivation by regressing the motivation outcomes on the fraction of each collector's teammates that were low-type during the tax campaign. Column 3 studies heterogeneity by collector type in the effect of their teammates' type on motivation. It regresses the motivation outcome on collector type, the fraction of each collector's teammates that were low-type during the tax campaign, and the interaction of both variables. We report robust standard errors (* = $p < 0.1$, ** = $p < 0.05$, *** = $p < 0.01$). The sample size is reported at the bottom of the table. We discuss these results in Section 8.3.

Table A19: Collector Motivation By Household Assignment Type

	(1)	(2)	(3)
<u>Panel A: Extrinsic Motivation</u>			
Coll. Low-Type	-1.207*** (0.275)		-1.353 (0.974)
Frac. Low-Type Households		-2.029 (1.842)	-2.716* (1.571)
Coll. Low-Type X Frac. Low-Type Households			0.365 (3.106)
<u>Panel B: Intrinsic Motivation</u>			
Coll. Low-Type	-0.892** (0.311)		-0.716 (1.052)
Frac. Low-Type Households		-1.690 (1.436)	-1.810 (1.703)
Coll. Low-Type X Frac. Low-Type Households			-0.630 (3.300)
<u>Panel C: Introjection</u>			
Coll. Low-Type	-0.787** (0.319)		-1.050 (1.076)
Frac. Low-Type Households		-2.250 (1.404)	-2.915** (1.227)
Coll. Low-Type X Frac. Low-Type Households			0.731 (3.478)
<u>Panel D: Goal Orientation</u>			
Coll. Low-Type	-0.714** (0.325)		-0.921 (1.204)
Frac. Low-Type Households		-1.313 (1.600)	-1.881 (1.114)
Coll. Low-Type X Frac. Low-Type Households			0.589 (4.006)
Observations	34	34	34

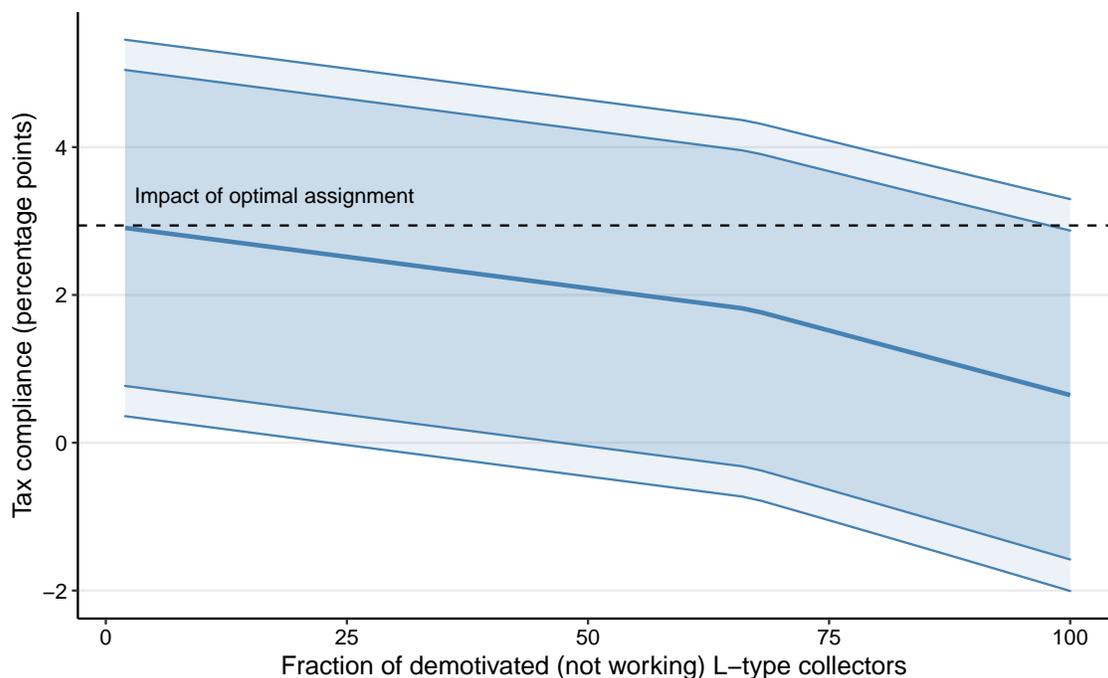
Notes: This table shows the impact of each collector’s own type (Column 1), of the household type they were assigned to (Column 2), and their interaction (Column 3) on endline measures of collectors’ extrinsic motivation (Panel A), intrinsic motivation (Panel B), introjection (Panel C), and goal orientation (Panel D) in collecting taxes during the 2018 property tax campaign. Each outcome variable is a standardized index for each motivation type. Column 1 reports the effect of collectors’ own type on motivation by regressing motivation on an indicator for the collector being low-type. Column 2 reports the effect of the household type they collected from on motivation by regressing the motivation outcomes on the fraction of each collector’s assignment that were low-type households during the tax campaign. Column 3 studies heterogeneity by collector type in the effect of the household type they collected from on motivation. It regresses the motivation outcome on collector type, the fraction of each collector’s assignment that were low-type households during the tax campaign, and the interaction of both variables. We report robust standard errors (* = $p < 0.1$, ** = $p < 0.05$, *** = $p < 0.01$). The sample size is reported at the bottom of the table. We discuss these results in Section 8.3.

Table A20: Collector Dropout By Teammate Type and Household Assignment Type

	(1)	(2)	(3)	(4)	(5)
Coll. Low-Type	0.059 (0.100)		0.590** (0.279)		0.108 (0.405)
Frac. Low-Type Teammates		-0.006 (0.293)	0.431 (0.345)		
Coll. Low-Type X Frac. Low-Type Teammates			-1.037** (0.502)		
Frac. Low-Type Households				-0.725 (0.480)	-0.626 (0.681)
Coll. Low-Type X Frac. Low-Type Households					-0.180 (0.980)
Observations	34	34	34	34	34
Mean	0.088	0.088	0.088	0.088	0.088

Notes: This table shows the impact of each collector's own type (Column 1), of their teammates' types (Column 2), of the interaction between collectors' own type and their teammates' types (Column 3), of the household type they were assigned to (Column 4), and the interaction between collectors' own type and the household type they were assigned to (Column 5) on an indicator for not completing the entire property tax campaign (i.e., "dropping out"). We report robust standard errors (* = $p < 0.1$, ** = $p < 0.05$, *** = $p < 0.01$). The sample size is reported at the bottom of the table. We discuss these results in Section 8.3.

Figure A24: Effects of the Optimal Assignment when a fraction of Low-Type Collectors Drop Out



Notes: This figure shows the potential impact of low-type tax collectors dropping out of the tax campaign (x-axis) on the effect of the optimal assignment on tax compliance relative to the status quo assignment (y-axis). We assume that collectors who drop out of the tax campaign stop working immediately and entirely (they collect no property taxes) and are not replaced by any other tax collector. Collector types are estimated using a fixed effects model described in Section 6.2. The shaded areas in dark blue represent the 90% confidence interval while the one in light blue represents the 95% confidence interval. Standard errors use bootstrap re-sampling (100 samples) at the neighborhood level. The dashed red horizontal line indicates the impact of the optimal assignment policy on tax compliance with no low-type collector dropout and when collector types are estimated using a fixed effects model, as reported in Column 1 of Table 1. The kink represents the point in which all low-type households are exhausted and then high-type households are matched to $L - L$ teams. We discuss these results in Section 8.3.

A10.2 Endogenous Learning Dynamics

A10.2.1 Learning from Teammates.

Endogenous learning could also affect the average tax compliance function if collectors learn tax collection skills from their teammates — e.g., high-type collectors might increase their teammates' performance by sharing skills and knowledge useful for tax collection, such as

techniques for convincing households to pay — and low-type collectors learn more tax collection skills than high-type collectors when assigned to high-type teammates.³⁰ Under these conditions, positive assortative matching on the collector-collector dimension would lead to low levels of learning from teammates among low-type collectors, which might lead us to overestimate the impact of the optimal assignment.

To investigate this possibility, we exploit the random assignment of collectors into different pairs over the course of the tax campaign. Specifically, we first estimate whether past assignment to a high-type teammate affects tax collectors' subsequent performance by estimating the following equation:³¹

$$y_{h,n,t} = \delta \cdot E_{c_1(n),c_2(n),t} + \lambda_t + \varepsilon_{h,n,t} \quad (18)$$

where h , n , and t index household, neighborhood, and tax campaign month, respectively. $y_{h,n,t}$ is the tax compliance decision of household h , and $E_{c_1(n),c_2(n),t}$ captures collector $c_1(n)$ and $c_2(n)$'s exposure to high-type collectors prior to campaign month t . λ_t are campaign month fixed effects. Standard errors are clustered at the neighborhood level. The coefficient of interest is δ , which captures whether the productivity of collector pairs in campaign month t is affected by past exposure to high-type teammates.

We use several measures of past exposure to high-type teammates. The first measure captures collector c 's exposure to high-type teammates during past campaign month l . Formally, it is defined by:

$$\text{Exposure}_{c,t}(l) = \sum_{c' \in C} 1_{[a_{c'}=H]} \cdot 1_{[m_c(t-l)=c']} \quad (19)$$

where $1_{[c'=m_c(t-l)]}$ is an indicator for tax collectors c' and c being teammates in tax campaign month $t-l$ and $1_{[a_{c'}=H]}$ is an indicator for collector c' being high-type. A second measure examines cumulative exposure to high-type teammates in all campaign months prior to month t . Formally, it is defined as:

$$\text{Exposure}_{c,t} = \frac{1}{t-t_c^0} \sum_{l=1}^{t-t_c^0} \text{Exposure}_{c,t}(l) \quad (20)$$

where t_c^0 is the first time period of tax collection for collector c . For ease of interpretation, we standardize this measure and the estimates should be interpreted as the effect of a one standard deviation change in cumulative past exposure to high-type teammates.

We use these measures to estimate the OLS regression specifications given by Equation

³⁰Learning tax collection skills might be more pronounced when paired with a high-type teammate than a low-type one because they have more skills to transfer or because they are viewed as higher prestige individuals and thus their partners are more attentive to them (e.g., [Bursztyn et al., 2014](#)).

³¹One challenge when studying skill transmission is that we do not separately observe the contribution of each collector to the team's output, but rather observe tax compliance at the team level. As a consequence, we cannot directly test whether collector c 's average tax compliance increases when assigned to a high-type collector during the campaign months when both collectors work together. Instead, we can test whether the teams collector c is a part of in subsequent periods are characterized by higher compliance after c was assigned to a high-type teammate.

(18). This equation relies on measuring exposure to high-type collectors prior to campaign month t , $E_{c_1(n),c_2(n),t}$, which is defined by one of the following two equations:

$$E_{c_1(n),c_2(n),t}(l) = \text{Exposure}_{c_1(n),t}(l) + \text{Exposure}_{c_2(n),t}(l) \quad (21)$$

$$E_{c_1(n),c_2(n),t} = \text{Exposure}_{c_1(n),t} + \text{Exposure}_{c_2(n),t} \quad (22)$$

depending on whether past exposure to high-type teammates is defined using $\text{Exposure}_{c,t}(l)$ or $\text{Exposure}_{c,t}$.³² We estimate collector types in the holdout sample, and we estimate equation (18) in the analysis sample, described in Section 3.³³

We find evidence of learning from high-type teammates (Table A21, Columns 1–3 and 6–8). A one standard deviation increase in cumulative past exposure to high-type teammates increases subsequent tax compliance by 3.53 percentage points ($p = 0.03$) (Column 1) and tax revenue by 83.02 CF ($p = 0.02$) (Column 6). Similarly, being assigned to a high-type teammate during the previous tax campaign month increases subsequent tax compliance by 2.34 percentage points ($p = 0.15$) (Column 2) and tax revenue by 50.56 CF ($p = 0.18$) (Column 7). The results are weaker for the effect of being assigned to a high-type teammate in an earlier campaign month (Columns 3 and 8).

These results suggest that collectors learn tax collection skills from high-type teammates. However, for learning from teammates to impact the average tax compliance function and the impact of the optimal assignment, it would have to affect collectors of different types differently. To see this, consider the expected tax compliance of household h in campaign month t when assigned to collectors of type a_1 and a_2 :

$$\mathbb{E} [y_{ht} | a_1, a_2] = m(a_1, a_2) + [l(a_1) + l(a_2)] \quad (23)$$

where $m(a_1, a_2)$ is the expected effect on compliance of an assignment to collectors of type a_1 and a_2 absent any learning. The additional effect of learning is captured by $l(a_1) + l(a_2)$, where $l(a)$ is the *expected* impact of what collector a has learned prior to campaign month t on tax compliance in month t , y_{ht} . The expectation is taken over the teammates collector a is assigned to under assignment function f .³⁴ We define the learning function of a collector of

³²Most, but not all, collectors started working in the first month of the tax campaign. When campaign month t is the first period of tax collection for collector c_1 , we calculate $E_{c_1(n),c_2(n),t}(l)$ as $2 \times \text{Exposure}_{c_2(n),t}(l)$ and vice-versa for collector c_2 . When campaign month t is the first period of tax collection for both collectors, we exclude the observation from the regression. As a consequence the data from the first period of tax collection are excluded from the estimation of Equations (18) and (25).

³³When estimating learning from teammates, we might overestimate the ability of collector c 's past teammates when c is high-type. We would then mechanically find that past assignment to high-type teammates is associated with high tax compliance.

³⁴Because we are now considering dynamics, this assignment function also depends on tax campaign month t . However, we restrict the assignment function to be identical at every t . For the particular type of average tax compliance in Equation (23), this restriction is harmless, since accounting for dynamics cannot improve over a static assignment.

type a as

$$l(a) = \sum_{a' \in A} g(a')f(a'|a) \quad (24)$$

where $g(a')$ is the effect on tax compliance of being assigned to a teammate of type a' in collection month $t - 1$. The likelihood that a type- a collector is assigned to a type- a' collector is $f(a'|a)$ where f the assignment function. $l(a)$ is the expected impact on collector type a of learning from a collector type a' in the previous period. If learning takes the form described in Equations (23) and (24), then Proposition 2 states that learning does not affect the difference in average compliance under two assignment functions that keep the composition of the workforce constant.

Proposition 2. *Assume that $\mathbb{E}[y_{ht}|a_1, a_2]$ takes the form defined in Equations (23) and (24). Consider two assignment functions $f^1(a_1, a_2)$ and $f^2(a_1, a_2)$ such that the marginal distributions of type $f^1(a) = f^2(a)$. Then the difference in average tax compliance under the two assignment functions is given by*

$$\sum_{a_1, a_2 \in A^2} m(a_1, a_2) (f^1(a_1, a_2) - f^2(a_1, a_2))$$

Proof:

The average tax compliance for the assignment function f is given by

$$\mathbb{E}[y_{ht}|f] = \sum_{a_1, a_2 \in A^2} f(a_1, a_2)m(a_1, a_2) + \sum_{a_1, a_2 \in A^2} f(a_1, a_2)[l(a_1) + l(a_2)]$$

where

$$\begin{aligned} \sum_{a_1, a_2 \in A^2} f(a_1, a_2)l(a_1) &= \sum_{a_1 \in A} f(a_1)l(a_1) \\ &= \sum_{a_1 \in A} f(a_1) \sum_{a' \in A} g(a')f(a'|a_1) \\ &= \sum_{a_1 \in A} \sum_{a' \in A} g(a')f(a'|a_1)f(a_1) \\ &= \sum_{a' \in A} \sum_{a_1 \in A} g(a')f(a_1, a') \\ &= \sum_{a' \in A} g(a')f(a') \end{aligned}$$

and as a result

$$\mathbb{E}[y_{ht}|f] = \sum_{a_1, a_2 \in A^2} f(a_1, a_2)m(a_1, a_2) + 2 \sum_{a' \in A} g(a')f(a')$$

The difference in average tax compliance between assignment functions f^1 and f^2 is

$$\mathbb{E}[y_{ht}|f_1] - \mathbb{E}[y_{ht}|f_2] = \sum_{a_1, a_2 \in A^2} f^1(a_1, a_2)m(a_1, a_2) - f^2(a_1, a_2)m(a_1, a_2)$$

since $2 \sum_{a' \in A} g(a')f^1(a') = 2 \sum_{a' \in A} g(a')f^2(a')$ when $f^1(a') = f^2(a') \forall a'$. \square

One scenario where Proposition 2 would not hold is if learning depends on collector type.³⁵ In particular, if low-type collectors were better learners than high-type collectors (e.g., because they have more to learn), then the results presented in Section 8 would *overestimate* the true effect of optimal matching by ignoring learning effects. Conversely, if high-type collectors were the better learners (e.g., because they are more open to learning from their peers), our results would *underestimate* the true effect of optimal matching by ignoring learning effects.

We provide evidence on whether learning from high-type teammates is more pronounced for low-type or high-type collectors by estimating the following equation:

$$y_{h,n,t} = \gamma_1 \mathbf{E}_{c_1(n), c_2(n), t} \cdot HH_{c_1(n), c_2(n)} + \gamma_2 \mathbf{E}_{c_1(n), c_2(n), t} \cdot LH_{c_1(n), c_2(n)} + \delta \mathbf{E}_{c_1(n), c_2(n), t} + \omega_1 HH_{c_1(n), c_2(n)} + \omega_2 LH_{c_1(n), c_2(n)} + \lambda_t + \varepsilon_{h,n,t} \quad (25)$$

which interacts past exposure to high-type teammates, $\mathbf{E}_{c_1(n)c_2(n)t}$, with indicators for *H-H* and *H-L* collector teams, $HH_{c_1(n), c_2(n)}$ and $LH_{c_1(n), c_2(n)}$, controlling for whether the team is *H-H* or *H-L*. Throughout the analysis, *L-L* teams are the comparison group. The coefficients of interests are γ_1 and γ_2 , capturing the additional learning accrued to *H-H* and *H-L* teams (relative to *L-L* teams), respectively.

The results presented in Table A21 do not show evidence that low-type collectors are better than high-type collectors in terms of learning tax collection skills when exposed to high-type teammates in past tax campaign months. If anything, we find suggestive evidence of more pronounced learning among high-type collectors, i.e., $\gamma_1 > 0$, across measures of past exposure to high-type teammates. As mentioned above, if high-type collectors are better at learning from high-type teammates than high-type collectors, our results would *underestimate* the true effect of optimal matching by ignoring learning effects. However, the γ_1 coefficients reported in Table A21 are not statistically significant at conventional levels, making the results only suggestive.

³⁵ Additionally, Proposition 2 would not hold if learning is not separable, i.e. if $[l(a_1) + l(a_2)]$ is replaced by $l(a_1, a_2)$ in Equation (23). We cannot directly test whether learning is separable, but separability is a standard assumption in the peer effects literature (e.g., Todd and Wolpin, 2003; Burke and Sass, 2013).

Table A21: Learning from High-Type Teammates

	Tax Compliance					Tax Revenue				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cumulative High-Type Exposure	3.53 (1.66) [0.03]			2.51 (1.31) [0.05]		83.02 (36.75) [0.02]			69.77 (29.67) [0.02]	
High-Type Exposure Lag 1		2.34 (1.62) [0.15]	3.41 (2.00) [0.09]		2.52 (1.47) [0.09]		50.56 (37.39) [0.18]	71.70 (48.15) [0.14]		41.19 (32.15) [0.20]
High-Type Exposure Lag 2			0.40 (0.92) [0.66]					22.26 (19.94) [0.26]		
Cumulative High-Type Exposure \times HH				5.90 (7.52) [0.43]					167.89 (170.57) [0.33]	
Cumulative High-Type Exposure \times LH				-38.05 (2.32) [0.69]					-36.53 (48.82) [0.44]	
High-Type Exposure Lag 1 \times HH					2.13 (4.62) [0.64]					91.28 (104.39) [0.38]
High-Type Exposure Lag 1 \times LH										-51.63 (43.55) [0.24]
Mean	7.92	7.92	6.54	7.92	7.92	236.00	236.00	212.62	236.00	236.00
Observations (Holdout Sample)	11,732	11,732	11,732	11,732	11,732	11,732	11,732	11,732	11,732	11,732
Observations (Analysis Sample)	7,665	7,665	5,166	7,665	7,665	7,665	7,665	5,166	7,665	7,665

Notes: This table shows the impact of past exposure to high-type teammates on collectors' current tax collection performance, measured by a property tax compliance indicator in Columns 1–5 and by property tax revenue per property owner (in Congolese Francs) in Columns 6–10. The tax compliance outcome in Columns 1–5 is multiplied by 100, and the coefficients can be interpreted as percentage point changes. Columns 1–3 and 6–7 report estimates from equation (18), using the cumulative high-type exposure measure (Columns 1 and 6), one high-type exposure lag (Columns 2 and 7), or two high-type exposure lags (Columns 3 and 8). Columns 4–5 and 9–10 estimate equation (25), using the cumulative high-type exposure measure interacted with indicators for the type of the tax collectors' pair (Columns 4 and 9) and the first lag exposure measure interacted with indicators for the type of the tax collectors' pair (Columns 5 and 10). Standard errors are clustered at the neighborhood level and presented in parenthesis while the corresponding p-values are presented in brackets ($*$ = $p < 0.1$, $**$ = $p < 0.05$, $***$ = $p < 0.01$). The average tax compliance and the sample sizes are reported at the bottom of the table. We discuss these results in Section 8.3.

A10.2.2 Learning-by-doing.

Endogenous learning could also affect the average tax compliance function if collectors learn tax collection skills over time (i.e., learning-by-doing) and low-type collectors learn more tax collection skills than high-type collectors when assigned to a high-type household. Then, positive assortative matching on the collector-household dimension would lead to low levels of learning-by-doing among low-type collectors, which would lead us to overestimate the impact of the optimal assignment.

To test for learning-by-doing, we analyze the relationship between tax compliance in month t and the number of households assigned to collector teams involving collector c in previous months, which we denote $X_{c,t-1}$. Formally, we estimate the regression:

$$y_{hnt} = \gamma \left(X_{c_1(n),t-1} + X_{c_2(n),t-1} \right) + \lambda_t + \varepsilon_{hnt} \quad (26)$$

where $c_1(n)$ and $c_2(n)$ are functions indicating the collectors assigned to neighborhood n and λ_t is a vector of campaign month fixed effects. If learning-by-doing is important $\gamma > 0$ since more opportunities to learn (i.e., more past assignments) should be associated with better tax collector performance. The coefficient γ is unbiased given that collectors were randomly assigned to neighborhoods of different size, as described in Section 3.

We find limited evidence of learning-by-doing in this context. If anything, increasing the number of past assignments by 1 SD *decreases* tax compliance by 1.58 percentage points (Table A22, Column 1), although the estimate is not significant at conventional levels ($p = 0.10$). This could suggest that a higher number of assignments causes exhaustion rather than learning. However, collectors assigned to a larger number of assignments in previous campaign months do not appear to reduce their tax collection effort level, as proxied by an indicator for being visited by tax collectors ($p = 0.91$, Column 4) or the number of visits by tax collectors ($p = 0.94$, Column 7).³⁶ We find similar results when analyzing the relationship between tax compliance or visits in month t and the number of households assigned to teams involving collector c in the previous month $t - 1$ (Columns 2, 5, 8) or in the two previous months $t - 1$ and $t - 2$ (Columns 3, 6, 9). Taken together, these results suggest a limited role for learning-by-doing in our setting.

³⁶The negative coefficient in Column 1 is thus more likely to reflect exogenous decreases in households' compliance behavior over time, rather than collectors exerting less effort. As discussed in Balan et al. (2022), tax compliance decreased over the course of the 2018 tax campaign due to increasing discontent with the incumbent president Joseph Kabila, who was ousted in a contentious election just after the tax campaign ended.

Table A22: Learning-by-doing

	Tax compliance			Visit Indicator			Number of Visits		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Past Nbhd Assignments Cumulative	-1.584 (0.969) [0.102]			0.425 (3.886) [0.913]			-0.005 (0.059) [0.938]		
Past Nbhd Assignments Lag 1		-0.345 (0.880) [0.695]	-1.379 (0.975) [0.157]		2.681 (1.604) [0.095]	2.171 (1.712) [0.205]		0.021 (0.025) [0.405]	0.016 (0.038) [0.575]
Past Nbhd Assignments Lag 2			-0.046 (0.475) [0.924]			-1.372 (3.204) [0.534]			0.000 (0.038) [0.998]
Mean	6.369	6.369	5.644	37.175	37.175	36.518	0.492	0.492	0.488
Observations	15,733	15,733	11,782	10,359	10,359	7,840	10,357	10,357	7,839

Notes: This table explores the relationship between tax collectors’ performance and their number of assignments in the previous campaign months. We consider three outcomes: an indicator for tax compliance by the owner (Columns 1–3), an indicator for receiving a post-registration visit (Columns 4–6), and the number of post registration visits (Columns 7–9). In Columns 1, 4 and 7, we report results from equation (26) by estimating the relationship between the outcome of interest and the number of assignments received by each collector in the pair during all the previous tax campaign months. In Columns 2, 5, and 8, we show the relationship between the outcome of interest and the number of assignments received by each collector in the pair in the previous tax campaign month ($t - 1$). In Columns 3, 6, and 9, we report the relationship between the outcome of interest and the number of assignments received by each collector in the pair in the previous tax campaign month ($t - 1$) and the month prior ($t - 2$). All regressions include campaign months fixed effects. We standardize the explanatory variable. We multiply the tax compliance and visit indicators by 100 and estimates for these variables are thus expressed in percentage points. Standard errors are clustered at the neighborhood level and presented in parentheses while the corresponding p-values are presented in brackets ($* = p < 0.1$, $** = p < 0.05$, $*** = p < 0.01$). The average for each outcome is reported at the bottom of the table, which also report the corresponding sample size. We discuss these results in Section 8.3.

A11 Effects on Secondary Outcomes

This section explores in more detail the effects of implementing the optimal assignment policy on bribes, payment of other formal and informal taxes, and views of the government.

A11.1 Bribe Payments

We test if the optimal assignment would impact bribery using three survey-based measures of bribes. First, households reported in the midline survey if they paid the “transport” of the collectors — a local code for bribes — and if so, how much they paid. Though self-reported,

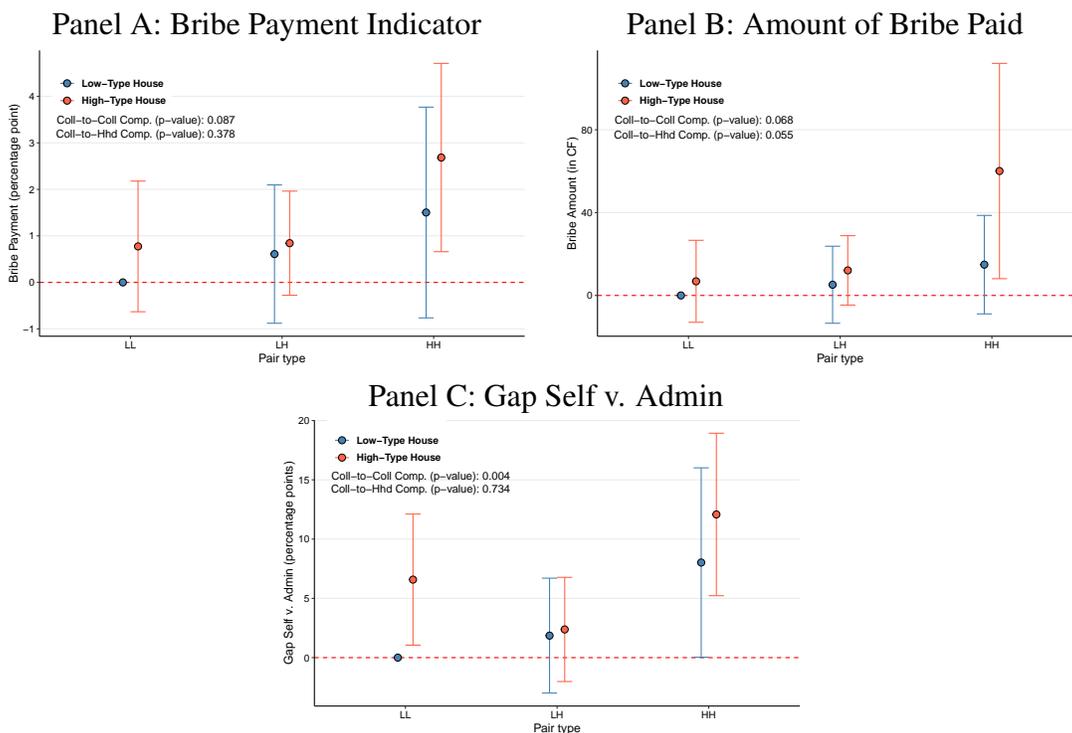
this bribe measure has been validated in past work in this same context.³⁷ Implementing the optimal assignment policy does not appear to significantly increase bribe payment on the extensive margin, though the coefficient is positive: 0.387 percentage points, $p = 0.268$ (Panel A of Table 2, Row 1). However, we find suggestive evidence of an increase of 13.896 CF ($p = 0.098$) — a 46% increase — in the amount of bribes paid per owner (Panel A of Table 2, Row 2). We find similar, albeit slightly larger, increases in amounts of bribes paid when the government aims at maximizing tax revenue per owner (Table A8, Column 2) and much smaller effects on bribe payments when the government’s objective is to maximize tax revenues net of the amount of bribes paid per owner (Table A8, Column 4).

As a second measure, we consider the gap between administrative tax data and citizen self-reports of payment at midline. Although it likely picks up social desirability responses, this measure may capture instances in which a citizen unwittingly paid a bribe or the collector simply pocketed the tax money without printing a receipt. According to this measure, the optimal assignment policy would increase bribe payments on the extensive margin by 2.253 percentage points ($p = 0.059$), a 24% increase (Panel A of Table 2, Row 3).

On net, we find suggestive evidence that the optimal assignment would slightly increase bribe payments. This increase reflects complementarities in collector type rather than complementarities in collector-household type (Figure A25). Complementarity tests confirm that the average bribe payment function exhibits complementarities in collector type when measuring bribes using the bribe payment indicator ($p = 0.087$), the amount of bribes paid ($p = 0.068$), or the gap between administrative tax data and citizen self-reports of payment ($p = 0.004$). The results on the collector-household dimension are more mixed: we fail to reject that the average bribe payment function exhibits complementarity in collector-household type for (extensive margin) indicators of bribe payments ($p = 0.378$, $p = 0.734$) but not for (intensive margin) amount of bribes paid ($p = 0.055$).

³⁷Reid and Weigel (2017) compare similar measures with less overt bribe measures in the context of motorcycle taxi drivers paying bribes at Kananga’s roadway tools. They find that they line up closely and that it does not appear to be taboo to discuss small payments to officials in Kananga.

Figure A25: Bribe Payments by Collector and Household Types



Notes: This figure shows the estimates of bribe payments for different types of collector pairs (low-low or LL, low-high or LH, high-high or HH) by households' type (low or high). The x-axis shows the three different types of collector pairs: LL, LH, HH. The y-axis is either an indicator for bribe payment (Panel A), the amount of bribe paid (Panel B), or the gap between administrative tax data and citizen self-reports of payments (Panel C), all measured at midline. The coefficients for the high- and low-propensity households are shown in red and blue, respectively. The points estimates are estimated using equation 7 with bribe payments as the outcome and low-type households assigned to a LL pair of collectors as the excluded category. The vertical lines show the 95% confidence intervals for each of the estimates using standard errors clustered at the neighborhood level. We report the p-value associated with a test for each outcomes, denoted Y , exhibiting increasing differences in collector type (we test $H_1: [Y(H, H, v) - Y(L, H, v)] - [Y(H, L, v) - Y(L, L, v)] > 0$ against $H_0: [Y(H, H, v) - Y(L, H, v)] - [Y(H, L, v) - Y(L, L, v)] \leq 0$) and in collector and household type (we test $H_1: [Y(H, H, 1) - Y(L, L, 1)] - [Y(H, H, 0) - Y(L, L, 0)] > 0$ against $H_0: [Y(H, H, 1) - Y(L, L, 1)] - [Y(H, H, 0) - Y(L, L, 0)] \leq 0$). We discuss these results in Section 8.4.

A11.2 Compliance with Other Formal and Informal Taxes

By increasing compliance with the property tax, implementing the optimal assignment could reduce the payment of other taxes if payments of the property tax and payments of other formal or informal taxes are substitutes (Olken and Singhal, 2011).

In Kananga, the most common contribution is an informal labor levy called *salongo*. *Salongo* is organized weekly by neighborhood chiefs and involves citizens contributing labor to public good projects, such as repairing roads. According to our midline survey data, 37% of citizens participated in *salongo* over a two week period, with participants contributing 4.3 hours on average. The optimal assignment does not appear to have significant effects on *salongo* participation on the extensive (3.890 percentage points, $p = 0.123$) or intensive margin (0.187 hours, $p = 0.299$) (Table 2, Panel B).

Other formal taxes paid by citizens in Kananga include the vehicle tax (3% of endline respondents reported paying), the market vendor fee (17%), the business tax (5%), the income tax (11%). These measures are self-reported but our endline survey included an obsolete poll tax to gauge potential reporting bias. Overall, we find no evidence that the optimal assignment would crowd out payments of other formal taxes (Table 2, Panel C).

A11.3 Views of the Government and Taxation

Finally, if high-type collectors' effectiveness in generating compliance reflects their use of coercion and threats of enforcement, the optimal policy could erode citizen's views of the government and of taxation. We investigate the effects on such beliefs using midline and endline survey data. The optimal assignment does not appear to significantly affect views of government (Table 2, Panel D). It appears to have mixed effects on citizens' view of taxation (Table 2, Panel E), slightly increasing citizen trust in the tax ministry ($p = 0.100$), while marginally reducing the perceived likelihood of enforcement and the perceived share of tax revenue spent on public goods ($p = 0.214$ and $p = 0.106$, respectively). We find no significant impact of the optimal assignment on tax morale ($p = 0.491$). Overall, then, there is little evidence of eroding views of the government or of taxation that might give the government pause in choosing the optimal assignment policy.

A12 Distributional Impacts Estimation

To estimate $\mathbb{E}_f[X_h|Y_h = 1]$ in Equation (12), we express it as a sum of different $\mathbb{E}_f[X_h|Y_h = 1, Z_h]$, where Z_h is the match-type for household h . If household h is of type v and was assigned to collectors of type a_1 and a_2 , then $Z_h = (a_1, a_2, v)$. Formally,

$$\begin{aligned}\mathbb{E}_f[X_h|Y_h = 1] &= \sum_z \mathbb{E}[X_h|Y_h = 1, Z_h = z] \cdot \Pr_f(Z_h = z|Y_h = 1) \\ &= \sum_z \mathbb{E}_f[X_h|y_h = 1, Z_h = z] \cdot w_f(z)\end{aligned}$$

where $w_f(z) = \frac{f(z)\Pr(Y_h = 1|z)}{\sum_{z'} f(z')\Pr(Y_h = 1|z')}$ is derived from Bayes' Rule. We can then estimate $\mathbb{E}_f[X_h|Y_h = 1]$ as:

$$\sum_z \sum_h \left(\frac{X_h \cdot 1[Y_h = 1] \cdot 1[Z_h = z]}{1[Y_h = 1] \cdot 1[Z_h = z]} \right) \cdot \hat{w}_f(z)$$

where $\widehat{w}_{f^*}(z) = \frac{f^*(z)\widehat{\beta}(z)}{\sum_{z'} f^*(z')\widehat{\beta}(z')}$ and $\widehat{w}_{f^{SQ}}(z) = \frac{f^{SQ}(z)\widehat{\beta}(z)}{\sum_{z'} f^{SQ}(z')\widehat{\beta}(z')}$.

A13 Selection Policies

Using the notation introduced in Section 5, we define two types of selection policies that involve reallocating a share $\rho \in [0, 1]$ of households previously assigned to low-type collectors. ρ captures the intensity of the selection policy. *Reallocation policies* reassign these households to currently employed high-type collectors while *hiring policies* reassign them to newly hired collectors. Selection policies thus consist in changing the number of assignments by collector type, and involve relaxing the workload constraint in the optimal assignment problem (Equation (4)).

The difference between *reallocation* and *hiring policies* can be summarized by λ , the probability that a household previously assigned to a low-type collector is re-assigned to a high-ability collector. For *reallocation policies*, $\lambda = 1$, while for *hiring policies*, $\lambda = \frac{1}{2}$.³⁸

Under a selection policy characterized by ρ and λ , the number of assignments to high-type collectors is given by:

$$N^{asgmt}(H; \rho, \lambda) = N_{f^{SQ}}^{asgmt}(H) + N_{f^{SQ}}^{asgmt}(L)\rho\lambda \quad (27)$$

$N_{f^{SQ}}^{asgmt}(H)$ is the number of households assigned to high-type collectors under the status quo assignment function. $N_{f^{SQ}}^{asgmt}(L)\lambda\rho$ is the number of households reallocated from low-type collectors to high-type collectors under the selection policy characterized by ρ and λ .

Selection policies represent a change in the composition of collector types, but they leave the dependence structure of the assignment unchanged. The joint distribution of collector and household types under the selection policy characterized by ρ and λ is:

$$f^S(a_1, a_2, v; \rho, \lambda) = f^S(a_1; \rho, \lambda) f^S(a_2; \rho, \lambda) f^{SQ}(v) \quad (28)$$

with $f^S(a; \rho, \lambda) \equiv \frac{N^{asgmt}(a; \rho, \lambda)}{N^{asgmt}}$.

We can then estimate the impact of the selection policy characterized by ρ and λ by computing its ARE, which is the difference in average tax compliance under the selection policy and the status quo assignment:

$$\tau(\rho, \lambda) \equiv \sum_{v \in V} \sum_{a_1, a_2 \in A^2} \left[f^S(a_1, a_2, v; \rho, \lambda) - f^{SQ}(a_1, a_2, v) \right] Y(a_1, a_2, v) \quad (29)$$

To estimate the impact of selection policies, $\tau(\rho, \lambda)$, we substitute the estimated average tax

³⁸For *reallocation policies*, $\lambda = 1$ because households previously assigned to low-type collectors are reallocated to high-type collectors. For *hiring policies*, $\lambda = \frac{1}{2}$ because we assume newly hired collectors will be low-type with probability $\frac{1}{2}$ and high-type with probability $\frac{1}{2}$. The effect of similar *hiring policies* have been studied in the teacher value-added literature (e.g., Chetty et al., 2014).

compliance function $\widehat{\beta}(a_1, a_2, v)$ in Equation (29), which gives:

$$\widehat{\tau}(\rho, \lambda) \equiv \sum_{v \in V} \sum_{a_1, a_2 \in A^2} \left[f^S(a_1, a_2, v; \rho, \lambda) - f^{SQ}(a_1, a_2, v) \right] \widehat{\beta}(a_1, a_2, v) \quad (30)$$

where the distributions $f^S(\rho, \lambda)$ and f^{SQ} in $\widehat{\tau}(\rho, \lambda)$ are the theoretical distributions.³⁹

³⁹This approach contrasts with the estimation of the optimal assignment ARE, which relies on an estimator of the assignment function.

A14 Detailed Survey-based Variable Descriptions

This section provides the exact text of the questions used to construct the survey-based variables considered in the paper.

A14.1 Property and Property Owner Surveys

1. *Ability to Pay the Property Tax.* This variable is derived from chief consultations in the analysis sample neighborhoods and equals 1 if the chief believes that the household can very easily afford the payment of the property tax. The exact survey question is as follows: ‘Does the household head have the financial means to pay the tax?’ [Hardly, Easily, Very easily]
2. *Roof Quality.* This is a Likert scale variable, increasing in the quality of the roof of the respondent’s house. It was recorded in the midline and endline survey in response to the prompt: ‘Observe the principal material of the roof.’ [thatch/ straw, mat, palms/ bamboos, logs (pieces of wood), concrete slab, tiles/slate/eternit, sheet iron]
3. *Wall Quality.* This is a Likert scale variable, increasing in the quality of the walls of the respondent’s house. It was recorded in the midline and endline survey in response to the prompt: ‘Observe the principal material of the walls of the main house.’ [sticks/palms, mud bricks, bricks, cement]
4. *Fence Quality.* This is a Likert scale variable, increasing in the quality of the fence of the respondent’s house. It was recorded in the midline and endline survey in response to the prompt: ‘Does this compound have a fence? If so, select the type of fence.’ [no fence, bamboo fence, brick fence, cement fence]
5. *Erosion Threat.* This is a Likert scale variable, increasing in the threat to the respondent’s house caused by erosion. It was recorded in the midline survey in response to the prompt: ‘Is this compound threatened by a ravine?’ [no, yes - somewhat threatened, yes - gravely threatened]
6. *Distance of the property to state buildings/ health institutions/education institutions.* These distances were based on a survey that recorded the GPS locations of all the important buildings in Kananga. The shortest distance between the respondent’s property and each type of location was then computed using ArcGIS.
7. *Distance of the property to the nearest road / to the nearest ravine.* These distances were also measured using GIS. The locations of roads and ravines were digitized on GIS by the research office enabling computation of the distance between the respondent’s property and the nearest road or ravine.
8. *Gender.* This is a variable reporting the respondent’s gender. It was recorded in the midline survey in response to the prompt: ‘Is the owner a man or a woman? ’

9. *Age*. This is a variable reporting the respondent's age. It was recorded in the midline survey in response to the question: 'How old were you at your last birthday?'
10. *Employed Indicator*. This is a dummy variable that equals 1 if the respondent reports any job (i.e., is not unemployed). It was recorded in the midline survey in response to the question: 'What type of work do you do now?' [Unemployed-no work, Medical assistant, Lawyer, Cart pusher, Handyman, Driver (car and taxi moto), Tailor, Diamond digger, Farmer, Teacher, Gardener, Mason, Mechanic, Carpenter, Muyanda, Military officer/soldier or police officer, Fisherman, Government personnel, Pastor, Porter, Professor, Guard, Work for NGO, Seller (in market), Seller (in a store), Seller (at home), Student, SNCC, Other]
11. *Salaried Indicator*. This is a dummy variable that equals 1 if the respondent reports one of the following jobs: medical assistant, lawyer, teacher, military officer/soldier or police officer, government personnel, professor, guard, NGO employee, bank employee, brasserie employee, Airtel (telecommunication services) employee, SNCC (national railway company of the Congo) employee. It was recorded in the midline survey in response to the question 'what type of work do you do now?' [responses noted above]
12. *Work for the Government Indicator*. This is a dummy variable that equals 1 if the respondent reports having one of the following jobs: military officer/soldier or police officer, government personnel, or SNCC (national railway company of the Congo) employee. It was recorded in the midline survey in response to the question 'what type of work do you do now?' [responses noted above]
13. *Relative Work for the Government Indicator*. This is a dummy variable that equals 1 if the respondent reports that someone in her/his family works for the government. It was recorded in the midline survey in response to the question: 'Does a close member of the family of the property owner work for the provincial government, not including casual labor?' [no, yes]
14. *Main Tribe Indicator*. This is a dummy variable that equals 1 the respondent reports being Luluwa, the main tribe in Kananga. It was recorded in the midline survey in response to the question: 'What is your tribe?' [Bindi, Bunde, Dekese, Dinga, Kefe, Kele, Kete, Kongo, Kuba, Kuchu, Kusu, Lele, Lualua, Luba, Lubakat, Luluwa, Lunda/Rund, Luntu, Lusambo, Mbala, Mfuya, Mongo, Ndumbi, Ngwandji, Nyambi, Nyoka, Pende, Rega, Sakata, Sala, Shi, Songe, Tetela, Tshokwe, Tutsi, Utu, Uvira, Wongo, Yaka, Yeke, Other]
15. *Years of Education*. This is variable reports the respondent's years of education. It was calculated using responses to two baseline survey questions:
 - 'What is the highest level of school you have reached?' [never been to school, kindergarten, primary, secondary, university]
 - 'What is the last class reached in that level?' [1, 2, 3, 4, 5, 6, >6]

16. *Has Electricity*. This variable equals 1 if the household reports in the baseline survey that they have access to electricity. The exact question text is: ‘Do you have any source of electricity at your home?’
17. *Log Monthly Income*. This variable is the self-reported (logarithm of) income of the respondent averaged over the baseline and endline surveys. It was recorded in both the baseline and the endline surveys in response to the question: ‘What was the household’s total earnings this past month?’
18. *Trust in Provincial Government / National Government / Tax Ministry / Chief*. This is a Likert scale variable, increasing in the level of trust the respondent reports having in different organizations. It was recorded in the baseline and endline survey in response to the question:
- ‘I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: no confidence at all, not much confidence, quite a lot of confidence, a great deal of confidence?’
 - Organizations:
 - (a) ‘Local leaders’
 - (b) ‘The national government (in Kinshasa)’
 - (c) ‘The provincial government’
 - (d) ‘The tax ministry’
19. *Paid Bribe*. This is a variable providing the respondent’s self-reported bribe payments. The underlying exact midline and endline survey questions are as follows:
- ‘Did you (or a family member) pay the transport of the collector?’
 - ‘Apart from the amount that you paid, did the collector ask you for another small sum on the side (for example, for his transport)?’
20. *Salongo Contributions*. This is a variable reporting the household’s contributions to the *salongo*. The exact survey questions are as follows:
- ‘Did someone from your household participate in *salongo* in the past 30 days?’ (Extensive margin)
 - ‘For how many hours in total did they participate in *salongo*? Please add together the time contributed by each member of your household in the past 30 days.’ (Intensive margin)
21. *Vehicle Tax*. This variable equals 1 if the household reports that they have paid a vehicle tax in 2018. The exact question text was: ‘Let’s discuss the vehicle tax. Did you pay this tax in 2018?’

22. *Market Vendor Fee.* This variable equals 1 if the household reports that they have paid the market vendor fee in 2018. The exact question text was: ‘Let’s discuss the market vendor fee. Did you pay this tax in 2018?’
23. *Business Tax.* This variable equals 1 if the household reports that they have paid a business tax in 2018. The exact question text was: ‘Let’s discuss the companies’ register. Did you pay this tax in 2018?’
24. *Income Tax.* This variable equals 1 if the household reports that they have paid an income tax in 2018. The exact question text was: ‘Let’s discuss the income tax. Did you pay this tax in 2018?’
25. *Obsolete Tax.* This variable equals 1 if the household reports that they have paid the obsolete poll tax in 2018. The exact question text was: ‘Let’s discuss the poll tax. Did you pay this tax in 2018?’
26. *Trust in Government.* This is a variable increasing in the respondent’s level of trust in both the provincial and national government. This variable is coded as an average of the answers to the question from the standardized index ‘Trust in Organizations’ about the national and provincial government.
27. *Responsiveness of Government.* This is a variable reporting the respondent’s perception of how responsive the provincial government is. The exact survey question was asked in both the baseline and the endline survey as follows: ‘To what degree does the provincial government respond to the needs of your avenue’s inhabitants?’ [Very responsive, Responsive, A little bit responsive, Not responsive] Values reversed to code this variable.
28. *Performance of Government.* This is a variable reporting the respondent’s perception of the overall performance of the provincial government. The exact survey question was asked in both the baseline and the endline survey as follows: ‘How would you rate the performance of the provincial government in Kananga?’ [Excellent, Very good, Good, Fair, Poor, Very poor, Terrible] Values reversed to code this variable.
29. *Property Tax Morale.* This is a variable reporting the respondent’s perception of importance of paying taxes. The exact survey question was asked in both the baseline and the endline survey as follows: ‘Now, imagine that next week a tax collector from the government comes and visits one of your neighbors. Imagine he absolutely refuses to pay the property tax. In your opinion, how acceptable is this?’ [Acceptable, Acceptable under some circumstances, Not acceptable]
30. *Perception of Enforcement.* This is a variable reporting the respondent’s perception of how likely it is that one gets sanctioned for not paying property tax. The underlying midline survey question is as follows: ‘In your opinion, do you think a public authority will pursue and enforce sanctions among households that did not pay the property tax in 2018? With which point of you do you agree?’ [they will definitely sanction them,

they will probably sanction them, they will probably not sanction them, they will definitely not sanction them] We use this variable to construct a dummy that equals 1 if the respondent answered either ‘they will definitely sanction them’ or ‘they will probably sanction them’ and 0 otherwise.

31. *Perception of Public Goods Provision.* This is a variable reporting the respondent’s perception of how likely it is that property tax revenue is spent on providing public goods in Kananga. The underlying midline survey question is as follows: ‘In your opinion, how much of the money collected in property taxes will be spent on public infrastructure, for example the roads in your neighborhood or elsewhere in Kananga?’ [All of it, most of it, some of it, none of it] We use this variable to construct a dummy that equals 1 if the respondent answered either ‘all of it’ or ‘most of it’ and 0 otherwise.

32. *Collector Messages.* We construct dummy variables that equal 1 if a message was used by the tax collectors during property tax collection, according to household self reports. It was recorded in the midline survey in response to the question: ‘Now let’s talk about the messages used by the property tax collectors in 2018 to convince property owners to pay the property tax. For each of the following messages, please indicate if you heard the tax collectors say this, or if you heard that they said this to other people.’

- ‘If you refuse to pay the property tax, you may be asked to go to the chief for monitoring and control.’ [no, yes]
- ‘If you refuse to pay the property tax, you may be asked to go to the provincial tax ministry for monitoring and control.’ [no, yes]
- ‘The Provincial Government will only be able to improve public infrastructure in your community if its residents pay property taxes.’ [no, yes]
- ‘The Provincial Government will only be able to improve public infrastructure in Kananga if residents pay property tax.’ [no, yes]
- ‘Pay the property tax to show that you have confidence in the state and its officials.’ [no, yes]
- ‘It is important.’ [no, yes]
- ‘Payment is a legal obligation.’ [no, yes]
- ‘Many households are paying; you should pay to avoid embarrassment in your community.’ [no, yes]
- ‘If you don’t pay, there could be violent consequences.’ [no, yes]

33. *Tax Visits.* This is a variable reporting tax collectors’ visits to households. The exact midline survey questions are as follows:

- ‘Has your household been visited by a tax collector or another authority in 2018 to raise awareness for collection of the property tax (even if no one was home)?’
- ‘How many times did they come in total since June, including the visit to assign a code?’ (Intensive margin)

A14.2 Tax Collectors Surveys

1. *Female*. This is a dummy variable that equals 1 if the respondent is female. It was recorded in the baseline collector survey in response to the prompt: ‘Select the sex of the interviewee.’ [female, male]
2. *Age*. This is a variable reporting the respondent’s age. It was recorded in the baseline collector survey in response to the question: ‘How old were you at your last birthday?’
3. *Main Tribe Indicator*. This is a dummy variable that equals 1 the respondent reports being Luluwa, the main tribe in Kananga. It was recorded in the baseline collector survey in response to the question: ‘What is your tribe?’ [Bindi, Bunde, Dekese, Dinga, Kefe, Kele, Kete, Kongo, Kuba, Kuchu, Kusu, Lele, Lualua, Luba, Lubakat, Luluwa, Lunda/Rund, Luntu, Lusambo, Mbala, Mfuya, Mongo, Ndumbi, Ngwandji, Nyambi, Nyoka, Pende, Rega, Sakata, Sala, Shi, Songe, Tetela, Tshokwe, Tutsi, Utu, Uvira, Wongo, Yaka, Yeke, Other].
4. *Years of Education*. This variable reports the respondent’s years of education. It was calculated using responses to two baseline collector survey questions:
 - ‘What is the highest level of school you have reached?’ [never been to school, kindergarten, primary, secondary, university]
 - ‘What is the last class reached in that level?’ [1, 2, 3, 4, 5, 6, >6]
5. *Math Score*. This variable is a standardized index increasing in the respondent’s math ability. The exact baseline collector survey questions used to create the standardized index are: ‘Now we would like to ask you some math problems. Don’t worry if you are not sure of the answer, just do your best to answer them.’
 - ‘Can you tell me what 2 plus 3 equals?’
 - ‘Can you tell me what 6 plus 12 equals?’
 - ‘Can you tell me what 32 minus 13 equals?’
 - ‘Can you tell me what 10 percent of 100 is?’
6. *Literacy*. This variable is a standardized index increasing in the respondent’s ability to read Tshiluba. The exact baseline collector survey questions used to create the standardized index are: ‘Now we would like to ask you if you could read two separate paragraphs about tax collection by the provincial government. The first paragraph is in Tshiluba and the second paragraph is in French. Don’t worry if you’re not sure of certain words, just do your best to read the paragraphs.’
 - ‘How well did they read the Tshiluba paragraph?’ [could not read, read with lots of difficulty, read with a little difficulty, read perfectly]
 - ‘How confidently did they read the Tshiluba paragraph?’ [not at all confident, not very confident, a bit confident, very confident]

- ‘How well did they read the French paragraph?’ [could not read, read with lots of difficulty, read with a little difficulty, read perfectly]
 - ‘How confidently did they read the French paragraph?’ [not at all confident, not very confident, a bit confident, very confident]
7. *Monthly Income*. This variable is the self-reported income of the respondent. It was recorded in response to the baseline collector survey question: ‘What was the household’s total earnings this past month?’ [amount in USD]
8. *Number of Possessions*. This variable report the number of possessions owned by the collector’s household. The exact baseline collector survey question is as follows: ‘In your household, which (if any) of the following do you own?’
- A motorbike [no, yes]
 - A car or a truck [no, yes]
 - A radio [no, yes]
 - A television [no, yes]
 - An electric generator [no, yes]
 - A sewing machine [no, yes]
 - None.’ [no, yes]
9. *Born in Kananga*. This is a dummy variable that equals 1 if the respondent was born in Kananga. The exact baseline collector survey question is as follows: ‘Were you born in Kananga?’ [no, yes]
10. *Trust in Provincial Government / National Government / Tax Ministry*. This is a Likert scale variable increasing in the level of trust the respondent reports having in each organization. The exact baseline collector survey question is as follows:
- ‘I am going to name a number of organizations. For each one, could you tell me how much confidence you have in them: no confidence at all, not much confidence, quite a lot of confidence, a great deal of confidence?’
 - Organizations:
 - (a) ‘The national government (in Kinshasa)’
 - (b) ‘The provincial government’
 - (c) ‘The tax ministry’
- The values were reversed to code this variable.
11. *Provincial Government Capacity*. This is a dummy variable equal to 1 if the collector believes that the government has the capacity to respond to an urgent situation. The exact baseline collector survey question is as follows: ‘Imagine that many of the roads in central Kananga have been badly damaged due to bad weather. Do you think the local government would fix this problem within three months?’ [no, yes]

12. *Provincial Government Responsiveness.* This is a Likert scale variable increasing in the respondent's perception of how responsive the provincial government is. The exact baseline collector survey question is as follows: 'To what degree does the provincial government respond to the needs of your avenue's inhabitants?' [Not very hard working, Hard working, Somewhat hard working, Not hard working]
13. *Provincial Government Performance.* This is a variable increasing in the respondent's perception of the overall performance of the provincial government. The exact baseline collector survey question is as follows: 'How would you rate the performance of the provincial government in Kananga?' [terrible, very poor, poor, fair, very good, excellent]
14. *Provincial Government Corruption.* This is a variable that reports what fraction of the tax revenues from the 2018 property tax campaign the respondent thinks the Provincial Government will put to good use. The exact baseline collector survey question is as follows: 'Now I would like to ask you what you think the provincial government will do with the money it receives from the property tax campaign this year. Imagine that the Provincial Government of Kasai-Central receives \$1000 thanks to this campaign. How much of this money will be put to good use, for example providing public goods?' [0-1000]
15. *Employed Through Connections.* This is a dummy variable equals to 1 if the respondent got his job as a tax collector for the Provincial Tax Ministry through a personal connection. The exact baseline collector survey question is as follows: 'How did you know that a position was available at the Provincial Tax Ministry?' [through a connection at the Provincial Tax Ministry, through a connection in the Provincial Government, I responded to job announcement from the Provincial Tax Ministry, I applied without knowing that the Provincial Tax Ministry was hiring]
16. *Relatives are Provincial Tax Ministry Employees.* This is a dummy variable that equals 1 if the respondent has a family member working at the Provincial Tax Ministry. The exact baseline collector survey question is as follows: 'Do you have a family member who is a Provincial Tax Ministry employee?' [no, yes]
17. *Relatives are Provincial Government Employee.* This is a dummy variable that equals 1 if the respondent has a family member working for the provincial government. The exact baseline collector survey question is as follows: 'Do you have a family member who is a Provincial Government employee?' [no, yes]
18. *Taxes are Important.* This is a Likert scale variable increasing in how important the respondent considers taxes to be. The exact baseline collector survey question is as follows: 'To what degree do you think that paying the property and rent taxes are important for the development of the province?' [not important, important, somewhat important, important, very important]

19. *Provincial Tax Ministry is Important.* This is a Likert scale variable increasing in how important the respondent considers the work of the Provincial Tax Ministry to be. The exact baseline collector survey question is as follows: ‘To what degree do you think the work of the Provincial Tax Ministry is important for the development of the province?’ [not important, important, somewhat important, important, very important]
20. *Paid Property Tax in the Past.* This is a dummy variable that equals 1 if the respondent declared having paid the property tax in the past. The exact baseline collector survey question is as follows: ‘Have you (or your family) paid your own property tax this year?’ [no, yes]
21. *Importance of Progressive Taxes.* This is a dummy variable that equals 1 if the respondent reports that taxes in general should be progressive. The exact baseline collector survey question is as follows: ‘Do you think all individuals should be taxed the same amount or should taxes be proportional to someone’s income/wealth?’ [everyone should pay the same amount, taxes should be proportional to someone’s income/wealth]
22. *Importance of Progressive Property Taxes.* This is a dummy variable that equals 1 if the respondent reports that property tax rates should be progressive. The exact baseline collector survey question is as follows: ‘According to you who should pay more property tax?’ [only the poorest, mostly the poorest but also a little bit the rest of society, everyone should contribute the same amount, mostly the wealthiest but also a little bit the rest of society, only the wealthiest]
23. *Important to Tax Employed Individuals.* This is a Likert scale variable reporting respondent’s view of the importance of taxing individuals with salaried jobs in Kananga. The exact baseline collector survey question is ‘How important do you think it is to pay the property tax for property owners who are employed?’ [not important, somewhat important, important, very important]
24. *Important to Tax Property Owners.* This is a Likert scale variable increasing in respondent’s view of the importance of taxing property in Kananga. The exact baseline collector survey question is ‘How important do you think it is to pay the property tax for property owners who have lived in a compound for many years?’ [not important, somewhat important, important, very important]
25. *Important to Tax Property Owners with a Title.* This is a Likert scale variable reporting respondent’s view of the importance of taxing property owners in Kananga. The exact baseline collector survey question is ‘How important do you think it is to pay the property tax for property owners who have a formal land title?’ [not important, somewhat important, important, very important]
26. *Extrinsic Motivation.* This variable is a standardized index increasing in tax collectors’ extrinsic motivation to work as a tax collector. The exact endline collector survey questions used to create the standardized index are: ‘Now, I want you to reflect on why you

worked as a tax collector for the IF campaign of 2018. I am going to give you a series of possible reasons for why you did this work. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you worked on the property tax campaign of 2018. Responses:

- ‘I did this work because of the income it provided me.’
- ‘I did this work because it allowed me to earn money.’
- ‘I did this work because it provided me financial security.’
- ‘I accept any paid job opportunity that is offered to me.’

27. *Intrinsic Motivation.* This variable is a standardized index increasing in tax collectors’ intrinsic motivation to work as a tax collector. The exact endline collector survey questions used to create the standardized index are: ‘Now, I want you to reflect on why you worked as a tax collector for the IF campaign of 2018. I am going to give you a series of possible reasons for why you did this work. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you worked on the property tax campaign of 2018.’ Responses:

- ‘I did this work because I derived much pleasure from learning new things.’
- ‘I did this work for the satisfaction I experienced from taking on interesting challenges.’
- ‘I did this work for the satisfaction I experienced when I was successful at doing difficult tasks.’

28. *Introjection.* This variable is a standardized index increasing in tax collectors being motivated to work due to introjected regulation. The exact endline collector survey questions used to create the standardized index are: ‘Now, I want you to reflect on why you worked as a tax collector for the IF campaign of 2018. I am going to give you a series of possible reasons for why you did this work. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you worked on the property tax campaign of 2018. Responses:

- ‘I wanted to succeed at this job, otherwise I would have been very ashamed of myself.’
- ‘I wanted to be very good at this work, otherwise I would have been very disappointed.’
- ‘I did this work because I wanted to be a "winner" in life.’
- ‘I took this job because I thought it was prestigious.’

29. *Goal Orientation.* This variable is a standardized index increasing in tax collectors being motivated to work due to goal orientation. The exact endline collector survey questions used to create the standardized index are: ‘Now, I want you to reflect on why

you worked as a tax collector for the IF campaign of 2018. I am going to give you a series of possible reasons for why you did this work. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you worked on the property tax campaign of 2018. Responses:

- ‘I did this work because I wanted to contribute to the economic development of Kananga.’
- ‘I did this work because I wanted to help the government do more for the citizens of Kananga.’
- ‘I did this work because I wanted to contribute to the increase in the collection of taxes.’

30. *Amotivation*. This variable is a standardized index increasing in tax collector being unmotivated to work as a tax collector. The exact endline collector survey questions used to create the standardized index are: ‘In any job, it can also be hard sometimes to feel motivated to work. When reflecting back on the IF campaign of 2018, indicate if any of the following reasons offers explanatory power for feeling unmotivated. For each reason, indicate if you strongly disagree, disagree, neutral, agree, strongly agree that this is a reason why you may not have felt motivated to work on the IF campaign of 2018.’ Responses:

- ‘I didn’t seem able to manage the tasks the job required of me.’
- ‘We worked under unrealistic working conditions.’
- ‘Our bosses expected too much of us.’

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