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Using Satellite Imagery to Revolutionize Creation of Tax Maps and Local Revenue Collection

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Abstract

The technical complexity of ensuring that tax rolls are complete and valuations current is often perceived as a major barrier to bringing in more property tax revenues in developing countries. This paper shows how high-resolution satellite imagery makes it possible to assess the completeness of existing tax maps by estimating built-up areas based on building heights and footprints. Together with information on sales prices from the land registry, targeted surveys, and routine statistical data, this makes it possible to use mass valuation procedures to generate tax maps. The example of Kigali illustrates the reliability of the method and the potentially far-reaching revenue impacts. Estimates show that heightened compliance and a move to a 1 percent ad valorem tax would yield a tenfold increase in revenue from public land.

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Using Satellite Imagery to Revolutionize Creation of Tax Maps and Local Revenue Collection[¶]

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1. Introduction

Population growth, agricultural mechanization, and climate change are commonly believed to be associated with high rates of urban growth in developing countries, especially in Africa, where most residents are still concentrated in rural areas and the demographic transition is still in its early stages. Historically, cities' ability to capitalize on spatial proximity and positive externalities from the agglomeration of skills (Glaeser 2011) implied that urbanization was a key driver of economic growth. Yet as globalization severed the link between agricultural surpluses and city formation (Gollin et al. 2016), urbanization without growth and the formation of 'consumption cities' has become a distinct possibility for cities that are unable to deal with issues such as planning, pollution, public health, crime, and provision of infrastructure and other services. This will make it difficult to attract highly skilled individuals or to produce tradable goods in a way that ensures competitiveness and allows to capitalize on benefits of global integration such as risk diversification and scale.

To generate the resources for urban service provision, the ability to raise funds in a non-distortionary way and to have effective delivery mechanisms has become an important precondition to realizing the potential of cities. Surging prices for urban land and the scope for using taxes on land and property to enhance revenues when the tax base for income or profit taxes is narrow make property taxes one of the few viable options to finance sustainable expansion of cities in developing countries (Youngman 2016). In fact, as most of the resulting benefits will be capitalized in land values (Collier and Venables 2017), taxes on real property have been identified as a highly inventive-compatible way to finance local services and infrastructure.

However, despite their conceptual advantages, developing-world revenue from recurrent property taxes is still far below that of developed countries, even in relative terms. Instead, developing countries often rely heavily on transfer taxes, which are counter-productive because they tend both to discourage efficiency-enhancing land transfers while encouraging reversion to informality by avoiding registration as well as corruption by under-declaring land values. Two issues that may contribute to the widespread failure of using property taxes are the high fixed cost of establishing and ensuring currency of the associated valuation infrastructure and collection systems and the difficulty of conducting counterfactual analysis (see, e.g., Bahl and Wallace 2008; Kelly 2013). As maps to identify taxable properties are often incomplete, out of date, and access to them is fragmented between government units it is not uncommon to find that less than 50% of taxable properties are on the tax roll (Blochliger 2015; De Cesare 2012). Ensuring property taxes can be collected in low-cost ways that are fair, progressively linked to property values, and buoyant, requires automated valuation methods based on market values to be updated routinely without a danger of triggering appeals (IIAO 2013). While data integration, automating processes, and use of technology are believed to have great potential (McIlhatton et al. 2012), there are few examples in the developing world where property taxes have been successfully implemented (Franzsen and McCluskey 2017; McCluskey et al. 2012).

Using the example of Kigali, we demonstrate how remotely sensed imagery can significantly reduce the cost of establishing and updating tax registers by allowing automated generation of building footprints and, based on building heights, an estimate of total built-up area. If data on land prices are available, this information, together with spatial data routinely available from statistical institutes, can be used to inform routine processes of computer-assisted mass appraisal (CAMA).[1] Imputed values for land and property from the CAMA model, together with administrative records on taxes collected on individual properties, allows us to provide information on (i) potential revenue gains from full collection of current lease fees; (ii) likely yields from and incidence of a uniformly applied 1% tax on residential land and property; and (iii) the implicit cost of exemptions currently being discussed by Rwandan policy makers. This could not only make collection of property taxes much easier but also ground the debate on tax reform by providing more reliable data on which to base scenarios.

For Rwanda, three findings stand out: first, only about 40 percent of the potential yield of US$4.9 million from current lease fees is collected, suggesting that more efficient collection could heighten returns. Efforts to reduce costs of compliance (e.g., automated billing or reminders) may thus have high returns even in Rwanda, where all properties have been mapped. Second, because lease fees are regressive, moving to a 1% value-based tax would not only spread the tax burden more equally but could also increase revenue to about US$19.3 million—almost 10 times what is currently collected. Finally, while there may be scope for exempting those at the very bottom, the exemptions for 'low-cost housing' currently proposed by policy makers are too generous: they would leave only 5% with any building tax obligation.

Defining built-up area based on building footprints and heights derived from remotely sensed imagery offers even more scope to ensure complete coverage in places where recent urbanization implies that tax rolls are no longer current. Combined with transparent valuation models and broad publicity, it could help municipalities to not only generate sustainable own-source revenue but also to gradually reduce reliance on transfer taxes, which in many places seem to be a major reason that land registries revert to informality.

In what follows, section 2 discusses the challenges confronted by cities, how recurrent taxes on land and property can help resolve them, the technical and political economy obstacles to implementing them, and the resulting priority given to using instruments to collect taxes that are less efficient and more distortionary. It describes property taxation in Rwanda, noting similarities to and differences from what can be observed elsewhere. Section 3 describes use of remotely sensed information to construct a map of built-up areas that

[1] In most countries, such information may need to be collected in surveys or from institutions, such as bank data on mortgage lending. As the only African country to have established a complete and fully digital registry of rights, Rwanda has price data available.

can complement other data and to estimate a model of computer-assisted mass valuation that makes it possible to compute potential yield from a 1% property tax and compare it to the yield from current lease fees. It also links the results to current reform proposals for Rwanda, discussing exemptions and ways to separate taxation of land and of buildings. Section 4 concludes by drawing out the implications of the study for policy and future research.

2. Conceptual Background

While cities make it possible to achieve unprecedented agglomeration effects, realizing these benefits in ways that enhance a city's long-term competitiveness hinges on the effectiveness of services to counter the negative aspects of density. As most benefits from local services will be capitalized in land values, taxes on land and other real property have long been advocated as a method of financing services that is incentive-compatible. Property taxes have other desirable properties in that they are progressive, difficult to avoid, with yields that are quite stable over time. Yet, even in relative terms, the contribution from such taxes to revenue is much lower in the developing world than in developed countries. This, together with reliance on distortionary transfer taxes instead, suggests that reducing the high fixed costs of collecting property taxes may be one way to increase use of property taxes and enhance their distributional fairness.

2.1 The Relationship of Public Services and the Competitiveness of a City

Historically, most human intellectual and material progress originated in cities (Jacobs 1986), which have fostered economic growth and innovation through a combination of spatial proximity and human capital externalities (Glaeser 2011). However, the potential of cities to act as engines of growth depends on their having institutions to effectively address the negative externalities, such as congestion, pollution, and disease, that have accompanied growth in cities virtually everywhere. For most of history, the institutional and financial prerequisites imposed by the need to overcome these "demons of density" implied that urbanization was contingent on a city having achieved a certain per capita income (Jedwab and Vollrath 2015). The scope for global trade and improvements in public health and technology together have lowered this threshold, creating the prospect of "urbanization without growth" (Fay and Opal 1999).[2]

Thus urbanization in "consumption" rather than "production" cities may be driven by a rural push or booms in the non-tradable sector that, in Africa, have often been fueled by resource rents (Gollin et al. 2016). While not eliminating the economic and risk diversification benefits of urbanization,[3] failure to develop institutions for effective planning and resource mobilization (Besley et al. 2013) to reduce the demons of density may lead to a situation where the costs of urbanization outweigh the benefits. Empirical evidence

[2] Unlike the traditional model, in which high agricultural productivity, was a precondition for city growth, today, in an interconnected world, high agricultural productivity may actually slow urbanization (Glaeser 2014).
[3] To the extent that climate-related shocks reduce economic opportunities and cause workers to emigrate from rural areas, the risk diversification that cities offer may be very important (Henderson, Styoreygard, and Deichmann 2017).

suggests that many African cities have thus far failed to live up to this challenge (Jedwab et al. 2017) and instead are crowded, costly, and disconnected (Lall et al. 2017).[4] In light of the durability of urban buildings and infrastructure, this may in the long term affect city structure and competitiveness. High transport and wage costs resulting from inappropriate infrastructure and lack of affordable services may trap some cities in a low-level equilibrium that leaves them unable to competitively produce goods that are tradable globally (Venables 2017). Considering its high expected rates of city growth in the near future and the high cost of providing services after cities are built, this is particularly pertinent for Africa.

Property taxes have long been identified as the largest source of untapped municipal revenue that could ease the revenue constraints on local governments and allow the emergence of competitive cities (Collier et al. 2017). Coverage with digital cadastral maps is a necessary precondition if property taxes are to be collected both effectively and fairly.[5] Where cities expand rapidly, it is also a precondition for effective planning and delivery of services. Yet, as table 1 shows, of 159 non-OECD countries in the World Bank's *Doing Business surveys*, only about a third have registered and mapped most of the main city's private plots (though not necessarily public land) and only about 20% percent have digital cadastral maps available. Only 5% of African and South Asian countries, where most of the expected surges in urban population will be concentrated, have digital cadastral records even for the main city. For those countries, use of digital products based on remotely sensed imagery can be transformational, opening new avenues for collecting local revenue and helping to clarify and realize other benefits from documenting ownership rights.

2.2 Pros and Cons of Taxes on Land and Other Real Property

In developing countries, taxation as a share of GDP is only 25–50 percent of that in developed economies (Besley and Persson 2014), primarily because (i) a great deal of the economic activity is informal, beyond the reach of traditional taxes on income and profits; (ii) institutional capacity to collect taxes is more limited; and (iii) even if taxes are assessed and levied, cultural and political factors such as fragmented polities, lack of transparency, and a minimal sense of national identity may cause widespread avoidance of payment.

It has long been noted that local taxes on land and property can avoid some of these shortcomings and that, because land cannot be moved, they are difficult to avoid, can be designed to fall mainly on the wealthy, and are relatively stable against shocks (Norregaard 2013). They are thus less distortionary and less subject to tax competition than consumption or income taxes.[6] Moreover, by raising the cost of holding property,

[4] Microdata confirm that developing countries are seeing a rapid reallocation of workers to densely populated areas (Gollin et al. 2017).
[5] Paper maps are susceptible to unauthorized tampering, difficult to update or use for planning, and imply that collection of property taxes will incur high transaction costs because they preclude low-cost electronic billing or tax collection via mobile money.
[6] In fact, a number of revenue-neutral tax reforms to boost growth often aimed to shift part of the revenue base from income taxes to consumption and property (Norregaard 2013).

such taxes may discourage speculation and encourage more intensive land use. Where provision of public infrastructure and other services causes rapid appreciation of land prices, taxes on land and property have been linked to benefits from such investment. In Mexico, infrastructure improvement, such as street asphalting in residential neighborhoods, was capitalized into higher property values within two years (Gonzalez-Navarro and Quintana-Domeque 2016). Support for a benefit view of land and property taxes also emerges in U.S. residential neighborhoods where housing supply is inelastic (Lutz 2015). As fiscal instruments and land use regulations interact (Blochliger et al. 2017), land taxes will affect land use and can reduce sprawl, as in Pittsburgh in the 1980s (Oates and Schwab 1997), in other U.S. settings thereafter (Banzhaf and Lavery 2010), and in Italy (Ermini and Santolini 2017).[7]

Although the high visibility of property taxes can make it difficult to gather broad political support (Bahl and Wallace 2008), it increases accountability for how tax proceeds are used—an observation supported by evidence from OECD countries where greater reliance on property taxes by subnational governments has enhanced fiscal discipline (Presbitero et al. 2014). Beyond the political issues arising from high salience of property taxes, the reason most often quoted as an obstacle to broader use of land and property taxes is the high costs and the administrative requirements for establishing a cadaster and maintaining it.[8] The time and human resources needed to conduct or adjust valuations and deal with appeals have often been viewed as a major deterrent to broader use of a registry, especially in cities with rapidly expanding populations where the potential from doing so would be greatest and property tax revenues could be quite buoyant. Studies from Latin America (Sepulveda and Martinez-Vazquez 2012), Pakistan (Piracha and Moore 2016), Indonesia (von Haldenwang 2017), Sierra Leone (Jibao and Prichard 2016), and many other African countries (Franzsen and McCluskey 2017), suggest that capacity constraints and the inability to fairly administer a property tax have often deterred reforms. Such constraints may also underpin the disproportionate reliance of developing countries on transaction taxes, despite their disadvantages in terms of undermining predictability, imposing frictions on land market operations, pushing transactions into informality, and creating incentives for fraudulent under-declaration of transaction values (Dachis et al. 2012).

2.3 Ways to Tap This Potential

The conceptual advantages of taxing property and the enormous variety of ways to implement it notwithstanding,[9] in developing countries recurrent taxation of land or property makes up a limited, and

[7] In Italy, differential tax rates between a city's core and periphery can make the core urban area more compact. In Spanish municipalities during 1994-2005, sprawl increased demand for new infrastructure, the cost of which was covered mainly by intergovernmental transfers, which created moral hazard incentives for local governments (Hortas-Rico 2014).

[8] Some support for this notion is provided by the fact that use of land taxes is often more advanced in cities than in countries as a whole (McCluskey and Franzsen 2013).

[9] For a comprehensive review of property tax systems globally, see Almy (2013).

often decreasing share of revenue. As table 2 illustrates, since the 1990s, the share of land and property taxes in GDP (1.7%) or total tax revenue (0.45%) stood unchanged in real terms in advanced markets; increased from 0.4–0.6% of GDP (equivalent to 0.15–0.22% of tax revenue) in emerging markets; and dropped from 0.09% to 0.05% of tax revenue (0.2% of GDP) in low-income developing countries.

Efforts to increase coverage by updating tax maps and updating valuation rolls by applying uniform mass valuation have been taken to enhance transparency and perceived fairness of the process in many countries (Almy 2014). This has generated large fiscal benefits even in developed countries like Italy (Casaburi and Troiano 2016); where fiscal and legal cadasters are interoperable, it has also made it easier to demonstrate ownership of land. In the Netherlands, valuations of some 8 million properties via CAMA are conducted annually, bringing real estate taxes up to 2.8% of GDP. Assessed property values are publicly available, allowing owners to update data online, increasing trust in and the transparency of the system, and because of interoperability and integration of the cadaster with other public data, provide additional benefits, e.g., by preventing mortgage fraud (Kuiiper and Kaathman 2015). In Cape Town, each dollar invested in property tax administration yielded a more than 50-fold return, and the ability to use tax receipts in documenting ownership resulted in significant outreach and impact on poverty (Barlow 2015). In Bogota, a series of reforms that started with self-assessment moved on to link the fiscal and legal cadasters, and then improved valuations that have more than tripled tax revenue. In Lithuania, assessed values more than quadrupled as a result of gradually refining the mass valuation system (Almy 2015); it is now the core of an elaborate private-sector-driven data information system that provides many benefits (Grover et al. 2017). Where effective and routine systems to collect property tax are lacking,[10] gains from administrative simplification could be much larger. In such situations, property taxation may also contribute to increasing state capacity and citizens' trust in the state, as Weigel (2017) argues to be the case in the Democratic Republic of Congo (Weigel 2017).

Even where tax maps and realistic valuations are in place, increasing collection effort may yield high returns in terms of increased revenue collection.[11] In the U.S., where property tax contributes 30% of local government revenue and some 73% of local taxes, the performance of local governments varies widely. Simple reminders, especially if combined with a description of the effect of nonpayment, have greatly increased collections (Chirico et al. 2017). In Peru a reminder to pay had a persistent positive impact on payment; disclosure of information on neighbors' level of compliance was even more effective (delCarpio 2015); similarly, in Argentina, a deterrence message also heightened taxpayers' propensity to pay (Castro and Scartascini 2015).

[10] Franzsen and McCluskey (2017) provide an excellent and exhaustive survey of land and property tax systems in Africa, noting that in many of these the level of taxes is based on self-declaration or the payment procedure is very cumbersome.
[11] For a comprehensive review of experiments to increase taxes more generally, i.e., well beyond the property tax, see Hallsworth (2014).

3. Applying a Mass Valuation Model to Kigali

Rwanda is of interest because it is the only African country that has established a complete and fully digital legal cadaster. While it is somewhat surprising that the data are not used for fiscal purposes, the registry reliably records prices for any transaction. Together with data on building heights or the volume of built-up area generated from high-resolution satellite imagery, this can feed into a CAMA model to impute the potential yield from a 1% tax on residential land and property. Beyond comparing the magnitude and incidence of such a tax to actual and potential yields from the current system, this also makes it possible to estimate the likely effects of proposed exemptions, thus laying the foundation for better-informed policy.

3.1 Context and Setting

Rwanda stands out among African countries for having recently completed a nationwide first-registration program that covered 11.6 million parcels (Nkurunziza 2015), thereby helping to establish the full cadastral database now commonly referred to as LAIS—the land administration information system. LAIS contains spatial and textual data for all registered land parcels in Rwanda; each parcel is unambiguously identified and mapped via a unique parcel identifier (UPI). The UPI is used to link via web services to the mortgage registry maintained by the Rwanda Development Board (RDB) and can also be accessed by the Rwanda Revenue Authority (RRA). However, lease fees—the equivalent of property taxes—are still based on self-declaration. This fails to take into account changes in land prices or to realize the potential cost savings from automated billing and issuance of reminders. Exemptions may further reduce tax yield; for example, in Kigali city 60% of all parcels and 99% of agricultural parcels are exempted from paying lease fees.[12] Efforts to address these shortcomings include preparation and debate of a draft property tax law,[13] a recent version of which aims to impose a base lease fee of RWF 0-500/m^2 (plus a surcharge of half of the base fee on oversized land), and a tax of 1% on the value of buildings above a threshold of RWF 30 million. One likely scenario, for expositional purpose, is to use the current flat lease fee of RWF 70/m^2, assigned to more than 85% of the parcels in Kigali city, for areas below 300 m^2 and then apply RWF 105/m^2 for the additional areas above 300 m^2.

With some 6% of land parcels formally transferred annually (Ali et al. 2017), Rwanda's land market is highly active in international terms. Sale prices are registered for all properties transferred and, because registration fees are independent of registered property values, incentives for misreporting are minimized.[14] Table 3 illustrates that, of some 11.6 million parcels covering 2.064 million ha nationwide (i.e., an average of 1,800 m^2/parcel or 1,300 m^2 for residential and 1,900 m^2 for agricultural land), 0.4 million or about

[12] Since a full exemption is granted to agricultural parcels smaller than 2 ha, with the average size of parcels being 0.19 ha virtually all agricultural land is exempt from paying lease fees.
[13] As discussed below, only 30% of residential parcels in urban Kigali paid lease fees in 2015—only $1.95 million of a potential $6.74 million.
[14] This is reinforced by the fact that reported land transfers and prices are similar to what emerges from household surveys.

70,000 ha are in Kigali city. While nationally 64% of parcels (66% of area) are used for agriculture and 12% (8% of area) for residential purposes, in Kigali 49% (56% of land area) are used for agriculture and 35% (17% of area) for residences. For 2013–16, sales were registered for some 85,000 properties, almost half in Kigali and some 20,000 in our study area. Property prices averaged US$28 per m^2 for residential and US$4 per m^2 for agricultural land nationwide and US$40 (US$ 7.5) or US$ 51 (US$ 11) per m^2 for residential (agricultural) land in Kigali and our study area, respectively.

To compare potential to actual revenue from land and more effective collection of current lease fees, we draw on 2015 parcel-level data for land tax revenue from the Rwanda Revenue Authority (RRA). Although RRA and RNRA use the same UPI to identify properties, so that in principle RRA could use the cadastral map to automatically bill owners for land lease fees owed (as assessed at the time of registration), this has not been done. Instead lease fee charges are still based on self-declaration. Table 4, based on using the UPI to link RRA and LAIS data, illustrates that only about 40% (45,000) of the 112,000 residential parcels in Kigali were subject to land lease fees and 37,000 did so. In urban Kigali in 2015, only US$1.95 million of US$6.74 million owed on residential properties was collected. Thus, in urban Kigali alone, closing the collection gap could more than triple revenue from land use fees.[15]

As the property registry does not contain data on many building characteristics needed for a mass valuation exercise, we drew on other data sources. Most importantly, to generate information on built-up area, we used 0.5m-resolution Pleaides Tri-Stereo imagery (acquired in August 2015) for a 340 km^2 study area that covers the central business district (CBD) and most of urban Kigali (see figure 1).[16] Applying a semi-global matching algorithm (Hirschmueller 2011) to this imagery made it possible to elaborate a Digital Surface and a Digital Terrain Model. After filtering out trees using the Normalized Differenced Vegetation Index (NDVI), building heights for each of the imagery's 0.5 m/pixels could then be recovered as the difference between the surface and the terrain model (Bärisch et al. 2017). We overlaid the result with boundaries of cadastral parcels obtained from LAIS, considered only heights above 2 m to exclude vehicles, and used the area covered by pixels with the same height as an estimate of building footprint. Building volume was then computed as the product of building footprint and height. Figures 2 and 3 illustrate the results for a low- and a higher-density neighborhood in central Kigali. While they illustrate some issues that might have been addressed by further processing, cost considerations led us not to proceed.[17]

[15] Comparing the potential revenue gain to the total cost of about US$50 million for the national land registration program suggests that the program did help to generate significant benefits.
[16] The size of the study area was dictated by data availability and cost considerations.
[17] The main issue that could be addressed by further processing would be to obtain more precise estimates of building footprints. This would also make it possible to address some sources of error in estimating the height of structures in steep areas and small and low buildings that might be hidden by trees or located in highly dense areas. Exploring ways to automate this process is an important area for future research.

The data thus generated are illustrated in table 5, highlighting that, with median parcel area of 400 m^2, building height of 3.7 m, and built-up volume of 304 m^3, about 20% of the area in the urban part of our study area is built up.[18] Complementing these data with the 2012 population and housing census, the 2014 establishment census, shapefiles for the location of schools from the National Institute of Statistics, and a map of road networks from the Rwanda Transport Development Agency made it possible to generate additional property attributes for inclusion in a computerized mass appraisal model.

Descriptive statistics suggest that the average property is 5.6 km from the CBD and 600 m from the closest primary school. Data on establishments, available only at cell level to protect respondent confidentiality, suggest better job opportunities in urban Kigali, where some 1,330 people per cell were employed by local establishments, compared to 360 in the city's rural cells. With a per km^2 cost of US$34 for imagery and $112 for processing (and ample scope for further reductions, e.g., by linking to open street map data or using local analysts), the total cost for the study area was about US$40,000.[19]

3.2 Factors Affecting Property Values and Model Suitability

CAMA models for property taxation typically involve estimation of a hedonic model on a set of properties for which prices are observed and then using the model to impute the values of properties for which price data are not available (IIAO 2013). Assuming that properties sold are a random sample, and following Rosen (1974), property prices are expressed as $P_i = f(S, L, N)$, where P_i is the sale price of property i; S denotes structural attributes such as parcel or lot size, building size, and quality; L is a vector of observable location-specific factors such as access to social services or jobs; and N denotes other factors capturing neighborhood quality. Estimating this function makes it possible to derive implicit market prices for specific attributes. Assuming that properties being sold are representative of the larger universe, prices can be imputed as a basis for mass valuation.

Testing for the presence of spatial autocorrelation using Moran's I statistic for residuals from OLS estimates (see appendix table 1) rejects the assumption of *iid* error terms. To identify a suitable alternative model, we used the Lagrange Multiplier test for model specification to identify the most important reason (omitted spatial lag or spatially autoregressive errors) for spatial dependence (Anselin et al. 1996).[20] As our objective was to predict prices to assess the potential for property tax, we focused on the squared mean prediction

[18] It should be noted that because here we consider only building structures, the total built-up area (including roads and other infrastructure) will be much higher in urban villages that include the central business district.

[19] The cost is as estimated by a team from GAF AG that includes the cost of imagery for the study area (340 km^2) and processing of the Normalized Digital Surface Model (NDSM) including filtering, tree elimination, quality enhancement, and calculation of relative building heights. The cost of imagery will be as high as US$56 if archived data are not available, and the cost of processing will be as low as US$56 if street map or cadaster data are available.

[20] Estimation results are highly significant for error and lag dependence models as well as their robust counterparts (appendix table 1).

error that favors a spatial error model (see appendix table 3) over spatial lag (appendix table 2) or OLS (appendix table 1) models. The spatial error model is specified as:

$$P_{iv} = S_{iv}\beta_S + L_{iv}\beta_L + N_v\beta_N + u_{iv}, \text{ with}$$

$$u_{iv} = \lambda W u_{iv} + e_{iv},$$

where P_{iv} is the log of the market price of residential property i located in village v; $\boldsymbol{S}_{iv}$ is a vector of continuous structural variables in log terms, i.e., parcel or lot size in square meters and volume of buildings in cubic meters; $\boldsymbol{L}_{iv}$ is a vector of locational variables consisting of distance from the parcel to the CBD and the nearest primary school or tarmac road; $\boldsymbol{N}_v$ is a vector of neighborhood attributes in log terms (except the density measure) including density of built-up area and average and standard deviation of building heights at village level, total residential land per cell and number of workers hired by business establishments per cell; u_{iv} is an error that follows a spatial autoregressive process with e_{iv} a vector of i.i.d. error terms; the β's are parameters to be estimated; λ is a scalar autoregressive parameter measuring spatial correlation in the errors; and W is a distance-based spatial weight matrix.[21]

The results from four specifications are reported in table 6 with successive columns for a basic regression with only parcel area and locational and time factors (col. 1), adding access to public amenities such as primary schools and tarred roads (col. 2), remote sensing data from satellite imagery (col. 3), and all of the above (col. 4). Although all variables have the signs expected, incorporating image-based attributes clearly and significantly improves goodness of fit.[22] Also, the spatial autoregressive coefficient, λ, is highly significant and, with an estimated coefficient of 0.79 for the preferred model, suggests a positive correlation between error terms of nearby properties.

With estimated elasticities of 0.56 and 0.17, parcel size and volume of buildings on a parcel are important predictors of the market prices of residential properties in Kigali even after locational and neighborhood factors are accounted for. Signs of coefficients of locational attributes are consistent with expectation. Size (-0.39 and -0.20) and significance of the coefficient on the property's distance to the CBD is consistent with a model of a monocentric city (Epple et al 2010), though it becomes insignificant once other locational variables are controlled for (cols. 2 and 4). Weak access to public amenities proxied by distance to primary schools (estimated coefficient of -0.05) and tarred roads (-0.14) is estimated to have a negative relationship to property prices.

Beyond the variables noted, neighborhood characteristics affect residential property prices in urban Kigali even after controlling for the spatial dependence of error terms. Coefficients of 1.62 on mean and -0.37 on

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[21] The spatial weights are based on threshold distance of 435m at which each property has at least one neighbor. Alternative distance band weights (750m, 1,500m and 5,000m) were used, but the one of 435m produced better goodness of fit using the likelihood ratio and AIC criteria.

[22] The log likelihood for models (4) and (3) is -13,835 and -13,983 as compared to -14,494 and -14,673 for models (2) and (1).

standard deviation of village building heights imply that sales prices are higher in villages with taller but more homogeneous buildings. Estimated coefficients of 0.17 on the volume of buildings and 1.09 on the density of village built-up area are consistent with the notion that, all else being equal, larger residential buildings in more dense neighborhoods fetch higher prices. Job opportunities as measured by number of workers hired by local establishments are estimated to have a significant positive association with the value of residential properties in urban Kigali, with an estimated elasticity of 6%. The stock of residential land on the other hand does not seem to affect the market value of properties.

3.3 Assessing Different Models' Predictive Power

To assess the models' predictive power and suitability for out-of-sample predictions and policy advice, we first compare estimated to actual sales prices within the sample by plotting results from the different models against building volume (figure 4) and parcel area (figure 5) as well as current lease fees. Figure 4 suggests that, because lease fees do not account for the fact that values increase with building volume, they fail to maximize potential tax revenue. Failure to include building volumes in a CAMA model used for valuations that form the basis of property taxes would thus be unfair in the sense that it would require owners of small residential properties to pay proportionately higher taxes than those owning larger properties. Figure 4 shows that this is no longer the case if property taxes are estimated using models that account for building volumes (models 3 and 4). Predicted values, though consistently below the true property value, track it closely, providing a justification for using the estimated parameters from model 4 to predict the value of residential properties in our urban Kigali sample.

Comparing predicted to actual land and property values (figure 5) suggests a good fit irrespective of the specification chosen and a positive relationship between tax revenue and parcel area. Note that current lease fees are more regressive than a hypothetical 1% property tax: average annual lease fees for the largest residential properties in the regression sample would be less than US$200, compared to US$400 for a 1% tax. The gap between property tax and land lease fees narrows as parcel size approaches the mean or median (525 or 399 m^2), implying that a property tax would be more progressive.

3.4 Exploring the Impact of Changes in Tax Base and Exemptions

Beyond using the results to predict residential property values in our study area and comparing the total revenue potential of a property tax to what is or could be collected under the current lease system, the hedonic regression allows us to explore via simulations what would happen if taxes were levied only on land or if certain exemptions were adopted. Table 7 shows that, using the current system, potential lease fees from all residential properties in urban Kigali sold in 2013-16 would be US$552,923. A 1% flat rate could raise some US$2.6 million—more than four times the lease fees.[23] Extrapolating this to all urban residential properties in Kigali suggests that a move from the current lease fee, which has tax revenue potential of US$ 4.9 million but collects only about US$ 2 million, to a 1% value-based tax could increase revenue to between US$ 16 and US$ 19.3 million based on predictions from the spatial error (table 7) or the lag model (appendix table 5).

Rather than a 1% flat fee, a proposal being discussed in government circles is to levy separate fees on land and on buildings. One such proposal is to exempt the first RWF 30 million of a residential property's market value from property tax and levy a 1% property tax on the remainder while also charging a land tax of RWF 70/m^2 (or more in premium locations) on properties below 300 m^2 plus a 50% surcharge on any area above 300 m^2. Without land price data or structure replacement cost, this requires decomposing the observed market value of properties into the values of land and structure. Using simple hedonic methods (Diewert et al. 2015; Kuminoff and Pope 2013), the value of the property is defined as:

$$V = P_l L + P_s S,$$

where V denotes the value of the property, L the quantity of land, S the quantity of structure, and P_l and P_s the prices of land and structure. As prices for land and structures are often correlated, restrictions on parameters are needed. Given it appears from our data that prices of land and structure vary by district, we also controlled for district fixed effects and, assuming that the fixed community characteristics affect only the value of the land (Eurostat 2013), attributed these to land values. We estimated a function of the form

$$V_{id} = \alpha_d + \delta_d L_{id} + \gamma_{dt} S_{id} + \upsilon_{id},$$

where V_{id} is the value of property i located in district d. The district fixed effects, α_d, and $\delta_d L_{id}$, measure the components of land value and $\gamma_{dt} S_{id}$ measures the structure value proxied by the volume of existing buildings in cubic meters of property i in district d; and υ_{id} is the error term at the property level. Results in appendix table 4 suggest that, at the mean of parcel area and building volume, the land share of property values is 39–40 percent in the city's three main districts,[24] resulting in an average value per residential parcel of US$ 12,175, US$ 11,611 and US$ 7,977 (or a value of US$ 24.6, US$ 19.5, and US$ 19.0/m^2, respectively) and an average building value of US$ 17,924, US$ 12,843 and US$ 12,881.

Using 40% as the average value of land, this suggests that, with the proposed exemption, only the top 5.1% of urban Kigali's residential properties would pay building tax. This would reduce potential tax revenue to 48% of what could be obtained using a flat 1% property tax (with 85% of yield from the land tax). A failure to ground proposed exemptions in actual price distributions and a failure to assess the revenue implications

[23] The difference in estimated property taxes using the actual sales price and predicted property values is about US$560,000.
[24] Mean parcel areas and building volumes in Gasabo district are 497 m^2 and 470 m^3; in Kicukiro district are 605 m^2 and 569 m^3; and in Nayrugenge district are 423 m^2 and 353 m^3.

of such proposals *ex ante* thus may result in adoption of approaches that are not only unfair but also yield only a fraction of what may be possible. To illustrate the usefulness of low cost methods to obtain potential yield from a property tax but also to *ex ante* assess revenue implications of alternative rate structures or exemptions, table 7 uses price predictions from the preferred (spatial error) model for exemption cut-offs set at 25% or 50% of mean property value.[25]

4. Conclusion and Policy Implications

With current processes of urbanization differing from those observed historically in several respects, a city's competitiveness will increasingly depend on its ability to address the 'demons of density' by planning ahead and raising the revenue needed to provide services effectively. The case of Kigali illustrates that high resolution remotely sensed imagery can be used to reliably check the completeness of valuation rolls and, if data on land values are available, also run land valuation models at a fraction of the time and resources required by more traditional technologies. This can enable cities in developing countries to augment the financial resources at their disposal, lessening dependence on central transfers; enhancing service quality; and possibly also helping to ensure currency of property registries to make private property rights more secure (Salm 2017).

To complement the results obtained here, three areas of enquiry seem promising. First, even if spatial data can be made available at low cost, least-cost (sampling) strategies to obtain the land values required to run a meaningful CAMA model are needed. Second, while several avenues to translate improved coverage with data on property tax into higher revenue exist—e.g., by reducing the cost of tax collection through mobile payments, applying peer pressure, etc.—knowledge on how to most effectively use these, or combine with adoption of differential rate structures, remains limited. Finally, the spatial data underpinning property tax rolls can also widen the range of options open to both the public and private sectors, from setting and enforcing building and planning standards to finding the most cost-effective ways to modernize infrastructure and other service provision and assessing the potential benefits from spatial data in this area would be of great interest for future research.

[25] Similar results for the spatial autoregressive lag model are presented in appendix table 5.

Table 1: Coverage of Registry or Cadaster in Main City by Region, 2017

	EAP	ECA	LAC	MENA	OECD	SAS	SSA	Total
Most plots in main city registered	56.0	57.7	18.8	47.6	87.1	14.3	14.6	42.1
Most plots in main city mapped	52.0	65.4	34.4	47.6	93.5	14.3	12.5	45.8
Cadaster is digital	28.0	46.2	28.1	14.3	87.1	14.3	4.2	32.1
Cadaster and registry linked	32.0	76.9	31.3	81.0	87.1	14.3	31.3	51.6
No. of countries	25	26	32	21	31	7	48	190

Source: Data from 2017 'Doing Business,' www.doingbusiness.org.

Note: EAP = East Asia and Pacific; ECA = Eastern Europe and Central Asia; MENA= Middle East and North Africa; SAS = or South Asia; and SSA = Sub-Saharan Africa regions.

Table 2: Trends in Collection of Property Taxes by Economic National Groups, 1990–2014, Percent

		1990–94	1995–99	2000–04	2005–09	2010–14
Property tax as share of GDP	Advanced market economies	1.8	1.7	1.7	1.7	1.7
	Emerging market economies	0.4	0.4	0.5	0.5	0.6
	Low income developing	0.2	0.2	0.2	0.2	0.2
Property tax as share of tax revenue (%)	Advanced market economies	0.047	0.045	0.046	0.046	0.045
	Emerging market economies	0.013	0.015	0.021	0.02	0.022
	Low income developing	0.009	0.007	0.009	0.007	0.005

Source: IMF Government Financial Statistics. Samples: 36 advanced economies, 62 emerging markets, and 22 low-income developing economies.

Table 3: The Land Registry in Rwanda, Kigali, and the Study Area, Parcel Characteristics and Transactions since 2013

	Rwanda	**Kigali city**	**Study area**
Characteristics of registered parcels			
Number of registered parcels	11,437,040	395,978	136,555
Area of registered parcels (ha)	2,064,176	69,831	14,210
Parcel size (ha)	0.18	0.18	0.10
Residential	0.13	0.09	0.07
Agricultural	0.19	0.20	0.19
Share of parcels (area) by land use type			
Residential	11 (8)	35 (17)	46 (72)
Agricultural	64 (66)	49 (56)	30 (16)
Commercial	1 (1)	1 (2)	4 (1)
Forest	8 (9)	3 (7)	3 (1)
Admin./science/social	0.3 (1)	0.5 (3)	4 (0)
Not categorized	13 (13)	9 (12)	10 (6)
Parcels under lease (%)	97.76	98.90	100
Transactions since 2013			
No. of properties sold	85,797	40,253	19,036
… *of which* residential	47,287	28,879	16,730
… *of which* agricultural	38,510	11,374	2,306
Sale value, residential property ($\$/m^2$)	27.52	39.98	51.16
Sale value, agricultural land ($\$/m^2$)	3.84	7.47	10.56

Source: RNRA LAIS database as of Dec 31, 2016.

Note: The study area covers that part of urban Kigali for which imagery to generate building heights was available (see figure 1).

Table 4: Lease Fee Collection in Urban Kigali, 2015

	Residential	Agricultural	Others
Parcels with lease fee obligation	112,143	454	3,496
Mean size (m^2)	726	49,925	4,781
Parcels with declared amount	44,985	245	1,130
Parcels paying lease fees	37,025	189	942
Mean size (m^2)	677	19,201	3,932
Lease fee obligation (US$)	6,742,827	7,548	743,042
Lease fees declared at RRA (US$)	2,444,347	14,774	205,640
Lease fees paid to RRA (US$)	1,947,081	10,215	122,046

Source: LAIS and RRA, 2015.

Note: 40,887 agricultural parcels smaller than 2 ha are exempt.

Table 5: Statistics for the Study Area Drawn from Satellite Imagery

	Total	Urban	Rural	Source
Parcels				
Mean parcel area (m^2)	544.04	524.27	699.00	LAIS
Mean parcel area (m^2)	419.56	399.15	565.11	LAIS
Property price (US$/$m^2$)	52.06	55.96	21.55	LAIS
Distance to CBD (km)	6.01	5.56	9.55	
Distance to tarred road (m)	475.48	391.76	1131.60	RF
Distance to primary school (m)	704.48	612.95	1421.83	SF
Mean building volume (m^3)	475.00	486.13	387.77	SI
Median building volume (m^3)	295.73	303.78	242.86	SI
No. of parcels	15545	13786	1759	LAIS
Villages				
Share of area under buildings	0.18	0.20	0.05	SI
Mean building height (m)	3.66	3.70	3.42	SI
SD building height	1.56	1.60	1.27	SI
Number of villages	740	648	92	
Cells				
Size (km^2)				
Residential area (m^2)	829361	840286	791580	LAIS
No. of residents employed in local establishments	1,111	1,329	360	EC
No. of cells	107	83	24	
Sector level				
No. of sectors	32	22	10	
Size (km^2)				

Source: Data from LAIS, NISR establishment census (EC), NISR population and housing census (PC), NISR school shapefile (SF), RTDA road network shapefile (RS), and stereo satellite imagery (SI).
Note: The observations include parcels sold several times in 2013–16. After dropping duplicates the regression analysis was based on 12,592 unique parcels from urban areas.

Table 6: Hedonic Price Regression Results, Urban Kigali, Spatial Error Model

	(1)	(2)	(3)	(4)
Log of parcel area in sqm	0.692***	0.665***	0.578***	0.558***
	(0.009)	(0.009)	(0.010)	(0.009)
Log distance from the village to the CBD in km	-0.390***	-0.124	-0.203***	-0.069
	(0.105)	(0.082)	(0.065)	(0.052)
Log number of workers at the cell level in 2014	0.108***	0.097***	0.070***	0.061***
	(0.021)	(0.020)	(0.019)	(0.018)
Log of residential land at the cell level	0.037	0.020	0.010	0.018
	(0.034)	(0.032)	(0.029)	(0.027)
Log distance to tarmac road in meters		-0.157***		-0.135***
		(0.008)		(0.008)
Log distance to a primary school in meters		-0.053***		-0.046***
		(0.020)		(0.018)
Log volume of buildings in m3			0.169***	0.165***
			(0.005)	(0.005)
Density of built up area of the village			1.225***	1.092***
			(0.130)	(0.127)
Log average height of buildings at the village in meters			1.590***	1.623***
			(0.147)	(0.142)
Log SD of building height at the village in meters			-0.312***	-0.373***
			(0.054)	(0.053)
Constant	4.665***	5.899***	2.654***	3.540***
	(0.451)	(0.431)	(0.401)	(0.386)
Number of observations	12,592	12,592	12,592	12,592
Log Likelihood	-14,672.830	-14,494.370	-13,982.850	-13,835.030
Wald Test (df = 1)	9,528.585***	5,194.450***	3,499.423***	2,296.457***
Lambda	0.905***	0.869***	0.834***	0.787***

Note: Dependent variable is the log of the sales price per parcel for residential properties in Kigali in 2013-16. The spatial weights are based on threshold distance of 435m at which each property has at least one neighbor. Alternative distance band weights (750m, 1,000m, 1,500m, and 5,000m) were used, but the one of 500m produced better fit using the likelihood ratio and AIC criteria. Standard errors in parenthesis: *** significant at 1%; ** significant at 5%; * significant at 10%. The 'spdep' package of R was used for the estimation.

Table 7: Predictions for estimated Tax Revenue from a 1% Property Tax with various exemptions

	Est. revenue (USD)	Share of baseline
A. Only properties sold in 2013-16 (in sample prediction)		
Lease fee ("current rate")	552,923	
1% property tax using reported sales price	2,616,113	
1% property tax using estimated price	2,081,242	
B. All properties in urban Kigali (out of sample prediction)		
Memo item: Potential lease fee using current rates	4,908,248	
Baseline: 1% property tax		
1% property tax using estimated price	15,984,606	
Scenario 2 (RWF 30 mn./ 300m^2):		
Land lease fee	6,534,196	0.41
Building tax	1,185,989	0.07
Total	7,720,185	0.48
Scenario 3 (25% or RWF 5 mn./ 300m^2):		
Land lease fee	6,534,196	0.41
Building tax	8,877,086	0.56
Total	15,411,282	0.96
Scenario 4 (median or RWF 9 mn./ 300m^2):		
Land lease fee	6,534,196	0.41
Building tax	7,463,678	0.47
Total	13,997,874	0.88
Scenario 5 (mean or RWF 13 mn./ 300m^2):		
Land lease fee	6,534,196	0.41
Building tax	6,202,656	0.39
Total	12,736,852	0.80

Note: Results are based on the error model (f) and apply to our study area.

Scenario 2 involves a 1% of building value exempting all structures with values less than RWF 30 million (US$ 38,120) plus a land tax (RWF 70 /m^2 for area < 300 m^2 plus RWF 105/m^2 for area > 300m^2) in line with the Government's current proposal. To illustrate revenue implications of different exemption structures, scenarios 3, 4, and 5 set the value of buildings to be exempted from taxation at the first quartile (US$ 4,927), median (US$ 8,277), and mean (US$ 11,055) of the building value distribution, respectively. Current lease fee rates imply that 0.45% pay RWF 5/m^2, 0.16% pay 10/m^2, 14% pay RWF 30/m^2, and 86% pay RWF 70/m^2.

Figure 1: Study Area Relative to Kigali's Administrative Boundary

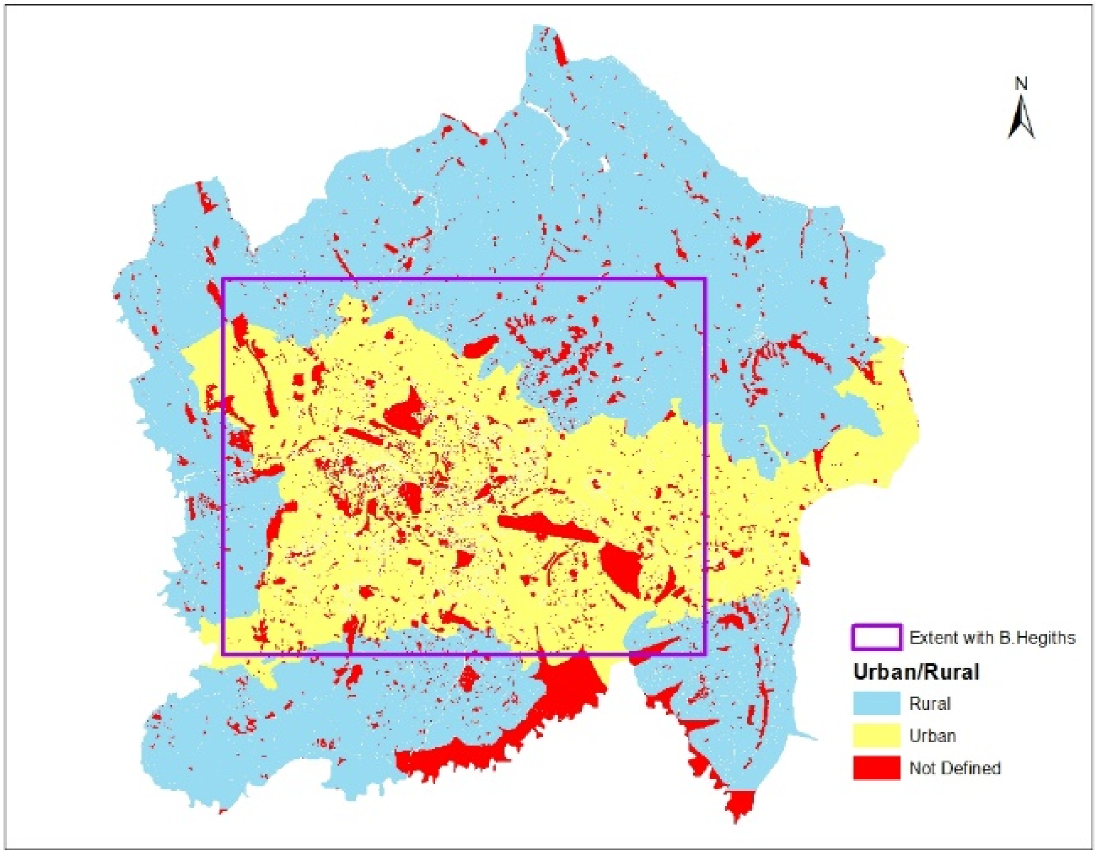


Figure 2: Estimated Building Heights, Central Kigali

Figure 3: Estimated Building Heights, Higher-Density Neighborhood

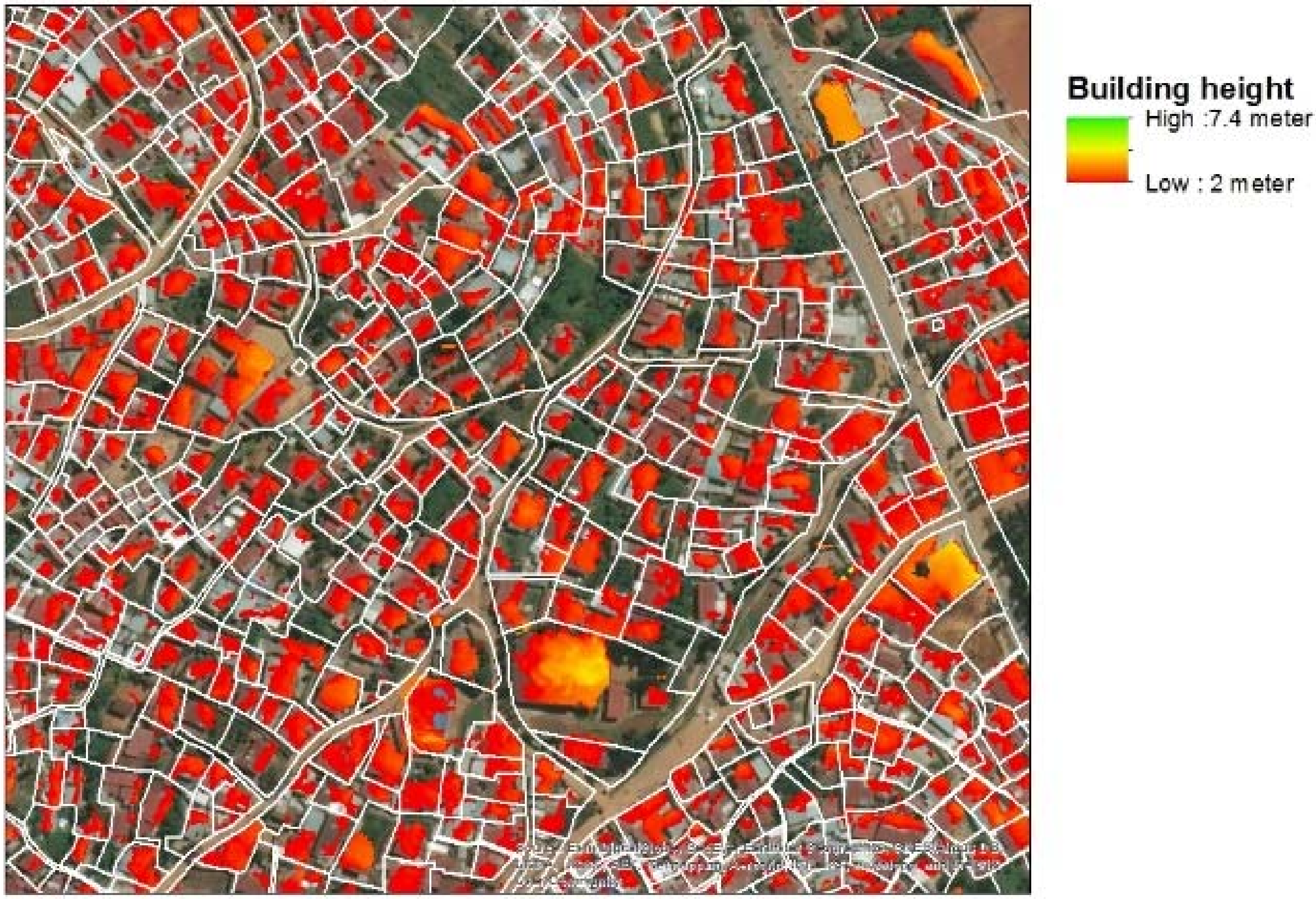
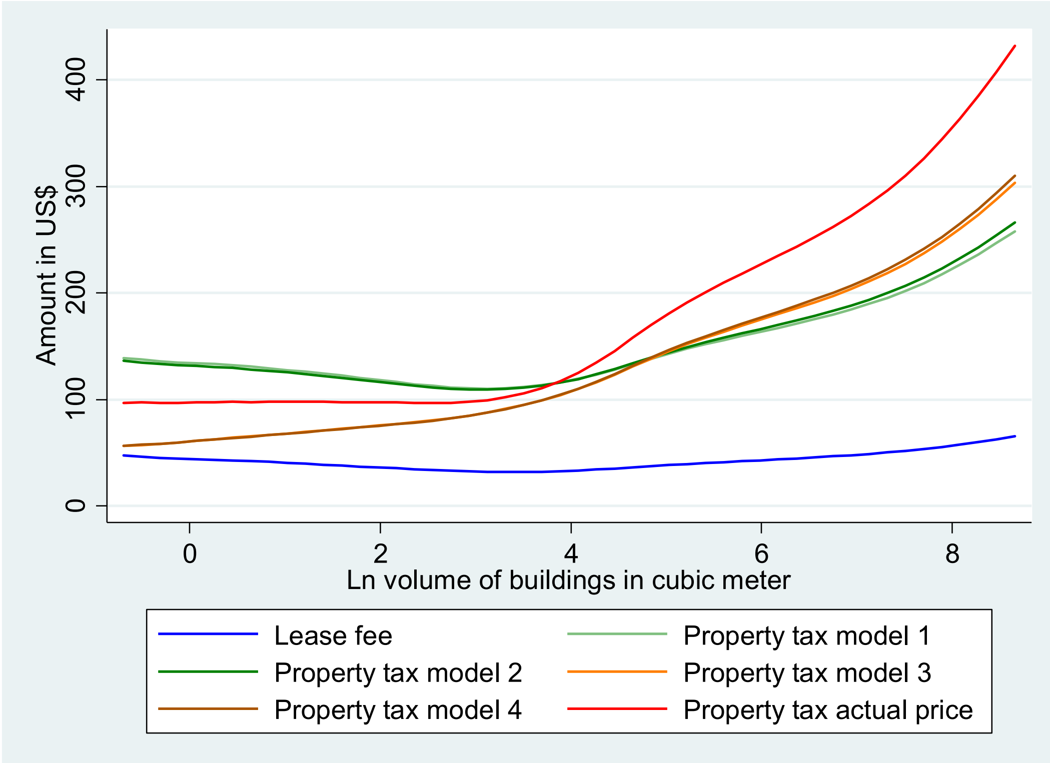
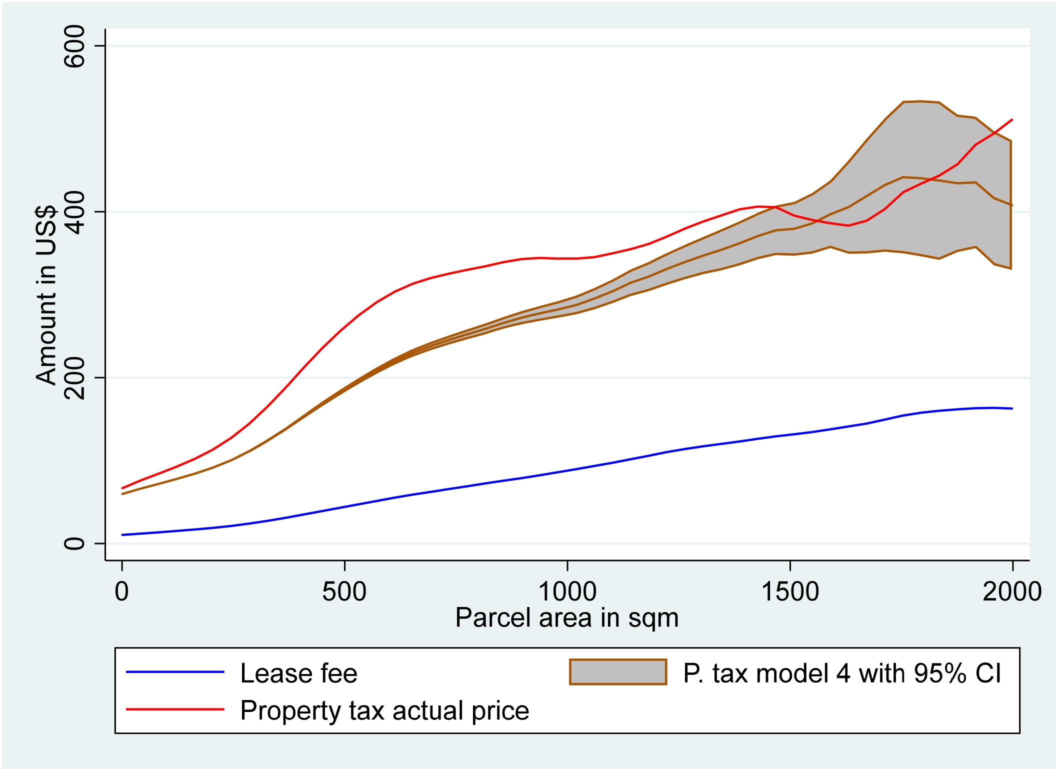


Figure 4: Within-sample Prediction of Potential Property Tax Liability, Model Results Compared



Note: A 1% ad valorem property tax rate is assumed throughout.

Figure 5: Within-sample Prediction of Property Tax Liability, Model Results Compared



Note: A 1% ad valorem property tax rate is assumed throughout.

Appendix Table 1: Hedonic Price Regression Results, Urban Kigali, OLS

	(1)	(2)	(3)	(4)
Log of parcel area in sqm	0.781***	0.717***	0.575***	0.552***
	(0.010)	(0.010)	(0.010)	(0.010)
Log distance from the village to the CBD in km	-0.280***	-0.016	-0.240***	-0.098***
	(0.030)	(0.029)	(0.026)	(0.026)
Log number of workers at the cell level in 2014	0.239***	0.152***	0.061***	0.044***
	(0.010)	(0.010)	(0.010)	(0.010)
Log of residential land at the cell level	-0.192***	-0.070***	0.004	0.040***
	(0.014)	(0.014)	(0.014)	(0.013)
Log distance to tarmac road in meters		-0.241***		-0.145***
		(0.006)		(0.006)
Log distance to a primary school in meters		-0.117***		-0.059***
		(0.011)		(0.010)
Log volume of buildings in m3			0.195***	0.186***
			(0.005)	(0.005)
Density of built up area of the village			2.571***	1.947***
			(0.093)	(0.095)
Log average height of buildings at the village in meters			2.783***	2.580***
			(0.098)	(0.096)
Log SD of building height at the village in meters			-0.506***	-0.538***
			(0.039)	(0.038)
Longitude, decimal degree	7.062***	3.936***	3.320***	2.032***
	(0.419)	(0.404)	(0.366)	(0.362)
Latitude, decimal degree	-0.327	0.079	1.918***	1.827***
	(0.399)	(0.379)	(0.346)	(0.341)
Constant	-206.820***	-111.092***	-95.100***	-55.417***
	(12.673)	(12.211)	(11.055)	(10.938)
Number of observations	12,592	12,592	12,592	12,592
R^2	0.359	0.432	0.529	0.551
Adjusted R^2	0.358	0.432	0.528	0.551
Residual Std. Error	0.910	0.856	0.780	0.762
F Statistic	1,172.842***	1,197.294***	1,411.107***	1,287.790***
Spatial autocorrelation tests on the OLS residual[a]				
Moran's *I*				0.104
p-value				2.2e-16
LMerr				3961.5
p-vlaue				2.2e-16
LMlag				1821.5
p-vlaue				2.2e-16
Robust LMerr				2407.3
p-vlaue				2.2e-16
LMlag				267.32
p-vlaue				2.2e-16

Note: Dependent variable is the log of the sales price per parcel for residential properties in Kigali over the 2013-16 period. Standard errors in parenthesis: *** significant at 1%; ** significant at 5%; * significant at 10%. The estimation is done in R.

[a]The reported test statistics are for the spatial weights defined at a threshold distance band of 435m for which each property has at least one neighbor. Alternative threshold distances (750m, 1000m, 1500m and 5000m) are also used, but the Moran's *I* is the highest at 435m. The same is true for the other statistics.

Appendix Table 2: Hedonic Price Regression Results, Urban Kigali, Spatial Lag Model

	(1)	(2)	(3)	(4)
Log of parcel area in sqm	0.622***	0.610***	0.524***	0.514***
	(0.009)	(0.009)	(0.009)	(0.009)
Log distance from the village to the CBD in km	-0.108***	-0.037**	-0.203***	-0.108***
	(0.014)	(0.016)	(0.065)	(0.015)
Log number of workers at the cell level in 2014	0.128***	0.095***	0.070***	0.049***
	(0.009)	(0.009)	(0.019)	(0.009)
Log of residential land at the cell level	-0.101***	-0.049	0.010	0.040***
	(0.010)	(0.011)	(0.029)	(0.027)
Log distance to tarmac road in meters		-0.119***		-0.096***
		(0.006)		(0.006)
Log distance to a primary school in meters		-0.052***		-0.023
		(0.010)		(0.016)
Log volume of buildings in m3			0.175***	0.171***
			(0.005)	(0.005)
Density of built up area of the village			1.391***	1.142***
			(0.100)	(0.100)
Log average height of buildings at the village in meters			0.721***	0.825***
			(0.106)	(0.117)
Log SD of building height at the village in meters			-0.076*	-0.150***
			(0.039)	(0.045)
Constant	-0.802***	0.523***	-1.551***	-0.589*
	(0.151)	(0.189)	(0.234)	(0.386)
Number of observations	12.592	12,592	12,592	12,592
Log Likelihood	-14,852.420	-14,645.330	-14,056.620	-13,923.010
Wald Test (df = 1)	5,324.495***	2,989.083***	1,661.369***	1,025.168***
Rho	0.770***	0.673***	0.576***	0.507***

Note: Dependent variable is the log of the sales price per parcel for residential properties in Kigali in the 2013-16 period. The spatial weights are based on threshold distance of 435m at which each property has at least one neighbor. Alternative distance band weights (750m, 1,000m, 1,500m and 5,000m) were used, but the one of 500m produced better goodness of fit using the likelihood ratio and AIC criteria. Standard errors in parenthesis: *** significant at 1%; ** significant at 5%; * significant at 10%. The estimation is done using 'spdep' package of R.

Appendix Table 3: Mean Squared Prediction Error Compared

	Model	MPE
1	OLS (all vars)	1.785
2	SAR (Model 1)	1.839
3	SAR (Model 2)	1.809
4	SAR (Model 3)	1.719
5	SAR (Model 4)	1.701
6	SER (Model 1)	1.794
7	SER (Model 2)	1.770
8	SER (Model 3)	1.696
9	SER (Model 4)	1.678

Appendix Table 4: Results, Decomposing Property Value into Components, OLS

	(1)
Area in sq. m., Gasabo district	25.17***
	(0.802)
Area in sq. m., Kicukiro district	5.288***
	(0.553)
Area in sq. m., Nayarugenge district	45.49***
	(1.985)
Volume of buildings in cubic m., Gasabo district	38.64***
	(0.764)
Volume of buildings in cubic m., Kicukiro district	22.24***
	(0.793)
Volume of buildings in cubic m., Nayarugenge district	35.83***
	(2.139)
Gasabo district	-1,027*
	(611.4)
Kicukiro district	8,030***
	(671.5)
Nayarungenge district	-10,860***
	(1,088)
Observations	12,592
R-squared	0.565

Standard errors in parentheses: *** significant at 1%; ** significant at 5%; * significant at 10%.

Appendix Table 5: Estimated Revenue from a 1% Property Tax, Study Area, Lag Model

	Est. revenue (USD)	Share of baseline
A. Only properties sold in 2013-16 (in sample prediction)		
Lease fee ("current rate")	552,923	
1% property tax using reported sales price	2,616,113	
1% property tax using estimated price	2,081,242	
B. All properties in urban Kigali (out of sample prediction)		
Potential lease fee (using current rates)	4,908,248	
Baseline: 1% property tax		
1% property tax using estimated price	19,279,541	
Scenario 2 (RWF 30 mn./ 300m^2):		
Land lease fee	6,534,196	0.34
Building tax	2,522,892	0.13
Total	9,057,088	0.47
Scenario 3 (25% or RWF 5 mn./ 300m^2):		
Land lease fee	6,534,196	0.34
Building tax	10,915,960	0.57
Total	17,450,156	0.91
Scenario 4 (median or RWF 9 mn./ 300m^2):		
Land lease fee	6,534,196	0.34
Building tax	9,455,471	0.49
Total	15,989,667	0.83
Scenario 5 (mean or RWF 13 mn./ 300m^2):		
Land lease fee	6,534,196	0.34
Building tax	7,832,834	0.41
Total	14,367,030	0.75

Note: Results are based on the lag model (4) and apply to our study area.
Scenario 2 involves a 1% of building value exempting all structures with values less than RWF 30 million (US\$ 38,120) plus a land tax (RWF 70/m^2 for area < 300 m^2 plus RWF 105/m^2 for area > 300m^2) in line with the Government's current proposal. To illustrate revenue implications of different exemption structures, scenarios 3, 4, and 5 set the value of buildings to be exempted from taxation at the first quartile (US\$ 4,795), median (US\$ 8,920), and mean (US\$ 13,334) of the building value distribution, respectively.

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