Discretion versus Algorithms: Bureaucrats and Tax Equity in Senegal*

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Abstract

Public policies such as taxation require individual-level information for success, but building the required registers is a challenge when administrative capacity is low. We investigate how the discretion of bureaucrats involved in the expansion of the tax roll affects its accuracy and equity. In the first digital property tax census in Dakar, Senegal, we randomly assign neighborhoods to valuation methods with different degrees of bureaucrat discretion. Compared to a benchmark of market values provided by licensed real estate assessors, bureaucrats in full discretion areas undervalue properties. This undervaluation is more severe for higher-value properties, resulting in a regressive tax profile: the median tax rate is 3.8% in the lowest quintile and 1.7% in the top quintile, instead of the expected 4.4% and 8.6% rates based on the tax code. A rule-based system in which an algorithm incorporates bureaucrat inputs to predict property values significantly reduces this tax gap, but a pure rule system with no bureaucrat input yields the highest accuracy and equity. Using a lab-in-the-field experiment, we identify bureaucrats' lack of knowledge about high-end properties and fairness concerns as key mechanisms. In contrast, we find no evidence of collusion between bureaucrats and property owners.

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1 Introduction

The ability of a government to gather accurate individual-level information is a crucial component of state capacity (Lee & Zhang, 2017; Scott, 1999). Indeed, the effectiveness of many public policies relies on the availability of comprehensive administrative data. This is equally important for targeted anti-poverty programs (Hanna & Olken, 2018), and for taxation (Pomeranz, 2015; Bowles, 2023), as both require identification and registration of eligible individuals, and evaluations of the amounts they should receive or contribute. In low-income countries, weak administrative capacity leads to incomplete and outdated policy registers (Banerjee *et al.*, 2019). This can have far-reaching welfare implications, for instance if many of the poorest households are not registered for an anti-poverty program, or if the wealth of the richest is strongly underestimated by the tax administration.

To build or update policy registers, governments in low-income countries often lack harmonized protocols, and instead rely on the discretion of bureaucrats. Discretion has advantages if bureaucrats have access to granular information that might not be integrated in a systematized process (Duflo *et al.*, 2018). However, discretion can be costly if bureaucrats' preferences are misaligned with the government's objective (Bandiera *et al.*, 2023), if they engage in rent-seeking (Niehaus *et al.*, 2013), if they lack the required knowledge or skills (Rogger & Somani, 2023), or if they are heterogeneous and difficult to screen. Rule-based or algorithmic processes may be implemented to reduce bureaucrats' discretion (Aghion & Tirole, 1997). Data driven rule-based processes are increasingly available thanks to digitization, the effects of which can be transformative for governance outcomes (Muralidharan *et al.*, 2016; Banerjee *et al.*, 2020, 2023; Dzansi *et al.*, 2022).

In this paper, we investigate how the discretion of bureaucrats involved in the expansion of a policy register affects its quality and equity, and we assess whether a rule-based process leads to more accurate and fairer policy outcomes. We do so by leveraging the roll-out of the first digitized property tax census carried out in Dakar, the capital city of Senegal. We experimentally vary the degree of discretion given to bureaucrats in determining the rental value of properties, which serves as the base of the property tax.[1] The

[1]The tax base is the market rental value of the property, the value that is or could be obtained from the property rented at market prices.

objective of the administration is to tax to the full potential by registering all properties, assigning values as close as possible to market values, while preserving horizontal equity – two properties with the same underlying value should face a similar tax bill – and vertical equity – more expensive properties should face higher tax bills.

We randomly assign 94 cadastral sections covering together approximately 40,000 properties into two treatment arms. In the *fully discretionary* arm, bureaucrats rely on their own judgment and interactions with occupants to estimate a property's value. Discretion is the status quo in this context. It's also a reasonable approach since there is no pre-existing information on the real estate: bureaucrats in the field can see properties up close, get a sense of neighborhood amenities, ask occupants about rents, all of this enabling them to form an opinion on the tax base.[2] In contrast, the *rule-based* arm uses an algorithm that relies on satellite images and observable property characteristics entered by bureaucrats to calculate property values. These characteristics are easy to verify for the administration which limits bureaucrats' discretion.[3] Additionally, we apply to the rule arm an alternative *pure rule* which predicts property values using only regressors that can be recovered remotely, without any bureaucrat input.[4] The pure rule has the potential advantage of totally removing bureaucrats' role, and of drastically reducing data acquisition costs.

We use market valuations by nationally certified real estate assessors from for a subset of 2,290 properties as a benchmark to compare these three valuation processes.[5] The deployment of the 268 bureaucrats involved in the property tax census is orthogonal to treatment and they are assigned to plots in a quasi-random way: these operations being

[2]It is standard for property tax liabilities to be determined in a discretionary way in low and middle-income countries, due to the absence of comprehensive real estate data, and a lack (or lack of affordability for governments) of certified assessors – see Chapter 2 in Franzsen & McCluskey (2017) for details.

[3]We developed this innovative rule-based system by tailoring Computer Assisted Mass Appraisal methods to the context, collaborating with the administration and international practitioners. The algorithm include 18 directly observable characteristics, a location fixed-effect, and built area. Other cities in low and middle-income countries are considering adopting similar approaches – see Knebelmann (2022) for a review of property tax digitalization initiatives.

[4]The R^2 of the rule with all covariates is 0.90, and the R^2 of the pure rule, using only section fixed-effect and built area, is 0.87. We calibrate the rules on a sample of 4,921 valuations by real estate assessors, using an elastic-net regression and 5-fold cross-validation.

[5]There is no pre-existing data with wide coverage on real estate prices in Dakar which is a common feature in low-income countries (Behr *et al.*, 2023). Reassuringly, we find a 62 percent correlation between these assessor values and reported values for rented properties in our baseline owner survey.

a first-of-a-kind in Dakar, tax office managers do not have any prior information on bureaucrats' performance they could use for assignments, nor are they aware of randomized section assignment *ex ante*.[6] As such, the setting offers a unique opportunity to measure the influence of bureaucrats and the effects of different degrees of discretion on the shaping of the tax roll and on vertical and horizontal tax equity.

Our first main result is that bureaucrats' discretion leads to a large undervaluation of the tax base and a strong regressivity of the tax profile. The median assessment ratio, defined as bureaucrats' value over market value, is 0.50. It varies by an average 115 percent around its median – this dispersion in the valuation roll harms horizontal equity. We shed light on an undervaluation gradient: bureaucrats undervalue high-value properties to a larger extent, which harms vertical equity. The median effective tax rate is 3 percent, instead of the expected 8.2 percent based on the tax code. Sorting properties by their annual rental market values, we find that the rate decreases from 3.8 percent in the lowest quintile to 1.7 percent in the top quintile, against the expected 4.4 and 8.6 percent respectively based on the tax code.[7] Lastly, bureaucrats are strongly heterogeneous: we exploit bureaucrats' quasi-random assignment to plots to estimate bureaucrat fixed-effects, and find that they explain 40 percent of the variation in the tax base gap – defined as the absolute difference between bureaucrat value and market value.

Second, the rule-based process yields substantial improvements both in accuracy and tax equity. The median assessment ratio is 0.95. Leveraging our randomization we estimate that in comparison, discretion increases the tax base gap by 3.9 million FCFA or 83 percent (significant at the one percent level). The rule-based process offers stronger vertical equity, as evidenced by a higher rank-rank correlation with benchmark market values.[8] The share of variation in the tax base gap explained by bureaucrats is reduced

[6]Once the census starts in a section, it needs to be completed before bureaucrats move to the following area. This prevents any sorting of bureaucrats once the valuation method is known. In Section 4, we show that bureaucrat characteristics are balanced across treatment arms and do not correlate with market values.

[7]The statutory tax rate is 8.6 percent, but there is a reduction in the tax base by a fixed amount if the property is the owner's main residence. The expected tax rate is thus increasing in property values, since for cheaper properties, the reduction represents a larger share of the total property value.

[8]Two factors allow us to be confident that these results are not mechanically driven by the fact that market values used as the benchmark and market values used to calibrate the rule are from the same source (assessor valuations). First, the sample used for the calibration of the rule includes 4,921 properties, only half of which are in our analysis sample, and the calibration is done through cross-validation. Second,

to 13 percent and valuations are less dispersed (the assessment ratio varies by an average 53 percent around its median), leading to higher horizontal equity. One drawback is that properties of the lowest quintile are often overvalued (the median assessment ratio is 1.25), while those of the highest quintile are more likely to be undervalued relative to the middle of the distribution, although much less so than under discretion. The median effective tax rate is 6.8 percent. It is 7.4 percent in the lowest quintile of properties and 5.2 percent in the top quintile.

Third, the pure-rule system strictly dominates the rule-based process. The median assessment ratio is in the vicinity of 1 throughout the distribution, except for the lowest quintile of properties (1.26). In comparison, discretion increases the tax base gap by 4.7 million FCFA or 166 percent, and the rule-based process increases the tax base gap by 1.84 million FCFA or 65 percent (significant at the 1 percent level in both cases) The rank-rank correlation between market values and values on the tax roll is 0.94. The median effective tax rate is 7.3 percent. It is 6.9 percent in the lowest quintile of properties and 7 percent in the top quintile. The pure rule performs better than the rule implemented by bureaucrats in spite of the fact that its model-fit statistics on the calibration sample are lower than those of the rule using all observable characteristics. This occurs because of distortions in the rule-based process when it is delegated to bureaucrats: in some instances, they enter incorrect property characteristics. Hence, in this setting, even limited delegation to bureaucrats harms tax fairness: the rule implemented by bureaucrats generates a lower effective tax rate for high-end properties compared to the pure rule.

Finally, we investigate the mechanisms that prevent bureaucrats from making accurate valuations and lead to the undervaluation gradient. First, we shed light on the major role of the knowledge channel. In a lab-in-the-field, bureaucrats are shown pictures of a cheap and an expensive property and asked to report their best value estimates. We find that a given bureaucrat is more accurate for the low-value property. On average, the expensive property is undervalued by so much that it is 'shifted down' from the fifth to the third quintile of market values. A randomized information treatment aiming to update

we perform a robustness check with an alternative rule that we calibrate on owner-reported values from our pre-program baseline survey. Although this formula is of lower quality ($R^2 = 0.33$), we still find that discretion significantly widens the tax base gap compared to this rule.

bureaucrats' beliefs on the distribution of market values is not enough to correct these misconceptions.[9] Second, we rule out the explanation that the regressive tax profile under discretion is due to rich owners bribing bureaucrats in exchange for lower tax liabilities. The aforementioned finding in the lab when there are no possible gains from undervaluation is a first piece of evidence. A second piece of evidence comes from the fact that we find no significant difference in the undervaluation gradient depending on whether or not the bureaucrat met the owner during the field visit. Finally, we find that bureaucrats are biased by their perceptions of the occupant, and of fairness. Using our lab-in-the-field setting we find that bureaucrats who are told that the owner is retired (versus employed) provide a 38 percent lower estimated value. Bureaucrats are 2.8 times more likely to state that the worse situation is one in which they overvalue a property, compared to one in which they undervalue.

The implications for local public finance outcomes are tremendous. Total tax liabilities amount to 8 billion FCFA in the discretion arm, against 19.6 billion if extrapolating the benchmark market values; liabilities amount to 11 billion FCFA in the rule arm, 19.7 billion if applying the pure rule to the rule arm. In a country with 3.4 billion total property tax collections, the implications from undervaluation are immense.[10] Importantly, under discretion, 49.6 percent of the tax burden is due by the 10 percent most expensive properties, while this figure is 63 percent under the rule, and 70 percent under the pure rule.[11] Removing delegation shifts the tax burden from low value to high value property owners.

Does this mean that the optimal strategy for the administration should be to rely solely on a rule-based process? Overall, using a rule always generates more accurate and consistent values.[12] Only for the cheapest properties does a trade-off exist: while the pure rule is still more accurate than discretion, it tends to overvalue properties in this segment of the market,[13] while at the same time, it is precisely for these properties that

[9] We also find that there is no learning in the field over time, nor from exposure to the rule.

[10] Pre-program, total revenues from all local taxes in the municipal budget of Dakar are 28 billion FCFA (Delbridge *et al.*, 2022).

[11] The share of tax burden is calculated by sorting properties by their market values for the representative subset visited by assessors.

[12] Under discretion, some gains could be made by screening bureaucrats on higher education, which correlates with bureaucrats' estimated fixed-effects, but at best top bureaucrats perform as well as the rule.

[13] This is an inherent feature of property valuation models, due to unobserved variables, see McMillen &

bureaucrats are performing relatively better, and are able to leverage information from owners and tenants to increase accuracy. If the government wants to minimize the risk of overvaluation of cheapest properties, while maximizing accuracy, an optimal policy is to use discretion for the lowest quintile of the market, and the pure rule elsewhere.[14]

We contribute to the literature questioning the respective advantages of rules and discretion in the work of organizations (Aghion & Tirole, 1997; Dessein, 2002). Empirically, the benefits of discretion have been shown for the targeting of polluting firms by auditors in India (Duflo *et al.*, 2013, 2018), for the work of procurement officers in Pakistan (Bandiera *et al.*, 2021), for the management of state owned firms in India (Kala, 2019). While Bachas *et al.* (2021) provide evidence on the effect of reduced discretion for the targeting of tax audits in Senegal, and Okunogbe & Pouliquen (2022) for tax filing in Tadjikistan, we are not aware of similar applications to the actual computation of tax liabilities.

Relatedly, we generate new evidence on the use of algorithms in government. While recent papers have shown that the adoption of data-driven rules better achieves policy objectives (Haseeb & Vyborny, 2022; Greenstone *et al.*, 2022), or that data-driven predictions may help individuals make better decisions (Sadka *et al.*, 2018), other findings highlight how these procedures may, intentionally or not, lead to regressive or discriminatory outcomes (Avenancio-León & Howard, 2022; McMillen & Singh, 2020; Elzayn *et al.*, 2023).[15] Finally, rules may be distorted if they leave room for some inputs by agents (Niehaus *et al.*, 2013), in which case policy recommendations need to anticipate these possible deviations (Björkegren *et al.*, 2022). In the realm of taxation, Battaglini *et al.* (2022) show that algorithmic audit selection could substantially raise arrear payments in Italy; Black *et al.* (2022) find that using machine learning to target audits could improve vertical equity in the United States. However, both rely on data from former audits, and are not the result

Singh (2020); Berry (2021); Amornsiripanitch (2023) for demonstrations in the United States context where rule-based methods are widespread.

[14] One could be worried of dynamic adjustments by property owners if they learn which characteristics used in the algorithm trigger higher tax liabilities. In the current state of the reform, the characteristics are not made public. Furthermore, using a pure rule which relies only on location and built area mitigates this risk.

[15] There may be political resistance hindering the adoption of algorithms in spite of their efficiency (Browne *et al.*, 2023). This is beyond the scope of our paper since we focus on the government's aim to generate the tax roll, while taxpayer compliance and reactions will be studied in a follow-up paper.

of an actual policy experiment.[16]

Our study is the first experimental comparison of an algorithm with discretion in the actual creation of a tax roll, and contributes to these strands of literature in the following ways. First, the agency problem in the realm of taxation differs in nature from other settings (Gordon, 2017): while rules (almost) always exist on paper in the tax code, discretion (almost) always comes into play at one point or another of the taxation process, making it crucial to learn more about the discretion of tax officials.[17] Moreover, while collusion with taxpayers is an obvious example of negative departures from rules, officials could also adjust liabilities to public services available to a given individual, hence implementing some form of benefit taxation which could strengthen the social contract. Second, our setting allows us to directly quantify *how* each degree discretion affects outcomes, since we can (i) evaluate the tax base independently; (ii) pinpoint which observable characteristics entered by bureaucrats generate distortions under partial delegation.

Furthermore, our findings contribute to the literature investigating how bureaucrats shape policy outcomes and state capacity. While a small but expanding number of papers have quantified the influence of bureaucrat heterogeneity on policy outcomes (Best *et al.*, 2023; Fenizia, 2022; Limodio, 2021), and shown how bureaucrats matter for tax enforcement (Bergeron *et al.*, 2022; Khan *et al.*, 2016, 2019), being able to directly measure bureaucrats' individual performance and effects of their discretion is rare (Besley *et al.*, 2022). Our finding that the substantial loss in tax liabilities under discretion is driven by bureaucrats' lack of knowledge rather than collusion is in line both with Rogger & Somani (2023) and with the concept of passive waste developed in Bandiera *et al.* (2009).[18] Finally, we build on papers showing that citizens' conceptions of fairness and knowledge about wealth and taxation are important to understand how tax policy is shaped (Hvidberg *et al.*, 2023; Hoy, 2022; Stantcheva, 2021); we innovate by measuring these perceptions among the actual implementers of tax policy and showing how strongly this affects effective tax-

[16]On property taxation more precisely, Casaburi & Troiano (2015) analyze the effects of using innovative data (although not exactly an algorithm), in an Italian government program which consisted in detecting ghost buildings by overlaying aerial imagery and cadastral maps.

[17]While we study discretion in the valuation process, in high-income countries, where there is more information on the tax base, this trade-off is perhaps more relevant in audit decisions for example.

[18]Bandiera *et al.* (2023) also find that delegation to bureaucrats makes a policy less progressive, but for different reasons (social ties).

ation.

Finally, our paper studies state capacity through the lense of property taxation (Besley & Persson, 2009; Weigel, 2020; Balan *et al.*, 2022; Okunogbe, 2021). Multiple studies in economics, history and political science have shown how informational investments in the form of cadastral updates may generate additional tax revenue (Martínez, 2023; D'Arcy & Nistotskaya, 2018; Christensen & Garfias, 2021; vom Hau *et al.*, 2023), and the importance of property taxation for fiscal capacity in general (Dray *et al.*, 2023). We contribute by studying this in a contemporary low-income context, assessing the role of new technologies, and comparing different modalities of improvements in an experiment at scale. Raising more tax revenues is a pressing issue for African governments and much more evidence is needed on how technology may help (Dzansi *et al.*, 2022; Okunogbe & Santoro, 2023), and how to pinpoint the optimal design of tax policy (Brockmeyer *et al.*, 2021; Bergeron *et al.*, 2023). Lastly, we generate new evidence on real estate prices, echoing the findings of Levitt & Syverson (2008) in the US on the role of asymmetric information in the reporting of property prices. Studies with a similar granularity of real estate data in a developing country metropolis are very rare (an exception being Anagol *et al.* (2022) in India), especially so for African capital cities.

In the following section, we describe the institutional context and the experiment. Section 3 lays out a simple conceptual framework. In Section 4, we describe the data, and in Section 5, we present our main results. Section 6 explores mechanisms. Section 7 describes the administration's optimal policy and cost-benefit considerations, and Section 8 concludes.

2 Context and Experimental Design

2.1 Background

In Senegal, all property owners are subject to a property tax. The national tax administration is responsible for generating the tax bills.[19] The tax base is the annual market rental

[19] In Appendix section A.1, we provide additional details on the institutional context.

value, the value that is or could be obtained from the property if rented at market prices. The rate is 8.6 percent, with an abatement for owner occupied properties, for which the share of the tax base below 1.5 million FCFA is only taxed at 3.6 percent. In theory, owners are supposed to come to the tax administration office once a year to declare their property's value, but only a very small minority respect this obligation. The administration is legally enabled to conduct field work to register new properties. In doing so, before the digital property tax census, bureaucrats used their own judgement to determine property values: the status quo is what we call discretionary valuation. In practice, these field operations were very rare before the program. As such the values on the pre-program tax roll originate either from self-declarations by owners, or from discretionary valuations by bureaucrats at one point in time, with no efficient strategy for expansions or updates.

Indeed, there is no systematic information on real estate prices. This is typical in cities of low-income countries (Behr *et al.*, 2023). Although 41 percent of properties are rented, only 2.6 percent have some form of contract, and these are rarely reported to the administration.[20] Rental agreements are typically channeled through informal brokers and real estate agencies mostly cover high-end segments of the market. When there are property sales outside of informal inheritance, they are rarely reported to the administration.[21] More generally, a significant challenge to use any type of data on property prices is the lack of a systematic addressing system, making it difficult to match entries across sources. Before the program, the administration does not make use of any data-driven strategy to improve the property tax roll, whether it be by computing neighborhood-level rental values, by using built area measurements, or even by assigning precise location details to already registered properties.

The tax strongly underperforms, a first order problem being the low registration ratio (around 16 percent): in the region of Dakar, approximately 61,000 properties were on the pre-program tax roll against an estimated 370,000 plots. The payment ratio is also low: in 2022, a payment was recorded for 10 percent of the tax bills, and collections amounted to

[20]Source: data from the property tax census operations described in Section 2.2. In our baseline property owner survey the share of properties that are rented is 30 percent.

[21]The record of property transfers the administration has only includes around 2,000 transactions reported by a dozen of notary offices over the past ten years.

16 percent of liabilities. Total revenues for the region were 3.4 billion FCFA or 5.8 million USD in 2022.[22] This underperformance of the property tax is a common feature in African countries (Franzsen & McCluskey, 2017).[23] However, in a context of recent decentralization policies and of willingness to expand the tax net while leveraging digitization, there is now in Senegal strong political will to strengthen the property tax.

2.2 Experimental Design

Our experiment is embedded in the roll-out of the first digital property tax census in the region of Dakar. We developed the new system in collaboration with the administration, it is innovative along two dimensions. First, it allows bureaucrats to conduct the census on tablets, and incorporates pre-loaded plot identifiers and GIS coordinates. Second, it enables a semi-automatized valuation method based on an algorithm (rule-based). Figure 2 provides illustrations.[24]

We introduce experimental variation in the degree of discretion bureaucrats have in the determination of property values. Our unit of randomization is the cadastral section. Sections include 417 plots on average and are the unit the administration uses to organize field work. In 48 sections, valuation follows the status quo *fully discretionary* method: bureaucrats use their knowledge and judgement to recover values. In 48 other sections, properties are valued using the new *rule-based* method. In either arm these values constitute the new tax roll. Figure 3 shows the geographical scope of the study and the experimental design. Taken together the two treatment arms include 42,423 plots. There are an additional 97 pure control sections, in which the property tax census did not take place.[25]

[22] These numbers are computed using administrative data from the tax administration and the national treasury. See Knebelmann (2021) for a more in depth exploration of the challenges in the functioning of the property tax before the program.

[23] Recent micro-estimates of property tax compliance rates highlight a similar problem in other countries: 10 percent of properties pay their bill in Kampala, Uganda (Manwaring & Regan, 2023), as little as 4.4 percent of properties are registered and 2.2 percent pay in some areas of Monrovia, Liberia (Okunogbe, 2021).

[24] In Appendix section A.2, we provide additional details on the new property tax management system. Similar digital applications for property taxation with GIS functionalities are still very new on the African continent but are being increasingly adopted (Dzansi *et al.*, 2022; Knebelmann, 2022).

[25] As a whole the broader experiment spans 83,360 plots. The 193 sections were selected by the administration based on tax potential, excluding informal settlements and industrial areas. The comparison between the census sections and the pure control sections will be addressed in a follow-up paper.

The following variables were used for stratification: tax office, section size, and share of plots eligible for taxation according to the baseline survey.[26]

There are 268 bureaucrats, they are temporary employees selected, trained, managed and paid by the administration. Bureaucrat assignment to plots is quasi-random. Assignment to sections is planned by the tax office and is orthogonal to the randomization (72.5 percent worked in both arms). The valuation method is programmed directly in the application. Neither tax office managers nor the field bureaucrats are aware of it before starting a given section, and once a section is started, it must be completed before the bureaucrats are deployed to the next. The program being rolled-out for the first time, there is no prior information on census outcomes nor on bureaucrat performance that the tax office could be using to assign bureaucrats. There are on average fourteen bureaucrats working in a given section with one supervisor who geographically assigns each bureaucrat to a set of plots on the map. A given property is visited by only one bureaucrat whose identification number is recorded in the application. In Section 4, we verify that bureaucrat characteristics are balanced across arms, and do not correlate with market values.

A plot visit lasts around ten to fifteen minutes. The bureaucrat first takes a picture and indicates whether the property is eligible for taxation.[27] Next, the detailed steps vary by arm. In the 48 *discretionary* sections, the bureaucrat tries to speak to the owner and/or the tenants and asks about their identification details, and about monthly rental values. If the bureaucrat is not able to ask occupants, or if the values provided seem unrealistic, (s)he uses her own judgment to provide the best estimate of the monthly rental value. Rents paid by tenants and the value of owner-occupied parts are entered separately. In the 48 *rule-based* sections, the bureaucrat starts by entering eighteen observable characteristics of the property, visible from the outside. This takes around three minutes. These inputs are used to automatically generate a predicted property value for the tax roll, which is not visible on the tablet.[28] In these areas too, the bureaucrat tries to speak to occupants

[26]There are eight tax offices covering the whole region. A plot is *not* eligible for property taxation if it is vacant, if it is a building totally under construction, if the building belongs to the state, if the building is a public school or religious institution.

[27]In Section 4 we verify that the probability of being covered by the census and of being classified eligible do not differ across arms.

[28]We provide details on the calibration of the algorithm in section 4.2. The eighteen characteristics are listed in Table A3.

to recover their identification details, and write down rental values if (s)he recovers any, although these are not used to compute tax liabilities.

The algorithm used in the rule-based arm is inspired by Computer Assisted Mass Appraisal (CAMA) methods for property valuation.[29] The characteristics were selected with the administration, they are all visible from the outside, for the valuation to be possible even if occupants don't let bureaucrats in. They are reported on tablets either by ticking 'Yes' or 'No' boxes, or by selecting a modality in drop-down menus. For some of the characteristics, the answer requires making a judgment on quality, for example indicating whether the fence is in a 'Good', 'Medium' or 'Bad' state.

The program first started in 2019, seven sections were covered between November 2019 and February 2020 (less than three percent of the plots in our sample). There was an interruption due to the covid-19 pandemic, the census resumed in June 2021 and ended in April 2023.[30]

3 Conceptual Framework

The objective of the administration is to register the maximum number of properties with values reflecting market rents ("accurate") in order to tax to the full potential, while ensuring tax fairness, more precisely vertical equity – which implies that more expensive properties should always face a higher tax bill than cheaper properties – and horizontal equity – which implies that two properties of similar market value should face similar tax bills. Overvaluation error is worse (than undervaluation) for low value properties, while undervaluation is worse (than overvaluation) for high value properties. How strongly this is true depends on the government's preference for vertical equity. Dispersion – large differences in valuations for a given market value – is problematic anywhere in the distribution. How strongly this is true depends on the government's preference for horizontal

[29] CAMA methods are widespread in some developed countries such as the United States and Canada for instance, but only strongly established in Sub-Saharan Africa in the case of some South African cities. We worked with practitioners having made suggestions on how to adapt these methods to the African context Franzsen & McCluskey (2017); Davis *et al.* (2012); McCluskey *et al.* (2013); Guan *et al.* (2011); Moore (2005); Ali *et al.* (2018); Fish (2018); International Association of Assessing Officers (2022).

[30] The tax bills generated from the new census operations will be distributed all at once, starting October 2023.

equity.

Bureaucrats' discretion in the field can have advantages: they may have local knowledge, they may be able to recover private information from occupants such as actual rents being paid. They may generate more equity if they adjust values to idiosyncratic information on the property or its owner that could not be captured in a systematized process. They may be better equipped to value some types of properties, for instance, around prices or neighborhoods they are more familiar with, or where occupants are more cooperative with the government.

On the other hand, discretionary bureaucrats could lack the required expertise to recover reliable values. They may be inconsistent in their valuations, they may be strongly heterogeneous, all of which would generate dispersion. They may also be biased towards or against certain types of occupants, and their values could intentionally or not be affected by their perceptions of what is fair. Finally, bureaucrats could have objectives that differ from those of the administration. There could be disutility associated with getting accurate values, if it implies additional effort, conflicts with occupants, or reduces the number of plots covered per day. Finally, they could engage in rent-seeking and try to collude with owners, asking for bribes in exchange for lower future tax liabilities.

A rule-based system is more systematic and predictable. Even with a rule implemented by bureaucrats, core components of the predictions (built area and location) do not depend on their input. This might allow to mitigate the effects of heterogeneity and inconsistency. In successful prediction formulas, errors are symmetric, meaning that for a given underlying market value, the probabilities of over and undervaluation are equivalent. This might be a positive feature overall, but could be problematic for the very bottom or very top of the distribution. Collusion under the rule implemented by bureaucrats is less straightforward since it requires sophisticated manipulation by bureaucrats who are not aware of the weight of each characteristic.

Finally, a pure rule process implemented using only data "from the office" removes all drawbacks due to delegation, but may lead to losses in accuracy if the characteristics collected in the field increase precision. There may also be a cost for the government of not collecting local information about occupants.

4 Data

4.1 Data Sources

Baseline property owner survey. Our baseline owner survey covers 2,474 plots, half of which are in the census sections and half in the pure control sections. We collected socio-demographic information on owners, rental status, declared property values. The survey was conducted in 2018, before the beginning of the property tax census.

GIS mapping of plots and properties. For all 83,300 plots of the census and control sections, we compile a geocoded dataset with plot identification number, plot area, ground built area measurement.[31] Plot identifiers and delimitations were provided by the tax administration. Built area was recovered by GIS experts hired by the research team relying on high resolution images from the Pleiade satellites (50cm resolution) made available by the French Space Agency.[32]

Market rental values. We hire licensed assessors from the real estate section of the Senegalese National Order of Experts[33] to build a dataset of market values for a representative sample of properties. We prepare a random selection of 5,806 plots to be valued, half in the census sections (spanning both the discretion and rule arms), and half in the pure control sections.[34] Figure A1 shows how our different samples overlap, and Appendix Section B.1 provides additional details on the data collection. Assessors go to each property in the field and were asked to provide a market rental value, as well as an upper and lower bound. Properties are valued from the outside to avoid any biases due to non-response. Assessors also collect the observable property characteristics used in the calibration of the rule. This work was carried out between June and August 2022, and resulted in a valuation for 4,921 properties.[35] Figure 1 shows the range of properties and their market values.

[31] This is the largest geocoded dataset with built area measurements and administrative plot identification made available to the Senegalese administration to date.

[32] *Centre National d'Etudes Spatiales* or CNES

[33] See: https://www.experts-ones.com/

[34] The daily fee of licensed assessors from the private sector is ten times the daily fee paid to field bureaucrats hired for the program. For this reason it is not feasible to directly hire assessors to value all properties.

[35] In Appendix Table A1 we show correlations with values from other sources: although the samples are small, we are reassured by the 0.62 correlation between assessor valuations and rents of fully rented properties reported in the owner baseline survey, and the 0.72 correlation with rents of properties with a rental contract recovered in the census.

Property tax census data from the digital tool. Out of the 96 targeted sections, 94 (comprising 41,609 plots) were covered by the census.[36] 38,227 (91.9 percent) of these plots were registered by a bureaucrat. In Table A9, we show that implementation does not differ across arms.[37] For each plot covered by the census, we recover bureaucrat identification and all variables collected by the bureaucrat in the field: identification details of owners and tenants, usage of the property, number of floors and of rooms, rental status, main residence status, whether the bureaucrat met the owner, rent value, value of owner-occupied parts. The observable property characteristics used for the rule are only collected in rule-based sections. In Appendix B.3 we provide details on the data cleaning we apply to software extractions.[38] Henceforth, we refer to the property values from the census as census values or tax roll values.

Analysis sample. Our main analysis sample is restricted to plots from the discretion and rule arms for which we have a market value from the assessors' dataset, built area measurement,[39] and that were not classified as non-eligible for taxation by bureaucrats.[40] The analysis sample includes 2,290 plots – 1,166 in the rule arm and 1,124 in the discretion arm – and 93 percent were covered by the census.[41]

Bureaucrat surveys. Bureaucrats fill-in a short baseline survey during their training, with information on their background, their social preferences and views about taxation. The endline survey has several modules: satisfaction with and opinions on the job, personality traits, socio-emotional skills, cognitive skills, persuasion exercise, tax knowledge. Finally, the survey includes experimental lab-in-the-field property valuations we use to test mech-

[36] For two sections (one in each arm), the census was interrupted in the first days because of pre-existing tensions between the local population and the tax administration regarding property titles. Only 11 out of 89 and 16 out of 404 plots were covered, and the associated tax bills will not be generated. We drop these two sections from our analysis sample.

[37] We regress the number of plots covered per day in a given section and find no significant difference across arms. In Panel (A) results are for the full sample, and in Panel (B) we restrict to the sample with market values.

[38] This includes replacements we conduct for a subset of properties for which some observable characteristics were not collected following a technical problem. In Appendix C, we present two robustness checks to ensure that the replacement strategy is not affecting our results.

[39] In Panel (A) of Table 1 we show that this is balanced across arms. Built area is missing for 7 percent of plots, this can be due to the plot being vacant land, or a mismatch between satellite images and plot borders for cases where there was a recent change.

[40] We show that this is balanced across arms in Table A9 column (3).

[41] We show that this is balanced across arms in Table A9 column (2).

anisms. We also survey supervisors and ask them to evaluate the bureaucrats on different dimensions. In Appendix Section B.5 we define bureaucrat survey variables. 247 out of the 268 bureaucrats completed the baseline survey, and 180 completed the endline.[42]

4.2 The Rule: Property Valuation Algorithm

We calibrate a property valuation model on the sample of all assessor valuations ($N = 4,921$, spanning both census and pure control sections) using an elastic-net regression and 5-fold cross-validation. The functional form is:

$$Ln(Value)_{ij} = \alpha + \beta Ln(BuiltArea)_{ij} + \gamma floors_{ij} + \sum_k \theta_k X_{k,ij} + Sec_j + \epsilon_{ij} \tag{1}$$

where $Value_{ij}$ is the annual rental value of property i in section j, $BuiltArea$ is total built area (ground area multiplied by the number of floors), $floors$ is the number of floors, the X_k variables are the property characteristics visible from the outside as reported by assessors, and Sec_j is a section fixed effect.[43] For the main rule implemented in the application under the rule-based system, we include all covariates. Table A3 shows the resulting coefficients and Table A2 shows the performance statistics. See Appendix B.2 for additional details and references. We use the standard calibration indicators from the property valuation literature: the R^2 is 90 percent, the out-of-sample mean absolute percentage error (MAPE) is 33.8, and 59.6 percent of out-of-sample predicted values fall within 30

[42]Among the 38,227 plots covered by the census, 98.8 percent were covered by a bureaucrat for which we have a baseline survey, and 81.4 percent were covered by a bureaucrat for which we have an endline survey. The lower number of bureaucrats completing the endline survey is due to the fact that bureaucrats who stopped over the pandemic period were more difficult to track down.

[43]The X_k covariates are: usage, type of fence, state of the fence, type of cladding, state of the cladding, cement wall, presence of decorative tiles, quality of doors and windows, landscape improvement, architectural improvement, presence and type of garage, balcony, location with respect to main road, type of road, presence of sidewalk, whether the property is at an angle, presence of street lights. All variables and response categories are listed in Table A3.

percent of the market value.[44][45] The application automatically computes predicted values by applying coefficients from the model to bureaucrats' inputs and pre-loaded plot location and built area (see Appendix B.2 for details).

The second rule, the pure rule, uses only covariates that could be recovered from the office: built area, number of floors, and section fixed-effect. Table A4 displays the performance statistics and summarizes the coefficients. The R^2 decreases to 0.87 and the MAPE increases to 41.4 percent. This suggests that section fixed-effects and built area explain a large share of the variation in property values, although the additional characteristics used in the main rule still add some valuable information.[46]

Additionally, we calibrate three rules used for robustness checks. The first is calibrated using values from our property owner baseline survey as the outcome variable ($N = 1,293$). The R^2 is 0.33 and the MAPE is 75.4. The second is a pure rule also calibrated on baseline values (only section fixed-effects and built area as regressors). The R^2 is 0.29 and the MAPE is 72. The second is calibrated using assessor values but restricting the sample to pure control sections ($N = 2,458$).[47] The R^2 is 0.88 and the MAPE is 51.6.

4.3 Balance Checks

In Table 1 we verify that section and bureaucrat characteristics are balanced across the rule and discretion arms. Section characteristics are balanced thanks to our randomiza-

[44]We also test a random forest prediction model, the out-of-sample R^2 is 0.83 and the MAPE is 43. The best performing model we test is an elastic-net-regression estimated through cross-validation using all covariates and adding quadratic and cubic terms for built area and number of floors, as well as interactions between all section fixed-effects and built area. 65.6 percent of predictions fall within 30 percent of the market value. We do not implement this rule in the application because the gains in precision seem limited when compared to the loss in transparency to policy-makers.

[45]Although lower than what is observed in high income contexts with higher data quality, our performance indicators are high if compared to results from similar settings. Ali *et al.* (2018) find and R^2 around 56 percent in Rwanda, Franklin (2019) finds an R^2 of 85 percent in Addis Ababa, Ethiopia. Behr *et al.* (2023) find an MAPE ranging between 0.30 and 0.64 in South Africa.

[46]In the current version of the pure rule we still rely on the number of floors reported by assessors to compute total built area. Indeed, a formula calibrated using only the ground floor built area is much less precise (R^2 of 0.62 and MAPE of 99). However, it is technically feasible to recover the number of floors directly from more sophisticated satellite images. The Senegalese administration has started the acquisition of such images which should become available in 2024.

[47]We use strata fixed-effects instead of section fixed-effects in order to be able to apply this rule to our census sections. Additionally, we control for the value of a standardized 200 m^2 house, this was a section-level question integrated in the assessor dataset.

tion, while the balance of bureaucrat characteristics results from their quasi-random assignment to areas. In Panel (A), we regress plot characteristics (from the cadastral data, the assessors' dataset, and the owner baseline survey) on a dummy taking value one for discretionary sections. In Panel (B), we regress baseline bureaucrat characteristics on a dummy taking value one for discretionary sections, observations are at the bureaucrat X section level. In Panel (C), we regress bureaucrat characteristics on market values, observations are at the plot level. We can rule out joint significance of all characteristics in the three Panels. None of the p-values for the coefficient of interest are below 0.05, except for one out thirteen of characteristics in Panel (C) but with a very small magnitude.[48] These verifications confirm that we can draw causal interpretations of the effects on the valuation roll of: (i) giving bureaucrats different degrees of discretion; (ii) bureaucrat characteristics.

5 Results

5.1 Removing Discretion Increases Accuracy and Tax Equity

Valuation profile by arm. In Figure 4, we show the scatter plot of property values on the tax roll over market values. The first striking observation is the strong dispersion of valuations under discretion (Panel (A)). We add a 6-degree polynomial fit curve with its 95 percent confidence interval. It reveals a significant undervaluation gap under discretion that increases with market value. These two problems seem to be mitigated by the rule-based process (Panel (B)), even more so by the pure rule (Panel (C)). In the remaining of this section we confirm and quantify these visual results.

First, we plot the median assessment ratio – computed as tax roll value over market value[49] – by quintiles of market value, separately for each valuation method. Results are shown in Figure 5, and in Table 2, we test whether the differences across quintiles are significant. There is a strong undervaluation gradient under discretion: the median

[48] A property with a one percent higher market value is 0.04 percentage points (0.09 percent) less likely to be visited by a bureaucrat with three years or more of higher education.

[49] The assessment ratio is a widely used indicator in the property tax literature (Avenancio-León & Howard, 2022; McMillen & Singh, 2020; Dray *et al.*, 2023).

assessment ratio is 0.83, 0.73, 0.50, 0.44 and 0.23 in quintiles one to five respectively, and these differences are significant at the 1 percent level (Panel (A) of Table 2).[50] Under the rule-based system, the ratio is in the vicinity of one for quintiles two to four, but significanly higher (1.25) in the bottom quintile and significantly lower (0.64) in the top quintile (Panel (B) of Table 2). The pure rule (Panel (C) of Figure 5) displays a median assessment ratio in the vicinity of one for all quintiles except the bottom one (1.26).[51] We provide additional results on the assessment ratios in Appendix Table A8.[52]

Second, we measure the correlation between a property's rank in market values and its rank on the tax roll – a slope closer to one suggests stronger vertical equity.[53] In Figure 6, properties are sorted into 20 bins of market values on the x-axis, and the y-axis shows the mean rank for properties of a given bin. The rank-preservation slope is 0.28 under discretion, 0.69 under the rule, and 0.94 with the pure rule.

Finally, we plot the median effective tax rates by quintile in Figure 7, and add the benchmark tax profile obtained by applying the tax code to market values. Panels (B), (C) and (D) show that the standard deviation of the tax rate in each quintile increases with each degree of discretion, which harms horizontal equity. The expected tax rate in the bottom quintile is 4.4 percent. The observed tax rates are 3.8 percent under full discretion,

[50] More precisely the significant differences are the ones between quintiles one and two versus three and four, and between quintile four and five. In Table A5 we conduct the following robustness checks: considering mean assessment ratios instead of the median (Panel (A)), grouping properties by quintile of market value per square meter (Panel (B)), grouping properties by quintile of predicted market value using a prediction on pure control areas where there is no census.

[51] In Appendix Figure A4 we show the assessment ratio by quintile for our calibration sample with assessor inputs. It still displays a slightly higher (resp. lower) assessment ratio in the bottom (resp. top) quintile, but to a much lower extent than when the rule is implemented by bureaucrats. Some degree of regressivity is inherent to the rules because of unobserved variables (such as property features the assessors saw in the field but not captured in the characteristics, or area characteristics at a lower level than the section). This has been shown extensively for property tax valuation models applied in the United States (McMillen & Singh, 2020; Berry, 2021; Amornsiripanitch, 2023).

[52] Appendix Table A8 reports horizontal and vertical equity statistics that are commonly used in the property valuation literature (McMillen & Singh, 2020; International Association of Assessing Officers, 2013). The price-related differential (PRD) is computed as the ratio of average assessment ratio over the market value-weighted average assessment ratio. The larger it is, the weaker vertical equity is. As a benchmark, the International Association of Assessing Officers suggests that the PRD should lie between 0.98 and 1.03 (International Association of Assessing Officers, 2013). We find that it is 1.60 under full discretion, 1.28 under the rule, and 1.02 using the pure rule. Second, we compute the coefficient of dispersion (COD), a measure of horizontal equity calculated as the average percentage deviation of the assessment ratio from its median. We display this statistic both overall and by quintile: dispersion in valuations is always the strongest under full discretion, and always the lowest under the pure rule.

[53] Methodologically, we follow the social mobility literature (Chetty *et al.*, 2019, 2020).

7.4 percent under the rule and 6.9 percent under the pure rule. The expected tax rate in the top quintile is 8.6 percent. The observed tax rates are 1.7 percent under full discretion, 5.2 percent under the rule and 7 percent under the pure rule. We provide additional results and robustness checks in Appendix Figure A6.[54]

Regression results for tax base gap outcomes. We define the tax base gap as the tax roll value minus market value. In the discretion arm, the tax roll value is bureaucrat's discretionary value, in the rule arm, the tax roll value is subsequently the rule-based value and the pure rule value. The sign and value of the tax base gap indicate whether there is over or under-valuation and by how much, in monetary amounts. We estimate:

$$Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk} \tag{2}$$

where Y_{ijk} is the outcome for plot i of section j and strata k, D_{jk} is a dummy taking value one if the section was assigned to discretion, and S_k is a strata fixed effect. Standard errors are clustered at the section level. Results are shown in Table 3, where Y_{ijk} is in turn the tax base gap (column (1)), the median tax base gap (column (2)), the absolute tax base gap (column (3)), and the assessment ratio (column (4)). Under the rule-based system, the mean (respectively, median) gap is -2.33 (resp. -0.16) millions FCFA, and the mean absolute tax base gap is 4.67 millions FCFA (Panel (B)).[55] The estimated $\hat{\beta}_{Discretion}$ shows that the gap is widened by -4.61, the median gap by -1.87, and the absolute tax base gap by 3.88 (or 83 percent) when switching to discretion, all coefficients being significant at the 1 percent level. In Panel (C), we run the same regression but applying the pure rule, and find larger $\hat{\beta}_{Discretion}$ coefficients: compared to the pure rule, discretion increases the absolute tax base gap by 4.71 million FCFA or 166 percent. In Appendix Table A6, we provide additional results and robustness checks.[56] In Tables A9 and A7, we decompose

[54] Panel (A) of Figure A6 shows the *mean* tax rates by quintile, in Panel (B) we calculate the share of property value subject to the owner-occupied abatement using the number of rooms in both arms (instead of using the number of rooms in the rule arm and the owner-occupied value provided by bureaucrats in the discretion arm), in Panel (C) we plot the median tax rate by *deciles*, and in Panel (D) we restrict to properties for which a positive valuation was made.

[55] All amounts are winsorized at the one percent level. The median annual rental market value is 15.80 millions FCFA.

[56] First, we add bureaucrat fixed-effects and find that the difference in tax base gap across arms is of the same order of magnitude within bureaucrat (Panel (A) of Table A6). Second, one might wonder whether

the effect of discretion into its extensive and intensive margins and carry out a Lee bounds exercise.[57]

Heterogeneity by market value. Next, we split the sample into low market value (quintiles one and two) and high market value (quintiles three to five) properties and re-estimate regression 2. Results are in Table 3. For low-value properties, the rule-based process slightly over-values and discretion slightly under-values. The coefficient for the absolute tax base gap is still significant, but much smaller: discretion increases the tax base gap by 25 percent, against 72 percent for high-value properties. The pure rule slightly outperforms discretion even for low value properties, but again, its strongest advantage compared to discretion is for the upper part of the distribution.

Tax liabilities. Translating to tax liability amounts illustrates how massive the effects of different degrees of discretion are for the tax burden and for how it is shared. Total liabilities amount to 8 billion FCFA in the discretion arm (16,651 eligible plots), against 19.6 billion if extrapolating the benchmark market values to all eligible plots; 11 billion FCFA in the rule arm (16,026 eligible plots), and 19.7 billion FCFA in the rule arm if using the pure rule. Based on the subsample with market values, the share of liabilities due by the bottom 10 percent of properties are 1.1, 0.95 and 0.64 percent respectively, and the share due by the top 10 percent are 49.6, 63 and 70 percent respectively.

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part of the result is mechanical since the algorithm is calibrated on assessor values, and assessor values are also used as the benchmark. This problem is mitigated by the fact that the algorithm calibration relies on cross-validation, and also has half of its observations in pure control sections which do not overlap with our analysis sample. Yet, in addition, we re-estimate regression 2 replacing values in the rule based arm by predictions using two rules calibrated on owner baseline survey values, one with all covariates and one being a pure rule (see Section 4.2). Discretion still significantly widens the median tax base gap even compared to these low quality rules (Panels (B) and (C) of Table A6, results are noisier when the outcome is the absolute tax base gap, the coefficient is still positive but not significant).

[57]In Table A9, we find that discretion leads to a 17.8 percentage point lower probability of being assigned a positive value, and this is driven entirely by values of owner-occupied parts. In Table A7 we verify that the rule outperforms discretion in terms of accuracy on the intensive margin as well. In Panel (A), we estimate equation 2 on the sample of properties with a positive value, the results are indicative and not causal. In Panel (B), we carry out a Lee bounds exercise and find that discretion significantly widens the tax base gap even with extreme assumptions on the nature of selection.

5.2 Removing Discretion Reduces Bureaucrat-Induced Variability

Estimating bureaucrat fixed-effects. To measure bureaucrat-induced variability in the quality of valuations, we estimate bureaucrat fixed-effects in the following specification, separately on the discretion and rule arms:

$$|Gap|_{ijb} = \alpha_b + Val_j + \epsilon_{ijb} \tag{3}$$

where $|Gap|_{ijb}$ is the absolute value of the tax base gap (in millions of FCFA and winsorized at the one percent level) for property i of section j covered by bureaucrat b, α_b is the bureaucrat fixed-effect, and Val_j is a section-level control for market values.[58] Errors are clustered at the section level. In the discretion arm, there are 1,055 properties and 198 bureaucrats; in the rule arm, there are 1,063 properties and 190 bureaucrats.[59] Thanks to the quasi-random assignment of bureaucrats to plots, the estimated α_b are an unbiased measure of the quality of a bureaucrats' valuations: a larger α_b means bureaucrat b drives values further away from market values, the best performing bureaucrats are the ones with the smallest α_b. Next, we shrink each estimated fixed-effect proportionally to the noise with which it is estimated using an empirical Bayes procedure, this yields the vector of adjusted fixed-effects $\alpha_{b,EB}$.[60] Finally, we measure the share of variance in the tax base gap explained by bureaucrats in each arm.[61] The kernel density estimates of the distribution of the fixed-effects are pictured in Panel (A) of Figure 8.[62] Summary statistics are reported in Table 4. The variance of the absolute tax base gap is much larger under discretion than under the rule (217.6, column (1), against 103.65, column (2)), but so is the variance of the estimated $\alpha_{b,EB}$, and to a larger extent. As a result, the share of variance in the tax base gap explained by bureaucrat fixed-effects is 40 percent under discretion,

[58] Val_j is a categorical variable indicating in which decile of market value per square meter section j is.

[59] Plots that are not covered by the census are dropped since no bureaucrat is associated to them. As shown in Table A9 column (2), the probability of being covered does not differ across arms.

[60] Our estimates may suffer from noise due to the limited number of observations for each bureaucrat. For the shrinkage procedure, we follow the methodology developed in Chandra *et al.* (2016), in line with Kane & Staiger (2008); Morris (1983).

[61] We can compute the share of variance as $Var(\alpha_{b,EB})/Var(|Gap|)$ since quasi-random assignment leads to $Cov(\alpha_{b,EB}, Val_j) = 0$.

[62] Figure A7 plots the correlation between each bureaucrats' fixed-effect under the rule and under discretion.

against 13 percent under the rule.[63]

Screening bureaucrats. Could discretion outperform the rule if the administration were able to successfully screen bureaucrats? First, we quantify how strong screening would need to be for the difference in the tax base gap between rule-based and discretion to fade. In Panel (B) of Figure 8, we sort bureaucrats by their $\alpha_{b,EB}$ estimated in the discretion arm and run specification 2 starting by the sample with all bureaucrats, and iterating by removing the worst bureaucrats one by one. The coefficient on discretion is no longer significant after removing the 81 (41 percent) worst bureaucrats, suggesting that restricting to top bureaucrats performs at best as well as the rule-based process.[64] Second, we investigate whether there are observable characteristics that predict being a top bureaucrat (Figure A8). Having three years or more of higher education is significantly associated with a 20 pp (35 percent) higher probability of being a top bureaucrat, defined as $\alpha_{b,EB} < 0$, and is also a straightforward variable to use for screening.[65] Next, we use a k-means clustering procedure to divide bureaucrats into the two groups with the strongest possible difference in all their characteristics, and find that one group has a 25 pp higher probability (significant at the 10 percent level) of being a top bureaucrat.[66] Finally, in Appendix D, we show how the tax profile differs for top versus bottom bureaucrats. First we split the sample based on the bureaucrat fixed-effects. Next, we split the sample by long higher education (Figure A20), and subsequently based on the k-means clustering exer-

[63] As a comparison, Bergeron *et al.* (2022) find that bureaucrats explain 21 percent of variance in tax compliance across neighborhoods in the Democratic Republic of Congo; Fenizia (2022) finds that managers of social security offices in Italy explain 9 percent of variation in productivity, measured by the efficiency in processing insurance claims; Best *et al.* (2023) find that bureaucrats explain 39 percent of variation in quality-adjusted prices in the Russian public procurement system. One reason why our results seem to be in the higher end of these findings is that in our setting, the outcome depends almost fully on what the bureaucrat is doing in the field. It does not depend for instance on the subsequent reaction of the taxpayer, of other co-workers, etc.

[64] The estimation becomes noisier as we remove bureaucrats since the number of observations decreases and we may be under-powered to conclude with precision once we have removed a large share of bureaucrats.

[65] 98 percent of bureaucrats have some higher education, 40 percent have three years or more. Other significant correlations show that a one standard deviation stronger baseline preference for widespread taxation is associated with a 11.4 percent higher probability of being a top bureaucrat (significant at the 10 percent level). Conversely, a one standard deviation higher emotions reading score (resp., agreeableness score) is associated with a 19 percent (resp., 15.7 percent) lower probability of being a top bureaucrat. See Appendix Section B.5 for a detailed description of the variables from the bureaucrat surveys, and see Appendix D for additional results on bureaucrats' skills and different measures of performance.

[66] See Appendix Section D for details.

cise (Figure A21), to see whether these screening procedures seem to replicate the same difference in tax profiles obtained when directly using bureaucrat fixed-effects. In both cases, the predicted 'low performance' group generates lower tax rates, a more regressive profile, and much stronger dispersion.

6 Mechanisms

The role of the knowledge channel. A main driver of the strong inaccuracies and the undervaluation gradient found under discretion is bureaucrats' lack of expertise with respect to property values. We first shed light on this by identifying *bureaucrats' implicit algorithm*: we show that their values are poorly explained by objective property characteristics. We regress discretionary valuations on property characteristics, following the exact same methodology as the one used for our main algorithm. Results are shown in Appendix Table A10. The R^2 is 0.25, the elastic-net procedure assigns a value of zero to 15 out of 34 coefficients and 18 out of 48 section fixed-effects (against 3 out of 34 and 22 out of 193 in the main calibration), and the coefficient on built area 0.43 is (against 0.57).

Second, to isolate the knowledge channel, we implement a lab-in-the-field valuation exercise. Bureaucrats are shown the picture of a property (with an indication of its neighborhood) and are asked to provide their best estimate of the monthly rental value. The exercise is done twice by each bureaucrat, for a low value property and a high value property.[67] The distribution of answers is plotted in Figure A14. The bottom property is given a value that is on average 73 percent higher than the true value, but still within the lowest quintile; it is accurately valued in 11 percent of cases, overvalued (respectively, undervalued) in 77 (resp., 15) percent of cases. On the other hand, the high value property is undervalued in 98 percent of cases, it is given an average value that is 70 percent lower than the true value, bringing it down from the highest to the third quintile of market values. We compare relative accuracy for the low versus high value property for a given

[67] The properties used in the experimental question are shown in Figure 1, Panels (A) and (C) respectively. These survey questions were not incentivized, they were presented as a means for the research team to better understand how the program was being implemented. We have no reason to believe that bureaucrats would strategically provide wrong answers, they were not aware that we had collected benchmark market values.

bureaucrat by estimating

$$AR_{ib} = \alpha_b + \beta High_{ib} + \epsilon_{ib} \tag{4}$$

where AR_{ib} for property i and bureaucrat b is the assessment ratio, α_b is a bureaucrat fixed-effect, and $High_{ij}$ is a dummy taking value one for the high value property. Results are shown in Table 6, column (1), and show that that a given bureaucrat is 68 percent less accurate for the high value property. While very few are property owners (4.8 percent), those who are tenants (49 percent) report paying an average rent of 73,067 FCFA, which is in the bottom 5 percent of market values. This lack of exposure to expensive properties could explain the results. The dispersion of the answers is also telling: considering the high-end property, the hypothetical tax bill would vary between 83 and 4,158 USD depending on the bureaucrat.

Third, we use an information treatment to test whether there are avenues for learning. Half of the bureaucrats are shown a fact sheet providing key numbers from the distribution of market values (see Figure A13).[68] In column (2) of Table 6, we estimate regression 4 with a dummy for receiving the information treatment. We find that the information treatment does not improve valuations, neither for low nor high value property.[69] Our findings echo those in Hvidberg *et al.* (2023) showing that people tend to underestimate inequality, and (Stantcheva, 2021; Hoy, 2022) showing individuals' misconceptions of income and wealth.

Ruling out the collusion channel. An alternative mechanism for the undervaluation gradient could be collusion, if owners of expensive properties offer bribes in exchange of

[68]The display of the fact sheet resembles the one used in Hoy (2022) to inform respondents about income distributions. Bureaucrats are randomized with a stratification on observed accuracy in the census data, gender, and education level. We verify bureaucrats' comprehension of the fact sheet using two simple interpretation questions that needed to be answered correctly before moving to the valuation.

[69]We also test whether we observe learning over time in the census data. First, we verify how the absolute tax base gap and values evolve with the number of days and the number of properties covered by a bureaucrat (Table A12). We find that the tax base gap *increases* with the number of days under discretion, while it decreases under the rule. This suggests that improvements in collecting observable characteristics might be easier to achieve compared to improvements in bureaucrats' ability to recover market values in a fully discretionary way. Second, we check whether bureaucrats having already been exposed to the rule do better under discretion than non-exposed colleagues, which could occur if they learn which characteristics matter (Figure A16). We don't find any difference in the assessment ratio by quintile across the two groups.

lower tax liabilities.[70] We rule this out using suggestive evidence. First, the lab-in-the-field finding proves that undervaluation is strong when there are no stakes. The hypothetical median effective tax rate based on bureaucrats' answers is 1.8 percent – strikingly close to the 1.7 percent found in the census for properties of the top quintile. Second, we test whether we find any difference in the undervaluation gradient in cases where the owner was met during the field visit, with the assumption that collusion would occur when the owner is met.[71] To do so we estimate:

$$AR_i = \alpha + \sum_{n=1}^{5} \beta_n Q(n)_i + \sum_{n=1}^{5} \gamma_n Q(n)_i \cdot M_i + \epsilon_i \tag{5}$$

where AR_i is the assessment ratio for property i, the $Q(n)$ dummies are indicators for each quintile of the distribution of market values, and M_i is a dummy taking value 1 if the bureaucrat met the owner. Errors are clustered at the section level. Results are plotted in Figure 9. We find that the interaction coefficients between each quintile and the dummy for meeting the owner are never significantly different from zero.[72]

Behavioral biases based on owner status and perceptions of fairness. We use our bureaucrat endline survey to show that bureaucrats are biased by what they consider fair. For each picture in the lab-in-the-field valuations, half of the bureaucrats are told that the owner is retired, and half that the owner is employed.[73] In the socioeconomic context

[70] One feature of the setting which makes corruption less likely is that there is no direct exchange of money between the bureaucrats and the occupants. Furthermore, according to our owner baseline survey, the vast majority of owners (85 percent) never received a tax bill before. For them to pay bribes, they would need to trust that there will be enforcement later on.

[71] This variable being reported by bureaucrats, one could worry that it is manipulated. However, we expect this to be unlikely: (i) bureaucrats are not aware we are making comparisons with market values; (ii) bureaucrats are incentivized to meet owners and recover their identification details, their monthly bonus takes into account the share of owners for which they recover this information; (iii) bureaucrats' supervisor spends the day with them in the neighborhood, knows more or less where each team member is at any given point in time, and also reviews the forms in the evening before submitting them to the server – if a bureaucrat tends to spend time discussing with owners asking for bribes, and reports not meeting them, this would likely be detected by the supervisor.

[72] Additionally, although self-declarations are of course to be considered with caution, direct survey responses suggest that corruption is at most very rare. When asked whether they were "offered arrangements by owners" (without any reference to whether or not they accepted), 79 percent of bureaucrats replied *Never*, 20 percent *Once or Twice*. When asked whether this happened to their colleagues, 64 percent replied to *None*, 20 percent *Almost None* and 14 percent a *Minority*.

[73] This variation is randomized using the same stratification variables as for the information treatment, although both randomizations are independent.

of Senegal, retired people are considered as vulnerable and deserving support. We then estimate:

$$Ln(Value)_{ibk} = \alpha + \beta_1 Retired_{ibk} + \beta_2 High_{ibk} + \beta_3 Retired_{ibk} \cdot High_{ibk} + A_k + \epsilon_{ibk} \quad (6)$$

$Ln(Value)_{ibk}$ is the value given by bureaucrat b for property i, $Retired_{ibk}$ is a dummy taking value 1 if the bureaucrat received the information that the owner of i is retired, $High_{ibk}$ is a dummy indicating the high value property, A_k is a fixed effect for the strata used for bureaucrat randomization. Results are shown in Table 6: bureaucrats provide a value that is 37.8 percent lower when the owner is retired (column (3)), and this is driven entirely by the low value property (column (4)). In Appendix Table A13, we test whether we find this correlation in the census data. Retired owner (compared to employed) correlates with a lower bureaucrat value, while there is no correlation with household income.[74]

Additionally, we rely on direct survey responses to illustrate how perceptions of fairness might affect valuations. When asked which direction of error is worse, 23 percent of bureaucrats consider that it is worse for bureaucrats to overvalue; while only 8 percent consider it is worse to undervalue.[75] Bureaucrats are almost symmetrically divided about whether it is fair for a retired person to pay a tax if (s)he owns a property: 44.8 percent agree while 42 percent disagree.[76] When asked which types of owners can benefit from tax rebates, only 36 percent select owner-occupied properties (which is the most common true rebate); 46 percent select retired owners; 11 percent select single mothers - although there is absolutely nothing in the tax code for this category of owners. Finally, bureaucrats differ in their 'naiveness' towards owner-declarations: 17 percent reply that owner values

[74]More precisely, we regress bureaucrat discretionary value on owner and owner X bureaucrat characteristics and control for property value, using the pure rule prediction. We use predicted value instead of market value because restricting to the overlapping plots between market value sample and baseline owner survey in the discretion arm would yield a too small number of observations. In Column (1) and (2), we use the full sample of properties in the discretion arm, and owner characteristics are reported by the bureaucrat. Meeting the owner, a deceased owner, a retired owner, a female owner (all relative to male owner) are correlated with a lower value, while multiple ownership and the area being the bureaucrat's home commune are correlated with a higher value. In Column (3) and (4), we rely instead on owner characteristics from our baseline survey.

[75]70 percent consider that both are equally problematic. Importantly, this topic is never mentioned in the trainings nor by the supervisor, this really reflects bureaucrats' individual perceptions.

[76]In the tax code, retired civil servants may benefit from a reduction in their tax bill. This applies only to a minority if owners in the region.

are somewhat overvalued, 53 percent that they are about correct, and 29 percent that they are somewhat undervalued.

Big effects of a small degree of discretion. The tax base gap we observe with limited delegation, under the rule-based system has two components: the first originates from prediction errors which do not depend on bureaucrats;[77] the second is caused by bureaucrats, when they enter erroneous property characteristics. This second component is informative on the effects of a limited degree of discretion, and we measure it by comparing predictions computed using assessor inputs with predictions relying on bureaucrats' inputs.[78] We estimate:

$$Y_{irjk} = \alpha + \beta RuleBur_{irjk} + S_k + \epsilon_{irjk} \tag{7}$$

where Y_{itjk} is the outcome for plot i of section j and strata k under rule r, $RuleBur_{irjk}$ is a dummy taking value one if r is the rule as implemented by bureaucrats, and zero if r is the benchmark rule. In Panel (A), the benchmark rule is the pure rule, and in Panel (B) the benchmark rule is the rule with assessor inputs. Each property appears twice in the dataset, and the discretion arm is excluded. S_k is a strata fixed effect and standard errors are clustered at the section level. Results are shown in Table 7. The rule with bureaucrat inputs increases the absolute tax base gap by 1.84 million FCFA or 65 percent compared to the pure rule, and by 1.89 million FCFA or 68 percent compared to the rule with assessor inputs (column (3)).[79][80]

[77] As shown in the calibration statistics in Appendix Table A2, the share of predictions that fall within 30 percent of the market value in the test sample is 59.6 percent.

[78] To support our assumption that assessors' characteristics are the correct ones, we conduct verifications a random subset of 100 pictures and find that assessors' reported number of floors is 2.2 times more likely to be correct than bureaucrats.

[79] Furthermore, we split the sample by market value. Looking at Panel (B), we see that the rule by bureaucrats slightly increases overvaluation at the bottom (although this is not significant for all outcomes), while significantly driving values down in the upper part of the distribution (the median gap decreases from -0.33 to -1.28 million FCFA). Thus even *partial* delegation generates more regressivity in the tax profile than what would occur with a correctly implemented rule.

[80] In Appendix Figure A11, we show the contribution of each characteristic X_c to the aggregate differences between the rule implemented by bureaucrats versus assessors measured in Panel (B) of Table 7 as $\sum_i |\gamma_c X_{c,RuleBur,i} - \gamma_c X_{c,RuleAss,i}|$, where subscript $RuleBur$ indicates the value taken by X_c when entered by bureaucrat and $RuleAss$ the value taken by X_c when entered by assessors for property i, γ_c is the coefficient for X_c in the formula. We find that the most contributing characteristic is cladding type. This is likely due to the fact that (i) it has six modalities, (ii) it takes some technical expertise to differentiate them. The second most contributing characteristic is area, which originates from a difference in the number of floors

What makes a successful field visit? The role of private information. In Table 5, we assess whether top bureaucrats behave differently during field work (these results are suggestive and not causal). We find that compared to other bureaucrats, they are 12.9 percentage points (22 percent) more likely to report a positive value (column (1)), 4.5 pp (19.6 percent) more likely to report meeting the owner (column (2)), are 5.6 pp (18 percent) more likely to recover owner identification details,[81] 10.8 pp (22 percent) more likely to leave a comment, and conditional on this, 5.8 pp (32 percent) more likely to signal that they used their own estimation for valuation instead of relying solely on what occupants said.

Next, we look at whether the difference in tax base gap across rule and discretion closes when restricting the sample in turn to these types of field visits. Results are shown in Table A14, both with and without bureaucrat fixed-effects. For cases where the owner is met (Panel (A)) and of rented properties (Panel (B)), the two most obvious instances where the bureaucrat accessed valuable private information, we further split the sample into low and high value properties.[82] We find that the difference in tax base gap across rule and discretion is no longer significant (and also displays very small coefficient sizes) in these two instances, for low-value properties. This suggests that bureaucrats are able to leverage valuable local information, but this only appears helpful in the lower part of the distribution.

7 Optimal Policy

Cost-benefit analysis. In Table A15, we lay out the costs and total tax liabilities, assuming each method in turn is applied to all eligible plots ($N = 32,677$). There are two types of costs to consider: field costs – 118.1 million FCFA[83] – and rule-specific costs – 16 million

entered. When the number of floors differs, in 56 percent of cases this is because the bureaucrat counted the ground floor as one instead of zero. In Appendix Table A11, we provide descriptive statistics on the share of observations for which each characteristic matches across the two sources

[81] This dummy takes value one if the bureaucrat recovered the name and/or national ID number of the property owner.

[82] In Figure A12 we plot the probability of meeting the owner (Panel (A)) and of the property being rented (Panel (B)) by quintile of property value.

[83] Corresponding to 8,560 bureaucrats-days with a 5,000 FCFA daily fee, and 10,040 supervisors-days with a 7,500 FCFA daily fee.

FCFA[84]. We abstract from fixed program costs that are common across both methods.[85] The the liabilities-to-costs ratios vary immensely: x133 under full discretion, x166 with the rule-based system, and x2416 with the pure rule.

Optimal Policy. The pure rule is the optimal policy if the government wishes to maximize overall accuracy.[86] However, since the pure rule tends to overvalue the cheapest properties, and this segment is also precisely where bureaucrats are relatively better in their valuations, there is a trade-off. If the government wants to maximize accuracy, while minimizing the risk of overvaluations at the bottom, the optimal policy is to predict which properties belong to the lowest quintile based on location and built area (the assumption is that the administration has no prior knowledge on values), send bureaucrats for discretionary valuations of these cases, and apply the pure rule elsewhere. In Figure A17, we plot the resulting tax profile.[87]

Policy uptake. Following the results from the randomized experiment, the administration has decided to incorporate rule-based methods in the general functioning of the property tax, and has asked the research team for support.[88]

8 Conclusion

We introduce experimental variation in the degree of discretion bureaucrats have to assess the tax base in a large scale property tax census conducted in Dakar with a new digital

[84]Corresponding to the hiring of assessors for the calibration sample, and what is paid to GIS experts recovering built area measurement from satellite images.

[85]These include: in-office managers, software development, data server, mobile data, training costs. This means the tax bill-to cost ratios presented in this section are only meaningful in relative terms.

[86]Sending bureaucrats in the field may still prove useful to get identification details on owners and tenants. One might be worried of costs in terms of job satisfaction and motivation of removing delegation for the determination of the tax base, but survey responses do not seem to suggest this. Among bureaucrats who did only the rule, 98 percent would participate in similar operations again, and 83 percent feel they have autonomy overall (these shares are similar when considering all bureaucrats). According to bureaucrats, the best strategy to recover accurate market values at scale is *Declared by tenant* (rank first) and *With an automatic formula* (rank second), *Bureaucrat's own knowledge* is ranked the lowest. See Figure A15.

[87]Two caveats are first, that the prediction of being in the lowest quintile yields 18 percent of false negatives – these properties will be overtaxed; second, using discretion will necessarily imply more dispersion and lower horizontal equity in that segment of the market.

[88]Investments that the administration should consider are: (1) working with licensed real estate assessors to enlarge the calibration sample to the whole region; (2) high quality satellite images to recover built area measurement for all properties.

application. Under full discretion, bureaucrats' property valuations are significantly below market values, they are strongly regressive harming vertical equity, and they display strong dispersion harming horizontal equity. Even with partial delegation under a rule-based system – relying on an algorithm incorporating bureaucrat inputs – the valuation profile is distorted and more regressive than with a pure rule.

We show that the knowledge channel plays a fundamental role, and that bureaucrats are biased by their perceptions of fairness. We use suggestive evidence to rule out the collusion channel. Higher education is the only easily screenable characteristic that correlates with bureaucrats' relative ability to approximate market values. However, at best top bureaucrats perform as well as the rule. Overall, a rule-based system is the most promising strategy for an equitable expansion of the tax net. The administration would only want to keep some discretion for low value properties, if its preference for minimizing the risk of over-valuation is stronger than its preference for horizontal equity.

Following the results from the randomized experiment, the administration has asked the research team to support the expansion of the new methodology in the whole region.

Our findings shed light on directions for future research. First, there are potentially many other promising applications of digitization for increased fiscal capacity in Africa (Okunogbe & Santoro, 2023). Second, whether the algorithm generates sufficient levels of tax compliance and political acceptability in the long run remains an open question, which we will address in a follow-up paper. Finally, it seems important to assess whether the finding that under the status quo, bureaucrats shape the policy register in a regressive way extend to other contexts, and how this can be mitigated beyond our setting.

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Figures

FIGURE 1
EXAMPLES OF LOW, MEDIUM AND HIGH VALUE PROPERTIES IN STUDY AREAS

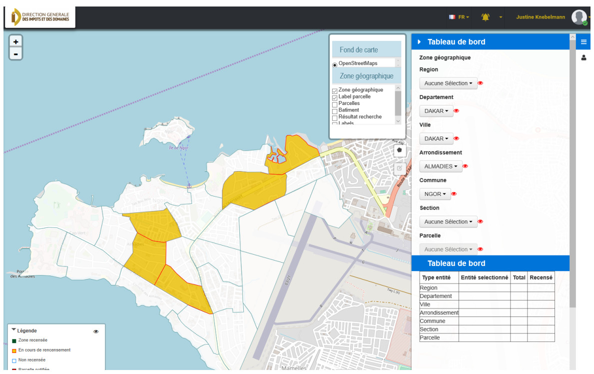
(A) LOW-VALUE PROPERTY

(B) MEDIUM VALUE PROPERTY

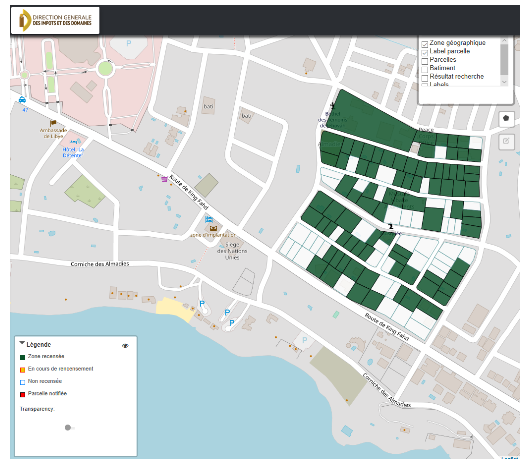
(C) HIGH VALUE PROPERTY

Notes: This Figure displays examples of properties from the study areas in the region of Dakar. Picture (A) shows a property from the bottom 10% of the property value distribution of our sample; Picture (B) shows a property with a value around the median of the distribution, and Picture (C) shows a property from the top 10% of the distribution. The monthly market rental values for each property are, respectively, 100,000 FCFA (163 USD); 520,000 FCFA (845 USD) and 2.3 million FCFA (3,740 USD) (source: licensed assessor valuations).

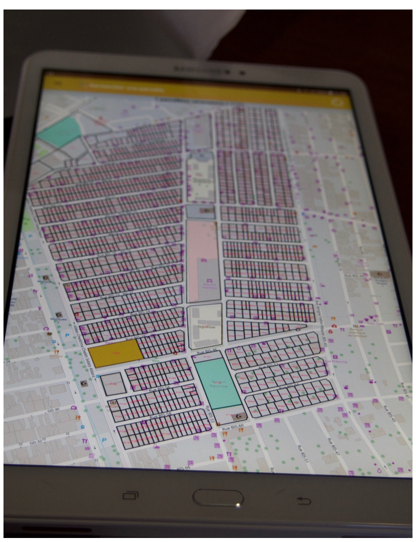
FIGURE 2
PROPERTY TAX CENSUS OPERATIONS WITH THE NEW DIGITAL TOOL



(A) WEB INTERFACE: ASSIGNMENT OF SECTIONS TO BUREAUCRATS



(B) WEB INTERFACE: PROGRESS WITHIN A SECTION

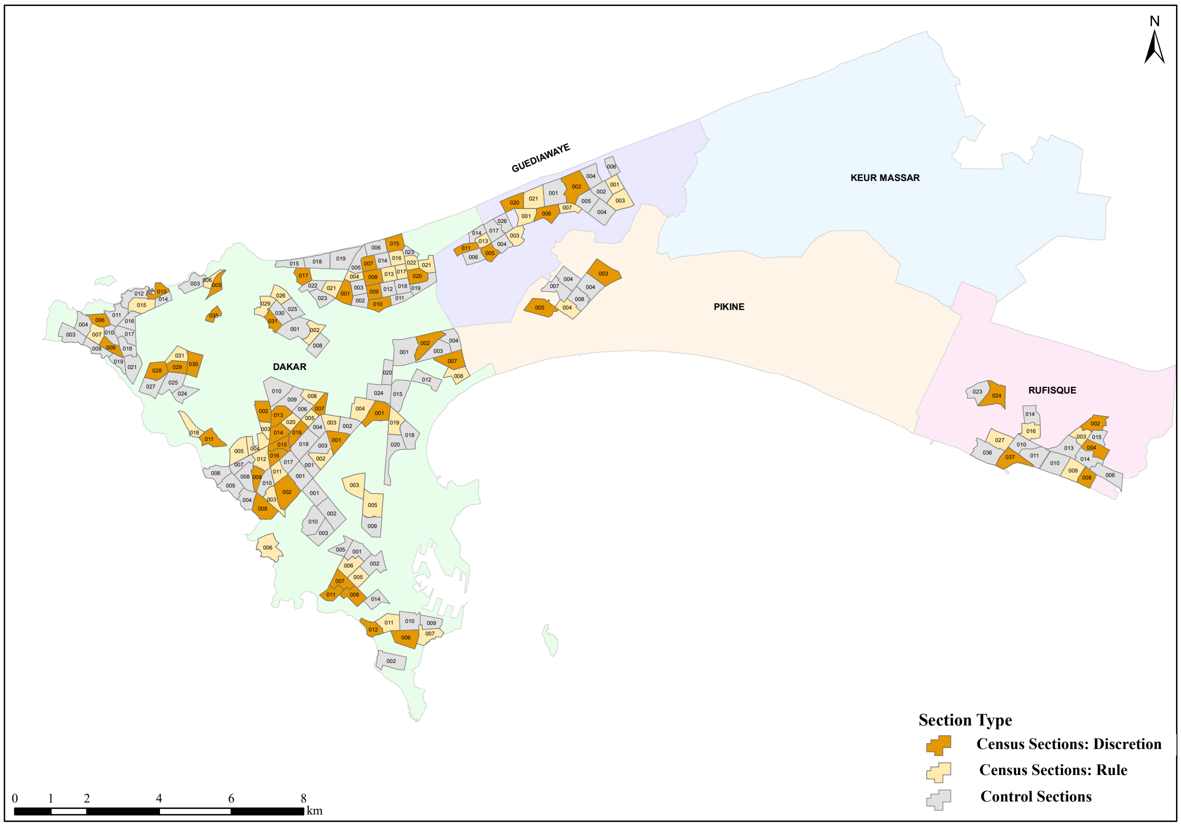


(C) TABLET INTERFACE: PRE-LOADED SECTION AND PLOT IDENTIFIERS

(D) BUREAUCRATS CONDUCTING PROPERTY TAX CENSUS

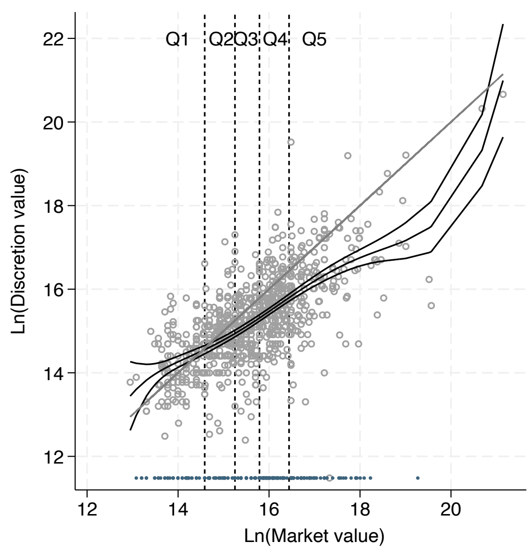
Notes: This Figure illustrates the property tax census operations using the new digital tool. The digital tool has a Web interface available from the office for managers, and a tablet interface used by bureaucrats in the field.

FIGURE 3
GEOGRAPHICAL SCOPE AND EXPERIMENTAL DESIGN IN DAKAR REGION

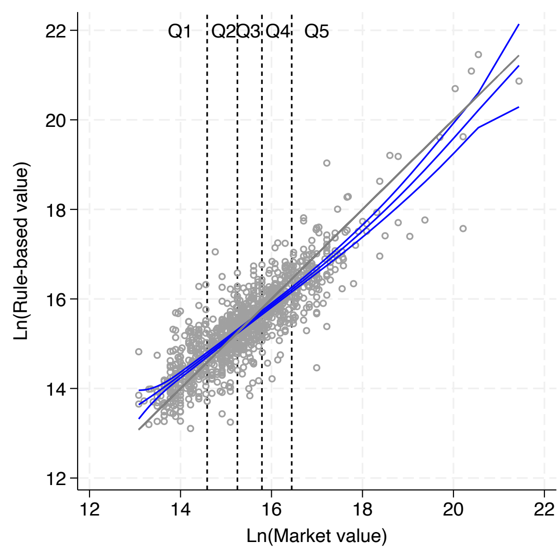


Notes: This Figure is a map of the Dakar region and displays the 193 cadastral sections included in our study. The sections were randomly divided intro three groups, stratifying by tax office, total number of plots, and share of plots eligible for the property tax. 97 sections are in the pure control group with no tax census (gray on the map). 48 sections are treated with the property tax census using the rule-based valuation method (yellow on the map). 48 sections are treated with the property tax census using the discretionary valuation method (orange on the map). As a whole all 193 sections comprise 83,300 plots.

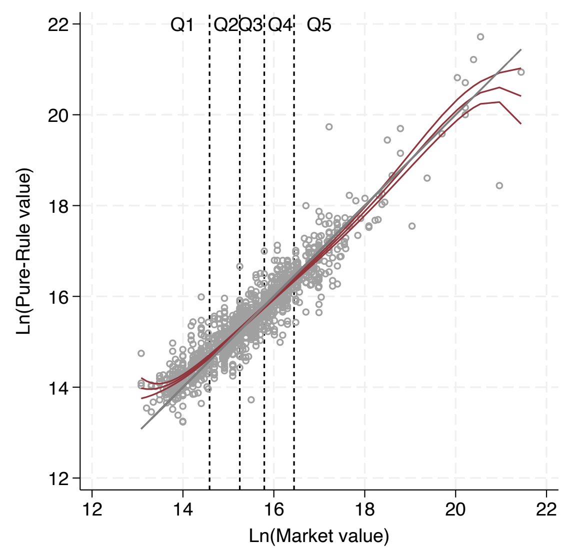
Figure 4
Valuations under Rule and Discretion



(A) Discretion



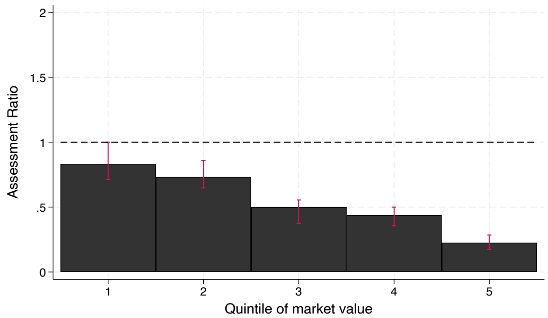
(B) Rule-Based



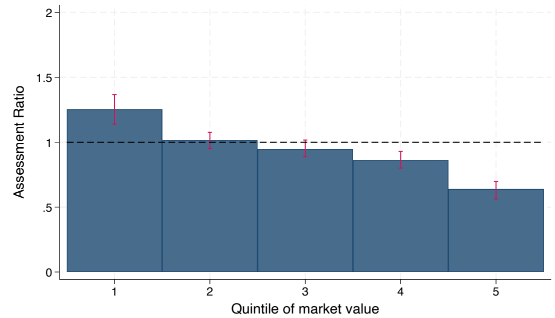
(C) Pure-Rule

Notes: This Figure plots valuations for the discretion arm (Panel (A)), the rule-based values in the rule arm (Panel (B)) and the pure rule values in the rule arm (Panel (C)). In each Panel, the x-axis plots $Ln(MarketValue)$ and the y-axis plots $Ln(CensusValue)$, the value from the census that ends up on the tax roll. The curve is the 6 degree polynomial fit between the two values, with its 95% confidence interval. The blue dots plot observations for which $CensusValue = 0$. The gray line is the 45-degree identity line. The dashed vertical lines show the limits of the quintiles of market values. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

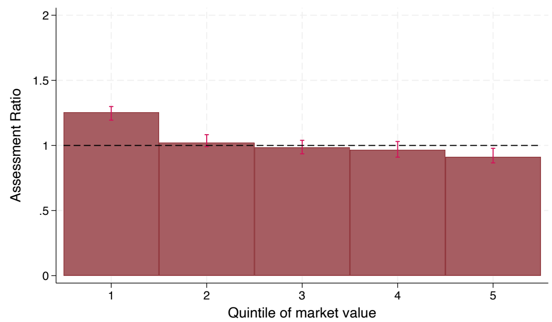
FIGURE 5
ASSESSMENT RATIO BY QUINTILE FOR DIFFERENT DEGREES OF DISCRETION



(A) FULL DISCRETION



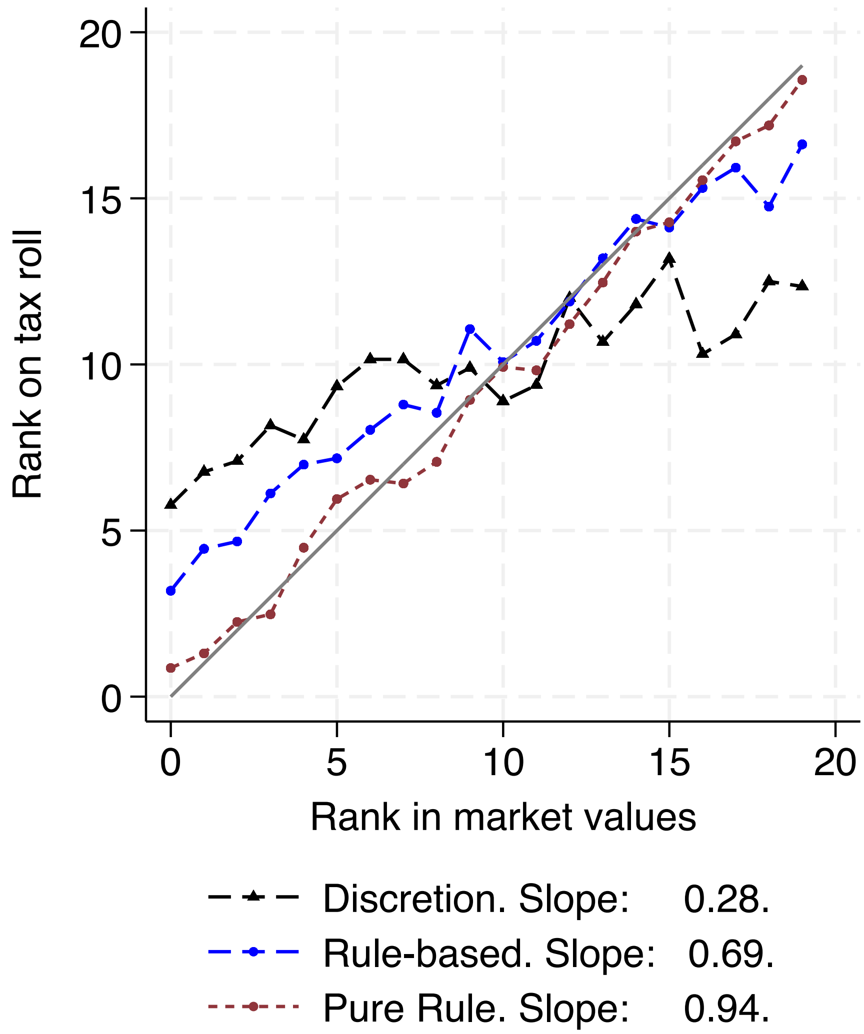
(B) RULE-BASED



(C) PURE RULE

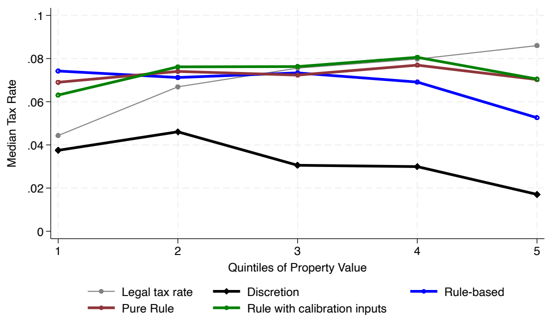
Notes: This Figure plots the median assessment ratio (census value over market value) by quintile in the discretion arm (Panel (A)), in the rule-based arm (Panel (B)), in the rule arm but applying the pure rule (Panel (C)). Quintiles are based on market values. The red line shows the 95% confidence interval for the median. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

FIGURE 6
VERTICAL EQUITY: RANK-RANK CORRELATIONS

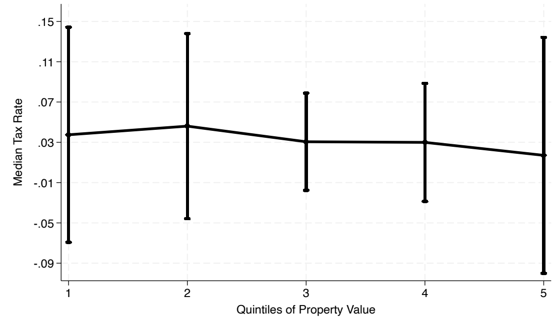


Notes: This Figure shows the rank-rank correlation between tax roll values from the census and market values, separately for discretion (black line), the rule-based arm (blue line) and the rule arm if applying the pure rule (red line). The x-axis shows a property's rank in market values, grouped in 20 bins. Ties are assigned the same rank. The y-axis shows the mean rank for the bin. We estimate the slope by regressing the binned tax roll rank on the binned market value rank. The gray line is the 45-degree identity line. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

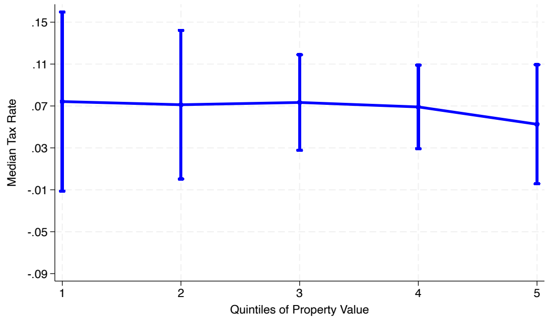
Figure 7
Tax Rates: Removing Discretion Increases Accuracy and Equity



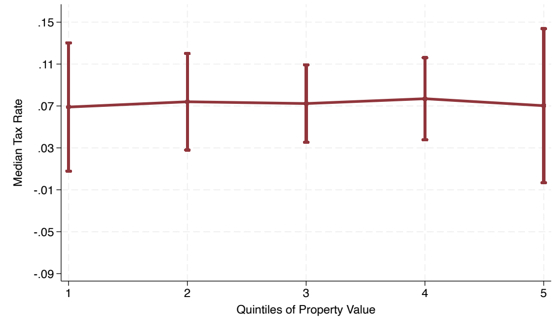
(A) Median Tax Rates by Quintile



(B) Full Discretion



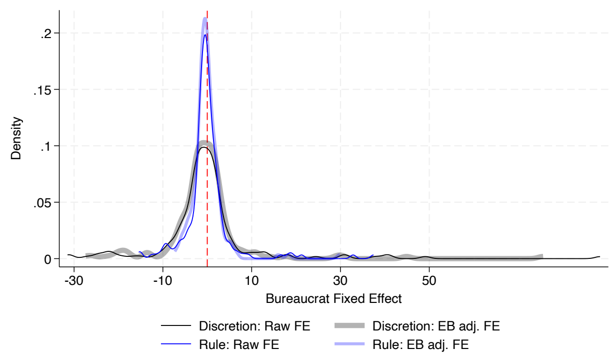
(C) Rule-Based



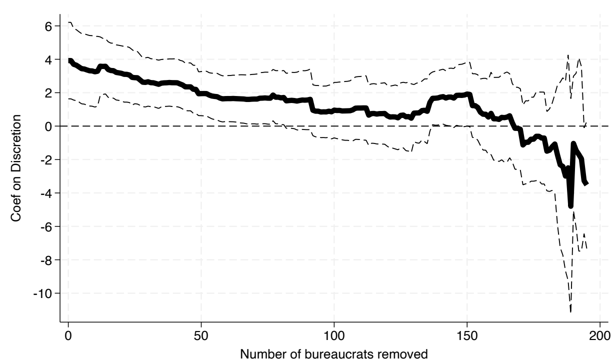
(D) Pure Rule

Notes: This Figure shows the median effective tax rate by quintile of market value for each valuation method. A property's effective tax rate is computed as tax liability (based on the value from the census) over market value. In Panel (A), we show the tax profile for all methods. In Panels (B), (C), and (D), we show the tax profile separately adding the standard deviation of the tax rate in each quintile. The gray line in Panel (A) is the benchmark tax profile computed by applying the tax code rates directly to market values (the tax rate is 8.6 percent with an abatement if the property is owner-occupied which explains the progressive profile). The black lines in Panel (A) and Panel (B) are for the discretion arm, the blue lines in Panel (A) and Panel (C) are for rule-based values in the rule arm, the red lines in Panel (A) and Panel (D) are for the pure rule values applied to the rule arm. Additionally in Panel (A) the green line plots the tax profile generated with the rule if using the characteristics from the calibration (assessors' dataset). Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

FIGURE 8
BUREAUCRAT FIXED-EFFECTS



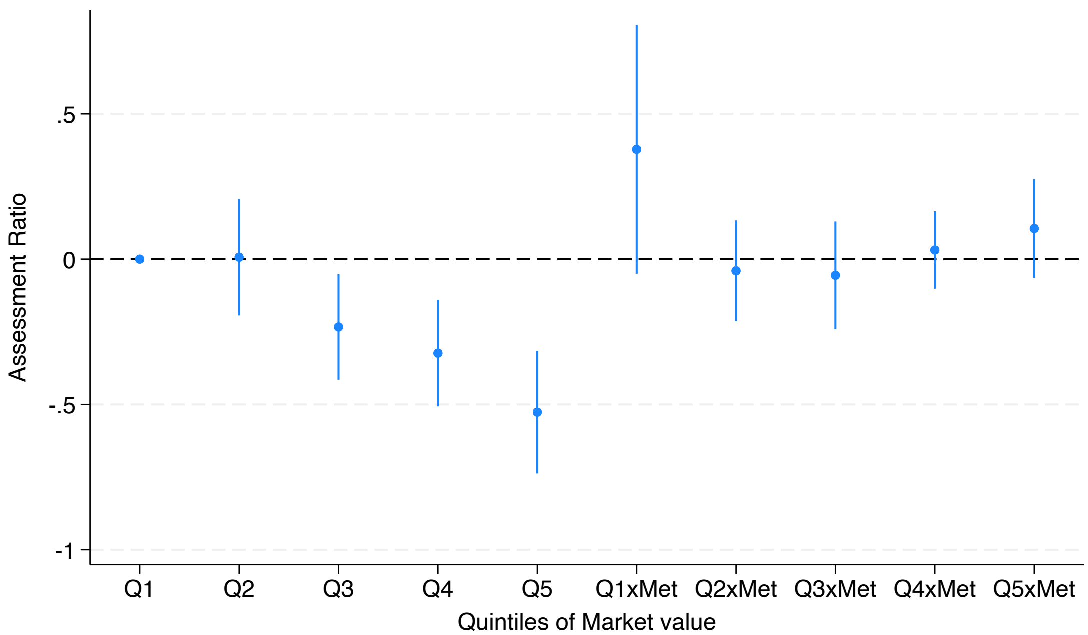
(A) ESTIMATED FIXED-EFFECTS



(B) SCREENING TO CLOSE THE GAP BETWEEN RULE-BASED AND DISCRETION

Notes: This Figure shows results from the bureaucrats fixed-effects estimation done in Section 5.2. The α_b are estimated in specification 3: $|Gap|_{ijb} = \alpha_b + Val_j + \epsilon_{ijb}$, run separately on each arm. We then apply an empirical Bayes adjustment to recover $\alpha_{b,EB}$. In Panel (A), we plot the kernel density estimate of the distribution of $\alpha_{b,EB}$ under discretion (in gray and black) and under the rule-based system (in blue). In Panel (B) we assess how much screening would be needed for the tax base gap difference between rule and discretion to fade. We rank bureaucrats based on their $\alpha_{b,EB}$. Then, we run regression (2) 195 times on the discretion arm, removing bureaucrats one by one starting by the worst one. The number of bureaucrats removed is indicated on the x-axis. The solid black line shows the estimated $\hat{\beta}$ coefficient on discretion, the dashed line indicates the the 95% confidence interval.

FIGURE 9
UNDER DISCRETION: THE UNDERVALUATION GRADIENT DOES NOT DIFFER WHEN THE OWNER IS MET



Notes: This Figure shows how the assessment ratio under discretion varies by quintile and depending on whether the owner was met. We plot the β_n and γ_n coefficients from regression 5 $AR_i = \alpha + \sum_{n=1}^{5} \beta_n Q(n)_i + \sum_{n=1}^{5} \gamma_n M_i \cdot Q(n)_i + \epsilon_i$, where AR_i is the assessment ratio (census value over market value) for property i, the $Q(n)$ are dummies for each quintile of the distribution of market values, M_i is a dummy taking value one if the bureaucrat reports meeting the owner. Errors are clustered at the section level. Sample: analysis sample with market values for the discretion arm ($N = 1,124$).

Tables

Table 1
Balance Table

Panel A: Section characteristics across treatment arm	Mean (SD)	$\hat{\beta}_{Discretion}$	P-value	N
Source: Cadastral data				
Number of plots	419 (177.61)	71.50 (37.40)	0.06	94
Built area (0/1)	0.93 (0.25)	0.01 (0.02)	0.51	41,609
Built area (m2)	282 (856.10)	−10.91 (27.45)	0.69	41,609
Source: Assessors				
Eligible (0/1)	0.87 (0.33)	0.02 (0.02)	0.39	2,844
Value (mil. winz)	10.71 (21.93)	1.91 (2.39)	0.43	2,469
Value per m2 (mil. winz)	0.02 (0.02)	0.00 (0.00)	0.24	2,410
Source: Baseline				
Non-response (0/1)	0.53 (0.50)	−0.03 (0.03)	0.32	2,537
Value (mil. winz)	3.95 (4.17)	−0.07 (0.32)	0.83	1,225
Rented (0/1)	0.30 (0.46)	0.03 (0.03)	0.30	1,238
Owner-occupied (0/1)	0.60 (0.49)	0.01 (0.03)	0.64	1,238
High household income (0/1)	0.22 (0.41)	0.00 (0.03)	0.94	1,238
In tax net (0/1)	0.18 (0.38)	0.00 (0.03)	0.93	1,238
Joint significance (1)			0.34	
Joint significance (2)			0.88	

Panel B: Bureaucrat characteristics across treatment arm	Mean (SD)	$\hat{\beta}_{Discretion}$	P-value	N
Age	31.51 (5.80)	0.15 (0.34)	0.66	1,288
Female	0.28 (0.45)	−0.01 (0.03)	0.61	1,288
Ever worked with tax adm.	0.18 (0.38)	0.03 (0.02)	0.20	1,288
From Dakar	0.48 (0.50)	−0.01 (0.03)	0.66	1,288
Commune of residence	0.06 (0.24)	0.00 (0.01)	0.94	1,266
Any higher education	0.98 (0.14)	−0.01 (0.01)	0.12	1,288
3 yrs higher education	0.40 (0.49)	−0.01 (0.03)	0.66	1,288
Ethnic group: Wolof (majority)	0.31 (0.46)	0.01 (0.03)	0.65	1,288
Religion: Tidjane (majority)	0.56 (0.50)	0.03 (0.03)	0.28	1,288
Public service motivation (index)	0.06 (0.85)	−0.02 (0.05)	0.73	1,288
In favor of government's role (index)	0.13 (0.97)	−0.07 (0.06)	0.21	1,268
In favor of widespread taxation (index)	0.01 (1.00)	−0.04 (0.06)	0.48	1,288
Joint significance			0.71	

Panel C: Bureaucrat characteristics and property values	Mean (SD)	$\hat{\beta}_{Ln(Value)}$	P-value	N
Age	31.53 (5.64)	0.03 (0.18)	0.86	2,236
Female	0.25 (0.43)	0.01 (0.01)	0.49	2,236
Ever worked with tax adm.	0.18 (0.39)	0.00 (0.01)	0.94	2,236
From Dakar	0.48 (0.50)	0.00 (0.02)	0.90	2,236
Commune of residence	0.09 (0.29)	0.00 (0.01)	0.56	2,187
Any higher education	0.99 (0.10)	0.00 (0.00)	0.79	2,236
3 yrs higher education	0.41 (0.49)	−0.04 (0.01)	0.01	2,236
Ethnic group: Wolof (majority)	0.32 (0.47)	0.00 (0.01)	0.92	2,236
Religion: Tidjane (majority)	0.57 (0.50)	−0.02 (0.02)	0.21	2,236
Public service motivation (index)	0.08 (0.80)	0.00 (0.02)	0.86	2,236
In favor of government's role (index)	0.08 (0.93)	0.02 (0.03)	0.55	2,214
In favor of widespread taxation (index)	−0.02 (0.99)	0.01 (0.03)	0.81	2,236
Joint significance			0.41	

Notes: This Table verifies that section and bureaucrat characteristics are balanced across treatment arms, and that bureaucrat characteristics do not correlate with market values. In Panel (A) we regress section characteristics on a dummy for discretion. $\hat{\beta}_{Discretion}$ is the coefficient on the discretion dummy followed by its standard error. The variable sources are indicated and are either cadastral data, assessors' dataset or owner baseline. All regressions are at the plot level except row one (at the section level). In Panel (B) we regress bureaucrat characteristics on a dummy for discretion. Observations are at the bureaucrat X section level. In Panel (C), we regress bureaucrat characteristics on market values $\hat{\beta}_{Ln(Value)}$. Observations are at the plot level. See Appendix Section B.5 for a detailed description of the variables from the bureaucrat surveys. In all regressions we control for strata fixed-effects and we cluster errors at the section level. At the bottom of each Panel we report the p-value for an F-test of joint significance. In Panel (A) this is done separately for cadastral and assessor variables (1), and for baseline variables (2).

TABLE 2
THE UNDERVALUATION GRADIENT

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5
Panel A: Discretion					
Median Ass. Ratio	0.83	0.73	0.50	0.44	0.23
$\hat{\beta}_n$	Ref.	-0.10	-0.33	-0.40	-0.61
P-value		0.31	0.00	0.00	0.00
P-value $\hat{\beta}_n \neq \hat{\beta}_{n+1}$		0.00	0.27	0.00	
Panel B: Rule-based					
Median Ass. Ratio	1.25	1.01	0.94	0.86	0.64
$\hat{\beta}_n$	Ref.	-0.24	-0.31	-0.39	-0.61
P-value		0.00	0.00	0.00	0.00
P-value $\hat{\beta}_n \neq \hat{\beta}_{n+1}$		0.15	0.10	0.00	
Panel C: Pure Rule					
Median Ass. Ratio	1.26	1.02	0.98	0.97	0.91
$\hat{\beta}_n$	Ref.	-0.23	-0.27	-0.29	-0.34
P-value		0.00	0.00	0.00	0.00
P-value $\hat{\beta}_n \neq \hat{\beta}_{n+1}$		0.34	0.61	0.14	

Notes: This Table tests whether the median assessment ratio changes significantly across quintiles of market values, under discretion (Panel (A)), under the rule-based system (Panel (B)), under the pure rule system applied to the rule arm (Panel (C)). We estimate $AR_i = \alpha + \sum_{n=1}^{5} \beta_n Q(n)_i + \epsilon_i$ where AR_i is the assessment ratio (census value over market value) for property i, the $Q(n)$ are dummies for each quintile of the distribution of market value. We run a quantile regression at the median. Standard errors are clustered at the section-level. The second row of each Panel reports the $\hat{\beta}_n$ coefficients. Below, we report the P-value indicating whether $\hat{\beta}_n$ is significantly different from the reference ($Q(1)$). P-val $\hat{\beta}_n \neq \hat{\beta}_{n+1}$ indicates whether the coefficients for two subsequent quintiles are significantly different from each other. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

TABLE 3
REMOVING DISCRETION INCREASES ACCURACY

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) |Gap| *mil.FCFA*	(4) Ass. Ratio
Panel A: Discretion				
Mean[1] (sd)	−7.14 (17.69)	−2.41	8.92 (16.87)	0.71
Panel B: Rule-based				
Overall				
Mean[1] (sd)	−2.33 (12.78)	−0.16	4.67 (12.12)	1.06
$\hat{\beta}_{Discretion}$	−4.61***	−1.87***	3.88***	−0.35***
	(1.28)	(0.38)	(1.38)	(0.05)
Low Value				
Mean[1] (sd)	0.44 (2.06)	0.20	1.25 (1.70)	1.27
$\hat{\beta}_{Discretion}$	−0.53***	−0.61***	0.32**	−0.24**
	(0.19)	(0.13)	(0.15)	(0.09)
High Value				
Mean[1] (sd)	−4.83 (17.13)	−1.58	7.74 (16.02)	0.87
$\hat{\beta}_{Discretion}$	−6.52***	−4.41***	5.51***	−0.34***
	(1.77)	(0.68)	(1.89)	(0.05)
Panel C: Pure Rule				
Overall				
Mean[1] (sd)	−0.36 (7.64)	0.12	2.83 (7.11)	1.13
$\hat{\beta}_{Discretion}$	−5.37***	−2.42***	4.71***	−0.38***
	(0.90)	(0.44)	(0.93)	(0.04)
Low Value				
Mean[1] (sd)	0.39 (1.13)	0.25	0.73 (0.94)	1.24
$\hat{\beta}_{Discretion}$	−0.28	−0.57***	0.88***	−0.13
	(0.20)	(0.14)	(0.14)	(0.09)
High Value				
Mean[1] (sd)	−1.04 (10.43)	−0.33	4.72 (9.36)	1.03
$\hat{\beta}_{Discretion}$	−8.25***	−5.44***	6.87***	−0.47***
	(1.27)	(0.55)	(1.28)	(0.05)
N plots: 2290				
N Sections: 94				
Mean (sd) market value: 77.00 (15.80)				
Median market value: 5.60				

Notes: This Table shows the effect of discretion on the tax base gap. We run regression 2: $Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk}$ with four different outcomes. Y_{ijk} is the outcome for property i of section j and strata k, D is a dummy for discretion and S_k is a strata fixed-effect. In column (1) the outcome variable is the tax base gap defined as census value minus market value, column (2) uses the same outcome but with a quantile regression at the median, in column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio (census value over market value). In Panel (B), values for the rule arm are the rule-based valuations based on bureaucrats' inputs. In Panel (C), values for the rule arm are the pure rule predictions based on remote covariates. The first sub-panel of each Panel uses the full sample of properties, the second is restricted to low value properties (quintile 1 and 2 of market values), the third is restricted to high value properties (quintiles 3 to 5 of market values). In each sub-panel, the first row displays descriptive statistics of the outcome variable in the rule arm; the second row show the coefficient of interest and its standard error. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm). [1]In column (2) the displayed value is the $median$ of the tax base gap.

TABLE 4
ESTIMATING BUREAUCRAT FIXED-EFFECTS

	(1) Discretion	(2) Rule-based
N obs	1,055	1,063
N Bur FE	198	190
Mean of Outcome (mil. of FCFA)	8.00	3.81
Var of Outcome	217.09	103.65
R2 without Bur FE	0.38	0.28
R2 with Bur FE	0.52	0.39
Var(Bur FE)	141.71	33.11
Var(Shrinked Bur FE)	86.77	13.37
Share Variance	0.40	0.13
P-value of F test on Bur FE	0.00	0.00

Notes: This Table summarizes results from the estimation of bureaucrat fixed-effects done in Section 5.2. We run specification 3: $|Gap|\_ijb = \alpha_b + Val_j + \epsilon_{ijb}$, separately on the discretion and rule-based arms. We then apply an empirical Bayes adjustment to recover the shrinked fixed-effects $\alpha_{b,EB}$. Share of variance refers to the share of variance in the tax base gap accounted for by bureaucrat heterogeneity, it is computed as $Var(\alpha_{b,EB})$ over $Var(|Gap|)$.

TABLE 5
WHAT DO TOP BUREAUCRATS DO DIFFERENTLY?

Depedent Variable (0,1)	Positive value (1)	Owner Met (2)	Owner Details (3)	Contract (4)	Comment (5)	Conflict (6)	Bureaucrat estimate (7)
Top bureaucrat	0.129***	0.045**	0.056***	0.004	0.105***	-0.005	0.060**
	(0.026)	(0.018)	(0.016)	(0.005)	(0.038)	(0.011)	(0.024)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	22314	22314	22314	20086	22314	10918	10918
R2	0.13	0.03	0.09	0.02	0.29	0.02	0.18
Adj. R2	0.13	0.03	0.09	0.01	0.29	0.02	0.18
Mean of dependent	0.58	0.23	0.31	0.03	0.49	0.09	0.18

Notes: In this Table we report results from regressing plot level outcomes on a dummy taking value one if the plot is covered by a top bureaucrat. We use the bureaucrat fixed-effects estimated in Section 5.2 to define top bureaucrats as those with $\alpha_{b,EB} < 0$. All outcome variables are dummies. Owner details takes value one if the bureaucrat recovered the name and/or ID number of the owner. Contract takes value one if there is at least one rental contract reported for the plot. Comment takes value one if the bureaucrat left a comment. Conflict and bureaucrat estimate are conditional on leaving a comment. We control by strata fixed-effects and errors are clustered at the section level. Sample: all plots of the discretion arm.

TABLE 6
LAB-IN-THE-FIELD: BUREAUCRATS' LACK OF KNOWLEDGE AND BIASES

Depedent Variable	Ass. Ratio (1)	Ass. Ratio (2)	Ln(Value) (3)	Ln(Value) (4)
High value property	-1.419***	-1.491***		1.232***
	(0.112)	(0.109)		(0.091)
Info treatment		-0.085		
		(0.150)		
Info X High value		0.127		
		(0.150)		
Retired owner			-0.378***	-0.241***
			(0.091)	(0.091)
Retired X High value				0.090
				(0.133)
Strata FE	No	Yes	Yes	Yes
Bureaucrat FE	Yes	No	No	No
N	280	280	280	280
R2	0.83	0.62	0.07	0.57
Adj R2	0.60	0.61	0.01	0.54
Mean in reference	1.74	1.78	12.84	12.08

Notes: This Table shows results from experimental questions in the bureaucrat endline survey in which bureaucrats are shown pictures of a high-end and low value property and are asked to provide an estimated rental value. Column (1) displays results from equation 4 $AR_{ib} = \alpha_b + \beta High_{ib} + \epsilon_{ib}$ with bureaucrat-fixed effects, column (2) is the same regression but adding a dummy for the information treatment that half of respondents saw (see Figure A13) and controlling for bureaucrat randomization strata. The outcome variable is the assessment ratio computed as bureaucrat value over market value. Columns (3) and (4) show results from regression 6 $Ln(Value)_{ibk} = \alpha + \beta_1 Retired_{ibk} + \beta_2 High_{ibk} + \beta_3 Retired_{ibk} \cdot High_{ibk} + A_k + \epsilon_{ibk}$, for each property half of the bureaucrats were told the owner was retired (versus employed). The two randomizations were independent. Observations are at the bureaucrat X property level. Standard errors are clustered at the bureaucrat level.

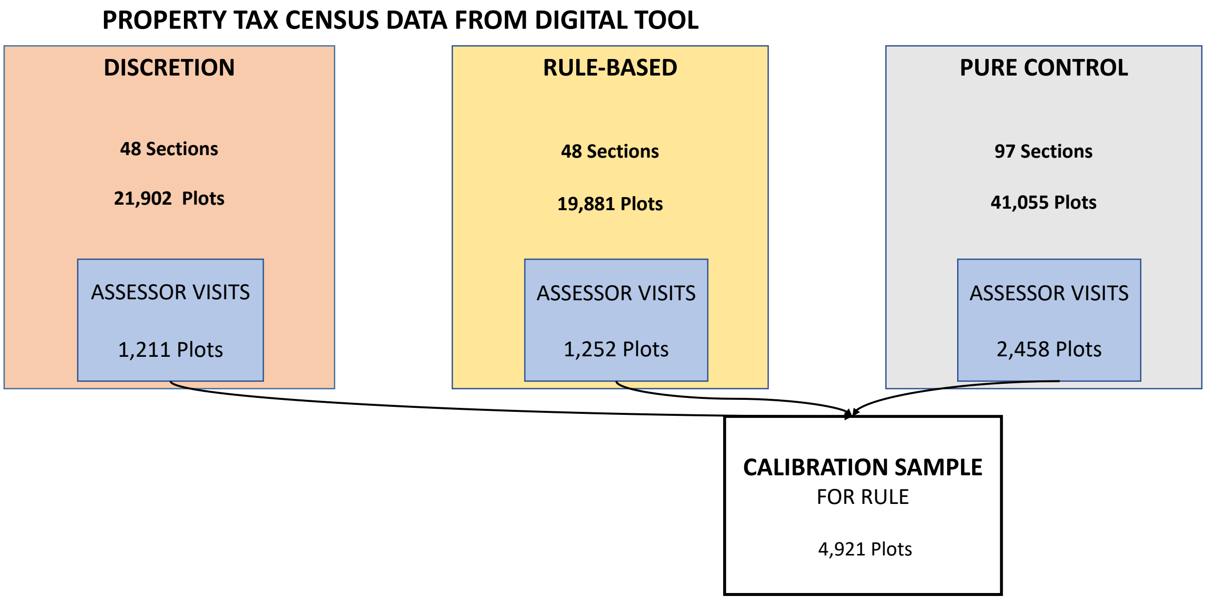
TABLE 7
RULE-BASED VS PURE RULE: MEASURING THE EFFECT OF A LIMITED DEGREE OF DISCRETION

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) |Gap| *mil.FCFA*	(4) Ass. Ratio
Panel A: Pure Rule				
Overall				
Mean[1] (sd)	−0.36 (7.64)	0.12	2.83 (7.11)	1.13
$\hat{\beta}_{RuleBur}$	−1.97***	−0.31**	1.84***	−0.07*
	(0.58)	(0.12)	(0.44)	(0.04)
Low Value				
Mean[1] (sd)	0.39 (1.13)	0.25	0.73 (0.94)	1.24
$\hat{\beta}_{RuleBur}$	0.06	−0.01	0.52***	0.03
	(0.12)	(0.07)	(0.10)	(0.05)
High Value				
Mean[1] (sd)	−1.04 (10.43)	−0.33	4.72 (9.36)	1.03
$\hat{\beta}_{RuleBur}$	−3.80***	−1.28***	3.03***	−0.17***
	(0.95)	(0.35)	(0.77)	(0.04)
Panel B: Rule with Assessor Inputs				
Overall				
Mean[1] (sd)	−0.40 (8.16)	0.14	2.78 (7.68)	1.10
$\hat{\beta}_{RuleBur}$	−1.94***	−0.33**	1.89***	−0.04
	(0.50)	(0.13)	(0.39)	(0.04)
Low Value				
Mean[1] (sd)	0.31 (0.90)	0.16	0.63 (0.72)	1.15
$\hat{\beta}_{RuleBur}$	0.13	0.01	0.62***	0.12**
	(0.12)	(0.07)	(0.10)	(0.05)
High Value				
Mean[1] (sd)	−1.03 (11.18)	−0.04	4.71 (10.19)	1.05
$\hat{\beta}_{RuleBur}$	−3.80***	−1.65***	3.03***	−0.19***
	(0.79)	(0.34)	(0.64)	(0.04)
N obs: 2331				
N plots: 1166				
N Sections: 47				
Mean (sd) market value: 86.00 (15.40)				
Median market value: 4.80				

Notes: This Table shows the effect on the tax base gap of the limited degree of discretion with the rule implemented by bureaucrats, compared to benchmark rules without any bureaucrat discretion. We run regression 7: $Y_{irjk} = \alpha + \beta RuleBur_{irjk} + S_k + \epsilon_{irjk}$ where Y_{itjk} is the outcome for plot i of section j and strata k under rule r, $RuleBur_{irjk}$ is a dummy taking value one if r is the rule as implemented by bureaucrats, and zero if r is the benchmark rule with no bureaucrat discretion. In Panel (A), the benchmark rule is the pure rule with remote covariates, in Panel (B) the benchmark rule is the rule calculated using the calibration inputs from the assessors' dataset. In column (1) the outcome variable is the tax base gap defined as rule value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as the rule value over the market value. Each panel is divided in three subpanels, the first one uses the full sample of properties, the second is restricted to low value properties (quintile 1 and 2 of market values), the third one is restricted to high value properties (quintiles 3 to 5 of market values). In each sub-panel, the first row displays descriptive statistics of the outcome variable with the benchmark rule; the second row show the coefficient of interest and its standard error. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. Sample: analysis sample with market values for the rule arm ($N = 1,166$). Each property appears twice in the regression sample. [1]In column (2) the displayed value is the $median$ of the tax base gap.

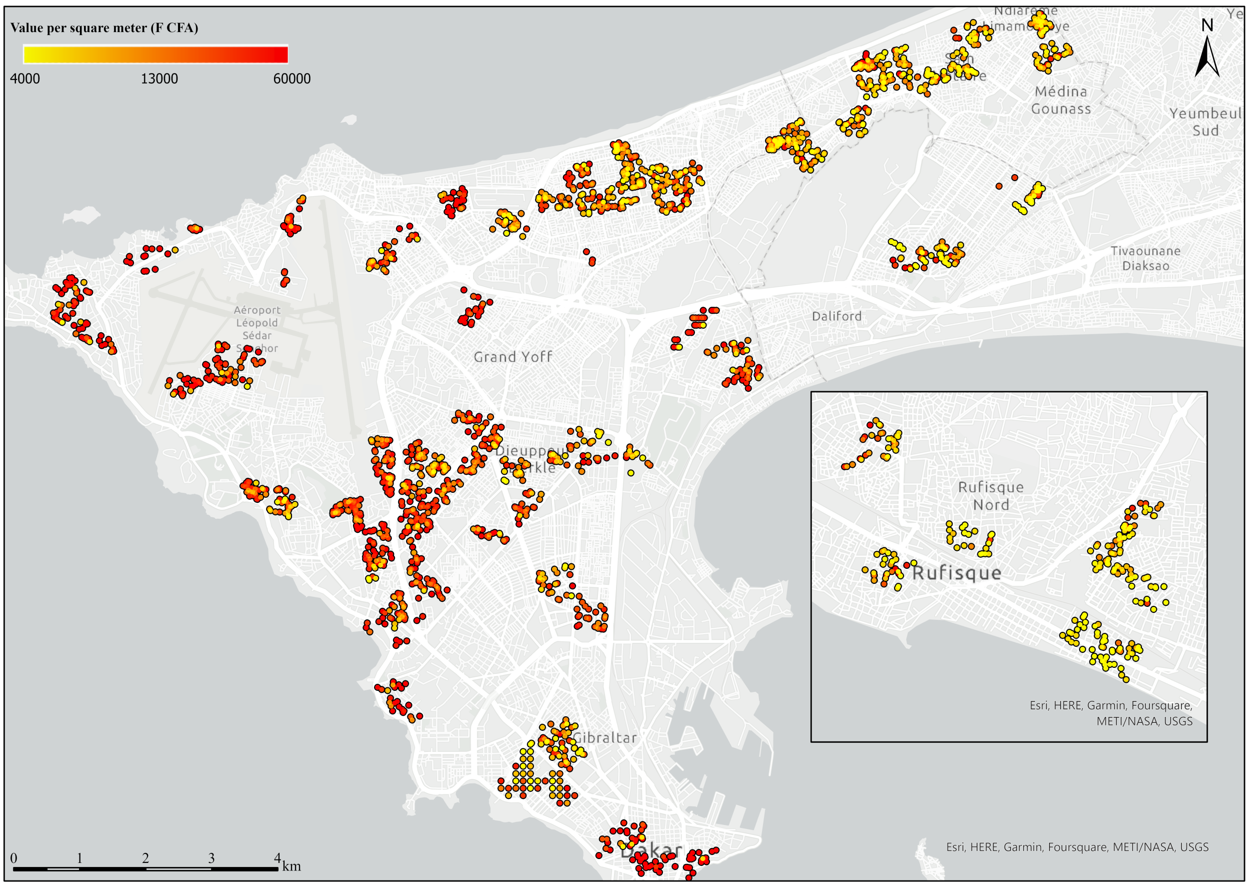
Additional Figures

FIGURE A1
OVERLAP BETWEEN TREATMENT ARMS AND ASSESSOR VALUATIONS



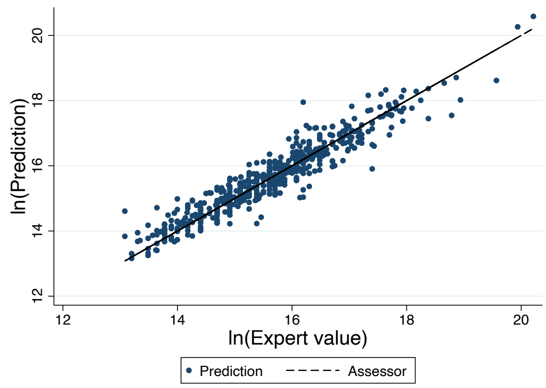
Notes: This Figure summarizes how our different samples overlap. Cadastral sections are randomly allocated either to the discretion arm, the rule arm, or the pure control arm. Plots to be visited by assessors are drawn randomly from the three types of sections (see details in Appendix section B.1). This is the calibration sample for the property valuation algorithm.

FIGURE A2
MARKET RENTAL VALUE PER SQUARE METER IN DAKAR

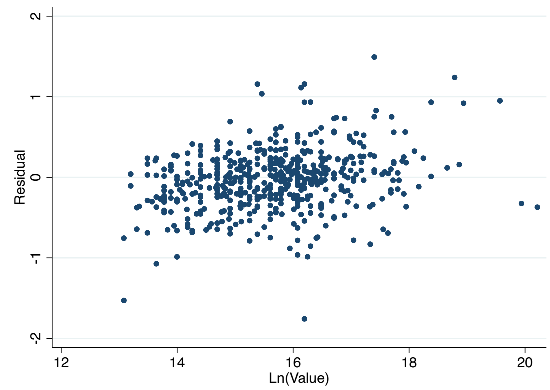


Notes: This Figure is a map of market rental values in Dakar. We compute annual rental value per square meter using market values provided by assessors. The map uses a different nuance of color for each quintile of the distribution. The color legend shows the mean values for quintiles one, five and ten. The map is restricted to the treated sections where the property tax census occurred.

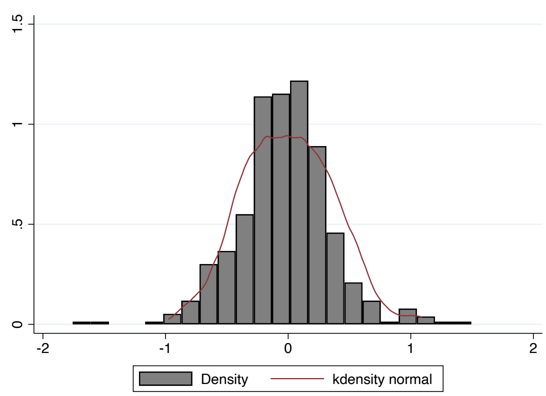
FIGURE A3
RESIDUALS IN THE PROPERTY VALUATION ALGORITHM



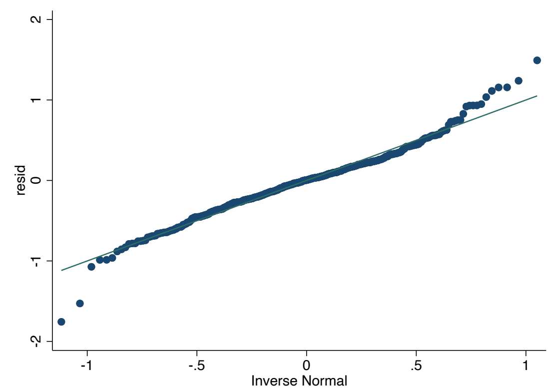
(A) PREDICTIONS OVER MARKET VALUES



(B) RESIDUALS OVER MARKET VALUES



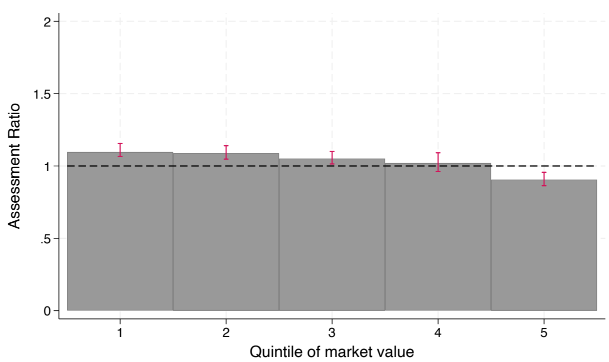
(C) DISTRIBUTION OF RESIDUALS



(D) DIAGNOSTIC: NORMALITY OF RESIDUALS

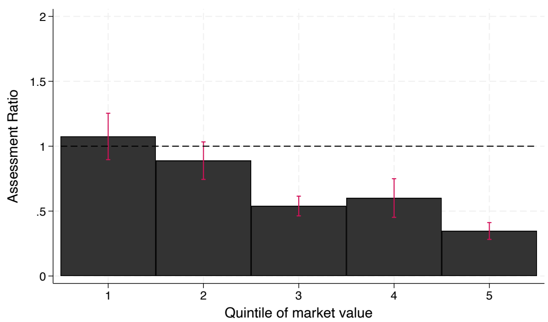
Notes: This Figure shows graphical results from the calibration of the property valuation algorithm described in Sections 4.2 and B.2. In Panel (A) we plot the predictions from the calibration sample $Ln(\widehat{Value})$ over assessor values $Ln(Value)$, in Panel (B) we plot residuals ($Ln(\widehat{Value}) - Ln(Value)$) over $Ln(Value)$, in Panel (C), the gray bars are the histogram of residuals, and as a comparison, we add the kernel density of a normal distribution of mean 0 and of the same standard error as the distribution of residuals (in red). Panel (D) is a Q-Q diagnostic plot, where quantiles of the residual are plotted over the expected quantiles for a normal distribution.

Figure A4
Assessment Ratio by Quintile for the Rule with Assessors' Inputs

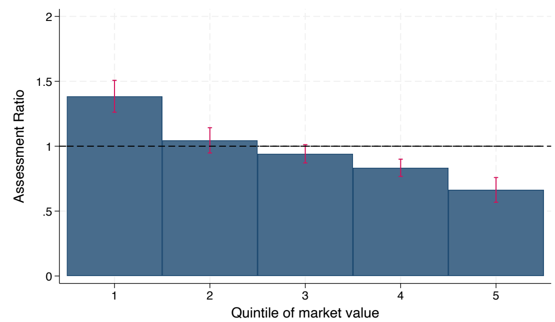


Notes: This Figure plots the median assessment ratio by quintile of market values in the rule arm, computing the predictions with rule using the characteristics from the calibration (assessors' dataset). Sample: Properties of the rule arm for which we have market values ($N = 1,166$).

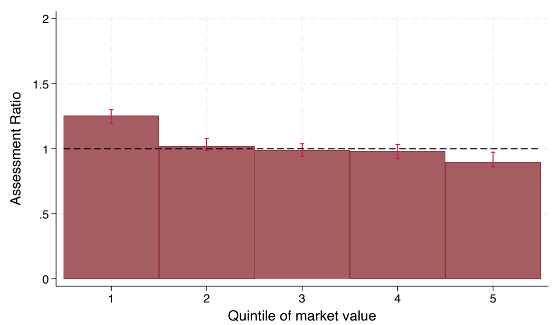
Figure A5
Assessment Ratio by Quintile for different Degrees of Discretion (Means)



(A) Full Discretion



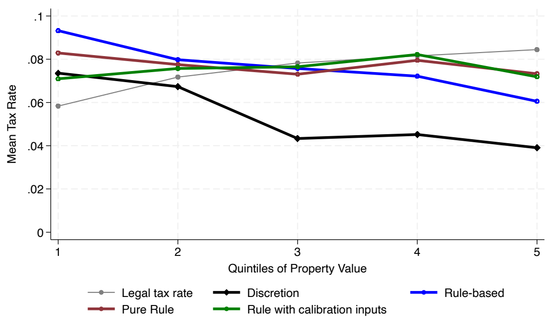
(B) Rule-Based



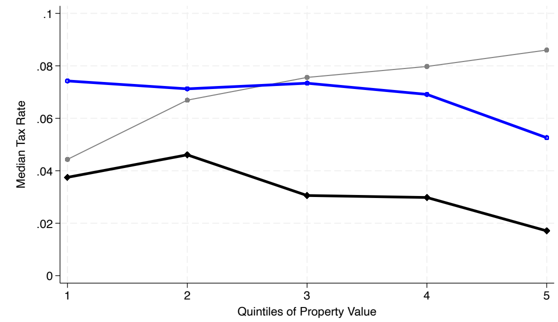
(C) Pure Rule

Notes: This Figure plots the mean assessment ratio (census value over market value) by quintile in the discretion arm (Panel (A)), in the rule-based arm (Panel (B)), in the rule arm but applying the pure rule (Panel (C)). Quintiles are based on market values. The red line shows the 95% confidence interval for the mean. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

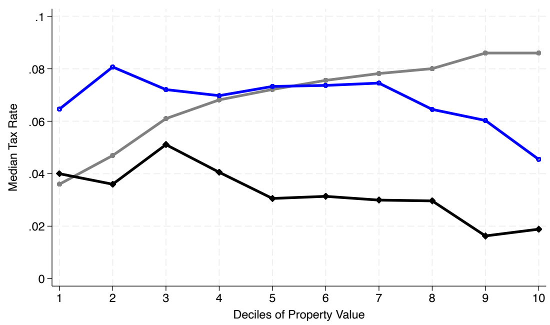
FIGURE A6
TAX RATES: ADDITIONAL RESULTS



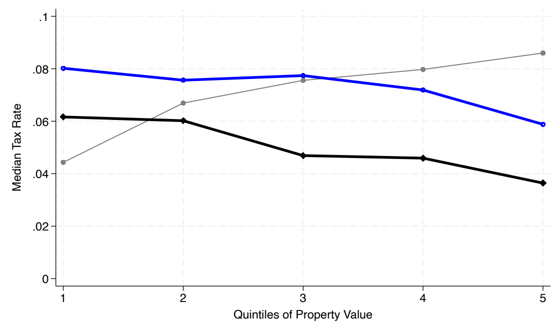
(A) MEAN TAX RATES



(B) ABATEMENT CALCULATED BASED ON OWNER-OCCUPIED ROOMS



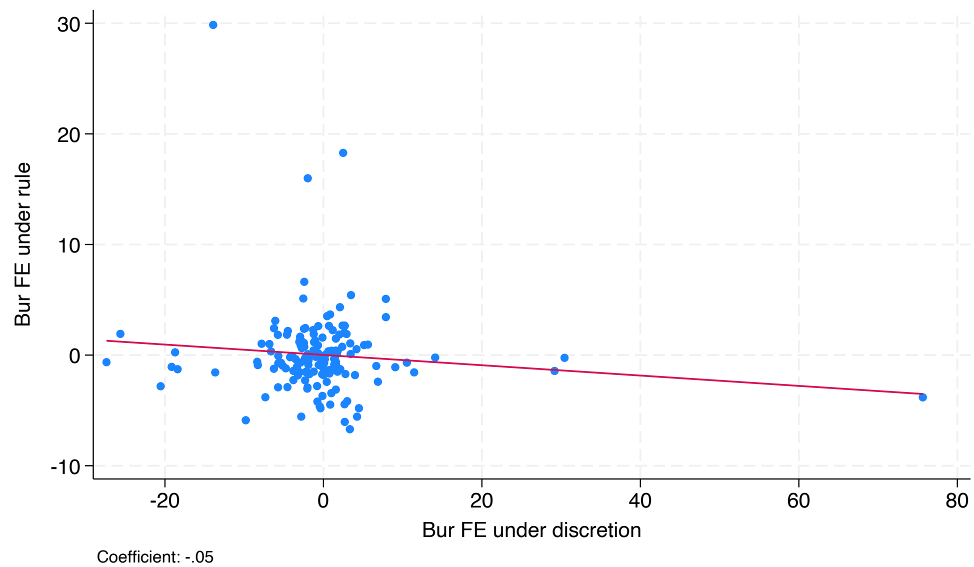
(C) TAX RATE BY DECILE



(D) RESTRICTING TO POSITIVE CASES

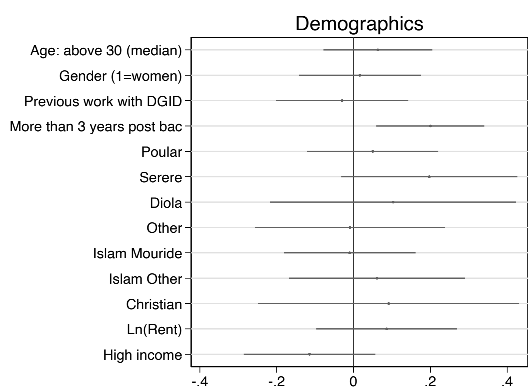
Notes: This Figure is a complement to Figure 7. In Panel (A), we plot the mean (instead of the median) tax rate by quintile of market values. In Panel (B), the main residence share of the property's value to which the abatement is applied is calculated identically in both arms, based on the number of rooms occupied by the owner (in Figure 7, for the discretion arm, the share is determined using the values bureaucrats report for owner-occupied parts). In Panel (C), we show the median tax rate by decile of market value. In Panel (D), we restrict the sample to properties to which a positive value was assigned by bureaucrats. Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

FIGURE A7
CORRELATION BETWEEN BUREAUCRAT FIXED-EFFECTS UNDER RULE AND DISCRETION

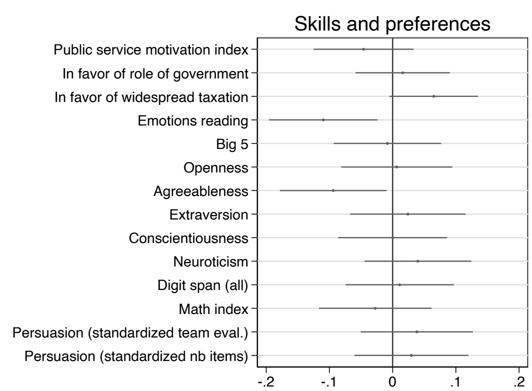


Notes: This Figure plots the correlation between the bureaucrat fixed-effects $\alpha_{b,EB}$ estimated separately on the rule and discretion sample, from specification 3.

FIGURE A8
CORRELATES OF BEING A TOP BUREAUCRAT



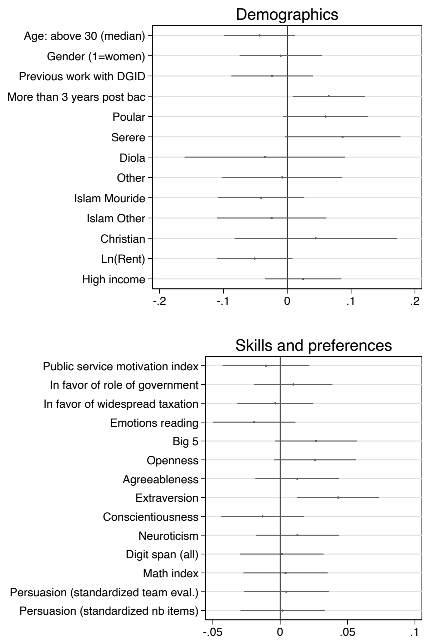
(A) DEMOGRAPHICS



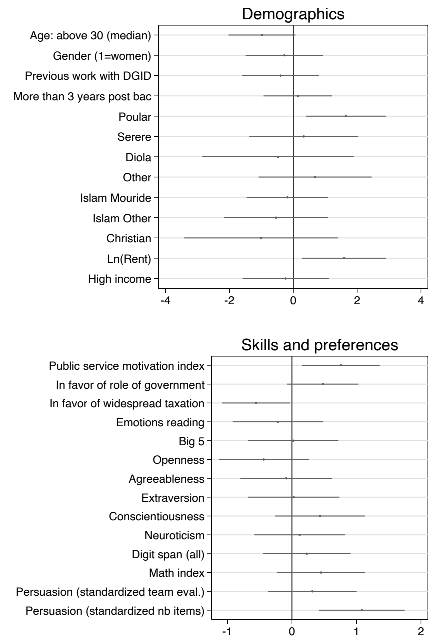
(B) SKILLS AND PREFERENCES

Notes: This Figure reports results from regressing a dummy for top bureaucrat on bureaucrat characteristics. We use the bureaucrat fixed-effects estimated in Section 5.2 to define top bureaucrats as those with $\alpha_{b,EB} < 0$. The source of the covariates are the bureaucrats baseline and endline surveys. The bar represents the 95% confidence interval on the coefficient of interest. See Appendix Section B.5 for a detailed description of the variables.

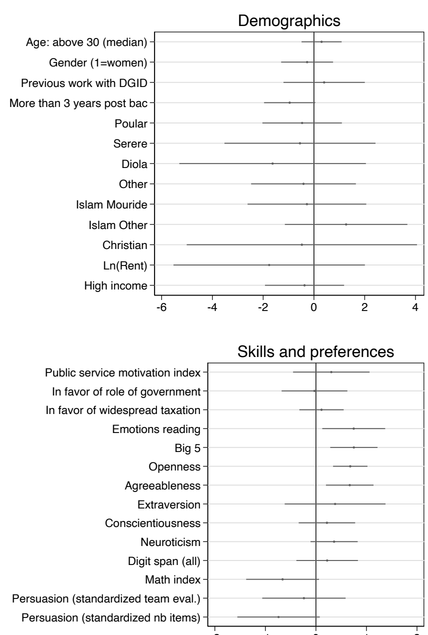
Figure A9
Correlates of Alternative Measures of Bureaucrat Performance



(A) Share of Plots with Owner Details



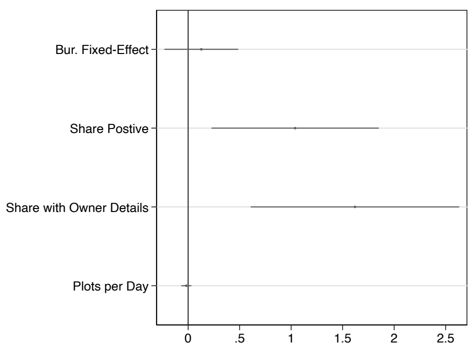
(B) Plots per Day



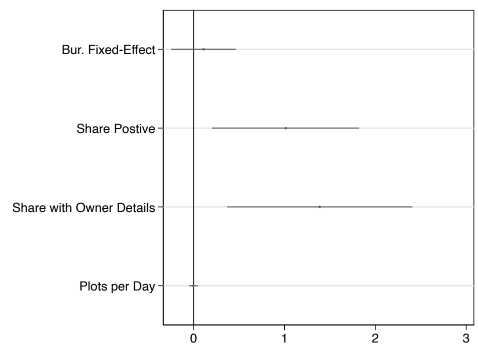
(C) Ability to Value High-End Properties in Full Sample

Notes: This Figure reports results from regressing alternative measures of bureaucrat performance on bureaucrat characteristics. In Panel (A), the performance measure is the share of plots visited by the bureaucrat for which (s)he recovered owner identification details (name and/or ID number). In Panel (B), the performance measure is the average number of plots visited by the bureaucrat in a day. The mean of the outcome variables are respectively 0.37 and 7. In Panel (C), the performance measure is a proxy for ability to value high end properties, we compute the outcome variable as the absolute tax base gap between bureaucrat values and a predicted value, where the prediction relies on the rule with remote covariates. The sample is restricted to properties for which the predicted value is above median. The bar represents the 95% confidence interval on the coefficient of interest. See Appendix Section B.5 for a detailed description of the variables.

FIGURE A10
WHAT DO SUPERVISORS VALUE IN BUREAUCRATS' PERFORMANCE?



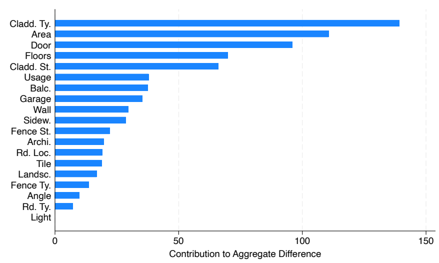
(A) OVERALL PERFORMANCE SCORE



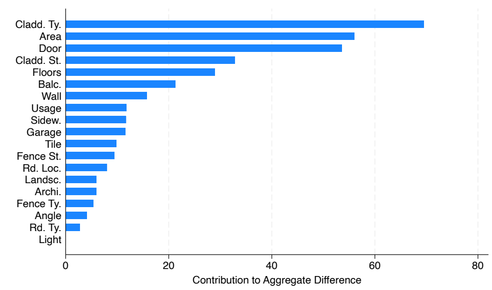
(B) SUM OF PERFORMANCE ITEMS

Notes: This Figure reports results from regressing supervisors' evaluation for a given bureaucrat on performance measures of the bureaucrat. In Panel (A), the outcome is the standardized global performance score a supervisor gave to a given bureaucrat. In Panel (B), the outcome is the standardized sum of scores for a list of performance items (social skills, fiscal knowledge, housing market knowledge, energy and stamina, negotiation skills, ease with technology, ease with reading maps). The performance measures are: a dummy for being a high performing bureaucrat ($\alpha_{b,EB} > 0$) as estimated in section 5.2); share of plots visited in the discretion arm for which the bureaucrat provided a positive value; share of plots visited for which the bureaucrat recovered owner identification details (name and/or ID number); average number of plots per day covered by the bureaucrat. The bar represents the 95% confidence interval on the coefficient of interest. See Appendix Section B.5 for a detailed description of the variables.

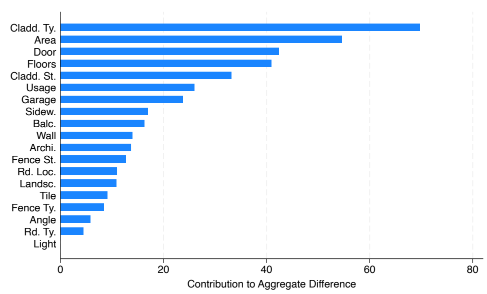
FIGURE A11
WHICH PROPERTY CHARACTERISTICS DRIVE THE EFFECT OF PARTIAL DISCRETION UNDER THE RULE-BASED SYSTEM



(A) ALL PROPERTIES



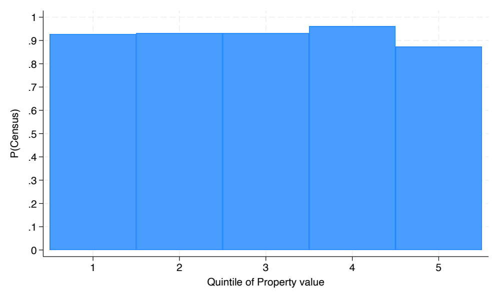
(B) LOW VALUE PROPERTIES



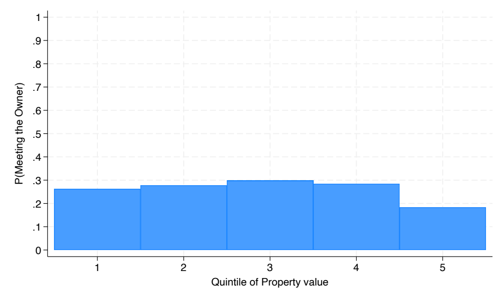
(C) HIGH VALUE PROPERTIES

Notes: This Figure shows the relative contribution of each observable characteristics to the differences between the rule implemented by bureaucrats, and the benchmark rule using inputs by assessors (measured in Panel (B) of Table 7). The contribution of characteristic X is calculated as the aggregate sum of the absolute difference in predicted values due to this characteristic, more precisely, $\sum_i |\gamma_c X_{c,RuleBur,i} - \gamma_c X_{c,RuleAss,i}|$ where the X_c are the 18 observable characteristics, subscript $RuleBur$ indicates the value taken by X_c when entered by bureaucrat and $RuleAss$ the value taken by X_c when entered by assessors for property i, γ_c is the coefficient for X_c in the formula (coefficients shown in Table A3). Panel (A) shows results for all properties from the analysis sample in the rule arm, in Panel (B) (resp. Panel (C)) we restrict to low value (resp. high value) properties.

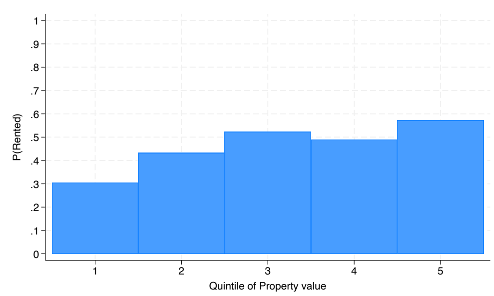
FIGURE A12
MODALITIES OF FIELD VISITS BY PROPERTY VALUE



(A) PROBABILITY OF PLOT BEING COVERED IN CENSUS



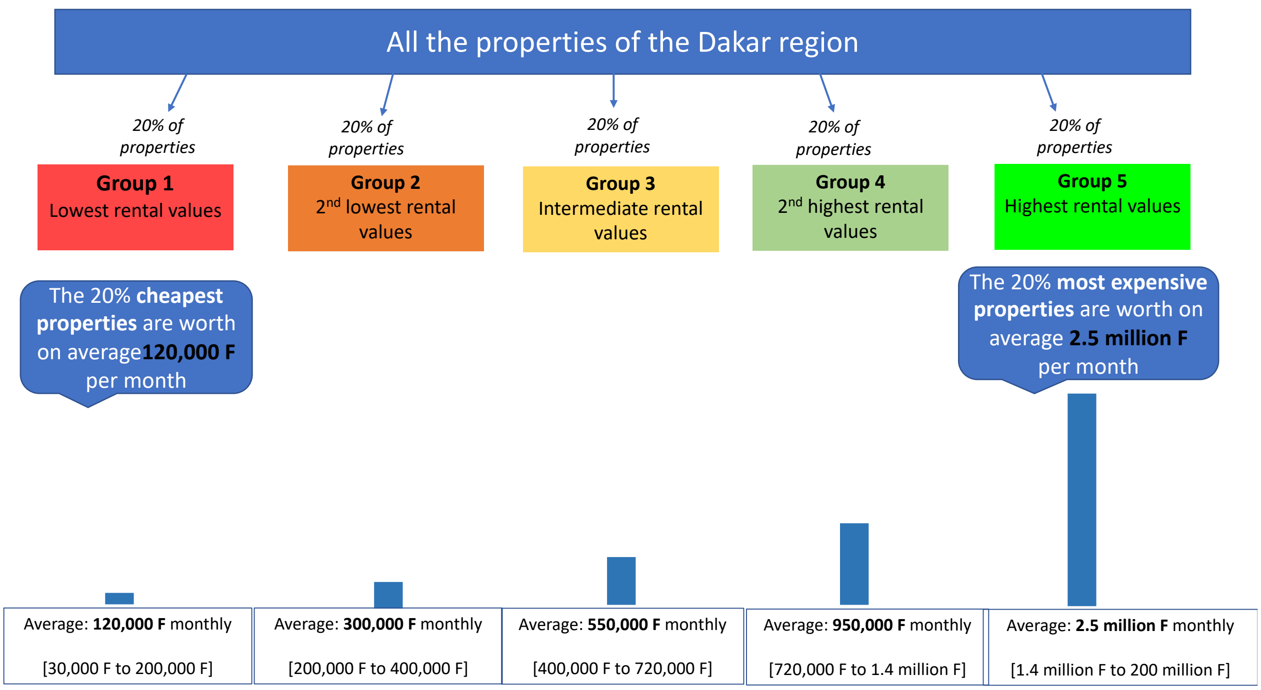
(B) PROBABILITY OF MEETING THE OWNER BY QUINTILE



(C) PROBABILITY OF PROPERTY BEING RENTED BY QUINTILE

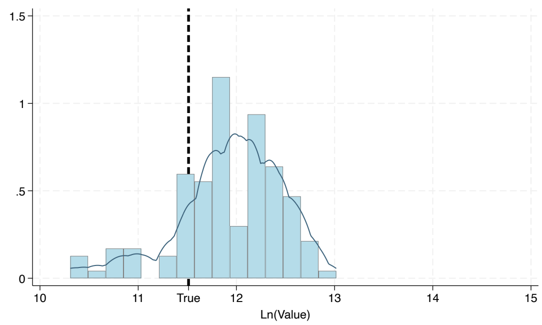
Notes: This Figure shows how three plot level outcomes vary by quintile of market value. In Panel (A) the underlying variable takes value one if the property is covered in the census. In Panel (B) the underlying variable takes value one if the bureaucrat reports meeting the owner. In Panel (C), the underlying variable takes value one if the bureaucrat classified the property as rented. Sample: analysis sample with market values, rule and discretion arms ($N = 2,290$).

FIGURE A13
INFORMATION TREATMENT FOR LAB-IN-THE-FIELD VALUATIONS

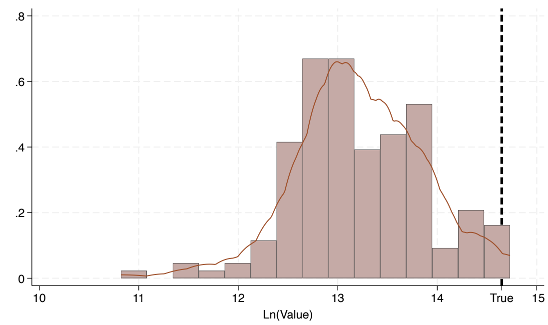


Notes: This Figure displays the information treatment shown to half the sample of bureaucrats in the endline survey. The information is based on market values. Bureaucrats are randomized into a treated and untreated group, stratifying by gender, accuracy rate observed in the census, and education level. In the survey, after seeing this pedagogical chart, bureaucrats were asked a simple comprehension question, to make sure they had carefully looked at the chart and understood its content.

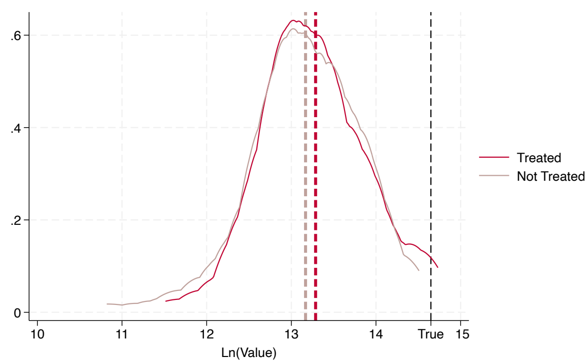
Figure A14
Lab-in-the-Field Valuations: Results



(a) Low-value property



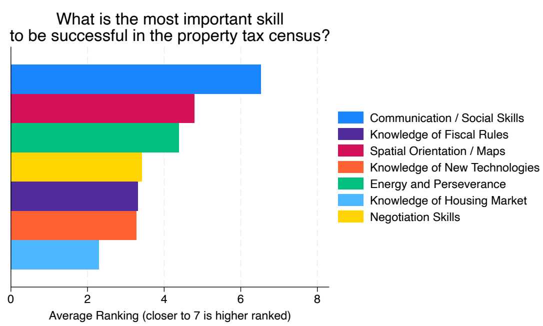
(b) High-value property



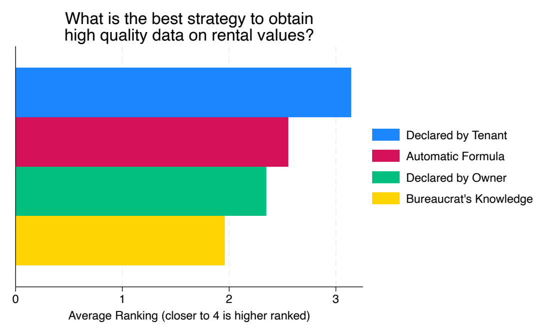
(c) High-value property - disaggregated by information treatment

Notes: This Figure shows the distribution of responses from the lab-in-the-field in which bureaucrats are asked to value two properties based on a picture, the low-value (respectively high-value) properties are depicted in Panel (A) (resp. Panel (C)) of Figure 1. We plot the histogram of $Ln(Value)$ where value is the monthly rental value provided by the bureaucrats. The vertical line indicates the benchmark market value. In Panel (C), we disaggregate responses for the high-value property by randomized information treatment status: a bureaucrat is treated if (s)he saw the information chart shown in Figure A13.

FIGURE A15
BUREAUCRATS' OPINION ON CONDITIONS FOR SUCCESSFUL PROPERTY TAX CENSUS



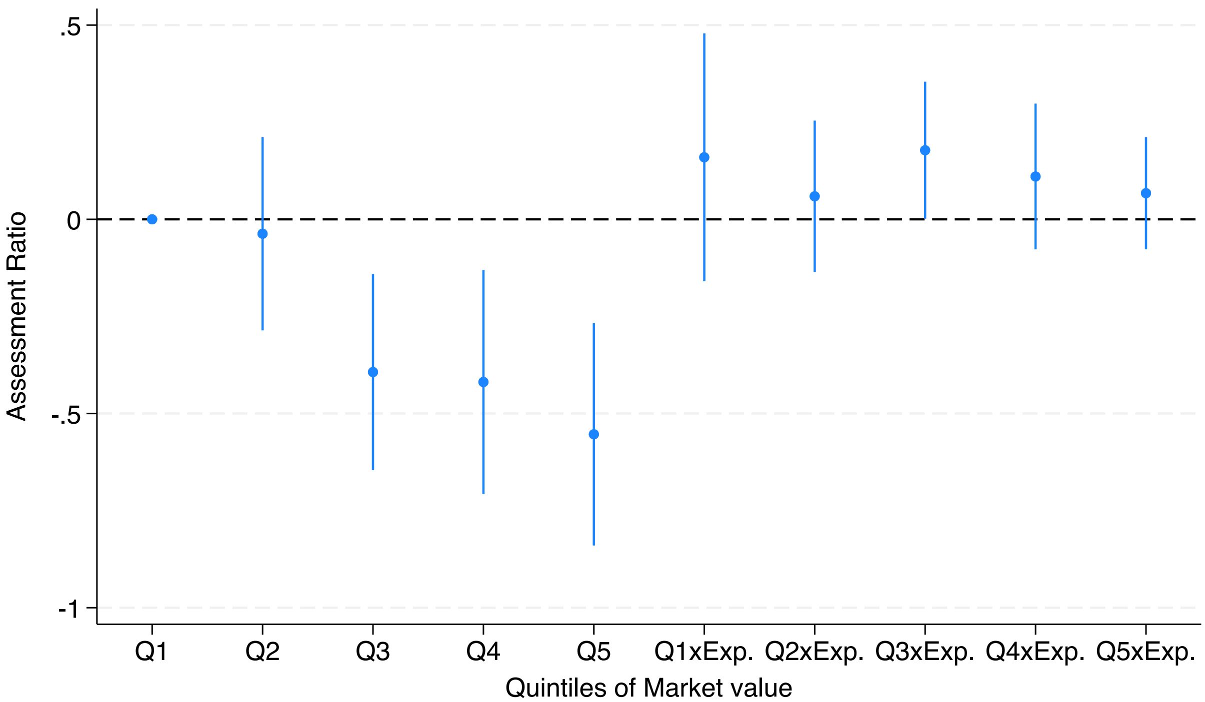
(A) MOST IMPORTANT SKILLS



(B) BEST STRATEGY TO RECOVER ACCURATE VALUES

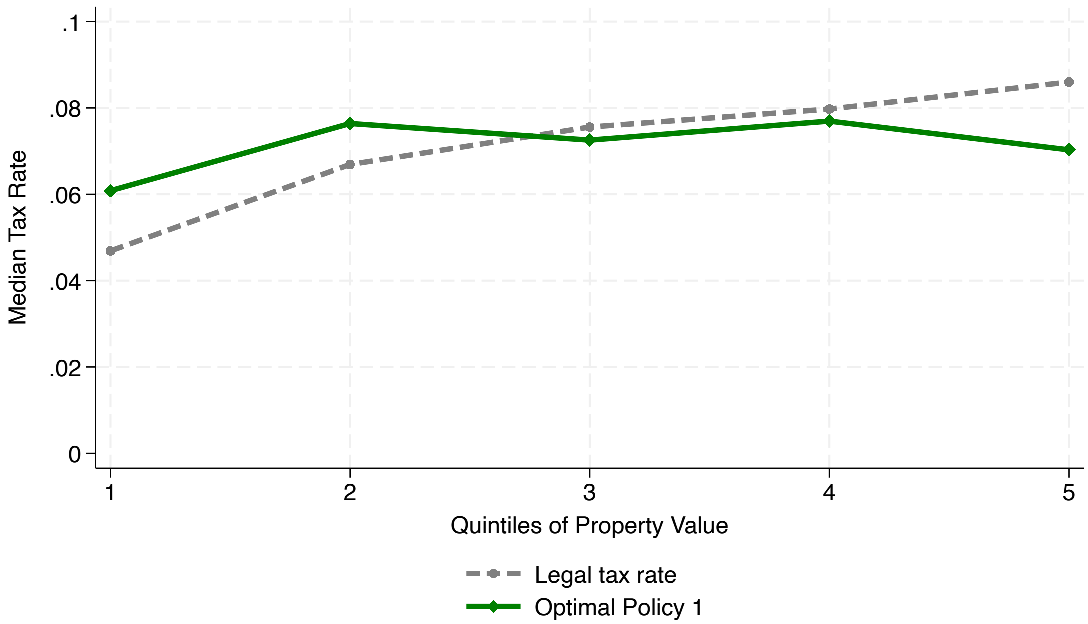
Notes: This Figure shows results from two survey questions from the bureaucrat endline survey. In Panel (A), respondents were asked "According to you, what are the most important skills to be successful in the property tax census?". They were then shown a list of 7 skills that they needed to rank from most to least important. We display the average ranking obtained by each skill, a higher value means the skill was ranked more important on average. In Panel (B), the question is "According to you, what is the best strategy for the DGID to recover high quality data on rental values in the region?". Respondents were then shown a list of 4 strategies that they needed to rank from most to least important. We display the average ranking obtained by each strategy, a higher value means it was ranked more important on average.

FIGURE A16
HETEROGENEITY BY EXPOSURE TO THE RULE



Notes: This Figure shows how the assessment ratio under discretion varies by quintile and depending on whether the bureaucrat was ever exposed to the rule yet. We plot the β_n and γ_n coefficients from the regression: $AR_i = \alpha + \sum_{n=1}^{5} \beta_n Q(n)_i + \sum_{n=1}^{5} \gamma_n Exposed_i \cdot Q(n)_i + \epsilon_i$, where AR_i is the assessment ratio (census value over market value) for property i, the $Q(n)$ are dummies for each quintile of the distribution of market values, $Exposed_i$ is a dummy taking value one if the bureaucrat has already been exposed to the rule previously. Errors are clustered at the section level. Sample: analysis sample with market values for the discretion arm ($N = 1,124$).

FIGURE A17
TAX RATES UNDER OPTIMAL POLICY



Notes: This Figure shows the median effective tax rate by quintile of market value under the optimal policy described in Section 7: based on section fixed-effect and built area, we predict whether a property belongs to the lowest quintile. If $Pred(Q1) = 1$, discretion is applied. If $Pred(Q1) = 0$, the pure rule is applied. A property's effective tax rate is computed as tax liability (based on the value from the census) over market value. The gray line is the benchmark tax profile computed by applying the tax code rates directly to market values (the tax rate is 8.6 percent with an abatement if the property is owner-occupied which explains the progressive profile). Sample: analysis sample with market values ($N = 1,124$ in the discretion arm and $N = 1,166$ in the rule arm).

Additional Tables

TABLE A1
CONSTRUCTION OF THE MARKET VALUES DATASET BY REAL ESTATE ASSESSORS

Panel A: Details on assessors' field work	
N sections	193
- per assessor	24.1
Info. from Office (%)	97.4
Info. from Agencies (%)	55.4
Info. from Occupants (%)	67.4
Panel B: Correlation with other sources of rental values	
Owner survey	0.39 (N=1,310)
Owner survey (rented)	0.49 (N=394)
Owner survey (fully rented)	0.62 (N=52)
Census (fully rented, met tenant)	0.50 (N=212)
Census (fully rented, met tenant, contract)	0.59 (N=48)
Census (full contract)	0.72 (N=63)
Census (full contract, met tenant)	0.83 (N=19)

Notes: In this Table we provide additional details on the construction of the market values dataset. In Panel (A), we show the share of sections covered by assessors for which they report having used information from their assessor office, from real estate agencies, and from occupants (tenants). In Panel (B), we show how the market values provided by assessors correlate with values from other sources, at the plot level. Owner survey refers to our property owner baseline survey, rented means the property has at least one space for rent, fully rented means the whole property is rented. Census refers to the data from the property tax census. Fully rented means the whole property is rented, met tenant means the bureaucrat reported the name of the tenant and reported not meeting the owner, contract means there is at least one rental contract on the property, full contract means there is a rental contract (or multiple contracts) covering the whole property.

Table A2
Performance statistics: Property valuation algorithm using all covariates

Estimated via 5x cross-validation	
R2	0.91
Adjusted R2	0.90
RMSE	0.36
Estimated on test sample	
MAPE	33.8
MAPE Q1	41.4
MAPE Q2	29.9
MAPE Q3	27.4
MAPE Q4	38.9
MAPE Q5	29.8
Freddie Mac 30%	59.6

Notes: This Table reports performance statistics for the property valuation algorithm, using all covariates listed in Table A3, and following specification 1. We calibrate the algorithm on the sample of market values by assessors ($N = 4,448$), using an elastic-net regression and 5-fold cross-validation, as explained in Section 4.2. We hold out a test sample of 521 observations to test model fit. Results are reported in the lower panel. MAPE refers to the mean absolute percentage error (it is computed using monetary amounts as the outcome variable, *not* on the ln() transformation). We report the MAPE within each quintile. Freddie Mac refers to the share of predictions that fall within 30% of the true value.

TABLE A3
COEFFICIENTS: PROPERTY VALUATION ALGORITHM USING ALL COVARIATES

Ln(BuiltArea)	0.57
Floors	.178
Residential	
Commercial	.195
Mixed	.119
Quality Doors and Windows	
Very Good	.116
Average	
Bad	-.199
Landscape	-.082
Architecture	.044
Garage	
Simple	.074
Double	.148
None	
Balcony	.164
On Main Road	.043
Near Main Road	.012
Off Main Road	
Road Type	
Tarmac	.007
Pavements	.028
Gravel	.077
Sand	
None	0
Sidewalk	.059
Angle	.111
Street Lights	0

Fence Type	
None	
Metal	-.167
Wall	.023
Wall w. wrought iron	.01
Fence State	
Very Good	.043
Average	
Bad	-.064
Cement	.141
Cladding Type	
Wis	-.074
Plain	-.118
Paint	
Tiles	0
Stone	.073
None	-.229
Cladding State	
Very Good	.077
Average	
Bad	-.124
Tiles	.049
Cons	11.712
Section FEs	
N zero	22/193
mean	.134
max	2.317
sd	.52

Notes: This Table reports the coefficients from the property valuation algorithm summarized in Table A2, following specification 1.

TABLE A4
PROPERTY VALUATION ALGORITHM USING REMOTE COVARIATES

Estimated via 5x cross-validation	
R2	0.88
Adjusted R2	0.87
RMSE	0.43
Estimated out of sample	
MAPE	41.4
MAPE Q1	65.7
MAPE Q2	33.7
MAPE Q3	25.7
MAPE Q4	42.7
MAPE Q5	34.0
Freddie Mac 30%	54.2

(A) PERFORMANCE STATISTICS

Ln(BuiltArea)	0.68
Floors	.214
Cons	11.317
Section FEs	
N zero	11/193
mean	.179
max	2.261

(B) COEFFICIENTS

Notes: This Table provides details on the property valuation algorithm using only 'remote' covariates (section fixed effects, built area, number of floors). Panel (A) reports the performance statistics and Panel (B) the estimated coefficients. We calibrate the algorithm on the sample of market values by assessors ($N = 4,448$), using an elastic-net regression and 5-fold cross-validation, as explained in Section 4.2. We hold out a test sample of 521 observations to test model fit. MAPE refers to the mean absolute percentage error (it is computed using monetary amounts as the outcome variable, *not* on the ln() transformation). We report the MAPE within each quintile. Freddie Mac refers to the share of predictions that fall within 30% of the true value.

Table A5
The undervaluation gradient: Robustness results under discretion

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) Q5
Panel A: Discretion					
Mean Ass. Ratio	1.15	0.92	0.57	0.56	0.47
$\hat{\beta}_n$	Ref.	-0.23	-0.58	-0.59	-0.69
P-value		0.05	0.00	0.00	0.00
P-value $\hat{\beta}_n \neq \hat{\beta}_{n+1}$		0.00	0.88	0.39	
Panel B: Values per m^2					
Median Ass. Ratio	0.89	0.69	0.54	0.50	0.23
$\hat{\beta}_n$	Ref.	-0.19	-0.35	-0.39	-0.66
P-value		0.04	0.00	0.00	0.00
P-value $\hat{\beta}_n \neq \hat{\beta}_{n+1}$		0.04	0.52	0.00	
Panel C: Quintiles computed out-of-sample					
Median Ass. Ratio	0.75	0.60	0.39	0.44	0.35
$\hat{\beta}_n$	Ref.	-0.15	-0.36	-0.31	-0.40
P-value		0.04	0.00	0.00	0.00
P-value $\hat{\beta}_n \neq \hat{\beta}_{n+1}$		0.00	0.54	0.24	

Notes: This Table shows robustness results as a complement to Table 2, plotting coefficients β_n from regression $AR_{ij} = \alpha + \sum_{n=1}^{5} \beta_n Q(n)_{ij} + \epsilon_{ij}$ where AR_{ij} is the assessment ratio (census value over market value) for property i of section j, the $Q(n)$ are dummies for each quintile of the distribution of market value. Errors are clustered at the section level. In Panel (A) we run a standard OLS regression. In Panel (B), we run the quantile regression at the median, but the five quintiles used as regressors are defined using market property value *per square meter*. In Panel (C), quintiles are defined using *predicted* property values using a prediction calibrated on pure control areas only. Sample: Properties of the discretion arm for which we have market values ($N = 1,124$).

TABLE A6
REMOVING DISCRETION INCREASES ACCURACY: ROBUSTNESS

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) $\mid$Gap$\mid$ *mil.FCFA*	(4) Ass. Ratio
Panel A: Rule-based (with bur. FEs)				
Mean[1] (sd)	−1.25 (10.80)	0.00	3.81 (10.18)	1.16
$\hat{\beta}_{Discretion}$	-5.55^{***}	-2.41^{***}	4.49^{***}	-0.39^{***}
	(1.29)	(0.50)	(1.24)	(0.06)
Mean[1] (sd) Discretion	−6.11 (15.62)	−2.40	8.00 (14.73)	0.76
N plots: 2118				
N Bureaucrats: 234				
Panel B: Rule-based (calibrated on owner survey)				
Mean[1] (sd)	−6.56 (18.05)	−1.72	6.98 (17.89)	0.76
$\hat{\beta}_{Discretion}$	−0.48	-0.75^{**}	1.45	−0.04
	(1.92)	(0.35)	(1.92)	(0.05)
Mean[1] (sd) Discretion	−7.54 (18.98)	−2.41	8.96 (18.35)	0.71
N plots: 2290				
Panel C: Pure rule (calibrated on owner survey)				
Mean[1] (sd)	−6.66 (18.05)	−1.77	7.10 (17.88)	0.75
$\hat{\beta}_{Discretion}$	−0.39	-0.73^{**}	1.34	−0.03
	(1.92)	(0.36)	(1.91)	(0.05)
Mean[1] (sd) Discretion	−7.54 (18.98)	−2.41	8.96 (18.35)	0.71
N plots: 2290				

Notes: This Table shows the effect of discretion on the tax base gap, similarly to Table 3, showing three robustness results. In Panel (A), we show the effect of discretion within bureaucrat: we control for bureaucrat fixed-effects. In Panel (B), for the rule arm, we use a rule calibrated on property values reported in our baseline property owner survey (instead of market values from the assessors). In Panel (C), for the rule arm, we use a pure rule (only built area and section fixed-effects) calibrated on property values from the owner baseline. We run regression 2: $Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk}$ with four different outcomes. In column (1) the outcome variable is the tax base gap defined as census value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as census value over the market value. In Panel (A), the number of observations drops to $2,191$, since plots that are not covered by the census are not assigned a bureaucrat identifier. The first rows of each Panel display descriptive statistics of the outcome variable in the rule arm; the second rows show the coefficient of interest on the dummy for Discretion. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. Sample: Properties of the Discretion and Rule arms for which we have market values ($N = 2,361$). [1]In column (2) the displayed value is the $median$ of the tax base gap.

TABLE A7
REMOVING DISCRETION INCREASES ACCURACY: INTENSIVE MARGIN

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) |Gap| *mil.FCFA*	(4) Ass. Ratio
Panel A: Discretion				
Mean[1] (sd)	−4.45 (15.39)	−1.32	6.89 (14.46)	0.97
Panel B: Rule-based				
Mean[1] (sd)	−1.25 (10.80)	0.00	3.81 (10.18)	1.16
$\hat{\beta}_{Discretion}$	-2.98^{***}	-1.11^{***}	2.65^{**}	-0.21^{***}
	(1.08)	(0.26)	(1.13)	(0.05)
Panel C: Pure Rule				
Mean[1] (sd)	−0.13 (6.77)	0.12	2.62 (6.24)	1.13
$\hat{\beta}_{Discretion}$	-3.78^{***}	-1.34^{***}	3.71^{***}	-0.18^{***}
	(0.88)	(0.30)	(0.89)	(0.05)
Panel D: Lee bounds				
Lower bound	−5.83		2.07	−0.37
Upper bound	−1.42		5.73	0.10
CI for $\hat{\beta}_{Discretion}$	[−6.74;−0.32]		[1.00;6.56]	[−0.45;0.17]
N plots: 1885				
N Sections: 94				
Mean (sd) market value: 73.90 (14.40)				
Median market value: 5.40				

Notes: This Table shows the effect of discretion on the tax base gap, similarly to Table 3, except that in this case we focus on the intensive margin: we drop plots for which the census value is 0 ($N = 490$). This can be because the plot was not visited, or because the plot was visited but the bureaucrat did not assign a value (the latter is only arises under discretion). We run regression 2: $Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk}$ with four different outcomes. In column (1) the outcome variable is the tax base gap defined as census value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as census value over market value. In Panel (A), we display summary statistics for the discretion arm. In Panel (B) and (C) we show results for the rule and pure rule respectively. The first rows of Panels (B) and (C) display descriptive statistics of the outcome variable in the rule arm; the second rows show the coefficient of interest on the dummy for Discretion. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. In Panel (D), we conduct a Lee bound estimation to correct for non-random attrition. Rows 1 and 2 display the estimated lower and upper bound of the treatment effect, and row 3 shows the final confidence interval of the effect, accounting for uncertainty coming both from non-random attrition and from sampling error. Mean and median property values listed at the bottom of the table are market values (from the assessor dataset). Sample: Properties of the Discretion and Rule arms for which we have market values, and a positive bureaucrat value ($N = 1,871$). [1]In column (2) the displayed value is the *median* of the tax base gap.

TABLE A8
HORIZONTAL AND VERTICAL EQUITY STATISTICS

	(1) Market Values	(2) Discretion	(3) Rule-based	(4) Pure Rule	(5) Rule (calibration inputs)
Mean Value	15.80	7.21	12.71	17.09	15.72
SD	76.98	37.52	88.00	112.13	92.67
Median Value	5.55	2.40	4.27	4.86	5.02
Mean Ass. Ratio		0.71	1.06	1.13	1.10
Median Ass. Ratio		0.50	0.95	1.04	1.05
Share Accurate		0.22	0.45	0.63	0.68
PRD		1.60	1.28	1.02	1.02
COD		114.75	52.86	31.05	25.50
Q1		103.34	54.91	29.02	25.17
Q2		86.07	45.67	27.40	23.05
Q3		84.50	41.90	25.37	22.71
Q4		99.60	37.78	26.25	22.19
Q5		188.53	64.51	40.74	35.84

Notes: This Table reports summary statistics on valuations with each method, as well as specific indicators measuring the horizontal and vertical equity of valuations. Column (1) reports on market values (from assessors). Column (2) reports on values from the discretion arm. Column (3) reports on rule-based valuations. Column (4) reports on pure rule valuations in the rule arm. Column (5) reports on rule-based valuations in the rule arm but using predictions obtained with the inputs used in the rule calibration (assessor inputs, instead of bureaucrats' inputs). Values are annual property rental values in millions of FCFA. Rows 4 and 5 show the mean and median assessment ratio (AR), computed as census value over market value. Row 6 shows the share of properties accurately valued, meaning that the census value is within 30% of the market value. The PRD is the Price Related Differential, a measure of vertical equity. The PRD is calculated as the mean AR divided by the weighted mean AR (weighted by market value). A PRD lower than one indicates that valuations are progressive, while the higher above 1 the value is, the more regressive valuations are. The COD is the coefficient of dispersion, a measure of horizontal equity (more precisely, uniformity of valuations). It is measured as average percentage dispersion of AR values around the median AR. Finally, we report the COD computed within each quintile of market values.

TABLE A9
EFFECT OF DISCRETION ON EXTENSIVE MARGIN

(A) FULL SAMPLE

Dependent Variable	Plots per day	Covered	Eligible	Valued	Rented	Main Res.	Rent value	Main Res. value	Owner Met	Conflict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Discretionary	1.156	0.002	-0.031	-0.228***	-0.006	-0.051**	-0.069***	-0.347***	0.002	-0.013*
	(1.306)	(0.019)	(0.021)	(0.023)	(0.017)	(0.021)	(0.020)	(0.032)	(0.014)	(0.007)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2309	41609	41609	41609	41609	41609	41609	41609	41609	41609
N sections	94	94	94	94	94	94	94	94	94	94
Adj R2	0.05	0.03	0.06	0.12	0.05	0.04	0.05	0.19	0.02	0.02
Mean of dep.	16.56	0.92	0.79	0.71	0.38	0.46	0.36	0.57	0.24	0.05

(B) SAMPLE WITH MARKET VALUES

Dependent Variable	Plots per day	Covered	Eligible	Valued	Rented	Main Res.	Rent value	Main Res. value	Owner Met	Conflict
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Discretionary	-0.011	0.027	0.031	-0.178***	0.019	-0.020	0.001	-0.310***	0.001	-0.008
	(0.087)	(0.021)	(0.022)	(0.030)	(0.023)	(0.028)	(0.024)	(0.040)	(0.025)	(0.010)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1104	2409	2409	2290	2290	2290	2290	2290	2290	2290
N sections	94	94	94	94	94	94	94	94	94	94
Adj R2	0.03	0.03	0.03	0.10	0.05	0.04	0.05	0.18	0.02	0.02
Mean of dep.	2.03	0.93	0.88	0.82	0.43	0.54	0.40	0.67	0.26	0.05

Notes: This Table shows the effect of discretion on extensive margin outcomes. Panel (A) shows results for the whole sample while Panel (B) is restricted to plots for which we have market values. The coefficient of interest is the coefficient for the 'Discretionary' dummy. In column (1) the outcome is the number of plots covered in a day and observations are at the day X section level. In columns (2) to (10) regressions are at the plot level and the outcome variables are dummies taking value 1, respectively, if: the plot is covered in the census, it is classified as eligible for the tax, there is a positive property value, it is classified as rented (at least in part), it is classified as main residence, there is a positive value for rented parts, there is a positive value for owner-occupied parts, the bureaucrat reports having met the owner, the bureaucrat reports that there has been tensions or conflict (scraped from text comments). In all regressions we control for strata fixed effects and errors are clustered at the section level.

Table A10
Bureaucrats' implicit algorithm

Ln(BuiltArea)	0.43
Floors	.143
Residential	
Commercial	.04
Mixed	.077
Quality Doors and Windows	
Very Good	0
Average	
Bad	-.134
Landscape	-.05
Architecture	0
Garage	
Simple	.05
Double	.009
None	
Balcony	.064
On Main Road	.074
Near Main Road	.072
Off Main Road	
Road Type	
Tarmac	0
Pavements	0
Gravel	.366
Sand	
None	0
Sidewalk	.054
Angle	.117
Street Lights	.066
Fence Type	
None	
Metal	0
Wall	0
Wall w. wrought iron	0
Fence State	
Very Good	0
Average	
Bad	0
Cement	0
Cladding Type	
Wis	-.204
Plain	-.102
Paint	
Tiles	0
Stone	0
None	-.137
Cladding State	
Very Good	0
Average	
Bad	-.01
Tiles	0
Cons	12.598
Section FEs	
N zero	18/48
mean	.086
max	1.277
sd	.353

Notes: This Table shows bureaucrats' implicit valuation algorithm, reporting the coefficients for different characteristics when calibrating the algorithm using bureaucrats' discretionary values. We follow the exact same methodology as described in Section 4.2, but using bureaucrats' discretionary values as the outcome variable, on the sample of properties from the discretion arm. We use the observable characteristics reported by the assessors as regressors, since bureaucrats do not report observable characteristics in the discretion arm.

Table A11
Rule-based valuation: observable characteristics reported by bureaucrats vs assessors

Characteristic	Share Identical
Easy/objective	
Floors	0.71
when $\neq$ % where bur. $=$ ass. $+1$	0.56
Usage	0.75
Wall (dummy)	0.79
Tiles (dummy)	0.65
Balcony (dummy)	0.78
Angle (dummy)	0.92
Street lights (dummy)	0.79
Garage	0.62
Road type	0.71
Complex/subjective	
Fence type	0.55
Fence state	0.51
Cladding type	0.14
Cladding state	0.48
Quality doors and windows	0.49
Landscape (dummy)	0.81
Architecture (dummy)	0.66
Road (main)	0.50
Sidewalk (dummy)	0.65

Notes: In this Table we compare observable characteristics reported by assessors versus by bureaucrats for all properties of the rule arm that were also visited by the assessors. For the number of floors: additionally we indicate the percentage of cases for which the bureaucrat reported 1 floor more than the assessor, among cases where there is a mismatch.

TABLE A12
LEARNING OVER TIME

Dependent Variable	Discretion			Rule		
	|Gap|	|Gap|	Value	|Gap|	|Gap|	Value
	(1)	(2)	(3)	(4)	(5)	(6)
Numb. properties	0.050*			-0.024*		
	(0.026)			(0.014)		
(Numb. properties)^2	-0.000			0.000*		
	(0.000)			(0.000)		
Numb. days		0.342**	0.011		-0.208**	-0.030
		(0.152)	(0.021)		(0.085)	(0.027)
(Numb. days)^2		-0.004	-0.001***		0.002**	0.000
		(0.003)	(0.000)		(0.001)	(0.000)
Section control for Market Value	Yes	Yes	Yes	Yes	Yes	Yes
Bureaucrat FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1055	1055	20086	1063	1063	17458
Mean	8.00	8.00	3.97	3.81	3.81	5.52
R2	0.51	0.51	0.15	0.44	0.44	0.33
Adj R2	0.39	0.39	0.14	0.31	0.31	0.32

Notes: In this Table, we assess whether there is any learning by bureaucrats over the course of the property tax census, by analyzing whether the tax base gap changes over time or with the number of properties covered, separately for the discretion arm (columns (1) to (3)) and the rule based arm (columns (4) to (6)). On average, a bureaucrat worked 32 days, and covered 142 properties in the full sample. In columns (1), (2), (4) and (5), the outcome is the absolute value of the tax base gap and the sample is restricted to properties for which we have market values, while in columns (3) and (6) the outcome is property value and the regression is on the full sample. All outcome variables are in millions of FCFA and winsorized at the 1% level. The regressors of interest are number of properties visited by a given bureaucrat and its squared value (columns (1) and (4)), and total number of days worked by a given bureaucrat and its squared value. We control for bureaucrat fixed-effects and a section level decile of market values, errors are clustered at the section level. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively.

Table A13
Valuations and Owner Characteristics

Dependent Variable	Value (winz.)	Ln(Value)	Value (winz.)	Ln(Value)
	(1)	(2)	(3)	(4)
Ln(remote pred.)	3.986***	0.705***	3.117***	0.662***
	(0.340)	(0.028)	(0.652)	(0.087)
Bureaucrat Met Owner	-0.600***	-0.159***		
	(0.197)	(0.024)		
Deceased	-0.927***	-0.278***		
	(0.288)	(0.040)		
Female	0.180	-0.059**		
	(0.185)	(0.023)		
Male	0.000	0.000		
	(.)	(.)		
Unknown	-1.677***	-0.045		
	(0.350)	(0.042)		
Multiple	6.511***	0.343**		
	(1.860)	(0.159)		
Owner is retired	-0.041	-0.070***		
	(0.166)	(0.024)		
Agents' Commune	1.294**	0.050		
	(0.563)	(0.089)		
Same ethnic group			0.087	0.113
			(0.370)	(0.071)
Missing			-0.591	-0.012
			(0.676)	(0.129)
Poor			0.000	0.000
			(.)	(.)
Rich			-1.265	-0.065
			(0.758)	(0.113)
Not employed			-0.303	-0.139
			(0.627)	(0.091)
Employed			0.000	0.000
			(.)	(.)
Retired			-0.257	-0.242**
			(0.690)	(0.105)
Female bur and owner			-0.508	0.158
			(0.979)	(0.112)
Female bur and male owner			0.651	0.048
			(0.587)	(0.124)
Male bur and female owner			0.999	0.255**
			(0.791)	(0.118)
Rented			0.756	0.083
			(0.467)	(0.094)
In Tax Net			0.278	0.001
			(0.595)	(0.099)
Strata FE	Yes	Yes	Yes	Yes
N	14451	11242	505	413
R2	0.31	0.50	0.41	0.51
Adj R2	0.31	0.50	0.35	0.46

Notes: In this Table we test whether owner characteristics correlate with values reported by bureaucrats under discretion. In columns (1) and (2) we use the full census sample from the discretion arm. In columns (3) and (4) we restrict to properties covered by the owner baseline survey. We control for $Ln(remotepred)$, which is the predicted property value based solely on remote covariates. We control for randomization strata. Errors are clustered at the section level.

TABLE A14
HETEROGENEITY DEPENDING ON HOW THE FIELD VISIT GOES

	No Bureaucrat FE			with Bureaucrat FE		
	(1)	(2)	(3)	(4)	(5)	(6)
	Value	|Gap|	Ass. Ratio	Value	|Gap|	Ass. Ratio
Panel A: Owner Met						
$\hat{\beta}_{Discretion}$	-2.76^{***}	1.93	-0.47^{***}	-3.69^{***}	1.24	-0.43^{***}
	(0.78)	(1.37)	(0.07)	(1.09)	(1.32)	(0.10)
Mean (sd) in Rule	7.21 (7.27)	4.07 (13.29)	1.17 (0.77)	7.21 (7.27)	4.07 (13.29)	1.17 (0.77)
N	597	597	340	597	597	340
Low Value						
$\hat{\beta}_{Discretion}$	-0.58	0.27	-0.31^{**}	-0.08	1.01^{*}	0.17
	(0.39)	(0.30)	(0.14)	(0.68)	(0.52)	(0.24)
Mean (sd) in Rule	3.00 (1.58)	1.07 (1.10)	1.38	3.00 (1.58)	1.07 (1.10)	1.38
N	257	257	257	257	257	257
High Value						
$\hat{\beta}_{Discretion}$	-4.70^{***}	2.98	-0.49^{***}	-5.16^{***}	4.01^{***}	-0.54^{***}
	(1.18)	(2.26)	(0.07)	(1.51)	(1.51)	(0.08)
Mean (sd) in Rule	10.80 (8.24)	6.64 (17.68)	0.99	10.80 (8.24)	6.64 (17.68)	0.99
N	340	340	340	340	340	340
Panel C: Rented						
$\hat{\beta}_{Discretion}$	-1.19	3.35^{**}	-0.16^{**}	-1.70	4.75^{**}	-0.20^{*}
Mean (sd) in Rule	8.98 (8.80)	4.33 (10.45)	1.18 (0.87)	8.98 (8.80)	4.33 (10.45)	1.18 (0.87)
N	977	977	977	977	977	977
Low Value						
$\hat{\beta}_{Discretion}$	0.36	0.72^{*}	0.13	0.94	1.18	0.51
	(0.49)	(0.39)	(0.19)	(1.00)	(0.80)	(0.32)
Mean (sd) in Rule	3.61 (2.82)	1.44 (2.30)	1.52	3.61 (2.82)	1.44 (2.30)	1.52
N	327	327	327	327	327	327
High Value						
$\hat{\beta}_{Discretion}$	-2.21^{*}	4.61^{**}	-0.23^{***}	-3.26^{*}	6.72^{**}	-0.31^{***}
	(1.15)	(2.13)	(0.06)	(1.70)	(2.96)	(0.10)
Mean (sd) in Rule	12.16 (9.56)	6.05 (12.78)	0.97	12.16 (9.56)	6.05 (12.78)	0.97
N	650	650	650	650	650	650
Panel C: Bureaucrats' estimate						
$\hat{\beta}_{Discretion}$	-2.15	2.41	-0.26^{***}	-1.65	4.00^{**}	-0.24^{**}
Mean (sd) in Rule	7.50 (8.21)	3.81 (10.18)	1.16 (0.77)	7.50 (8.21)	3.81 (10.18)	1.16 (0.77)
N	1,193	1,193	1,193	1,193	1,193	1,193
Panel D: Conflict						
$\hat{\beta}_{Discretion}$	-3.04	0.06	-0.55^{***}	-5.61	-2.79	-0.64^{***}
Mean (sd) in Rule	7.91 (8.16)	5.70 (15.87)	0.98 (0.55)	7.91 (8.16)	5.70 (15.87)	0.98 (0.55)
N	110	110	110	110	110	110

Notes: This Table reports results from regression 2: $Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk}$, restricting the sample to specific subsets of observations. In Panel (A), the Discretion sample is restricted to cases where the bureaucrat reports having determined the value herself (scraped from text comments); in Panel (B), the sample is restricted to cases where the bureaucrat reports meeting the owner; in Panel (C) the sample is restricted to cases where the bureaucrat indicated that the property was rented at least in part; in Panel (D), the sample is restricted to cases where the bureaucrat reports that there was some tensions or conflict (scraped from text comments). In columns (1) and (4) the outcome variable is the property value, in columns (2) and (5), the outcome variable is the tax base gap defined as census value minus market value. All amounts are in millions of FCFA and winsorized at the 1% level. In columns (3) and (6) the outcome is the assessment ratio, computed as census value over the market value.

TABLE A15
COST-BENEFIT ANALYSIS

	Costs	Tax liabilities	Ratio
Assessors	503.3 mn	38.5 bn	x76
Discretion	118.1 mn	15.7 bn	x133
Rule	134.7 mn	22.4 bn	x166
Pure Rule	16.6 mn	40 bn	x2416
Optimal Policy	17.4 mn	45 bn	x2588

Notes: This Table displays costs, total tax liabilities and the liabilities to cost ratio under each method. Costs correspond to field costs and rule calibration costs, and excluded program costs that are invariant across methods. Tax liabilities are total liabilities without any assumptions on compliance. Both are calculated assuming each method in turn is applied to all eligible plots of the 96 study sections ($N = 32,677$).

A Details on Institutional Context and Program

A.1 Institutional Context

The creation of the property tax valuation roll and the tax bills is the responsability of the national tax administration, *Direction Générale des Impôts et Domaines du Sénégal* or *DGID*. Once emitted, the tax bills are physically distributed by the national treasury, and owners pay in a treasury office. Revenues accrue to municipalities at the end of the year. The region includes four cities: Dakar, Guediawaye, Pikine, Rufisque. Each city is divided in municipalities or *Communes*. Each municipality is divided into cadastral sections. In our paper, we call *the property tax* the combination of the property tax and the garbage tax. Indeed, both are managed through the same tax bills and have the same base. Their exact denominations are *Contribution Foncière des Propriétés Bâties* or *CFPB* and *Taxe d'Enlèvement des Ordures Ménagères* or *TEOM*. The garbage tax has a rate of 3.6 percent. The property tax has a 5 percent rate, and if the property is the owner's main residence, there is a reduction of the tax base by 1.5 million CFAF. The discretionary valuation method which is the status quo before the program is called the *comparative method* in the tax code (meaning that bureaucrats should compare the property with similar ones for which they have values in mind). The tax code also provides for a *cadastral valuation method* where experts from the cadastral division of the administration conduct in depth visits and measurements to value a property. Due to length and cost, in practice, these inspections barely ever occur. Resource constraints are the main reason why property census operations were extremely rare before the program. The staff available to conduct this field work is limited and also works on other taxes, the registrations were extremely time consuming since all the information was collected on paper and needed to be typed into the system once back into the office. Several factors explain why there is now this push by the government to expand the property tax net. First, in 2013, a decentralisation bill was passed reshaping the responsibilities of local governments and requiring that they assist the national tax administration in enforcing local taxation. These decentralisation policies have also made it more crucial to grow the budgets of local governments, now responsible for more services. These incentives are also built in Senegal's relationship with international donors: starting 2019, a budget support agreement with the World Bank and bilateral donors set objectives in terms of local tax revenues and municipalities' capacity, disbursements are conditional on increased property tax registrations. Furthermore, the government is interested in expanding the tax net in general, and due to its intrinsic geographical component, the property tax is considered as a promising entry point to build better information sets on taxpayers' wealth, income, and address (none of the existing tax registers have precise addresses). As an illustration, in 2021, the tax administration launched both its *Yaatal* (or "expansion") program, aiming to double the number of registered taxpayers, and a national property census project (*Recensement National des Propriétés Bâties*), with the objective for all properties of the national territory to be covered by property tax census operations in the near future. Finally, in this context, some resource constraints were lifted thanks to the support of the African Development Bank encouraging the modernization of public administration, these funds were instrumental in the financing of the program.

A.2 Program

The application was developed starting 2017 by the administration, a private Senegalese company, and the research team. It has a Web components (to assign tasks, visualize and validate information, monitor advancement on maps, create tax bills), and an android component allowing to conduct the census on tablets in the field with pre-loaded maps. The section and plot identification system integrated in the software were already used by the administration since 2012 (introduction of the unique cadastral plot identification number *NICAD*), however it is the first time this mapping was digitized and incorporated in an interactive application. The bureaucrats working on the census were hired through several channels: some had already done similar tasks for the administration in the past, some had been suggested by the municipalities, finally, many were recruited through an online job advertisement on a public employment platform. They receive a four day training delivered by the tax administration, covering local public finance concepts, the utilization of the application, reading maps, property characteristics, and interactions with occupants. In the field, they are equipped with caps, shirts and badges showing their affiliation to the tax administration. They are paid a monthly fee and a bonus based on the number of plots they cover, and the share of plots for which they recover the name and identification details of the owner. Thus the incentives are exactly the same across arms. There is a supervisor for every fourteen bureaucrats on average. The supervisors were hired through the same channels. They need to validated the forms submitted by the bureaucrats before these are sent to the server. Based on responses in the bureaucrat endline survey, 61 percent of bureaucrats completely agree and 35 percent agree with the statement *the administration closely verifies the data I collect*.

B Data: Additional Details

B.1 Market Values by Assessors

The assessors we hired are licensed real estate experts, who work in the private sector and are affiliated to the Senegalese National Order of Experts.[89] Their usual job is to provide certified market valuations of properties for insurance purposes, before a sale or a inheritance, in relation to construction projects, etc. To design the data collection, we relied on discussions with practitioners to build on methodologies used in more established property tax systems such as the United Kingdom and South Africa. Before starting the field work in a given section, the assessors were asked to gather location specific information from their office as well as from real estate agencies and brokers they are in close contact with, we show the frequency with which this occurs in Appendix Table A1. For each property, we pre-load the built area measurement in the questionnaire on tablet to help the assessors in their valuations.

The sampling of properties to be visited by assessors was done in way to allow partial overlap between assessor valuations and (i) the baseline property owner survey; (ii) plots covered by the census for which a rental contract is noted (this is very rare, 2.6 percent of census observations). The rationale for doing so is to be able to check correlations between different sources of rental values. We first draw 26 plots randomly in each section. If less than 13 plots also included in the owner baseline were drawn, we do some replacements to reach 13/26 overlapping plots (or the maximum number possible if there are fewer baseline plots in the section). If less than 2 plots covered by the census and with a rental contract were drawn, we do some replacements to reach 2/26 of these (or the maximum number possible). Then we add a random draw of replacement plots for each section. As a result, among the 5,806 plots sampled for assessor valuation, 1,383 were covered in the property owner survey, and 138 were covered by the tax census and a rental contract was reported.

B.2 Property Valuation Algorithm

Selection and coding of characteristics. We selected the observable characteristics to be used in the property valuation algorithm by drawing from on existing methodologies of the cadaster department, and through work sessions bringing together members of the admiistration, the research team, and international practitioners. As much as possible, the phrasing of the characteristics and of their different modalities were preserved from pre-existing forms. The retained characteristics are: usage (residential, commercial or mixed), type of fence (four options), state of the fence (very good, average, bad), type of cladding (six options), state of the cladding (very good, average, bad), cement ('hard') wall (yes or no), presence of decorative tiles (yes or no), quality of doors and windows (very good, average, bad), landscape improvement (yes or no), architectural improvement (yes or no), garage (simple, double or none), balcony (yes or no), location with respect to main road (on, near, off), type of road (five options), presence of sidewalk (yes or no), whether the

[89] See: https://www.experts-ones.com/

property is at an angle (yes or no), presence of street lights (yes or no). The characteristics that have 'yes' or 'no' answers are coded as dummy variables. The characteristics that have multiple choice answers are all coded as categorical variables (using dummies for each modality), including characteristics related to state or quality. This enables us to be agnostic on the relative importance of each modality.

Calibration. For the functional form as well as the calibration details, we follow recent recommendations from the property valuation literature (Davis *et al.*, 2012; McCluskey *et al.*, 2013; Franzsen & McCluskey, 2017; Ali *et al.*, 2018; Fish, 2018; Guan *et al.*, 2011; Moore, 2005; International Association of Assessing Officers, 2022).[90] Out of our sample of 4,921 plots with market values, we randomly assign 10 percent of observations to the test sample (we draw within section to have observations from each section and recover section fixed-effects). Using cross-validation, we run an elastic net regression five times, and recover the median value of each coefficient. The elastic net is retained because we find that it performs better out-of-sample than the simple OLS and the Lasso regression. Next, we apply the resulting coefficients to the dataset to obtain predicted values, and identify outliers. Outliers are defined as predictions for which the residual is more than three standard deviations away from the mean value of residuals. These observations ($N = 55$) are dropped (following McCluskey *et al.* (2013)). We repeat the calibration of the elastic net regression with 5-fold cross-validation. We recover the median value for each coefficient, these are our final coefficients. The R^2 and RMSE values reported in the performance statistics in Table A2 are the mean value of each statistics over the 5 iterations. The additional performance statistics reported in the lower panel of Table A2 are estimated on the test sample. See Figure A3 for a graphical analysis of predictions and residuals.

Computation of predicted values in monetary amounts. The algorithm predicts $\widehat{Ln(Value)}$. To compute predicted property value $\widehat{Value}$, a correction term needs to be applied to $exp(\widehat{Ln(Value)})$.[91] The corrected predicted value can be written as $\widehat{Value} = \alpha_c \cdot exp(\widehat{Ln(Value)})$ where α_c is a correction term. If it is assumed that the error term in the prediction model is normally distributed, it can be shown that predicted values should be computed with $\alpha_c = exp(\frac{\hat{\sigma^2}}{2})$ and thus $\widehat{Value} = exp(\frac{\hat{\sigma^2}}{2})exp(\widehat{Ln(Value)})$ where $\hat{\sigma^2}$ is the estimator of the variance of the error term. Based on the distribution of residuals (Panels (C) and (D) of Figure A3), we assume that the error term is normally distributed. We compute $\hat{\sigma^2}$ using the RMSE and find $\alpha_c = 1.07$. This is the correction term we use to recover predicted values in monetary amounts.

Computation of the sub-components of property value. The predicted value is at the plot level. We are interested in dividing this value into different sub-components in two instances: (i) when there are multiple owners on the plot – this is a rare feature in

[90] We had the opportunity to interact directly with some of these practitioners and experts between 2017 and 2022.

[91] See Woolridge (2012) *Introductory Econometrics: A Modern Approach 5th edition*, Chapter 6 Section 4.

the Dakar real estate, less than 0.7 percent of plots in the census data – since each owner needs to receive a tax bill; (ii) when the property is partly rented and partly occupied by the owner (18.8 percent of plots in the census data) since in these cases the abatement only applies to owner-occupied parts. The administration has no information at all on built areas at a more precise level than the plot, therefore we rely on the number of rooms to divide plot value into its different components. If the property is partly rented and partly occupied by the owner: the corresponding values are computed as a share of total plot value, based on the number of rooms allocated to each usage. If there are multiple owners on the plot, each owner's value is computed based on her number of rooms out of total number of rooms. When we compare tax liabilities across arms, we provide a robustness check where the share of value subject to the abatement is computed in the exact same way in both arms, using number of rooms (see Figure A6 Panel (B)).

Implementation in the new digital tool. The implementation of the algorithm is integrated into the software. The integration of geocoded plot details and cadastral data into the software allows to automatically recover built area measurement and location fixed-effects. The software administrator can modify the coefficients associated to each characteristic, and also add, remove or modify observable characteristics used in the computation and that appear on the tablets in the field. This flexibility is key for the sustainable adoption of the digital tool by the administration. For this pilot phase, the calculation was done by the research team, in order to include the most recent updates in the algorithm and in the GIS dataset. The prediction will be automatically computed in the software starting 2024.

B.3 Data from the Property Tax Census

The information recorded in the field on tablets by the bureaucrats is automatically sent on a data server hosted by the tax administration. We receive regular data extractions from the server and use this to compile our dataset for the analysis.

Extractions. We mainly use two extractions, one recovered on January 31st, 2023 (for census operations carried out between 2019 and January 2023), and one recovered on May 5th, 2023 (for census operations between January and May 2023). We add to these extractions a subset of plots recovered from earlier extractions and that were deleted from the server due to a technical problem. There is a very small number (0.7% of plots) of plots covered twice. In these cases, we keep the observation from the most recent visit.

Sections. Initially, instead of 96, there were 97 treated sections. However for one treated section the administrative borders were modified before the census started, the section 'disappeared' and its plots were redistributed into two control sections. The section which was dissolved was in the Rufisque Ouest Commune, attached to the Rufisque tax office, the plots were redistributed into one section in the same Commune, and one in Rufisque Est, also linked to the same tax office. In our main analysis we control by randomization strata, and tax office is one of the stratification variables, thus we do not expect this to be an issue for the causal interpretation of the comparison between rule and discretion. Out of the 96 targeted sections for the census, the census was interrupted in two of them at its very start, because of pre-existing tensions between the local population and the tax administration on another topic, property titles. Only 11 out of 89 and 16 out of 404 plots were covered before the interruption, and they will not be exploited to prepare tax bills. We drop these two sections from the analysis. One was in the discretion arm, one in the rule arm, both in the Commune of Yoff (Ngor-Almadies tax office).

Creating the plot level dataset. The raw dataset is at the owner X tenant level. For our analysis, we build a plot level dataset. For 99.32% of the 38,417 plots covered in the census, there is only one owner per plot, making the plot level analysis relevant for this context. We use 'plot' and 'property' indifferently. The raw data needs to be treated differently for the discretion and rule arms. We are interested in total property value, and share occupied as main residence, since this determines the abatement for tax liabilities. In the discretion arm: we add up all rent values to generate total rent value for the plot, if there are several values for owner-occupied parts we also add these up, and thus generate the plot level total property value, which is the sum of rents and owner-occupied values. We categorize the plot as main residence if the bureaucrat ticks main residence, and as rented if the bureaucrat ticks rented. Note that this can occur even if the bureaucrat does not provide the associated values. Under the rule, we first compute the plot level predicted value by applying the coefficients from the property valuation formula, using the built area measurement we have from our GIS cadastral dataset and the section fixed-effect based on each plot's location. If the property is fully rented, or fully occupied by the owner, the predicted plot level value allows to generate the tax liability. If there are multiple owners on the property, and/or if the property is partly rented and partly occupied by the owner, we assign values proportionally to the number of rooms allocated to each owner or usage, as described in Section B.2. The number of rooms is recorded by bureaucrats. When we compare tax liabilities across arms, we provide a robustness check where the share of value subject to the abatement is computed in the exact same way in both arms, using number of rooms (see Figure A6 Panel (B)).

Corrections: values entered manually. We correct two types of entries which we assume are due to typos during the field work. First, we identify cases were property values are negative. We replace these by the absolute value. There are only 2 cases. Second, we identify cases where a monthly value is too small to be realistic, below 10,000 FCFA (16 USD). We replace these by 0. There are 610 cases out of 20,079 plots in the discretion arm (30 out of the 1,237 in the sample with market values).

Corrections: observable characteristics. There were several occurrences of technical challenges leading to the temporary absence of some or all of entries for observable characteristics on the tablets in the field. 192 properties out of the 18,148 of the rule arm have all observable characteristics missing. 8,744 have one characteristics or more missing, most often these four: Architecture, Sidewalk, Quality of Doors and Windows, Presence of a Cement Wall. This involves 569 out of the 1,166 plots of the sample with market values. All the characteristics are categorical variables entered as dummy variables in the property valuation algorithm. Therefore our replacement strategy is as follows: we replace each missing characteristic by its mean value in a given section. If there are no occurrences of the characteristic in the section, we replace the missing characteristic by its mean value overall.[92]

Comments. Bureaucrats can leave comments associated to each plot they visit. There is a comment in 54% of cases. Since these are open ended text entries they are not immediately usable. We process comments relying on key words to identify three relevant cases for our analysis: the bureaucrat reports there is conflict or tensions between her and the occupants (6.4% of observations); the bureaucrat reports having estimated the value herself without relying on any information from occupants (12.8% of observations); the bureaucrat reports that the property is managed by a real estate agency (6.7% of cases).

B.4 Verifications using Photos

We carry out some verifications based on pictures on a random sample of 100 properties that were visited both during the property tax census and by the real estate assessor. Among cases for which we have a picture from the census and from the assessors, the property matches for 92.5% of observations. The picture is missing or not interpretable for 20 cases in the census. Among cases where the picture matches, the same number of floors was entered in 68.9% of cases. When the floor numbers were different, the assessor is correct in 68% of cases. The most frequent situation is one in which the bureaucrat erroneously counted the ground floor as ′1′ instead of ′0′ (69.6% of cases where the floor number mismatches).

B.5 Description of Variables from the Bureaucrat Surveys

Baseline bureaucrat survey

Ever worked with the tax administration: Takes value one if the bureaucrat did any work with the tax administration before the program, either as a civil servant or a temporary employee.

From Dakar: Takes value one if the hometown of the bureaucrat is Dakar or one of the suburbs.

Any higher education: Takes value one if the bureaucrat completed high school and studied in a higher education institution (including vocational training).

Three years or more of higher education: Takes value one if the bureaucrat completed a three year degree or more in higher education.

Ethnic group: Self-reported with a possibility not to answer: Wolof or Lebou, Poular, Serere, Diola, Other.

Religion: Islam Tidjane, Islam Mouride, Islam Other, Christian.

Public service motivation: Standardized score computed from the sum of Likert-scale responses to the following questions: It is important for me to work in the public sector;

[92] We have these characteristics as recovered by the assessors, but we prefer not using this as our main replacement strategy since we are also measuring the gap between predictions based on bureaucrats versus assessor inputs.

I would not mind doing the same job in the private sector; It is not necessarily important for me that my work is useful for the community; I do not hesitate to devote all my energy to work.

In favor of government's role: Standardized score computed from the sum of Likert-scale responses to the following questions: According to me, the government can do a lot to make society more fair; the state should have the responsibility to satisfy everyone's basic needs (versus individuals taking care of their own needs).

In favor of widespread taxation: Standardized score computed from the sum of Likert-scale responses to the following questions: It is fair for a retired person to pay taxes if (s)he owns property; Only the richest people should pay taxes.

Endline bureaucrat survey

Rent: Amount of rent paid by the bureaucrat if (s)he is a tenant in current dwelling.

Income: Monthly income before the job with the tax administration for this program.

Emotions reading: Standardized score from a multiracial version of the Read the Mind in the Eyes Test (Weidmann & Deming, 2021; Dodell-Feder *et al.*, 2020).

Big five score: Standardized score from a 10 questions francophone version of the big five personality traits test (Plaisant, 2008). We also use separately the standardized score for each subcomponent: *Openness, Agreeableness, Extraversion, Conscientiousness, Neuroticism.*

Digit span: Standardized score for the combination of a forward and backward digit span test.

Math index: Standardized score obtained for six math questions: $10 + 5$; $27 - 4$; $32 - 13$; 7×6; 150000×4; 70000×12.

Persuasion evaluation: Standardized score given by members of the research team to bureaucrats for a verbal exercise, where the bureaucrat is told: Consider you are doing the census, and the owner of a property refuses to cooperate and provide information. What would you tell them? The graders were told to grade according to how persuasive the bureaucrats' discourse was. This exercise builds on (Chioda *et al.*, 2021).

Persuasion sum of items: Standardized sum of eight potential persuasion arguments that the bureaucrat included in his or her reply in the verbal exercise. The items are: giving more explanations on how the information will be used; suggesting to change languages or make polite salutations adapted to the owners' profile; suggesting to break the ice with some small talk or jokes; mentioning the public services the tax revenues will fund; reassuring the owner by saying that all owners of the neighborhood are getting the census; suggesting to have the supervisor of the tax office intervene; threatening the owner by mentioning possible prosecutions; offering to plan a meeting for later.

Endline supervisor survey

Overall performance score: Standardized score given by supervisors when asked: How would you grade the overall performance of bureaucrat [Name]? for each bureaucrat they supervise.

Performance items: Standardized sum of scores given by supervisors when grading each bureaucrat they supervise on the following items: social skills, fiscal knowledge, housing market knowledge, energy and stamina, negotiation skills, ease with technology, ease with reading maps.

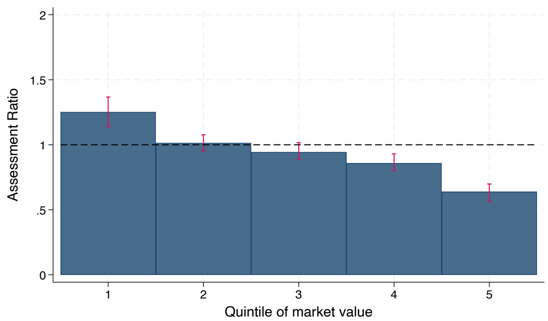
C Robustness: Missing Property Characteristics

In the sample of 1,166 plots of the rule arm with market value, there is at least one of the observable property characteristics missing from the census data in 595 observations. There are four characteristics (architecture, sidewalk, quality of doors and windows and wall) missing in 569 cases. This is due to a technical problem which occurred during some weeks of the census: these variables were simply absent from the form on bureaucrats' tablets. In the main analysis, we carry out some replacements as explained in Appendix B.3. In this Appendix, we use two strategies as robustness checks: first, we drop the plots for which at least one observable characteristic is missing from bureaucrats' inputs; second, we re-calibrate our property valuation formula excluding the four characteristics that are missing for a large number of cases.[93]

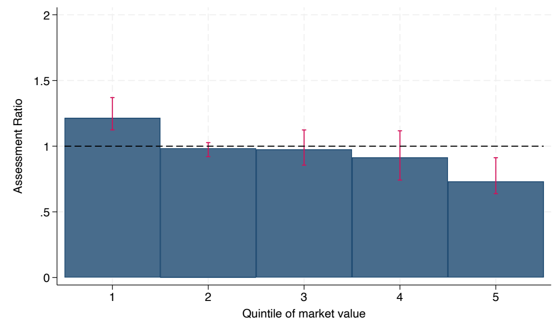
Our main results are unchanged: the rule outperforms discretion, and this is mainly driven by the upper part of the distribution, the pure rule outperforms the rule implemented by bureaucrats. Compared to when the rule is calculated using assessors' inputs, the rule implemented by bureaucrats is more regressive since it undervalues more strongly high-end properties.

[93] This rule performs as well as our main rule, the R^2 is 0.89, the MAPE is 32.6.

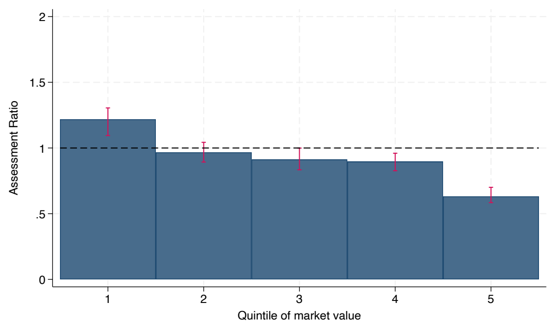
FIGURE A18
ASSESSMENT RATIO BY QUINTILE



(A) RULE-BASED - MAIN RESULTS



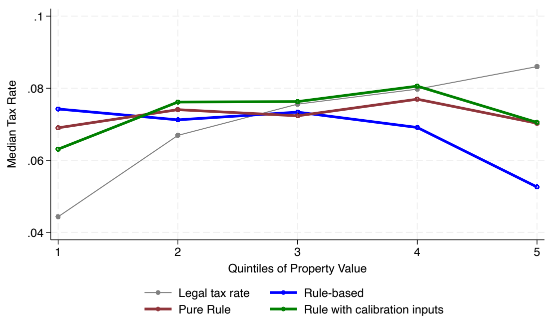
(B) ROBUSTNESS: DROPPING MISSING



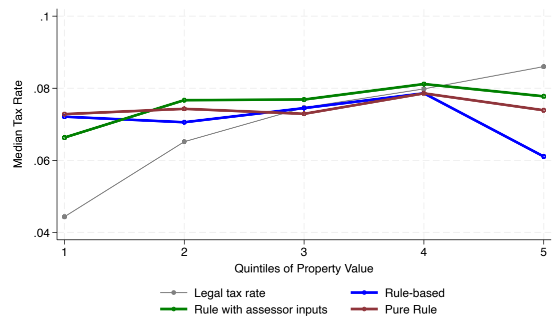
(C) ROBUSTNESS: RECALIBRATING RULE

Notes: This Figure plots the median assessment ratio by quintile, in Panel (A) we reproduce our main results for the rule arm from Figure 5. In Panel (B) we show results after dropping plots with at least one observable characteristic missing. In Panel (C) we show results using the rule re-calibrated without the four often missing characteristics. The assessment ratio is computed as assessed value for a given property divided by the market value of the same property. The red line shows the confidence interval for the median value of each quintile. Quintiles are based on market values.

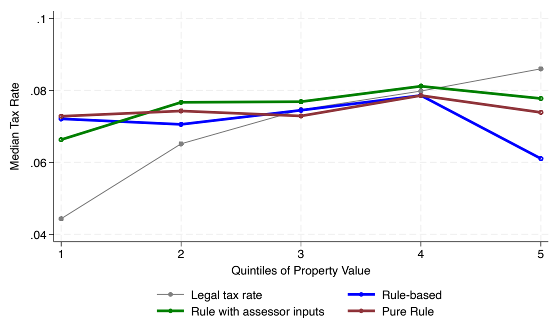
FIGURE A19
TAX RATES UNDER THE RULE



(A) RULE-BASED - MAIN RESULTS



(B) ROBUSTNESS: DROPPING MISSING



(C) ROBUSTNESS: RECALIBRATING RULE

Notes: This Figure shows the median tax rate by quintile in the rule arm. Panel (A) reproduces our main results from Figure 7. In Panel (B) we show results after dropping plots with at least one observable characteristic missing. In Panel (C) we show results using the rule re-calibrated without the four often missing characteristics. The gray line is the benchmark tax profile computed directly on market values. The blue line is the tax profile with the rule, the red line is the tax profile using the pure rule with remote covariates only. Additionally, the green line shows the tax profile generated with the rule if using the characteristics from the calibration (assessors' dataset). The tax rate is 8.6 percent with an abatement if the property is owner-occupied which explains the progressive profile.

TABLE A16
REMOVING DISCRETION INCREASES ACCURACY: DROPPING MISSING

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) |Gap| *mil.FCFA*	(4) Ass. Ratio
Panel A: Discretion				
Mean[1] (sd)	−7.14 (17.69)	−2.41	8.92 (16.87)	0.71
Panel B: Rule-based				
Overall				
Mean[1] (sd)	−2.58 (11.58)	−0.18	4.29 (11.06)	1.00
$\hat{\beta}_{Discretion}$	−2.85*	−0.91**	2.53	−0.18**
	(1.55)	(0.38)	(1.58)	(0.07)
Low Value				
Mean[1] (sd)	0.19 (2.08)	0.01	1.21 (1.70)	1.18
$\hat{\beta}_{Discretion}$	−0.06	−0.16	0.14	−0.04
	(0.22)	(0.17)	(0.19)	(0.12)
High Value				
Mean[1] (sd)	−6.96 (17.58)	−2.68	9.16 (16.54)	0.71
$\hat{\beta}_{Discretion}$	−3.79	−3.38***	3.18	−0.19**
	(2.69)	(1.26)	(2.73)	(0.08)
Panel C: Pure Rule				
Overall				
Mean[1] (sd)	−0.29 (6.38)	0.11	2.03 (6.06)	1.12
$\hat{\beta}_{Discretion}$	−4.62***	−1.79***	4.24***	−0.32***
	(1.10)	(0.51)	(0.99)	(0.06)
Low Value				
Mean[1] (sd)	0.23 (0.86)	0.14	0.61 (0.66)	1.19
$\hat{\beta}_{Discretion}$	0.00	−0.43***	0.91***	−0.01
	(0.22)	(0.14)	(0.16)	(0.11)
High Value				
Mean[1] (sd)	−1.12 (10.15)	−0.15	4.27 (9.28)	1.01
$\hat{\beta}_{Discretion}$	−8.1414.1	−5.77***	6.62***	−0.49***
	(1.75)	(0.76)	(1.55)	(0.05)
N plots: 1695				
N Sections: 85				
Mean (sd) market value: 64.10 (14.10)				
Median market value: 5.40				

Notes: This Table shows the effect of discretion on the tax base gap, similar to our Table 3, except that we drop plots with at least one observable characteristic missing. We run regression 2: $Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk}$ with four different outcomes. In column (1) the outcome variable is the tax base gap defined as bureaucrat value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as the bureaucrat's value over the market value. In Panel (A), we display summary statistics for the discretion arm. In Panel (B), values for the rule arm are the rule-based valuations based on bureaucrats' inputs. In Panel (C), values for the rule arm are the pure rule predictions based on remote covariates. Each panel is divided in three subpanels, the first one uses the full sample of properties, the second is restricted to low value properties (quintile 1 and 2 of market values), the third one is restricted to high value properties (quintiles 3 to 5 of market values). In each subpanel, the first rows display descriptive statistics of the outcome variable in the rule arm; the second rows show the coefficient of interest on the dummy for Discretion. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. [1]In column (2) the displayed value is the $median$ of the tax base gap.

TABLE A17
REMOVING DISCRETION INCREASES ACCURACY: RECALIBRATING RULE

	(1)	(2)	(3)	(4)
	Gap	Gap (median)	$\lvert$Gap$\rvert$	Ass. Ratio
	mil.FCFA	*mil.FCFA*	*mil.FCFA*	
Panel A: Discretion				
Mean[1] (sd)	−7.12 (17.72)	−2.41	8.94 (16.88)	0.71
Panel B: Rule-based				
Overall				
Mean[1] (sd)	−2.17 (12.93)	−0.21	4.80 (12.20)	1.05
$\hat{\beta}_{Discretion}$	−4.77***	−1.93***	3.76***	−0.35***
	(1.27)	(0.42)	(1.38)	(0.05)
Low Value				
Mean[1] (sd)	0.38 (2.09)	0.11	1.27 (1.70)	1.23
$\hat{\beta}_{Discretion}$	−0.45**	−0.52***	0.32**	−0.21**
	(0.20)	(0.13)	(0.16)	(0.10)
High Value				
Mean[1] (sd)	−4.47 (17.39)	−1.31	7.97 (16.09)	0.89
$\hat{\beta}_{Discretion}$	−6.86***	−4.50***	5.32***	−0.37***
	(1.77)	(0.67)	(1.89)	(0.05)
Panel C: Pure Rule				
Overall				
Mean[1] (sd)	−0.36 (7.64)	0.12	2.83 (7.11)	1.13
$\hat{\beta}_{Discretion}$	−5.37***	−2.42***	4.71***	−0.38***
	(0.90)	(0.44)	(0.93)	(0.04)
Low Value				
Mean[1] (sd)	0.39 (1.13)	0.25	0.73 (0.94)	1.24
$\hat{\beta}_{Discretion}$	−0.28	−0.57***	0.88***	−0.13
	(0.20)	(0.14)	(0.14)	(0.09)
High Value				
Mean[1] (sd)	−1.04 (10.43)	−0.33	4.72 (9.36)	1.03
$\hat{\beta}_{Discretion}$	−8.2515.8	−5.44***	6.87***	−0.47***
	(1.27)	(0.55)	(1.28)	(0.05)
N plots: 2290				
N Sections: 94				
Mean (sd) market value: 77.00 (15.80)				
Median market value: 5.60				

Notes: This Table shows the effect of discretion on the tax base gap, similar to our Table 3, except we use the rule re-calibrated without the four often missing property characteristics. We run regression 2: $Y_{ijk} = \alpha + \beta D_{jk} + S_k + \epsilon_{ijk}$ with four different outcomes. In column (1) the outcome variable is the tax base gap defined as bureaucrat value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as the bureaucrat's value over the market value. In Panel (A), we display summary statistics for the discretion arm. In Panel (B), values for the rule arm are the rule-based valuations based on bureaucrats' inputs. In Panel (C), values for the rule arm are the pure rule predictions based on remote covariates. Each panel is divided in three subpanels, the first one uses the full sample of properties, the second is restricted to low value properties (quintile 1 and 2 of market values), the third one is restricted to high value properties (quintiles 3 to 5 of market values). In each subpanel, the first rows display descriptive statistics of the outcome variable in the rule arm; the second rows show the coefficient of interest on the dummy for Discretion. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. [1]In column (2) the displayed value is the *median* of the tax base gap.

TABLE A18
RULE-BASED VS PURE RULE: DROPPING MISSING

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) |Gap| *mil.FCFA*	(4) Ass. Ratio
Panel A: Pure Rule				
Overall				
Mean[1] (sd)	−0.29 (6.38)	0.11	2.03 (6.06)	1.12
$\hat{\beta}_{RuleBur}$	−2.29***	−0.33	2.27***	−0.13*
	(0.77)	(0.00)	(0.59)	(0.07)
Low Value				
Mean[1] (sd)	0.23 (0.86)	0.14	0.61 (0.66)	1.19
$\hat{\beta}_{RuleBur}$	−0.04	−0.19	0.61***	−0.02
	(0.15)	(0.00)	(0.13)	(0.07)
High Value				
Mean[1] (sd)	−1.12 (10.15)	−0.15	4.27 (9.28)	1.01
$\hat{\beta}_{RuleBur}$	−5.84***	−2.17	4.89***	−0.30***
	(1.52)	(0.00)	(1.24)	(0.09)
Panel B: Rule with Assessor Inputs				
Overall				
Mean[1] (sd)	−0.27 (6.71)	0.11	1.97 (6.42)	1.09
$\hat{\beta}_{RuleBur}$	−2.31***	−0.34*	2.33***	−0.10
	(0.72)	(0.17)	(0.58)	(0.07)
Low Value				
Mean[1] (sd)	0.22 (0.79)	0.11	0.54 (0.61)	1.12
$\hat{\beta}_{RuleBur}$	−0.03	−0.13	0.67***	0.05
	(0.16)	(0.00)	(0.14)	(0.07)
High Value				
Mean[1] (sd)	−1.04 (10.70)	−0.04	4.22 (9.88)	1.04
$\hat{\beta}_{RuleBur}$	−5.91***	−2.20**	4.93***	−0.33***
	(1.40)	(0.96)	(1.19)	(0.09)

N obs: 1141
N plots: 571
N Sections: 38
Mean (sd) market value: 59.20 (9.80)
Median market value: 3.50

Notes: This Table shows the effect on the tax base gap of the limited degree of discretion which remains under the rule based process implemented by bureaucrats, compared to benchmark rules without any bureaucrat discretion. It is similar to our Table 7, except that we drop plots with at least one observable characteristic missing. We run regression 7: $Y_{irjk} = \alpha + \beta RuleBur_{irjk} + S_k + \epsilon_{irjk}$ where Y_{itjk} is the outcome for plot i of section j and strata k under rule r, $RuleBur_{irjk}$ is a dummy taking value one if r is the rule as implemented by bureaucrats, and zero if r is the benchmark rule with no bureaucrat discretion. In Panel (A), the benchmark rule is the pure rule with remote covariates, in Panel (B) the benchmark rule is the rule calculated using the observable characteristics recovered in the assessors' dataset. In column (1) the outcome variable is the tax base gap defined as rule value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as the rule value over the market value. Each panel is divided in three subpanels, the first one uses the full sample of properties, the second is restricted to low value properties (quintile 1 and 2 of market values), the third one is restricted to high value properties (quintiles 3 to 5 of market values). The first row of each subpanel display descriptive statistics of the outcome variable under the benchmark rule; the second row show the coefficient of interest on the dummy for $RuleBur$. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. Each property appears twice in the regression sample. [1]In column (2) the displayed value is the *median* of the tax base gap.

TABLE A19
RULE-BASED VS PURE RULE: RECALIBRATING RULE

	(1) Gap *mil.FCFA*	(2) Gap (median) *mil.FCFA*	(3) |Gap| *mil.FCFA*	(4) Ass. Ratio
Panel A: Pure Rule				
Overall				
Mean[1] (sd)	-0.36 (7.64)	0.12	2.83 (7.11)	1.13
$\hat{\beta}_{RuleBur}$	-1.81^{***}	-0.31^{**}	1.97^{***}	-0.08^{**}
	(0.57)	(0.12)	(0.46)	(0.04)
Low Value				
Mean[1] (sd)	0.39 (1.13)	0.25	0.73 (0.94)	1.24
$\hat{\beta}_{RuleBur}$	0.00	-0.09	0.54^{***}	0.00
	(0.12)	(0.08)	(0.10)	(0.05)
High Value				
Mean[1] (sd)	-1.04 (10.43)	-0.33	4.72 (9.36)	1.03
$\hat{\beta}_{RuleBur}$	-3.43^{***}	-1.19^{***}	3.25^{***}	-0.15^{***}
	(0.94)	(0.35)	(0.78)	(0.04)
Panel B: Rule with Assessor Inputs				
Overall				
Mean[1] (sd)	-0.62 (8.24)	0.06	2.76 (7.79)	1.08
$\hat{\beta}_{RuleBur}$	-1.55^{***}	-0.30^{**}	2.04^{***}	-0.03
	(0.45)	(0.13)	(0.40)	(0.03)
Low Value				
Mean[1] (sd)	0.26 (0.90)	0.14	0.61 (0.71)	1.13
$\hat{\beta}_{RuleBur}$	0.12	-0.02	0.66^{***}	0.10^{**}
	(0.12)	(0.08)	(0.10)	(0.05)
High Value				
Mean[1] (sd)	-1.42 (11.26)	-0.18	4.69 (10.34)	1.03
$\hat{\beta}_{RuleBur}$	-3.05^{***}	-1.24^{***}	3.28^{***}	-0.14^{***}
	(0.74)	(0.32)	(0.65)	(0.04)

N obs: 2331
N plots: 1166
N Sections: 47
Mean (sd) market value: 86.00 (15.40)
Median market value: 4.80

Notes: This Table shows the effect on the tax base gap of the limited degree of discretion which remains under the rule based process implemented by bureaucrats, compared to benchmark rules without any bureaucrat discretion. It is similar to our Table 7, except that the rule used here is the one re-calibrated without the four often missing characteristics. We run regression 7: $Y_{irjk} = \alpha + \beta RuleBur_{irjk} + S_k + \epsilon_{irjk}$ where Y_{itjk} is the outcome for plot i of section j and strata k under rule r, $RuleBur_{irjk}$ is a dummy taking value one if r is the rule as implemented by bureaucrats, and zero if r is the benchmark rule with no bureaucrat discretion. In Panel (A), the benchmark rule is the pure rule with remote covariates, in Panel (B) the benchmark rule is the rule calculated using the observable characteristics recovered in the assessors' dataset. In column (1) the outcome variable is the tax base gap defined as rule value minus market value, column (2) uses the same outcome but with a quintile regression at the median. In column (3) the outcome is the absolute value of the tax base gap. All amounts are in millions of FCFA and winsorized at the 1% level. In column (4) the outcome is the assessment ratio, computed as the rule value over the market value. Each panel is divided in three subpanels, the first one uses the full sample of properties, the second is restricted to low value properties (quintile 1 and 2 of market values), the third one is restricted to high value properties (quintiles 3 to 5 of market values). The first row of each subpanel display descriptive statistics of the outcome variable under the benchmark rule; the second row show the coefficient of interest on the dummy for $RuleBur$. *,** and *** indicate statistical significance at the 10,5 and 1% level respectively. We control for strata fixed effects and errors are clustered at the section level. Each property appears twice in the regression sample. [1]In column (2) the displayed value is the $median$ of the tax base gap.

D Screening Bureaucrats: Additional Results

D.1 Bureaucrat skills and measures of performance

In Figure A9, we show correlations between bureaucrat characteristics and other measures of performance: the share of plots for which the bureaucrat recovered owners' identification details, the number of plots per day, and the ability to value high end properties in the full sample of the discretion arm, where we rely on predicted values as a benchmark. Social skills such as openness and extraversion correlate with the ability to recover owner details. Social skills are also deemed crucial by bureaucrats themselves, as shown in Figure A15. Persuasion correlates with the number of plots covered per day, and with a lower absolute tax base gap for above median properties in the full sample. Supervisor evaluations correlate with some measures of performance as shown in Figure A10, but not with the bureaucrat fixed-effects.

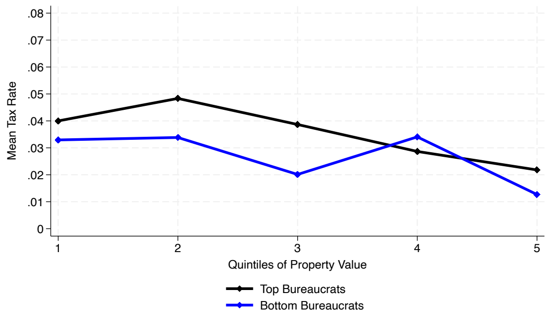
D.2 k-means clustering

We use 18 continuous bureaucrat characteristics, and the k-means clustering procedure constitutes two groups with the maximum Euclidean distance across all these characteristics (see Table A20 for the mean values of each characteristic across clusters). One caveat is that due to missing observations for some bureaucrat covariates we are able to assign a cluster only to 67 bureaucrats. Yet, we find that the two groups distinguish bureaucrats of different performance: bureaucrats from cluster 2 are 25 percentage points more likely to be a top bureaucrat (p-value of 0.07), and in a regression on the discretion arm only, we find that the absolute tax base gap is 2.64 millions FCFA smaller for a bureaucrat from cluster 2 compared to a bureaucrat from cluster 1 (p-value of 0.11).

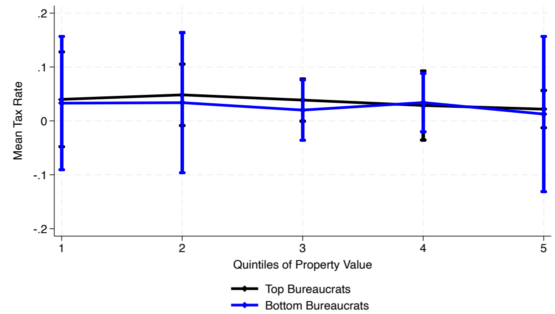
D.3 Tax profiles

When splitting bureaucrats into different groups, it is important to consider two dimensions to assess whether one group is better at generating the tax roll: accuracy of the tax profile (tax rates and how they vary through the distribution); and dispersion. First, in Figure A20 we show the tax profiles for top and bottom bureaucrats as estimated in our fixed-effect analysis of Section 5.2, where top bureaucrats are those for which $\alpha_{b,EB} < 0$. The tax profile generated by top bureaucrats is clearly preferable, which is mechanical since bureaucrat types are defined based on their relative tax base gap. Next, in Panels (A) and (B) of Figure A21, we assess whether similar results could be obtain if screening on three years or more of higher education, which is the main demographic and easily screenable variable that bureaucrat type correlates with. The difference in tax rates is not as clear-cut as when using bureaucrat type directly, but still, the tax profile for higher educated bureaucrats is preferable, and they also generate much less dispersion than bureaucrats without this level of education. Finally, in Panels (C) and (D) of Figure A21, we sort bureaucrats based on the k-means clustering exercise. There is a slight difference in the tax profile across the two clusters, but more striking is again the difference in terms of dispersion. Bureaucrats from cluster 2 generate more horizontal equity throughout most of the distribution.

FIGURE A20
TAX RATES BY BUREAUCRAT TYPE



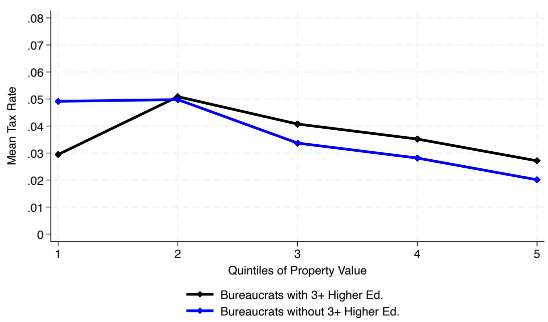
(A) TAX RATES



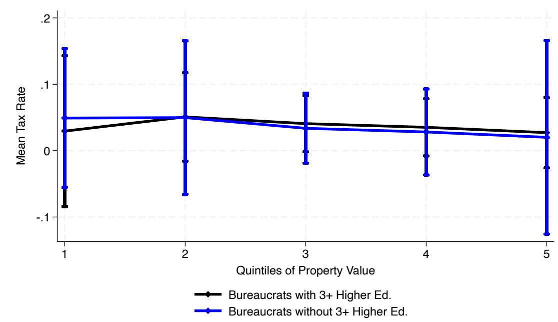
(B) DISPERSION

Notes: This Figure shows the median tax rate by quintile in the discretion arm, splitting the sample into plots covered by top versus bottom bureaucrats. Bureaucrat type is defined based on the fixed-effects estimated in Section 5.2: a top bureaucrat is one for which $\alpha_{b,EB} < 0$.

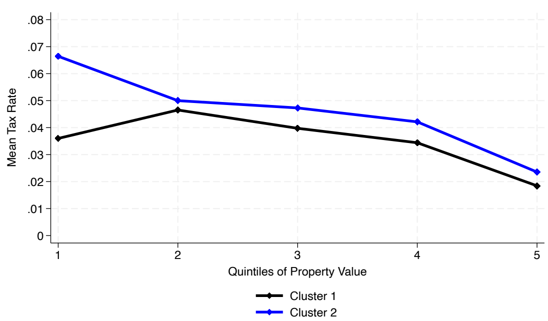
FIGURE A21
TAX RATES WHEN SCREENING BUREAUCRATS



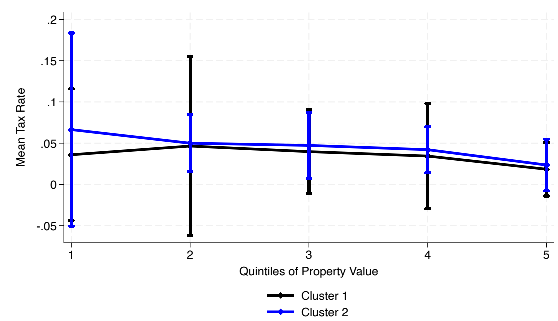
(A) BY EDUCATION: TAX RATES



(B) BY EDUCATION: DISPERSION



(C) BY CLUSTER: TAX RATES



(D) BY CLUSTER: DISPERSION

Notes: This Figure shows the median tax rate by quintile in the discretion arm when screening bureaucrats. In Panels (A) and (B): bureaucrats are sorted into with (81) or without (112) 3 years or more of higher education. There are $N = 1,087$ plots in the Figures. In Panels (C) and (D), bureaucrats are sorted into two clusters obtained by k-means clustering. Only 67 bureaucrats are assigned a cluster, 47 in cluster 1 and 20 in cluster 2 (there are $N = 408$ plots in the Figures).

TABLE A20
K-MEANS CLUSTERING RESULTS

	Cluster 1	Cluster 2
Age	28.33	38.00
Education Level	11.02	11.26
Index for PSM	0.05	−0.14
Index for Govt	0.02	0.00
Index for Tax morale	0.10	0.37
Emotions	0.00	0.00
Big Five	−0.16	0.12
Digit span	−0.10	0.05
Math	−0.05	−0.12
Persuasion score	−0.13	−0.03
Persuasion sum	−0.24	0.33
Supervisor Eval.	0.07	0.26
Gap High End Prop.	−0.71	−0.65
Gap Low End Prop.	0.56	0.77
Tax Magnitude score	−0.25	−0.07
Tax Questions score	0.06	0.03
Fair to Tax Retired	0.60	0.58
Only Rich should Pay	0.15	0.11
N	48	19

Notes: In this Table we report the mean value of each characteristic used in the k-means clustering of bureaucrats, column (1) reports the mean for the first cluster and column (2) reports the mean for the second cluster. The k-means clustering procedure constitutes two groups with the maximum Euclidean distance across all characteristic. We only include continuous variables. Education Level is a scale between 1 (secondary education completed) and 8 (university beyond bachelors); PSM is a public motivation score, Govt measures the perception of the role of government, and Tax morale perceptions that taxation should be widespread, all three are measured at baseline. Emotions is the Read the Mind in the Eyes test score, Persuasion score and Persuasion sum are scores from a verbal exercise graded by the research team, Supervisor Eval. is the score provided by the supervisor for this given bureaucrat. The Gap and Tax score variables are from the endline survey questions where we measure bureaucrats knowledge of property values and tax rules. Fair to Tax Retired and Only Rich should Pay are perceptions measured at endline. All scores are standardized.