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Location, Location, Location Revisited

Evidence from Antananarivo, Madagascar

Atsushi Iimi

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Abstract

Understanding how land prices are determined is of particular importance for policy makers; however, there is little evidence in African countries, which are currently experiencing rapid urbanization. The paper examines the relationship between land prices and locational characteristics using data from Antananarivo, the capital of Madagascar. It is found that the land value gradients are relatively steep, indicating that the land and housing prices tend to overshoot in the middle of the city, pushing the poor away from the city to suburban areas. It is also found that access to transport infrastructure and services, such as minibuses, is an important determinant of land value. Not only transport connectivity, but also other factors, such as proximity to amenities and administrative centers, are found to be important. Better land management and urban transport policies are called for to promote these aspects in the city.

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Location, Location, Location Revisited: Evidence from Antananarivo, Madagascar

Atsushi Iimi[¶]

Africa Infrastructure, Transport Global Practice
World Bank Group

Key words: Land price gradient; Spatial autoregressive model.

JEL classification: C21, C26, O18, R41

¶ Corresponding author.

I. INTRODUCTION

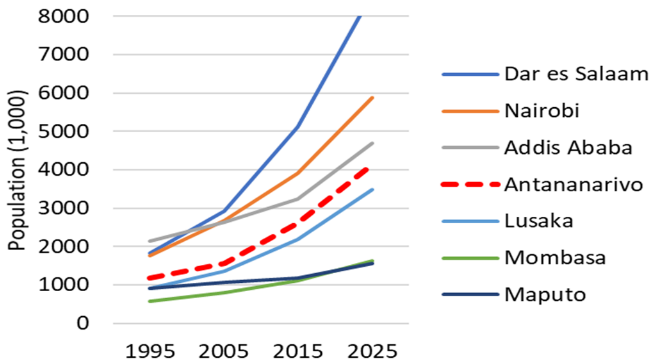
1. How the land values are determined has long been the central topic of urban economics. As summarized by Atack and Margo (1998), in theory, the land value declines with distance from the central business district (CBD) in a simple monocentric city model. The land value gradient also flattens as a city expands and transport connectivity improves. With various locational characteristics developed, the power of this monocentric urban model may decrease. Atack and Margo show that the land prices in New York City evolved in this way during the nineteenth and twentieth centuries.

2. More recent studies discuss multidimensionality and complexity of land value determinants. "Land" constitutes not only land itself but also all aspects of a developed property, including location, property attributes and neighborhood amenities (Davis, 2009; Jaeger, 2013; Chen et al., 2017). With data between 2003 and 2011, Gedal and Ellen (2018) show that the land value gradient in New York is relevant to the distance to CBD but also affected by neighborhood attributes, such as proximity to quality parks and neighborhood demographics, including local poverty and ethnicity. In China, land prices vary across categories of land use: While residential land prices depend more on accessibility to the CBD, commercial land prices are more sensitive to proximity to rail stations (Qin et al., 2016). In the Singapore condominium market, the proximity to metro stations and good schools (i.e., top 10 secondary schools and universities) is important (Tu et al., 2007).

3. Currently, Africa is experiencing very rapid urbanization. According to UN-Habitat (2016), for example, the population of Dar es Salaam, which is the largest city in East and Southern Africa, increased from 1.8 million in 1995 to 5.1 million in 2015 (**Figure 1**). It is followed by Nairobi (3.9 million), Addis Ababa (3.2 million) and Antananarivo (2.6 million). These cities have been growing at about 5 to 6 percent per annum – nearly twice as high as the total population growth – and are expected to continue growing. In Africa, however, land use and urban transport policies often lag behind such rapid urban growth. In theory, the residential locational choice model predicts that urban population can overshoot the socially

optimal level (Turner, 2005). In addition, the supply of land is normally highly inelastic. As the result, significant traffic congestion is often generated, raising land and housing prices around a city center disproportionately and pushing the poor out of the city or crowding them into informal settlements.

Figure 1. Population of major cities in East & Southern Africa



Source: UN-Habitat (2016).

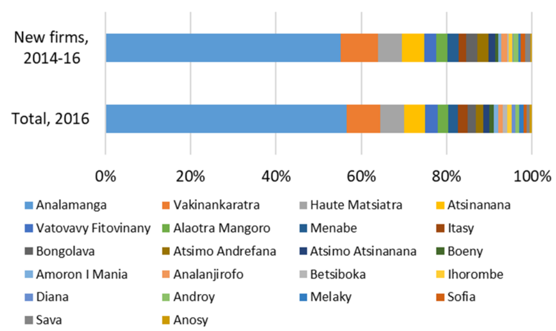
4. Although it is of particular importance for policy makers to understand how land prices are determined, there is little evidence in the developing world, except for China, of which urbanization has also been accelerated in recent years (e.g., Zheng and Kahn, 2008; Qin et al., 2016). The current paper examines the relationship between land prices and locational characteristics using data from Antananarivo, the capital of Madagascar. The contribution of the paper is twofold: First, it aims at adding new evidence from a developing country to the literature. The paper intends to withdraw policy recommendations for proper urban planning and transportation development in not only Antananarivo, but also other major cities in Africa. Methodologically, second, the paper applies spatial autoregressive models to newly collected spatial data from Antananarivo. It is shown that Ordinary Least Squares (OLS) regression is likely to be biased because of various neighborhood effects in the data.

5. The remaining sections are organized as follows: section II provides a brief overview of Antananarivo; section III develops our empirical strategy, and section IV explains our data; section V presents the main results and discusses policy implications of the results; section VI examines the robustness of the results; then, section VII concludes.

II. Overview of Antananarivo

6. Madagascar is one of the least developed countries in Africa. GDP per capita is about US$450. The country's total population is about 25 million, of which about 2.6 million live in Greater Antananarivo. It is estimated to increase up to 4.1 million by 2025 (UN-Habitat, 2016). Antananarivo is a historic city, which was established in the early 1600s (Wade, 2015). Since then, it has been always the primary urban area in Madagascar. In the country, there are 120,000 establishments that are officially registered. More than half are located in Antananarivo (**Figure 2**). Analamanga is a region surrounding Antananarivo and its neighboring communes.

Figure 2. Share of registered enterprises by region

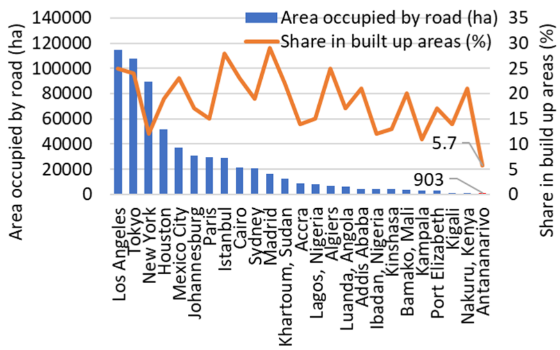


Source: INSTAT Madagascar

7. In recent years, Antananarivo has been facing unmanageable traffic congestion. The average speed of public buses, called taxi-be, is only less than 15 km per hour during peak hours. From the transport infrastructure point of view, the city crucially lacks space dedicated to roads. Global experiences indicate that many large cities use 15 to 25 percent of built-up areas for transport infrastructure (Angel et al., 2016). In Antananarivo, the share is estimated at only 5.7 percent, meaning that roads are too narrow and there are few alternative routes to avoid congestion (**Figure 3**). As mentioned above, this is partly attributed to the fact that many structures in the city are historic, and geographically, it is surrounded by hilly mountains. It is also because significant land in the city is still used to produce rice, which is the country's

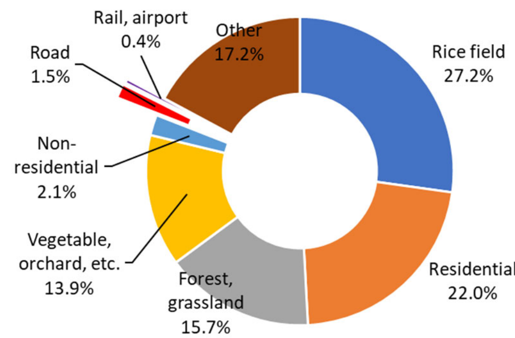
most important food crop (**Figure 4**). The rice fields are important for flood protection purposes: Antananarivo experiences massive flood almost every year (**Figure 5**).

Figure 3. Road space in selected cities



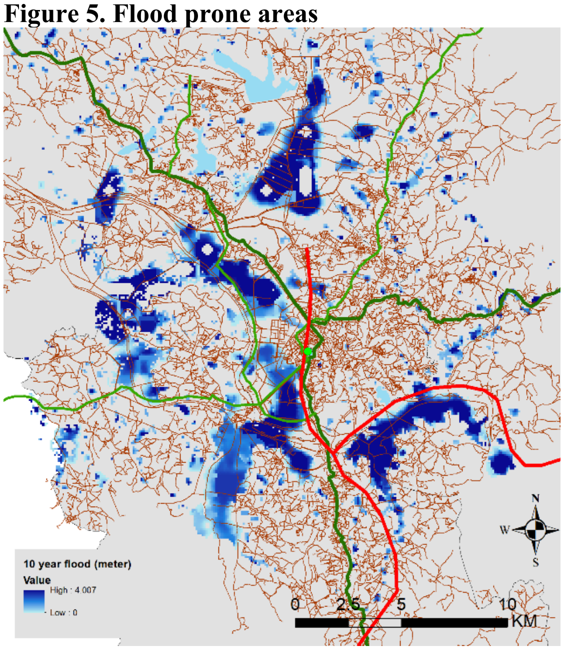
Source: Angel et al. (2016).

Figure 4. Land use in Antananarivo



Source: World Bank estimate.

Figure 5. Flood prone areas

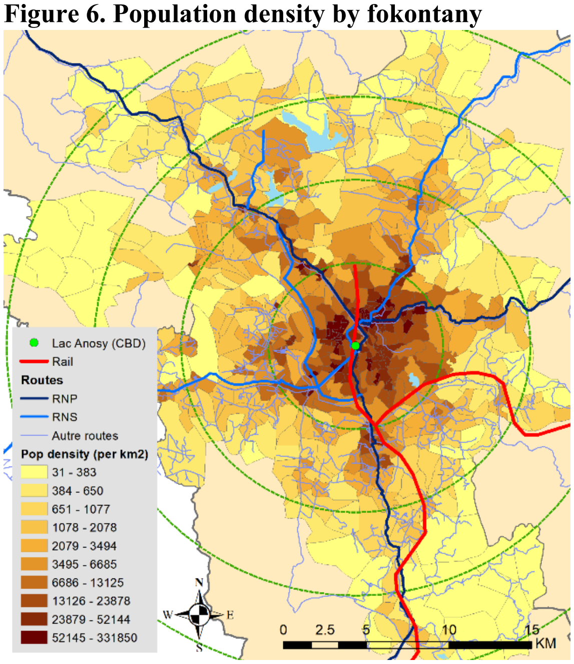


Source: Based on SSBN Global Flood Hazard Data.

8. The development of Greater Antananarivo has been very linear along major national roads, all of which converge on the middle of the city. Because of limited transport accessibility and chronic traffic congestion, many people prefer to live near the center of the city. About 60 percent of the total city population live within 5 km of the CBD, which is assumed to be Lake Anosy in this paper (**Figure 6**).

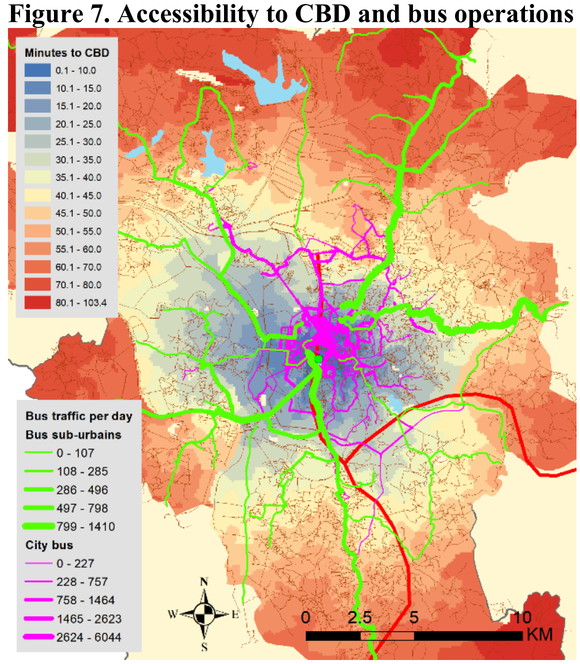
9. A main transport means for most of the city residents is minibus, called taxi-be. There are also suburban buses. It is estimated that more than 300,000 people use minibuses every day. The bus services are provided along about 130 routes by about 80 operators with over 4,000 buses. They are normally organized as cooperatives at the commune level but not well regulated or coordinated. As the result, many bus routes are duplicated and concentrated on certain routes, aggravating, not easing, traffic congestion (**Figure 7**).

Figure 6. Population density by fokontany



Source: Based on data by the Ministry of Health.

Figure 7. Accessibility to CBD and bus operations



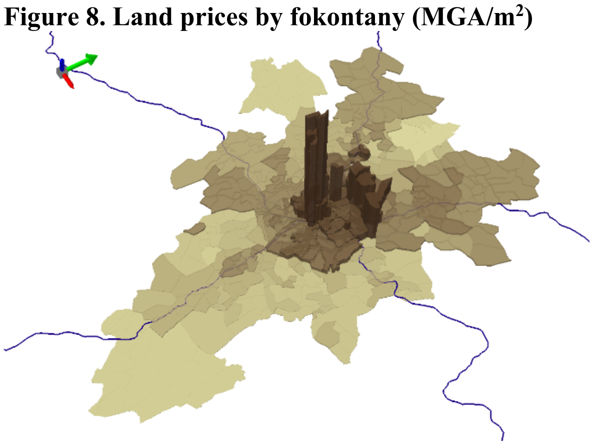
Source: World Bank estimates.

10. Since available residential areas are limited and transport accessibility is poor, land prices in the city tend to be elevated. The highest rate around Lake Anosy is about 1.1 million Malagasy ariary (MGA) or US\$300 per m^2 (**Figure 8**). The land prices no doubt skyrocket around the CBD and taper off quickly as one moves away from the center. In other words, the city is very thin. The land price gradients look very steep (**Figure 9**).

11. The figure indicates the current underdevelopment of transportation means connecting suburban areas and the center of the city as well as the lack of development of other towns

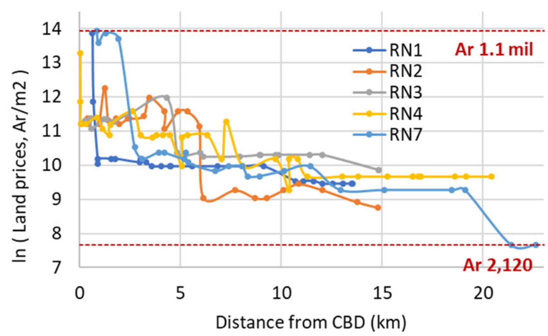
and agglomerations than the current CBD. The suburban areas remain underdeveloped in the case of Greater Antananarivo, and the space dedicated to transport infrastructure tends to decrease as one moves toward suburban areas (**Figure 10**). These findings clearly call for early urban planning and transport development to restore effective mobility of goods and people in the city.

Figure 8. Land prices by fokontany (MGA/m^2)



Source: Based on the Government data.

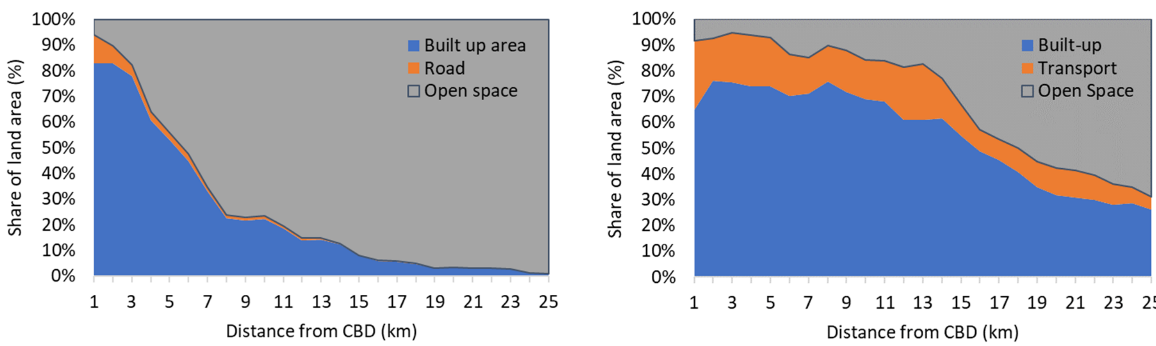
Figure 9. Land price gradients along major roads



Source: World Bank estimates.

Figure 10. Land use and distance from CBD

(Antananarivo) **(Paris)**



Sources: World Bank estimates; Lall et al. (2017).

III. Empirical Strategy

12. In the literature, a common approach to examine how land values are determined is hedonic regression, which in theory reveals how much residents or other land users would pay for neighborhood characteristics, such as proximity to employment opportunities, social

facilities and other amenities (e.g., Orford, 2000; Tu et al., 2007; Jaeger, 2013; Gedal and Ellen, 2018). The current paper follows this approach:

$$\ln V_i = \beta_0 + \beta_1 X_i + \sum_k \beta_k \ln Z_{ki} + u_i \qquad (1)$$

where V_i is the land value at location i. While X is a variable representing connectivity to the CBD, Z contain a set of locational characteristics observed.

13. In the literature, the connectivity X is often defined by distance between a parcel of land and the CBD. Unlike earlier studies, the current paper uses more realistic variables: travel time estimates and the Job Accessibility Index (JAI). First, travel time is used, which is estimated by spatial software with road conditions and traffic taken into account. This is a more realistic measurement to capture the people's actual accessibility to the CBD, because the accessibility can be different depending on actual traffic speed even if the distance is the same.

14. Second, the JAI is also used, which is considered to be even more comprehensive. Instead of measuring the distance or travel time to one particular place, i.e., the CBD, it takes into account the accessibility to multiple potential destinations. It is defined by the average size of economic activities or job opportunities inversely weighted by transport connectivity. The CBD is generally a good proxy of destination for many people, but where they actually go may differ: The CBD is only one of the destinations in reality. Therefore, the JAI is constructed based on the level of attractiveness of each destination and the transport connectivity from location i to that destination. Formally, it is calculated by this:

$$JAI_i = \left(\sum_m Y_m / d_{im}\right) / \max JAI \qquad (2)$$

where Y_m represents the size of job opportunities at destination m, which can be understood as the probability to visit this place. d_{im} is the connectivity between location i and destination *m*. In our case, travel time is used for d_{im}. Then, the index is normalized to zero to one. Note that the higher *JAI* means better connectivity, that is, location *i* is closer to job opportunities.

15. To estimate Equation (1), one empirical issue is that spatial autocorrelation would likely matter to any locational data, such as land prices. This is often ignored in the existing literature. The land value at a particular place is likely to be related to its neighboring values because of unobserved neighboring factors and transport connectivity. Of particular note, transport infrastructure typically forms a network, which creates autocorrelation among neighboring area: Roads must be connected with each other.

16. One approach to mitigate such unobserved spatial autocorrelation is to introduce the location-specific fixed-effects in the model. For instance, Chen et al (2017) use the county-specific fixed-effects to analyze the relationship between housing market thinness and proximity to the CBD in Maryland. In our case, unfortunately, panel data are not available.

17. Another approach to control for potential autocorrelation is the spatial autoregressive model (Meen, 1996; Orford, 2000; Tu et al., 2007), which the current paper relies on. That is, land value, V_i, at a particular place, i, is correlated to its neighboring values, V_j. That is, $Cov(u_i, u_j) \neq 0$.

$$\ln V_i = \lambda \sum_j w_{ij} \ln V_j + \beta_0 + \beta_1 X_i + \sum_k \beta_k \ln Z_{ki} + \rho \sum_j w_{ij} u_j + \varepsilon_i \tag{3}$$

where w is an element of the spatial-weighting matrix. λ and ρ are spatial autoregressive parameters in the dependent variable and error term, respectively. ε is an idiosyncratic error distributed independently and identically. Under the normality assumption, this can be estimated by the maximum likelihood estimation procedure (e.g., Anselin, 1988; Amaral and Anselin, 2011).[1]

[1] For estimation we applied a STATA command ***spreg*** developed by Drukker, Prucha and Raciborski (2013).

18. For the spatial weighting matrix, inverse distances between two locations *i* and *j* are used. The distance is calculated using the Euclidean distance between the two locations. The intuition is that two locations are more closely related to each other, if they are located closely. This follows Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things (Tobler 1970)."

IV. DATA

19. Our unit of analysis is fokontany, which is the fourth-level of administrative boundaries, following regions, districts, and communes. In Greater Antananarivo, there are 556 fokontany in 4 districts. From the analysis, 8 observations are excluded, of which some data are missing. The summary statistics are shown in (**Table 1**). The average land prices were collected at each fokontany in 2018. The prices vary substantially between MGA 110 and MGA 1.3 million, with an average of about MGA 64,000 or US$18 per m^2. Travel time is estimated using spatial software based on the road network data with road conditions and bus traffic attached (see **Figure 7** above). It takes 42 minutes on average, but from some fokontany, it may take more than an hour and a half.

20. As discussed, the JAI is calculated based on the size of job opportunities at each destination and the travel time between the origin and the destination. To identify and quantify the size of job opportunities, satellite imagery was used. The following areas were considered: Administrative Zone; Commerciale Zone; Industrial Zone; Cultural Facilities; Hotel Buildings; Market Area; and Office Buildings. In total, 1,094 land parcels were identified (**Figure 11**). The size of each parcel of land was measured as a proxy of the number of job opportunities.[2] It differs from 0.007 ha to 37 ha.

[2] This was found to be a good proxy in our case: The measured land area is highly correlated with the number of registered businesses in the same area. Of course, some businesses may employ more people than others even though they occupy the same size of land. In general, however, there is strong correlation between them.

21. As discussed, the population distribution is highly skewed. The fokontany population density differs from 31 to 331,000 per km^2. As locational attributes, travel time to the nearest health facility is calculated (*CSB*). In Antananarivo, in general, people have good accessibility to health care services, but in suburban areas, the accessibility may be poorer (**Figure 12**). In addition, the climatic vulnerability, *VUL*, is measured by the projected changes in travel time to the CBD when a 10-year flood happens, which is essentially assumed to reduce the average speed along affected roads. How much the speed would be reduced depends on flood depth.

22. Available transport space is also measured by the share of road space in total built-up areas, *RD*. It is expected that greater road space would be desirable because traffic congestion might be eased. Moreover, the information is included on whether each fokontany is connected to the commune capital by all-weather roads during the rainy season. In Madagascar, the passability during the rainy season has been a matter of particular concern.

23. The impact of rice fields on land prices is also of particular interest. It is measured by the share of rice fields in the total fokontany land area, *RICE.* In some fokontany, a significant amount of land is used for rice production.

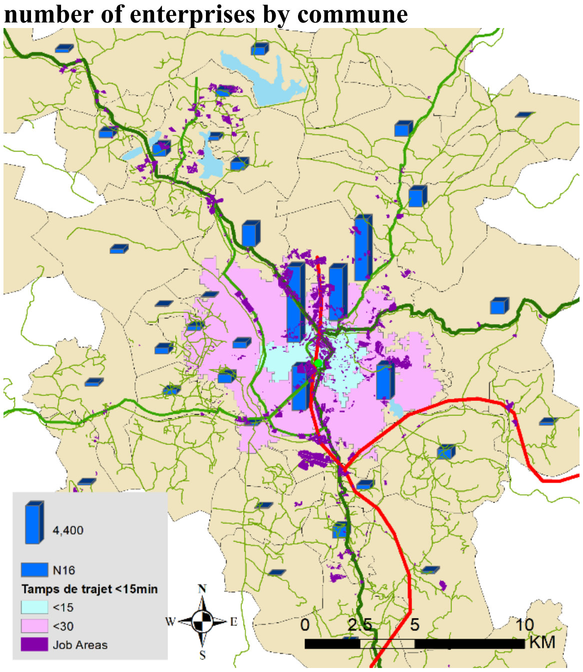
24. Proximity to public transportation is expected to be captured by two dummy variables: *TAXIBE* and *SUBU* are set to unity if there is a taxi-be and suburban bus route within 200m of fokontany (centroid). This threshold of the distance will be relaxed later in the analysis.

Table 1. Summary statistics

Variable	Abb.	Obs	Mean	Std. Dev.	Min	Max
Land price (Ar/m2)	PRIX	548	64,308	172,984	110	1,298,500
Travel time to CBD (minutes)	MIN	548	42.20	21.42	2.41	98.07
Job Access Index (0 to 100)	JAI	548	19.83	11.52	0.01	100.00
Population density (per km2)	POPDEN	548	16,244	30,794	31	331,850
Travel time to the nearest basic health center (minutes)	CSB	548	5.07	4.33	0.002	28.58
Vulnerability (change in travel time to CBD under the flood scenario)	VUL	548	1.20	3.68	0	43.40
Share of road areas in total built up areas	RD	548	0.06	0.05	0	0.36

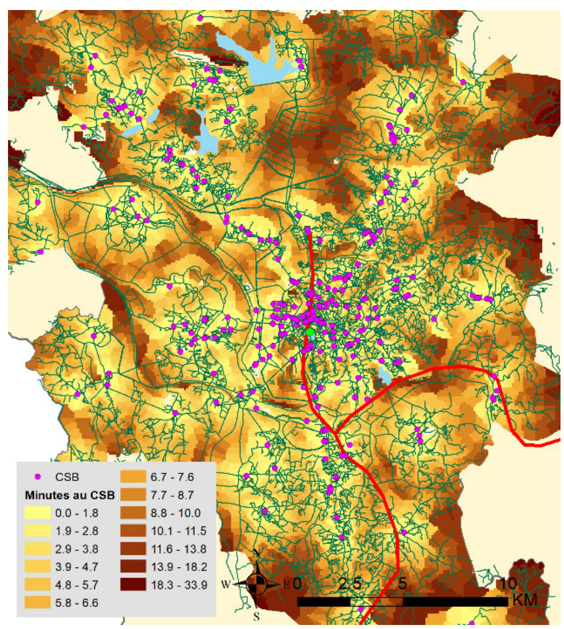
Dummy variable for fokontany which is connected to its commune capital by all-weather road (paved road) during the rainy season	ALLWEARD	548	0.57	0.50	0	1
Share of rice field in total land area	RICE	548	0.20	0.22	0	0.93
Share of amenity areas in total land area	AMENITY	548	0.01	0.04	0	0.36
Dummy variable for fokontany where a city taxi-be route exists within 200m	TAXIBE	548	0.41	0.49	0	1
Dummy variable for fokontany where a suburban bus route exists within 200m	SUBU	548	0.51	0.50	0	1
District dummy:						
Antananarivo Atsimondrano		548	0.28	0.45	0	1
Antananarivo Avaradrano		548	0.20	0.40	0	1
Antananarivo Renivohitra		548	0.35	0.48	0	1
Population density in 2007 (per km2)		548	13,228	19,883	60	187,173
Dummy variable for fokontany where a city taxi-be route exists within 500m	$TAXIBE_{500}$	548	0.55	0.50	0	1
Dummy variable for fokontany where a suburban bus route exists within 500m	$SUBU_{500}$	548	0.81	0.39	0	1
Distance to the nearest taxi-be route (km)	KM_{TAXIBE}	548	1.65	2.45	0	12.70
Distance to the nearest suburban bus route (km)	KM_{SUBU}	548	0.29	0.62	0	5.24

Figure 11. Identified job opportunity areas and number of enterprises by commune



Sources: INSTAT; World Bank estimates.

Figure 12. Estimated travel time to health facilities



Source: World Bank estimates.

V. ESTIMATION RESULTS

25. First, OLS regression is performed (**Table 2**). Although the results may not be unbiased because of the possible autocorrelation across the observations, the estimated coefficients are broadly consistent with our prior expectation: The land prices decrease with the distance from the CBD and increase with the job accessibility. Better connected places tend to be more expensive.

26. To control for the autocorrelation, the spatial autoregressive model is used. The results are shown in **Table 3**. The results are broadly similar, but the spatial autoregressive coefficients, λ and ρ, are both significantly positive, confirming that autocorrelation does matter to our data. Therefore, the OLS results are likely inconsistent. The following discussion is concentrated on the results based on the spatial autoregressive models.

27. As expected, the land value gradient is negative: The coefficient of travel time to the CBD is estimated at -0.402, which is statistically significant. On the other hand, the estimated gradient is also found to be significant when the JAI is used as a connectivity measurement. The coefficient is 0.122, meaning that the land value would increase by 1.2 percent if the job accessibility is improved by 10 percent. When both are included in the model, the travel time variable seems to dominate the JAI.

28. Regardless of whether the connectivity is measured by travel time or JAI, the estimated land price gradients are within the range of the estimates in the literature but look relatively steep. For example, In New York City, the elasticity is estimated at -0.65 to -0.04, depending on the time period. It tends to be declining over time (Atack and Margo, 1998). According to Gedal and Ellen (2018), it is estimated at -0.06 to -0.1. In China, it was estimated at about -0.05 for residential areas and -0.01 for commercial areas (Qin et al., 2016). Policy implications are clear: The land and housing prices in the middle of the city tend to overshoot, pushing the poor away to suburban areas. The housing affordability and the lack of transport connectivity are two important policy issues to be addressed.

29. Road space is found to be an important determinant of land value. The more road space there is, the higher is land value. This is understood to mean that people value transport infrastructure because of less traffic congestion and better mobility, and possibly as an element of spatial amenity. In fact, amenity areas, such as cultural facilities, commercial zones, hotels and restaurants, are preferred: The coefficient of *AMENITY* is significantly positive.

30. All-weather connectivity to the commune capital is also important. The coefficient of *ALLWEARD* is always significantly positive. This is another piece of evidence supporting the importance of transport infrastructure for land values. Access to taxi-be services is also likely to contribute to increase land values. It is interpreted to mean that taxi-be is an essential transport means for people, which is consistent with and reflects the reality in Antananarivo.

31. With respect to other coefficients, not surprisingly, flood-prone areas are undesirable: The vulnerability has a negative impact on land prices. The coefficient is found to be always significantly negative. On the other hand, the impact of rice fields looks inconclusive. The coefficient is found to be negative as expected, but statistically insignificant. Thus, the land prices may be underestimated because of the presence of massive rice fields in the city. But further investigation is needed to determine the implication of possible changes in land use.

Table 2. OLS estimation results

	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
ln*MIN*	-0.314	(0.118) ***			-0.283	(0.134) **
ln*JAI*			0.131	(0.048) ***	0.063	(0.063)
ln*POPDEN*	0.111	(0.034) ***	0.123	(0.032) ***	0.101	(0.034) ***
ln*CSB*	-0.049	(0.036)	-0.045	(0.037)	-0.046	(0.037)
VUL	-0.048	(0.007) ***	-0.047	(0.007) ***	-0.048	(0.007) ***
RD	2.923	(0.717) ***	3.086	(0.774) ***	2.852	(0.717) ***
ALLWEARD	0.214	(0.072) ***	0.249	(0.065) ***	0.209	(0.071) ***
RICE	-0.121	(0.153)	-0.168	(0.160)	-0.158	(0.157)
AMENITY	2.270	(1.388) *	2.731	(1.489) *	2.312	(1.392) *
TAXIBE	-0.004	(0.082)	0.019	(0.084)	-0.012	(0.083)
SUBU	-0.003	(0.069)	-0.030	(0.070)	-0.010	(0.070)
Constant	9.408	(0.659) ***	7.719	(0.279) ***	9.209	(0.759) ***

Obs.	548	548	548
No. of district dummies	3	3	3
R-squared	0.674	0.670	0.675
F-statistic	76.31	74.82	70.99

Table 3. Spatial autoregressive estimation results

	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
ln*MIN*	-0.402	(0.131) ***			-0.329	(0.141) **
ln*JAI*			0.122	(0.061) **	0.093	(0.067)
ln*POPDEN*	0.044	(0.030)	0.034	(0.030)	0.036	(0.030)
ln*CSB*	-0.037	(0.028)	-0.034	(0.028)	-0.033	(0.028)
VUL	-0.024	(0.008) ***	-0.022	(0.008) ***	-0.024	(0.008) ***
RD	1.8208	0.562 ***	1.8744	0.5598 ***	1.7532	0.5632 ***
ALLWEARD	0.189	(0.070) ***	0.171	(0.070) **	0.180	(0.070) **
RICE	-0.151	(0.159)	-0.220	(0.158)	-0.184	(0.160)
AMENITY	1.271	(0.787) *	1.707	(0.782) **	1.283	(0.786) *
TAXIBE	0.187	(0.087) **	0.169	(0.087) *	0.182	(0.087) **
SUBU	-0.034	(0.058)	-0.039	(0.059)	-0.041	(0.059)
Constant	1.509	(2.051)	-12.508	(2.634) ***	1.254	(2.216)
Obs.	548		548		548	
No. of district dummies	3		3		3	
Wald chi2	181.15		164.45		184.97	
Spatial parameters:						
λ	0.801	(0.193) ***	2.010	(0.260) ***	0.783	(0.210) ***
ρ	2.772	(0.123) ***	2.416	(0.054) ***	2.786	(0.125) ***

VI. DISCUSSION

32. One may be concerned about the robustness of the above estimation results. In particular, the definition of bus service access was an ad hoc assumption in the above. To address this issue, the accessibility to bus services was redefined using a different threshold, i.e., 500 meters. The results are shown in the first two columns of **Table 4**. The statistical significance associated with access to taxi-be routes disappeared, while the rest of the coefficients remain broadly unchanged. It can be understood to mean that the close proximity to taxi-be services is particularly important to local people. The 500-meter distance seems too long, suggesting that an extensive bus network needs to be developed to meet the people's needs, which are reflected in the observed land values.

33. In addition, the bus access variables can be replaced with the direct measurements of the distance to a bus route. The results are presented in the last two columns of the table. Both distance variables are found to have negative coefficients as expected. That is, as one moves away from a bus route, the land value would likely decline. But there is no statistical significance, except for one: In the last column model, the land value is found to decrease significantly with the distance to the nearest taxi-be route. The coefficient is estimated at -0.038, meaning that a 10 percent increase in distance to taxi-be routes would reduce the land price by about 0.4 percent. All the indications are that the proximity to bus services is an important element of land value in Antananarivo.

Table 4. Spatial autoregressive models with alternative bus accessibility variables

	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
ln*MIN*	-0.062	(0.133)			-0.350	(0.124) ***		
ln*JAI*			0.106	(0.064) *			0.094	(0.065)
ln*POPDEN*	0.029	(0.030)	0.033	(0.030)	0.021	(0.030)	0.029	(0.030)
ln*CSB*	-0.040	(0.028)	-0.031	(0.028)	-0.033	(0.028)	-0.032	(0.028)
VUL	-0.023	(0.008) ***	-0.023	(0.008) ***	-0.024	(0.008) ***	-0.023	(0.008) ***
RD	1.8513	0.5606 ***	1.8443	0.555 ***	1.7186	0.5552 ***	1.7953	0.5565 ***
ALLWEARD	0.137	(0.069) **	0.163	(0.068) **	0.145	(0.071) **	0.143	(0.071) **
RICE	-0.076	(0.162)	-0.183	(0.160)	-0.230	(0.157)	-0.198	(0.160)
AMENITY	1.476	(0.784) *	1.810	(0.777) **	1.635	(0.784) **	1.859	(0.779) **
$TAXIBE_{500}$	0.087	(0.101)	0.116	(0.097)				
$SUBU_{500}$	0.084	(0.078)	0.067	(0.079)				
$\ln KM_{TAXIBE}$					-0.034	(0.022)	-0.038	(0.023) *
$\ln KM_{SUBU}$					-0.014	(0.016)	-0.012	(0.016)
Constant	-2.756	(1.431) *	-11.519	(3.115) ***	-9.968	(2.926) ***	-11.281	(3.148) ***
Obs.	548		548		548		548	
No. of district dummies	3		3		3		3	
Wald chi2	134.05		165.52		169.57		167.12	
Spatial parameters:								
λ	1.132	(0.124) ***	1.909	(0.306) ***	1.922	(0.276) ***	1.896	(0.309) ***
ρ	3.406	(0.178) ***	2.673	(0.098) ***	2.424	(0.047) ***	2.678	(0.097) ***

34. Another matter of concern may be endogeneity. Especially, people's locational choice is potentially endogenous with land prices. While the land prices increase where many people move in, people may refrain from living in the places where land prices are high. Thus, the

population density could be correlated with the error term in the equation. To test this possibility, the spatial autoregressive instrumental variable (SPIV) model was performed. Taking advantage of lagged variables is one approach. The population density in 2007 is used as an instrument in this model.

35. As shown in **Table 5**, the results are broadly unchanged. The Hausman endogeneity test statistics indicate that the SPIV models are better. The test statistics are estimated at 8.68 and 16.51, which can reject the hypothesis of no autocorrelation. Based on the SPIV estimation, the land prices are found to decrease with the accessibility to jobs (JAI). The elasticity is 0.108. The other coefficients are broadly similar to the above results: The access to taxi-be is important. Road infrastructure and all-weather road connectivity are also found to be essential. While proximity to amenity zones is appreciated, the areas that are vulnerable to flood are not preferred.

Table 5. Spatial autoregressive IV estimation results

	Coef.	Std.Err.		Coef.	Std.Err.	
ln*MIN*	-0.131	(0.132)				
ln*JAI*				0.108	(0.065)	*
ln$POPDEN_{07}$	0.063	(0.037)	*	0.049	(0.037)	
ln*CSB*	-0.031	(0.029)		-0.030	(0.029)	
VUL	-0.025	(0.008)	***	-0.024	(0.008)	***
RD	1.911	0.5694	***	1.848	0.5678	***
ALLWEARD	0.149	(0.071)	**	0.152	(0.071)	**
RICE	-0.019	(0.163)		-0.080	(0.164)	
AMENITY	1.552	(0.782)	**	1.558	(0.771)	**
TAXIBE	0.142	(0.087)	*	0.157	(0.087)	*
SUBU	-0.027	(0.059)		-0.037	(0.059)	
Constant	6.938	(3.825)	*	5.152	(3.222)	
Obs.	548			548		
No. of district dummies	3			3		
Wald chi2	139.05			142.39		
Spatial parameters:						
λ	0.187	(0.356)		0.290	(0.329)	
ρ	3.549	(0.708)	***	3.453	(0.746)	***
Hausman endogeneity test:						
Chi2 test statistic	8.680			16.510		

VII. CONCLUSION

36. Understanding how land prices are determined is of particular importance for policy makers; however, there is little evidence in the developing world, particularly in Africa. Many African countries are currently experiencing very rapid urbanization. The paper examined the relationship between land prices and locational characteristics using data from Antananarivo, the capital of Madagascar, where over 2.6 million people live.

37. It was found that the land prices in Antananarivo are much elevated in the center of the city and taper off quickly toward suburban areas. Since spatial data, such as land prices, are normally autocorrelated, the spatial autoregressive model was applied. The land value gradients were found to be relatively steep. The elasticity is -0.402 with respect to travel time to the CBD and 0.122 with respect to the accessibility to jobs, i.e., JAI. This confirms the facts that the land and housing prices in the middle of the city overshoot and push the poor away from the city to suburban areas, because they are not affordable.

38. The results also indicate that transport infrastructure and services, such as taxi-be and suburban bus systems, are underdeveloped, restricting people's mobility. With wider suburban development, the land price gradients would be less steep. In particular, our estimation results suggest that an extensive bus network needs to be developed to meet the people's needs. The proximity to taxi-be services was always found to be an important determinant of land value in Antananarivo.

39. Not only transport connectivity but also other factors, such as proximity to amenities and administrative centers, were also found to be important to determine the land values. The climate vulnerability also has a negative impact on land prices. These elements cannot be ignored to stimulate urban development in Antananarivo. On the other hand, the impact of rice fields looks inconclusive.

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