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Spatial distributions of job accessibility, housing rents, and poverty: The case of Nairobi

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A B S T R A C T

The inter-connectedness of workers' residential locations and job opportunities is a key determinant of labor market outcomes. This study provides an analysis of the spatial distributions of job accessibility, housing rents, and poverty in a large African city. In Nairobi, Kenya, workers and jobs are not well connected: On average, residents can access fewer than 10 percent of existing jobs by foot within an hour. Even using a minibus, they can reach only about a quarter of jobs. This study further demonstrates that poorer households and residents living in informal settlements are even more limited. Living closer to job opportunities is costly in Nairobi. Not only are housing quality and living conditions frequently better in such areas, but the high value placed on job accessibility also makes these areas more expensive. This severely affects the residential location choices of low-income households.

1. Introduction

Job accessibility is a key determinant of not only the productivity of labor forces in cities but also their welfare and poverty. While the concept and measurement of accessibility are not straightforward (see Duranton and Guerra 2016), job accessibility is commonly referred to as the number or share of existing job opportunities a city resident can reach within a given amount of time. At the level of an urban area, a low level of job accessibility for city residents can inhibit the productivity gains from agglomeration economies by constraining a better match between jobs and job seekers (Combes and Gobillon 2015; Duranton and Puga 2004). More importantly, limited job accessibility may disproportionally affect the economic performance of disadvantaged workers. In many African cities, numerous people lack affordable and reliable transport and just walk to work (Lall et al., 2017).[1] Low-income households that live farther away from clusters of jobs face higher commuting and job search costs. As the spatial mismatch hypothesis posits (see a review by Gobillon and Selod 2014), low levels of job accessibility could make them even poorer by limiting their employment outcomes.

However, which city residents face limited access to job opportunities depends on a variety of factors, such as the shape of the city, the clustering patterns of employment, the function of housing markets, and transport networks. For example, low-income households may live in inner-city informal settlements by prioritizing their proximity to job opportunities over more desirable living conditions, thus incurring environmental and health risks due to overcrowding and inadequate access to basic services. Living near clusters of jobs may be particularly important for the urban poor, who often engage in multiple temporary and casual jobs. However, the long-term influence of unfavorable living conditions on their well-being is a concern. Thus, it is imperative to empirically assess who suffers from limited job accessibility and whether choosing to live in informal settlements offers better job accessibility to low-income populations in exchange for poor living conditions. In a

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[1] In the United States, the poor live in central cities with better access to public transport (Glaeser, Khan, & Rappaport 2008).

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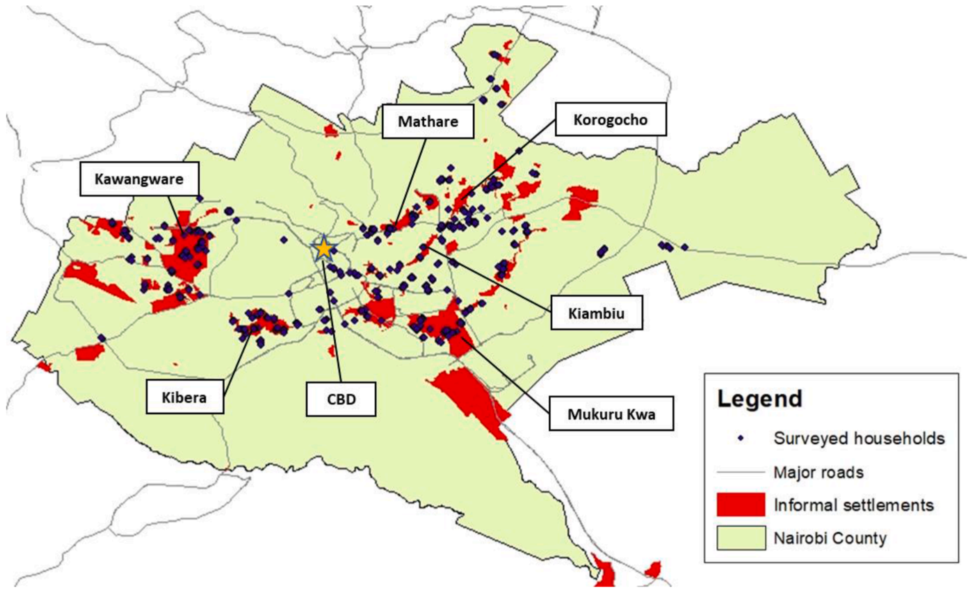

Fig. 1. Map of surveyed households and informal settlements in Nairobi. *Source*: Authors' work based on the Cities Baseline Survey, OpenStreetMaps, and Bird et al. (2017). Note: Only tenants are shown.

worse case, informal settlements provide neither good access to jobs nor a healthy environment, instead creating poverty traps (Marx et al., 2013; Turok and Borel-Saladin 2018).

Unfortunately, empirical evidence on how job accessibility and poverty are linked in African cities is scarce. Such an analysis requires data on (a) the spatial distribution of jobs, (b) transport networks, and (c) housing rents and household consumption. Spatial distribution of jobs is hard to obtain for African cities, given the prevalence of informal jobs. Information about minibus networks, a common transport mode in many African cities, is even more difficult to obtain. Although housing rents and household consumption are usually available in Living Standards Measurement Survey (LSMS)-type household surveys, they are rarely representative of both informal and formal residential areas. By addressing all these data challenges, this paper examines the link between job accessibility and urban poverty in an African city by assessing the spatial distributions of job accessibility, housing rents, and poverty.

Our approach is threefold. First, we assessed the overall level of job accessibility for a city. Our study focuses on Nairobi, Kenya. A relatively monocentric city (Antos et al., 2016; Henderson et al., 2016), Nairobi accommodates more than 1 million residents in informal settlements, most of whom are tenants (KNBS 2012). The severity of the living conditions in Nairobi's informal settlements (particularly Kibera) has been widely documented (for example, Bird et al., 2017). In line with previous studies (for example, Prud'homme, Rémy, and Lee 1999; Peralta-Quirós and Mehndiratta 2015), we measured job accessibility based on the number of jobs accessible within a certain range of travel time from a residence or neighborhood. Second, we investigated who has better or worse job accessibility in Nairobi by focusing on poorer people and residents of informal settlements. The analysis utilizes a recently collected household survey, the Cities Baseline Survey, which is representative of both the formal and informal residential areas in Nairobi. Finally, we analyzed the trade-off Nairobi residents face in selecting residences by examining the link between job accessibility and housing rents in the city. When housing rents are determined in equilibrium in functioning (even informal) housing markets, the rents reflect job accessibility among other characteristics (Rosen 1974). We estimated hedonic regression models to examine the costs of better job accessibility in Nairobi.

Our analysis illustrates how job accessibility is linked to the spatial distributions of housing rents and poverty in Nairobi. We found that Nairobi's average job accessibility is indeed limited. By spending 30 min traveling, Nairobi residents can, on average, reach 2 and 4 percent of existing jobs by foot and minibus, respectively. They can reach 7 and 24 percent of jobs within an hour by foot and minibus, respectively. Given the fact that a large fraction of Nairobi residents—particularly low-income individuals—walk to work, this limited job accessibility must have created considerable inefficiencies in the labor market. Moreover, we found that the job accessibility of poorer households and/or residents of informal settlements is overall worse in Nairobi. Compared to richer households (in the fourth per-capita consumption quartile), poor households (in the first per-capita consumption quartile) can, on average, reach 20 percent fewer jobs by foot within 60 min. Similarly, the number of jobs that residents of informal settlements can reach by foot within 60 min is 30 percent less than residents in formal residential areas. Our hedonic regression analysis demonstrates that it is costly to live in housing with better job accessibility in Nairobi, explaining in part why poorer households have such limited job accessibility.

Our findings illustrate the need to assess and enhance access to economic opportunities for disadvantaged workers in African cities, and Nairobi is a case in point. While the poverty headcount ratio in Nairobi declined from 21 percent in 2005/06 to 17 percent in 2015/16, the number of poor residents slightly increased during this period (KNBS 2018). Despite the overall low poverty rate, nearly 30 percent of residents in informal settlements still remain in poverty (World Bank 2018). More than 20 percent of the poor in Nairobi are unemployed, and about 40 percent of the poor are casual workers. The 2015/16 Kenya Integrated Household Budget Survey (KIHBS) also showed that only 15 percent of the poor use a minibus for commuting, while 70 percent of the poor walk to work. Despite the concentration of poverty, worse living conditions, and limited job accessibility in Nairobi's informal settlements, it is difficult for many residents to pursue living arrangements elsewhere. In such situations, it is critically important to enhance job accessibility to support the poor and/or residents of informal settlements to escape from poverty.

Our research is related to three bodies of literature. First, our work is related to the literature focusing on job accessibility from a perspective of agglomeration economies. Facilitating a better match between firms and workers is, among other channels such as sharing and learning effects, a critical component of agglomeration economies (Duranton and Puga 2004). A body of empirical studies estimated the effects of city size and density on productivity, though most of them focused on developed countries (see Combes and Gobillon 2015 for a review). Limited job

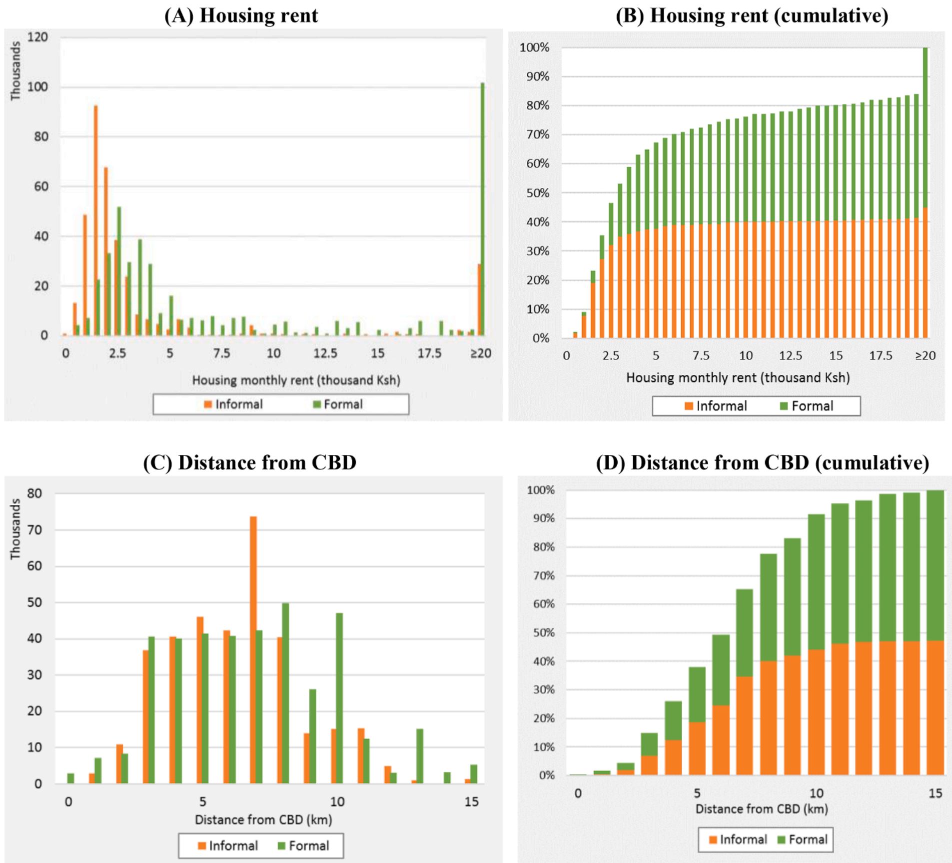

Fig. 2. Distributions of housing rents in Nairobi. Source: Authors' calculation based on CIties Baseline Survey 2013.

accessibility could, however, restrict such benefits of agglomeration economies. Viewing cities as labor markets (Bertaud 2014), studies have assessed accessibility, measured as the number of opportunities an individual can access within a given amount of time, for Buenos Aires (Peralta-Quirós and Mehndiratta 2015), Dakar (Stokenberga 2017), Nairobi (Avner and Lall 2016), and a group of eleven cities in Africa (Peralta-Quirós et al., 2019). We advance the Nairobi study by Avner and Lall (2016) by focusing on accessibility to *jobs* instead of *opportunities* proxied by land use.

A second line of literature our work is aligned with is that on spatial mismatch. Originally developed by Kain (1968) for the racial segregation context in the United States, the spatial mismatch literature argues that unskilled workers who are segregated away from job opportunities tend to be unemployed and have lower wages due to high commuting and job search costs (see a review by Gobillon and Selod 2014). This is relevant to African cities as well. A randomized control trial (RCT) conducted in Addis Ababa, Ethiopia, found that providing a transport subsidy to disadvantaged job seekers increased their chance of finding better jobs (Abebe et al., 2017; Franklin 2018). Analyzing such causal impacts of job accessibility on labor market outcomes must follow detailed assessments of job accessibility for disadvantaged workers. Our study aims to provide such diagnostics of job accessibility among Nairobi residents by paying specific attention to informal settlements.

Finally, our research is related to the literature on hedonic regression analysis for housing prices. The urban land use theory (Alonso 1964; Mills and Hamilton 1995; Muth 1968) explains how the rent gradient over distance from the central business district (CBD) is determined in a monocentric city. In reality, however, jobs are not necessarily concentrated in the CBD. We add to the hedonic regression literature by estimating the link between job accessibility and housing rents, by explicitly including housing in informal residential areas. Various studies have estimated hedonic regression for informal housing in the developing world, including Gulyani et al. (2012) and Marx et al. (2019) for Nairobi and Nakamura (2017) for Pune, India.[2] Atuesta et al. (2018) found a clear link between job accessibility and housing values in Mexico City.

The rest of this paper is structured as follows: Section 2 describes the context about job accessibility challenges in Nairobi. Section 3 discusses the methodology by explaining various data sets and analytical methods employed in this study. Section 4 presents the results on the job accessibility calculated for the city, the levels of job accessibility by different household groups, and hedonic regressions. Section 5 concludes with a brief summary of the findings.

2. Context: spatial challenges in Nairobi

Accommodating 4.4 million people—and an additional 5 million people in the metropolitan area (KNBS 2019)—, Nairobi is one of the largest cities in Sub-Saharan Africa. While the population of the capital city accounts for less than 10 percent of the national population, its economy is estimated to contribute to more than 20 percent of the national gross domestic product (GDP) (Bundervoet et al., 2015). In addition to its vibrant economy, Nairobi is known for the proliferation of informal settlements, accommodating more than 1 million people (Fig. 1). The Kenya National Bureau of Statistics (KNBS) defines informal settlements as those "characterized by at least two of the following: inadequate access to safe water; inadequate access to

[2] Some other older studies are Jimenez (1983, Jimenez, 1984); Follain and Jimenez (1985), Kaufmann and Quigley (1987); Friedmann et al., 1988; Daniere (1994), and Malpezzi (1998).

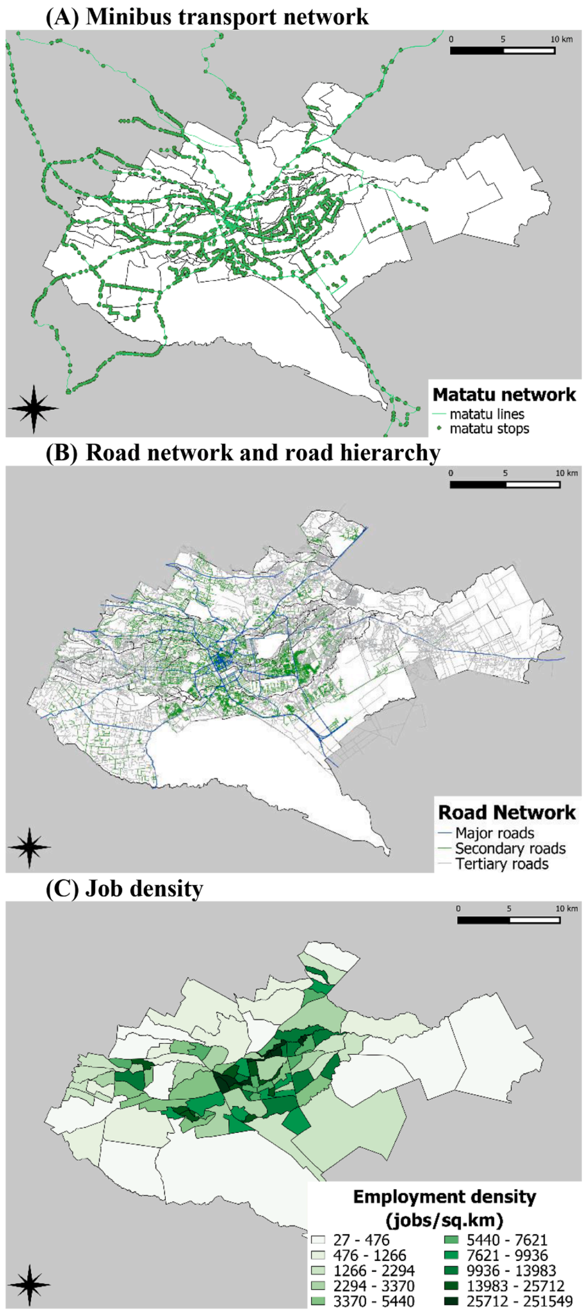

Fig. 3. Transport networks and job distribution in Nairobi. Source: Authors' calculations based on JICA (2013), Digital Matatus Project and OpenStreetMaps.

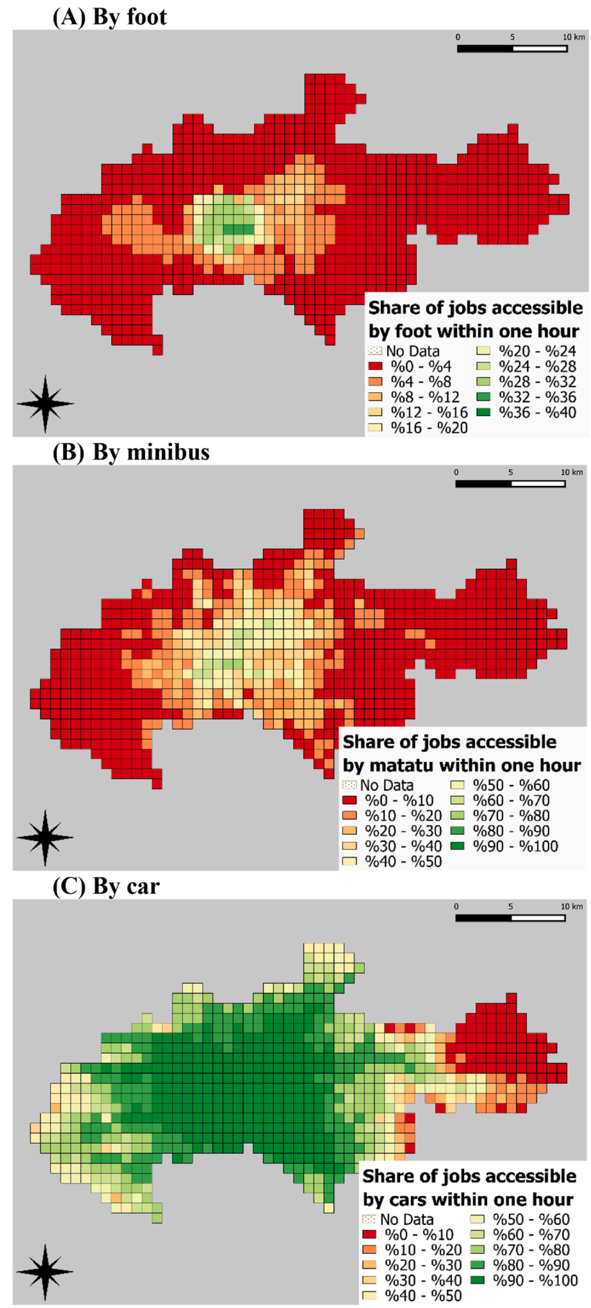

Fig. 4. Share of accessible jobs within 60 min. Source: Authors' calculation based on JICA (2013), Digital Matatus Project, and OpenStreetMaps.

sanitation and other infrastructure; poor structural quality of housing; overcrowding and insecure residential status" (KNBS 2012, 4 – 5).[3]

Collected surveys are used to grasp spatial challenges in Nairobi. Most Nairobi residents are rent-paying tenants, and low-cost rental units are mainly located in informal residential areas. According to the Cities Baseline Survey (explained in Section 3), the distribution of housing rents in Nairobi is skewed with a small group of very high rents (Panels A and B in Fig. 2). The average housing rent among the surveyed rental units is K Sh 5315.[4,5] A quarter of the rental units have a rent lower than K Sh 1800, half the rental units have rents less than K Sh 2500, and 75 percent of the rental units have rents less than K Sh 4400. About 10 percent of the units have very high rents (more than K Sh 30,000). The mean rent value in informal settlements (K Sh 3600) is less than half of that in formal residential areas (K Sh 9000), and the majority of cheap rental units (less than K Sh 2500) in the city are located in informal residential areas.

As reflected in the rent gap, there is a stark contrast in housing quality and living conditions between formal and informal residential

[3] The number of residents in Nairobi's informal settlements varies depending on the sources used to measure the population, and it is possible that the 2009 Census undercounted them. Even the population count of Kibera, the largest informal settlement in Nairobi, ranges from 170,070 to 270,000 (Lucci, Bhatkal, and Khan 2018).

[4] The housing rents used in this study include utilities.

[5] K Sh 5,315 was roughly equivalent to US$61 as in 2013.

Table 1
Household and housing characteristics in Nairobi (only tenants).

	Consumption quartile				Informal area	
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Yes (5)	No (6)
Household characteristics						
Living in informal neighborhood (%)	62.6	49.2	40.8	34.8	100.0	0.0
Per capita monthly expenditure (K Sh)	2,351	4,505	7,419	18,046	6,560	9,405
Age of household head	34.5	34.0	33.4	33.3	32.7	34.7
Years of household head's education	11.1	11.4	12.4	14.8	11.0	13.7
Household size	3.9	3.1	2.6	2.2	2.8	3.1
Travel time to work (one way, in minutes)	31.7	30.7	33.7	29.0	28.6	33.6
Commute by foot (%)	39.3	29.8	31.9	28.2	40.9	24.8
Commute by minibus (%)	43.4	53.4	51.3	50.3	41.0	57.1
Housing characteristics						
Housing rent (K Sh)	2,409	3,391	5,803	14,342	3,609	8,995
Written tenancy agreement (%)	8.1	14.7	31.2	52.7	14.0	37.9
Floor area (m^2)	16.36	16.57	22.06	24.35	16.71	22.49
Wall: stone/brick/block (%)	38.8	57.3	64.9	82.9	25.0	92.7
Wall: corrugated iron sheet (%)	47.6	32.2	29.2	11.6	56.9	6.1
Wall: mud/wood (%)	13.6	10.5	5.9	5.4	18.0	1.2
Roof: corrugated iron sheet (%)	92.0	89.1	82.3	66.0	92.9	73.2
Roof: clay tiles (%)	1.6	3.3	7.5	23.7	4.2	13.2
Roof: concrete (%)	6.5	7.6	10.1	10.3	2.9	13.6
Floor: earth/clay (%)	8.2	5.7	5.1	3.9	11.6	0.7
Floor: tiles (%)	0.0	1.6	5.4	28.2	4.8	12.2
Floor: cement (%)	91.8	92.7	89.5	68.0	83.5	87.1
Water: piped inside (%)	0.9	4.0	11.0	17.2	3.2	12.7
Water: piped outside (%)	1.7	3.4	6.5	10.2	3.7	6.9
Water: shared tap (%)	40.3	50.2	48.2	50.6	28.1	64.3
Water: other (%)	57.1	42.5	34.4	22.1	65.0	16.1
Toilet: flush inside (%)	2.3	11.8	25.4	51.6	9.3	34.6
Toilet: flush/VIP latrine outside (%)	27.8	35.8	29.1	20.6	16.7	38.5
Toilet: private pit latrine (%)	14.7	8.7	11.8	4.7	16.0	4.7
Toilet: shared toilet (%)	53.8	43.1	33.3	22.8	57.1	21.9
Toilet: other (%)	1.3	0.7	0.3	0.2	0.9	0.3
Electricity (%)	74.2	80.9	83.7	93.2	69.8	94.4
Garbage dump as problem (%)	52.1	47.4	42.9	27.7	60.6	26.7
Factory as problem (%)	12.4	5.9	10.1	9.8	14.0	5.5
Secure (%)	55.7	55.9	64.1	74.1	51.6	72.1
Bus stop within 500 m (%)	71.1	75.6	77.5	83.2	65.8	85.9

areas. Most dwellings in Nairobi are structured with walls made of either stone/brick/block (52 percent) or corrugated iron sheet (35 percent) (Table 1 and A1 in Appendix). About 93 percent of the dwellings in formal residential areas have walls made of stone/brick/block, while only 25 percent of informal dwellings have such walls. Nearly 20 percent of the units in the city have no access to electricity, which is a very low standard even compared with other African cities.[6] About 94 percent of the dwellings in formal residential areas have electricity in Nairobi, whereas only 70 percent of informal housing has electricity. Security is also a big concern in Nairobi: 40 percent of surveyed households report security as a problem in their neighborhoods. Residents in informal settlements are more likely to worry about security (50 percent) than residents of formal residential areas (30 percent). With respect to environmental hazards, 47 percent of households report a garbage dump in their neighborhood as a problem. As expected, a larger proportion of residents in informal settlements face such problems (60 percent).

Due to the limited availability of affordable transport, a large fraction of people—particularly in informal neighborhoods—walk to work in Nairobi. Most rental units are located within 3 – 12 km from the CBD, with some agglomerations of informal settlements.[7] Informal and formal housing are equally distributed within 5 km from the CBD, while a large informal area (Kibera slum) exists around 6 – 7 km from the CBD (Panels C and D in Fig. 2). Most informal houses are located within 10 km from the CBD.[8] Given such a spatial distribution of residences, 35 percent of the heads of household walk to work, while 43 percent use minibuses for commuting.[9] Under 10 percent commute using their own car in Nairobi. The share of the heads of household walking to work is larger in informal settlements (41 percent) than in formal residential areas (25 percent), reflecting income gaps between those areas (Table 1).[10] In addition, even getting to a bus stop itself takes more time in informal residential areas. A larger proportion of housing is located more than 500 m away from the nearest bus stop in informal settlements (34 percent) than in formal residential areas (only 14 percent).

To understand the trade-off faced by households in their residential choices, a detailed spatial diagnostic is necessary. Job accessibility for a housing depends on the distance from job clusters and the availability of transport. If housing rents are determined in the market by not only the dwelling and neighborhood characteristics but also the level of job accessibility, households face a trade-off in their residential choices. The existing stock of housing with good job accessibility may be scarce in a not-well-connected city like Nairobi, thus it can be expensive to live in such housing. Some may have to sacrifice living conditions to live in proximity to job opportunities, given the importance of job accessibility in their labor performance. Low-income households could particularly face a challenge to access job opportunities if low-rent residences in informal settlements do not offer reasonable job accessibility. Therefore, it is critically important to investigate the spatial distribution of job accessibility in the city and its relationship to spatial distribution of poverty (or households in different income groups) and housing rents.

3. Methodology

3.1. Data

3.1.1. Transport

To calculate job accessibility in Nairobi, it is necessary to account for various transportation modes: walking, driving and using the semi-formal minibus (matatus) network. Data for the 'minibus network' travel times are available online in the General Transit Feed

[6] For example, more than 95 percent of houses in the slums of Greater Accra (Ghana) and Addis Ababa (Ethiopia) have access to electricity (Nakamura and Yoshida 2018).

[7] Distance from the CBD is measured based on the Euclidian distance without considering road networks. We also carried out all the analyses using network distance from the CBD and obtained similar results (not reported).

[8] Other major informal settlements, such as Kiambiu and Mathare, are 5km from the CBD. Mukuru Kwa, Korogocho, and Kawangware are around 9km away from the CBD.

[9] According to the 2015/16 KIHBS, 39 percent of Nairobi residents walk to work, and 38 percent of workers use minibuses for commuting. Private cars account for only 5 percent. Walking is the main commuting mode for the poor (75 percent), followed by minibus (15 percent).

[10] The distributions of commuting time do not substantially differ between informal and formal residential areas. In Nairobi, most households spend less than 1 hour on commuting (one way). Half of the heads of the household in Nairobi spend 30 minutes or less getting to their workplaces. No substantial difference is observed in the mean commuting time among households with different consumption quartiles and within/outside informal residential areas.

Table 2
Average shares of accessible jobs in Nairobi.

	Nairobi Walking (1)	Nairobi Minibus (2)	Nairobi Cars (3)	Dakar Transit	Buenos Aires Transit	Lusaka Transit	Dar Es Salaam Transit	Douala Transit
Within 30 min	1.8%	3.9%	43.7%		7%			
Within 45 min	4.0%	10.8%	71.8%		18%			
Within 60 min	7.3%	23.9%	88.7%	52.0%	34%	34.1%	12.2%	39%

Note: Numbers are the average share of jobs in the city that the Nairobi residents can reach by foot (column 1), minibus (column 2), and car (column 3) within 30, 45, and 60 min. Figures for Dakar and Buenos are borrowed from Stokenberga (2017) and Peralta-Quirós (2015) respectively. Figures for Lusaka, Dar Es Salaam and Douala come from Peralta-Quirós et al. (2019).

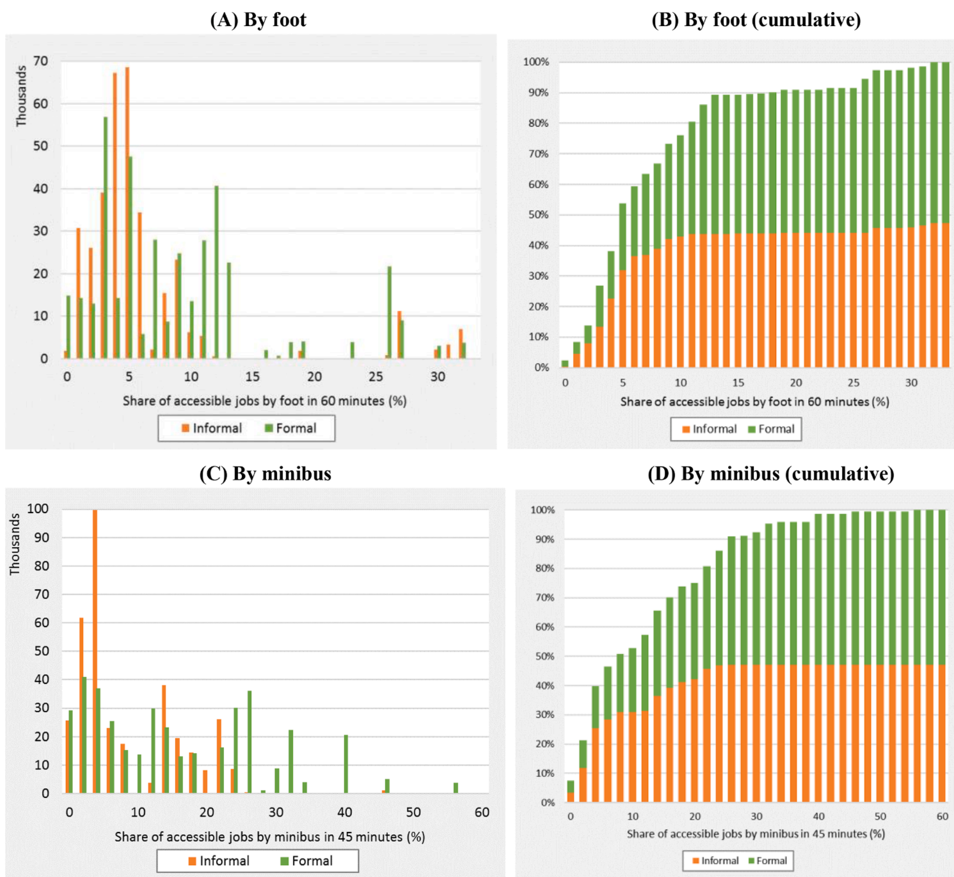

Fig. 5. Distribution of job accessibility in Nairobi. Source: Authors' calculation based on the Cities Baseline Survey, JICA (2013), Digital Matatus Project, and OpenStreetMap.

Specification (GTFS) format (see Panel A of Figure 3 for the minibus network).[11] These data were compiled by the Digital Matatus consortium comprising University of Nairobi, Columbia University, Massachusetts Institute of Technology, and Groupshot (Klopp et al., 2015; Williams et al., 2015). The GTFS data were processed using a Dijkstra algorithm, which provided times to reach any minibus station from any other in the urban area.[12] Travel times to reach the closest minibus station were computed based on a straight-line distance or 'as the crow flies' from the center of each grid cell.

The transport times for cars were computed through a network analysis using the road layers provided by OpenStreetMap (Panel B of Figure 3). Three different travel speeds were assumed based on the road category. Taking congestion into consideration, first-class roads carry vehicles traveling at 30 km/h, second-class roads at 16 km/h, and third-class roads at 12 km/h. These speed assumptions for the road network are broadly consistent with congestion figures reported in the Kenya Urbanization Review (World Bank 2016). Finally, walking times were

Table 3
JAI by consumption quartile and informal status.

	Consumption quartile				Informal area	
	Q1 (1)	Q2 (2)	Q3 (3)	Q4 (4)	Yes (5)	No (6)
Distance from the CBD (km)	7.3	7.1	7.4	6.8	6.8	7.5
Share of accessible jobs by foot in 60 min (%)	7.8	8.7	8.5	9.6	7.0	10.0
Share of accessible jobs by minibus in 45 min (%)	11.8	13.3	13.6	15.7	9.6	17.1

[11] GTFS data are a common format for public transportation schedules and associated geographic information. They are a collection of multiple comma-separated values (csv) files that describe transit routes, stops (including geographic coordinates), travel times between stops, and a number of other public transit properties.
[12] Dijkstra's algorithm is an algorithm for finding the shortest path between two nodes in a graph that may represent, for example, road networks.

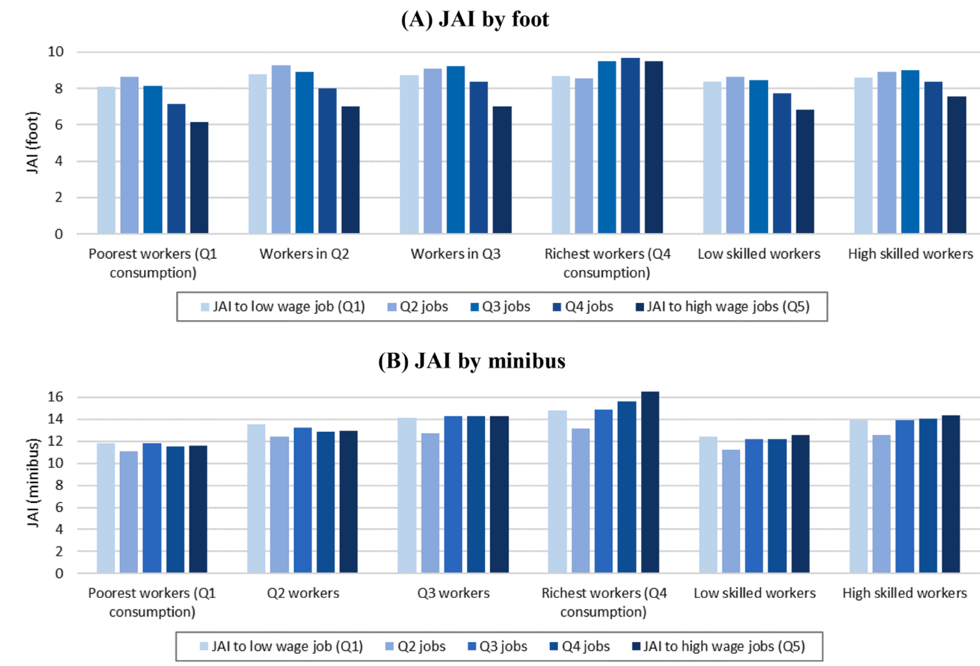

Fig. 6. JAI of different wage levels to different workers. Note: Only working-age populations are included in the analysis. Source: Authors' calculation based on the Cities Baseline Survey, JICA (2013), Digital Matatus Project, and OpenStreetMap.

calculated using the road network assuming an average walking speed of 4 km/h for all road links, irrespective of their class.

3.1.2. Jobs

The information about the volume and distribution of jobs is extracted from the Japan International Cooperation Agency (JICA) personal travel survey conducted in 2013 (JICA 2013). The JICA personal trip survey asked 38,000 persons in 10,000 households a number of questions about their mobility behaviors and employment status. The sampling was prepared based on 106 traffic zones to make the information represent Nairobi County. Among these questions were the status of occupation of the respondent, the sector of employment, and the approximate location of the employment at the census sublocation level within Nairobi County. Population counts were also provided through the personal travel survey at the census zone level. The job density pattern at the census zone level is represented in Panel (C) of Figure 3.

Given that the census zones range from 0.12 km^2 to 58.5 km^2, and the transportation data have a high resolution, an effort was made to achieve a more disaggregated distribution of jobs and people. The finer grain distribution was obtained by using a grid constituted of 1 km^2 grid cells. Population and jobs were attributed to each grid cell in proportion to the land area intersected with census zones. The underlying assumption is that population and jobs are homogeneously distributed over census zones.

3.1.3. Housing and households

The data used for the locations and characteristics of housing and households are from the Cities Baseline Survey, which were collected in 15 Kenyan cities in 2013. The survey used a two- or three-stage stratified cluster sampling design intended to be representative of poor and non-poor households living in formal and informal settlements within each municipality.[13] The first-stage sampling frame was based on the 2009 census frame of enumeration areas (EAs). In the census sample frame, EAs are identified as urban, peri-urban, or rural. EAs are further identified as containing formal or informal settlement types. For the first-stage sampling, EAs were selected from strata identified as informal, urban-formal, peri-urban-formal, and rural. The second stage involved a random selection of households from each selected EA. A fixed number of households from each selected EA was drawn, irrespective of EA size. Main data collection was conducted between July 17, 2012, and March 14, 2013.

A total of 1182 households (582 in informal areas and 600 in formal areas) were surveyed for Nairobi. According to geocoded information, 989 households are rent-paying tenants (551 tenants in informal areas and 438 tenants in formal areas). In the data, informal and formal residential areas were categorized adopting the 2009 census framework. Table 1 reports household and housing characteristics by per capita consumption quartiles and informal status of their neighborhoods (see Table A1 for detailed summary statistics). Table A2 in Appendix A reports summary statistics for rental units in the city.

3.2. Methods

3.2.1. Job accessibility at the city level

We used an urban accessibility metric to measure job accessibility in Nairobi, in line with the recent literature (for example, Avner and Lall 2016; Peralta-Quirós and Mehndiratta 2015; Stewart and Zegras 2016; Peralta-Quirós et al., 2019). The model counts the number of reachable opportunities within a travel time isochrone. The most commonly used accessibility indicator is the share of opportunities that can be reached within a given time threshold. This normative choice has been recognized as meaningful (Bertaud 2014), although necessarily imperfect. The accessibility metrics, the job accessibility index (JAI), can be described by the following:

$$JAI_i = \frac{\sum_j O_j * (t_{ij} < \bar{t})}{\sum_j O_j}. \tag{1}$$

where JAI_i is the accessibility indicator for location i, O_j represents the number of opportunities in location j, t_{ij} is the travel time between location i and location j and $\bar{t}$ is a time threshold. $(t_{ij} < \bar{t})$ in the

[13] Nairobi, Mombasa, Kisumu, Nakuru, Eldoret, Malindi, Naivasha, Kitui, Machakos, Thika, Nyeri, Garissa, Kericho, Kakamega, and Embu. See NORC 2013 and World Bank (2016) for details.

Table 4
Estimation results of hedonic regression models (OLS).

	JAI = Distance from CBD		JAI = Share of accessible jobs by foot		JAI = Share of accessible jobs by minibus	
	(1)	(2)	(3)	(4)	(5)	(6)
JAI	−0.014**	−0.186***	0.008***	−0.037	−0.000	−0.022
	(0.006)	(0.060)	(0.002)	(0.025)	(0.002)	(0.014)
JAI squared		0.018***		0.004**		0.001
		(0.007)		(0.002)		(0.001)
JAI cubed		−0.0005**		−0.00008**		−0.00001
		(0.0002)		(0.00004)		(0.00001)
Informal neighborhood	−0.033	−0.028	−0.024	−0.014	−0.049	−0.049
	(0.047)	(0.048)	(0.051)	(0.052)	(0.051)	(0.051)
Written agreement	0.147**	0.160**	0.135**	0.150**	0.134**	0.143**
	(0.062)	(0.062)	(0.063)	(0.062)	(0.064)	(0.065)
Floor area	6.704***	6.182***	6.606***	6.401***	6.426***	6.156***
	(2.073)	(2.005)	(2.164)	(2.149)	(2.180)	(2.180)
Floor area squared	−21.90***	−20.23***	−21.44***	−21.10***	−21.62***	−21.02***
	(8.003)	(7.713)	(7.972)	(8.054)	(8.025)	(8.002)
Wall [base: stone/brick/block]						
Corrugated iron sheet	−0.195***	−0.183***	−0.185***	−0.177***	−0.183***	−0.175***
	(0.048)	(0.050)	(0.049)	(0.051)	(0.048)	(0.048)
Mud/Wood	−0.299***	−0.286***	−0.278***	−0.274***	−0.275***	−0.256***
	(0.067)	(0.069)	(0.066)	(0.068)	(0.064)	(0.068)
Roof [base: corrugated iron sheet]						
Clay tiles	0.194	0.178	0.194	0.174	0.196	0.208
	(0.131)	(0.131)	(0.127)	(0.124)	(0.129)	(0.128)
Concrete	0.078	0.082	0.084	0.090	0.069	0.082
	(0.068)	(0.068)	(0.070)	(0.069)	(0.071)	(0.071)
Floor [base: earth/clay]						
Tiles	1.134***	1.164***	1.191***	1.207***	1.180***	1.159***
	(0.146)	(0.145)	(0.158)	(0.159)	(0.157)	(0.155)
Cement	0.356***	0.388***	0.347***	0.343***	0.345***	0.321***
	(0.056)	(0.058)	(0.060)	(0.061)	(0.059)	(0.063)
Water [base: other]						
Piped inside	0.125	0.126	0.142	0.146	0.128	0.137
	(0.134)	(0.135)	(0.136)	(0.129)	(0.138)	(0.135)
Piped outside	0.325***	0.333***	0.311***	0.314***	0.298***	0.298***
	(0.113)	(0.113)	(0.114)	(0.111)	(0.115)	(0.113)
Shared tap	0.145***	0.153***	0.144***	0.140***	0.137***	0.138***
	(0.037)	(0.038)	(0.039)	(0.041)	(0.038)	(0.039)
Toilet [base: private pit latrine]						
Flush toilet (inside)	0.835***	0.884***	0.864***	0.871***	0.844***	0.844***
	(0.120)	(0.120)	(0.124)	(0.125)	(0.132)	(0.132)
Flush toilet/VIP latrine (outside)	0.009	0.050	0.010	0.033	−0.004	0.017
	(0.051)	(0.053)	(0.055)	(0.056)	(0.057)	(0.057)
Electricity	0.357***	0.355***	0.378***	0.375***	0.373***	0.371***
	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)	(0.032)
Garbage dump	−0.067*	−0.055	−0.079**	−0.077**	−0.065*	−0.053
	(0.037)	(0.038)	(0.037)	(0.039)	(0.038)	(0.038)
Factory	−0.112**	−0.094*	−0.088	−0.071	−0.098*	−0.075
	(0.054)	(0.055)	(0.055)	(0.057)	(0.055)	(0.057)
Secure	0.046	0.045	0.038	0.038	0.042	0.038
	(0.030)	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)
Bus stop within 500 m	0.086**	0.070*	0.036	0.038	0.067	0.072*
	(0.037)	(0.037)	(0.042)	(0.041)	(0.041)	(0.040)
F-test (p-value)		0.006		0.108		0.107
Adj-R2	0.778	0.781	0.781	0.782	0.777	0.778
Obs.	980	980	950	950	950	950

Note: Robust standard errors in parentheses. * $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$. Dependent variable is the natural logarithm of monthly housing rents. Housing types and constant terms are not shown. VIP=ventilated improved pit. F-tests compare models with higher order terms of JAIs (columns 2, 4, and 6) to the nested models (columns 1, 3, and 5).

numerator is a test that takes the value of either 0 or 1. In the latter case, opportunities in location j can be reached and are added to the total of reachable opportunities. In the other case, they are assigned the value 0. When averaged over the whole urban area $\overline{JAI}$, localized accessibilities are weighted by population n_i to account for the fact that higher population densities are generally found in areas that benefit from good accessibility.

$$\overline{JAI} = \frac{\sum_i n_i * \left(\sum_j O_j * \left(t_{ij} < \bar{t}\right)\right)}{\sum_i n_i * \sum_j O_j} \tag{2}$$

Furthermore, we compute the accessibility index in Eqs. (1) and (2) for specific jobs. Specifically, we differentiate jobs by their wage levels (quantile) and occupancy types (employer, employee, or self-employed work).

3.2.2. *Job accessibility at the subgroup level*

We also calculated the JAI for different groups of households based on their neighborhood status (informal or formal), consumption quartiles, and education levels. Some previous studies have reported that low-income workers benefitted more from better job accessibility. For example, Norman et al. (2017) found a stronger negative relationship between employment accessibility and unemployment rates among low-educated workers than other workers in Sweden. Another study in

Table 5
Estimation results of hedonic regression models (spatial regressions).

	OLS (1)	GS2SLS-HET (2)	SARAR/ML (3)	SEM (4)
Model 1				
JAI: Distance from CBD	−0.014**	−0.014**	−0.015**	−0.013**
	(0.006)	(0.006)	(0.006)	(0.006)
Model 2				
JAI: Share of accessible jobs by foot	0.008***	0.006**	0.007**	0.006**
	(0.002)	(0.003)	(0.003)	(0.003)
Model 3				
JAI: Share of accessible jobs by minibus	−0.000	−0.002	−0.002	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)

Note: Robust standard errors in parentheses. * $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$. Dependent variable is the natural logarithm of monthly housing rents. Only the coefficient estimates for the JAI are shown. Full results are available upon request.

Table 6
Estimation results of hedonic regression models with accessibility to different types of jobs.

	JAI = Share of accessible jobs by foot				JAI = Share of accessible jobs by minibus			
	All (1)	Employer (2)	Employee (3)	Own-account worker (4)	All (5)	Employer (6)	Employee (7)	Self-employed worker (8)
JAI	0.008***	0.007***	0.008***	0.006**	−0.009*	−0.002	−0.009*	−0.011*
	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
JAI squared					0.000**	0.000	0.000**	0.000
					(0.000)	(0.000)	(0.000)	(0.000)

Note: Robust standard errors in parentheses. * $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$. Dependent variable is the natural logarithm of monthly housing rents.

Sweden by Aslund et al., (2010) found better employment conditions among a group of refugees that had settled in proximity to jobs, compared to other refugees. Nonetheless, it is not clear a priori who benefits from better job accessibility between poor and non-poor households. Richer households may indeed choose to live at a further distance from the CBD and most job clusters, to enjoy larger houses—as is often assumed in the urban economic theory—in exchange for longer commutes. They can, however, compensate for the longer distances with higher commuting speeds if they are equipped with cars and benefit from both good accessibility and larger dwellings. Yet, because only a tiny fraction of people commute by car in Nairobi, even richer people may prioritize living closer to jobs. Poorer people are often constrained to live in informal settlements, so their job accessibility depends on (a) the overall level of job accessibility in informal residential areas compared to formal areas and (b) the variation of job accessibility across informal neighborhoods. Thus, it is worth examining the JAI for different groups.

3.2.3. Hedonic models

In the standard hedonic framework developed by Rosen (1974), the market prices of housing units represent the sum of expenditures in a bundle of characteristics that can be priced separately (see Taylor [2008] for a general introduction of hedonic analysis). Let Z represent a housing bundle with characteristics $Z = z_1, z_2, \dots z_r$. With the consumption on non-housing items C, the utility of household i is written as

$$U^i(\mathrm{C}, \ z_1, z_2, \ \dots z_r; d^i) \tag{3}$$

where d^i is the demographic characteristics of household i. The budget constraint for household i is given as $Y_i = C + P(Z)$, where Y_i is the income of household i, and P is the price schedule for Z determined in an equilibrium. The household seeks to maximize the utility by choosing C and each element of Z such that the following marginal condition is satisfied for each z_j:

$$\frac{\partial P}{\partial z_j} = \frac{\partial U / \partial z_j}{\partial U / \partial C} \tag{4}$$

Given the hedonic framework above, the base hedonic regression model used for this study is an ordinary least squares (OLS) model expressed as follows:

$$\ln(\mathrm{rent}_i) = \alpha + \beta_1 \mathrm{JAI}_i + \beta_2 \mathrm{X}_i + \varepsilon_i \tag{5}$$

where the dependent variable is the natural logarithm of the monthly rent of the i th housing; JAI_i is the JAI for the i th housing; X_i is a vector of structural characteristics, access to services, and neighborhood and environmental factors; and ε_i is a random error. The parameter estimate β_1 indicates the degree of association between the JAI and housing rents after controlling for other observed characteristics in X. The coefficient estimate β_1 can also be interpreted as the Marginal Willingness to Pay for living closer to jobs. We also add squared and cube terms of the JAI to account for non-linearity.

To reduce a bias in the OLS estimation above, we also estimate several spatial regression models. Estimates from OLS-based hedonic regression models can be biased due to spatial dependence and spatial autocorrelation, which motivates the use of spatial econometrics models (Nakamura 2017). We estimated generalized spatial two stage least squares heteroscedasticity models (GSTSLS-HET), developed by Kelejian and Prucha (1999, 2010), which also deal with heteroscedasticity in error terms. As a robustness check, spatial error models (SEM) and spatial autoregressive models with autoregressive disturbances (SARAR) are additionally estimated based on a maximum likelihood (ML) estimator (Anselin 1988; Kelejian and Prucha 1998).[14]

4. Results

4.1. Job accessibility at the city level

Combining information about the distribution of jobs and travel times, we calculate the JAIs in Eq. (2). These accessibility indicators were computed for (a) all jobs and each individual occupation and employment sector, (b) for each travel mode: car, minibus, and pedestrian travel, and (c) for three different time thresholds: 30 min, 45 min, and 60 min. The overall picture is one of higher accessibility levels in the more central areas of the city, regardless of the travel mode. Traveling by car provides significantly higher accessibility levels compared to using a minibus. Finally, traveling by foot considerably limits accessibility to jobs. Figure 4 displays the maps of accessibility levels to all jobs within 60 min when traveling by foot, minibus, and car, respectively.

The average share of accessible opportunities for different time

[14] For the estimations of the spatial econometric models, a spatial weight matrix is constructed based on the inverse distance between each pair of households. The spatial weight matrix is then normalized as each element is divided by the minimum of the largest row sum and column sum of the matrix.

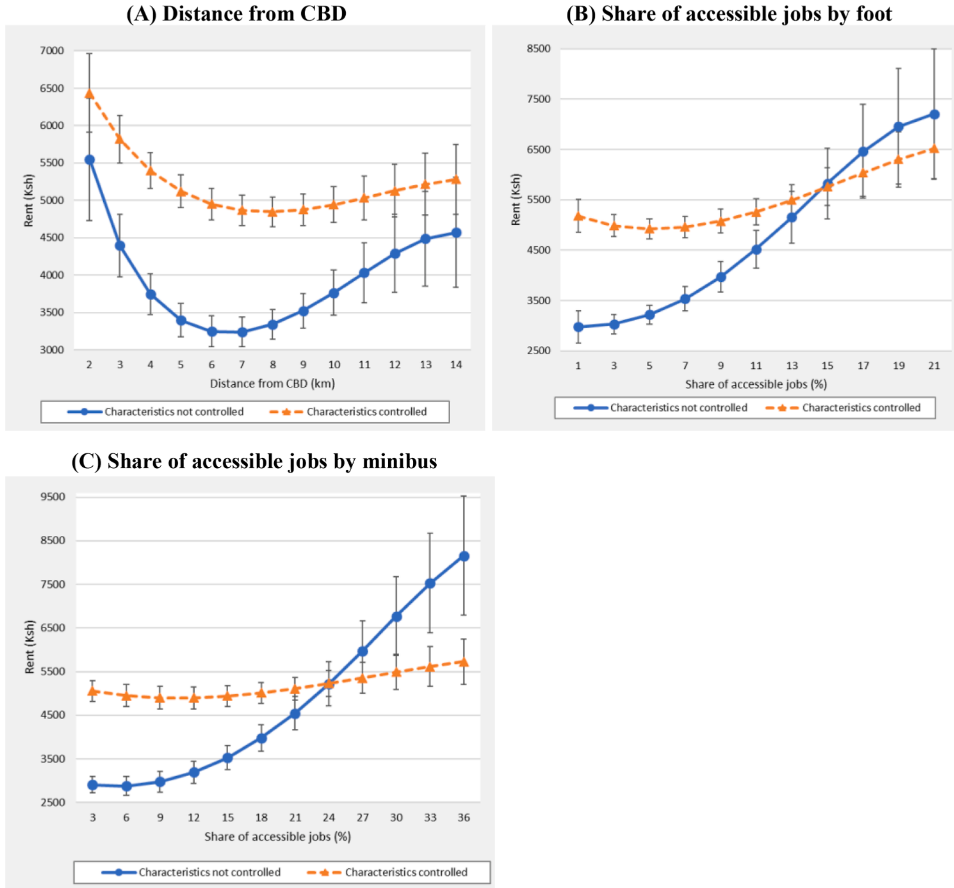

Fig. 7. JAI and rent. *Source:* Authors' calculation based on the Cities Baseline Survey, JICA (2013), Digital Matatus Project, and OpenStreetMap. Note: Panels (A) to (C) are based on the estimation of hedonic regression models with the JAI (including its second- and third-order terms). The 90 percent confidence intervals are also shown.

Table 7
Affordability of housing units with good JAI (> 6% by foot in 60 min).

Housing quality index	Predicted monthly rent (K sh)	Expenditure share by consumption quartile (%)				Share of households that can afford	
		1	2	3	4	<20%	<30%
1 [very bad]	1,580	24.7	13.8	8.8	3.0	81.1	93.4
2 [bad]	2,181	34.1	19.0	12.2	4.1	63.9	84.4
3 [good]	3,190	49.8	27.9	17.8	6.0	42.2	65.2
4 [very good]	7,325	114.5	64.0	40.9	13.7	13.8	23.3

Note: Housing quality index indicates the quartiles of scores calculated by principal component analysis based on the characteristics of dwelling structure, access to services, and neighborhoods. Housing rents are predicted based on a JAI (share of accessible jobs by foot within 60 min) and housing quality index.

thresholds, and different travel modes is summarized in Table 2. The average accessibility drastically differs by transport mode and time thresholds. Using a minibus, the main form of motorized transport, on average a resident in Nairobi can reach 4, 11, and 24 percent of the jobs within 30, 45, and 60 min of travel, respectively. By comparison, in the metropolitan area of Buenos Aires, an urban area with four times the population, accessibility figures using public transportation are 7, 18, and 34 percent for the same time thresholds (Peralta-Quirós 2015). In addition, in Greater Dakar, an urban area roughly equivalent in size to Nairobi with a population above 3 million, the share of accessible jobs within 1 hour is 52 percent, more than twice the level of Nairobi (Stokenberga 2017). Douala and Lusaka also display an average accessibility level using transit, which are higher but much closer to Nairobi at 34 percent. However, Nairobi outperforms Dar Es Salaam's transit accessibility, which only stands at 12 percent (Peralta-Quirós et al., 2019). Finally, average accessibility levels in Nairobi for pedestrians are much lower, standing at 7 percent of accessible opportunities. Given the limited use of private cars as a commuting mode in Nairobi, the most relevant average accessibility figures are those that concern pedestrians and minibus riders.

4.2. Job accessibility by household groups

Our analysis confirms that residents in informal settlements have a lower level of job accessibility. Fig. 5 shows the distributions of the JAIs for households in informal and formal areas (see Fig. A1 for the distributions of the JAIs with different time thresholds, as well as the JAIs by car).[15] The distribution of job accessibility for households in informal neighborhoods by foot within 60 min is low, clustered within the 0 to 5

[15] Figure A2 in Appendix A shows that the JAIs are not necessarily, and not linearly, related to the distance from the CBD, which motivates the use of the JAI over distance to the CBD.

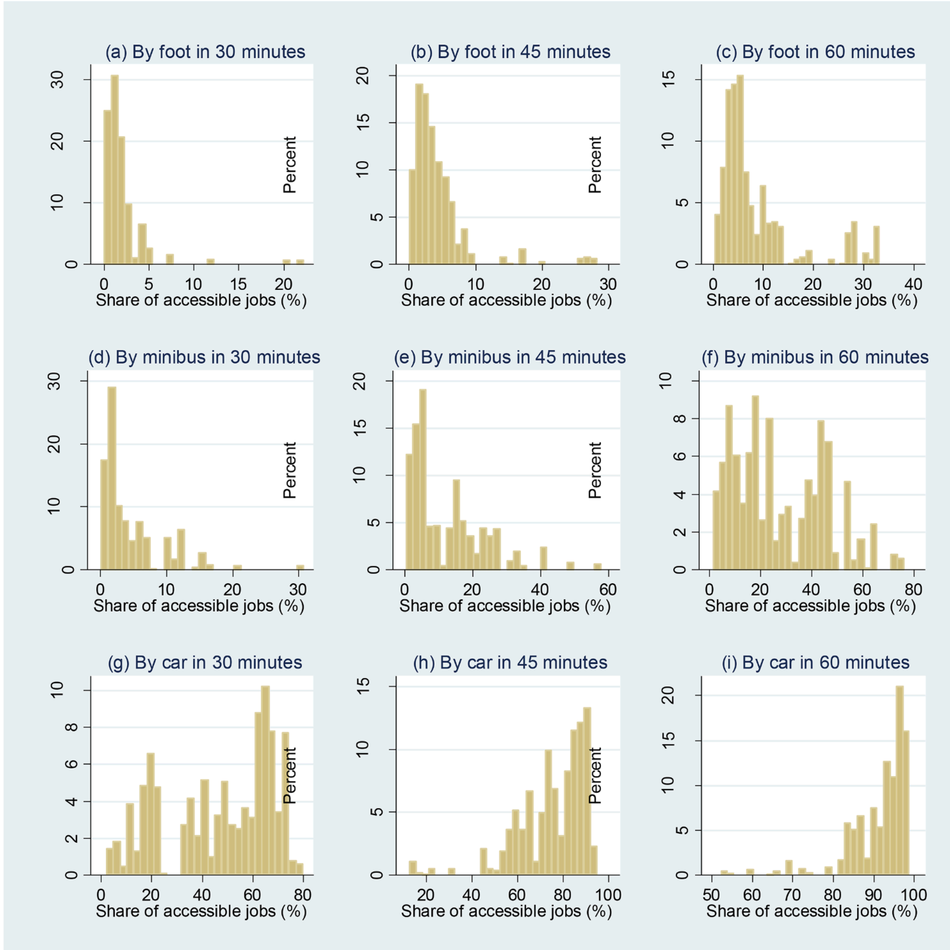

Fig. A1. Distribution of job accessibility in Nairobi. Source: Authors' calculation based on the Cities Baseline Survey, JICA (2013), Digital Matatus Project, and OpenStreetMap. Note: Panels (a) to (i) show the distribution of job accessibility indicators for tenants in the Cities Baseline Survey.

percent range (panels C and D). Except for residents in informal settlements living very close to the CBD, most households in informal areas can reach fewer than 10 percent of existing jobs by foot.[16] The mean values of the JAIs for households in informal settlements (7.0 percent) are 30 percent lower than those of households in formal residential areas (10.0 percent). The share of accessible jobs by minibus in 45 min is distributed more widely (panels C and D). Almost all houses with a JAI of greater than 25 percent are located in formal residential areas. When measured for minibuses, the JAIs of households in informal neighborhoods (9.6 percent) are 44 percent lower than households in formal areas (17.1 percent).

Overall, richer households enjoy better job accessibility (Table 3). Regardless of the transport mode to measure the JAIs, households in the first (i.e., poorest) consumption quartile have the lowest scores, while households in the fourth (i.e., richest) quartile have the highest scores. For example, households in the first consumption quartile can access 7.8 percent of Nairobi jobs by foot within 60 min, whereas households in the fourth quartile can access 9.6 percent. By minibus, households in the first and fourth quartiles can access 11.8 percent and 15.7 percent of jobs within 45 min, respectively. Thus, the gap in the average job accessibility (either by foot or by minibus) between the poorest and richest groups of households is more than 20 percent. In other words, poor households can reach 20 percent fewer jobs than richer households, in the case of the same transport mode being used for the same travel time. The gap becomes wider if we also consider the difference in their main transport modes (foot vs minibus/car).

The results also highlight how informal settlements are disconnected from the rest of the city. The gap in the JAIs between households in informal and formal areas (30 percent by foot and 40 percent by minibus) is wider than the gap between the poor and the rich (20 percent by both foot and minibus). Even using the minibus, residents in informal settlements can, on average, reach only 10 percent of existing jobs in Nairobi. There are two possible interpretations to explain why accessibility to jobs is low in informal neighborhoods. The first is that, except for inner-city neighborhoods, informal settlements tend to be located in less desirable areas, typically those disconnected from employment opportunities. A second explanation, however, might reside in the structure of the informal settlements themselves, with high densities and limited rights-of-way, thus constraining the supply of public transport and forcing inhabitants to walk through often large informal areas to access jobs. In fact, a third of the houses in informal settlements are located more than 500 m away from the nearest bus stop, as opposed to 14 percent in formal residential areas.

The next analysis looks at the JAI for different types of jobs among households with different characteristics. The idea motivating this analysis is that accessibility to specific types of jobs (for example, high-skilled jobs) may be restricted to a group of workers (for example, high-skilled workers). We classify jobs based on the wage levels (by quintile) and calculate the JAI for each of them. Fig. 6 illustrates how such JAIs

16 A small cluster of dwellings in informal neighborhoods have very high (>25) JAI scores in Panel A of Figure 6. While being located near the CBD area, the quality of these dwellings is observed to be low.

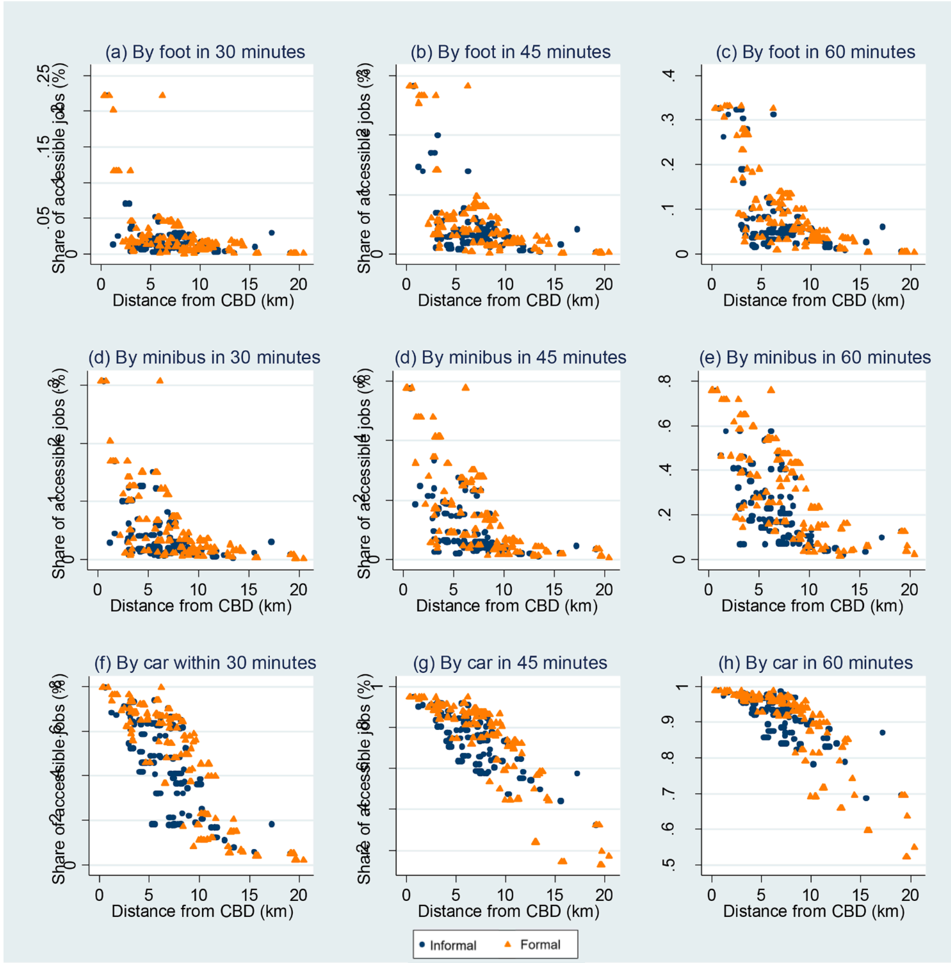

Fig. A2. Distance to the CBD and job accessibility in Nairobi. Source: Authors' calculation based on the Cities Baseline Survey, JICA (2013), Digital Matatus Project, and OpenStreetMap. Note: Markers indicate rental units in informal and formal residental areas based on the Nairobi survey.

vary by workers' consumption levels (quartile) and skill levels (those who have not completed secondary education are considered as low-skilled workers). The results for the foot-based JAI (Panel A) show that the accessibility level to well-paid jobs is overall lower than the accessibility to low-paid jobs. Therefore, richer workers tend to have a good level of job accessibility to well-paid jobs. This finding is consistent with the idea of spatial sorting of households to minimize the commuting costs of the jobs in which they are interested. In the results for the minibus-based JAIs (Panel B), job accessibility levels are related not to the types of jobs but to worker characteristics. Richer (and better educated) workers have better job accessibility irrespective of the type of job. This could be because they tend to live closer to public transport and value its availability. Nevertheless, as low-income households cannot afford the minibus, the analysis highlights that their access to well-paid jobs is limited.

4.3. *Trade-off over job accessibility, living conditions, and living costs*

Table 4 reports the estimation results of hedonic regression models in Eq. (5). Columns 1 and 2 present the models with the distance from the CBD as a proxy of job accessibility. Columns 3 and 4 are the results with the share of accessible jobs by foot, while columns 5 and 6 report the share of accessible jobs by minibus. The models fit well overall: The adjusted R-squared is around 0.78 in all models. The estimate of each variable is also reasonable. Rents are higher for the units with written

Table A1
Summary statistics of households in Nairobi.

	Count	Mean	SD	Min	Max
Living in informal neighborhood (1 = yes; 0 = no)	1095	0.532	0.499	0.000	1.000
Household monthly expenditure (K Sh)	1089	20,268	25,104	1,268	255,600
Per capita monthly expenditure (K Sh)	1081	7,888	10,100	211.3	157,000
Age of household head	1021	35.04	10.85	18.00	87.00
Years of household head's education	1015	12.15	4.185	0.000	21.00
Household size	1086	3.080	1.734	1.000	13.00
Travel time to work (one way, in minutes)	905	30.54	21.40	1.000	120.0
Commute by foot (1 = yes; 0 = no)	1095	0.354	0.479	0.000	1.000
Commute by minibus (1 = yes; 0 = no)	1095	0.431	0.495	0.000	1.000
There is a bus stop within 500 m (1 = yes; 0 = no)	1095	0.723	0.448	0.000	1.000
Distance from the CBD (km)	1095	7.155	3.406	0.301	20.46
Share of accessible jobs by foot in 45 min (%)	1095	4.311	4.562	0.093	28.21
Share of accessible jobs by minibus in 45 min (%)	1095	12.36	10.98	0.432	57.61
Share of accessible jobs by car in 45 min (%)	1095	75.28	15.40	12.74	94.77

Table A2
Summary statistics of rental units in Nairobi.

	Count	Mean	SD	Min	Max
Monthly rent (K Sh)	989	5,315	9,123	300.0	123,300
Informal neighborhood (1 = yes; 0 = no)	989	0.557	0.497	0.000	1.000
Written tenancy agreement (1 = yes; 0 = no)	981	0.208	0.406	0.000	1.000
Type: single housing (1 = yes; 0 = no)	989	0.351	0.477	0.000	1.000
Type: single housing shared (1 = yes; 0 = no)	989	0.006	0.078	0.000	1.000
Type: single-story shared (1 = yes; 0 = no)	989	0.278	0.448	0.000	1.000
Type: a room in a house (1 = yes; 0 = no)	989	0.022	0.148	0.000	1.000
Type: shack (1 = yes; 0 = no)	989	0.002	0.045	0.000	1.000
Type: multistory (1 = yes; 0 = no)	989	0.335	0.472	0.000	1.000
Type: other (1 = yes; 0 = no)	989	0.006	0.078	0.000	1.000
Floor area (1/1000 m^2)	960	0.018	0.024	0.001	0.336
Wall: stone/brick/block (1 = yes; 0 = no)	989	0.523	0.500	0.000	1.000
Wall: corrugated iron sheet (1 = yes; 0 = no)	989	0.350	0.477	0.000	1.000
Wall: mud/wood (1 = yes; 0 = no)	989	0.127	0.334	0.000	1.000
Roof: corrugated iron sheet (1 = yes; 0 = no)	989	0.869	0.338	0.000	1.000
Roof: clay tiles (1 = yes; 0 = no)	989	0.067	0.250	0.000	1.000
Roof: concrete (1 = yes; 0 = no)	989	0.065	0.246	0.000	1.000
Floor: earth/clay (1 = yes; 0 = no)	989	0.083	0.276	0.000	1.000
Floor: tiles (1 = yes; 0 = no)	989	0.062	0.241	0.000	1.000
Floor: cement (1 = yes; 0 = no)	989	0.855	0.352	0.000	1.000
Water: piped inside (1 = yes; 0 = no)	989	0.465	0.499	0.000	1.000
Water: piped outside (1 = yes; 0 = no)	989	0.067	0.250	0.000	1.000
Water: shared tap (1 = yes; 0 = no)	989	0.044	0.206	0.000	1.000
Water: other (1 = yes; 0 = no)	989	0.424	0.494	0.000	1.000
Toilet: flush inside (1 = yes; 0 = no)	989	0.173	0.378	0.000	1.000
Toilet: flush/VIP latrine outside (1 = yes; 0 = no)	989	0.268	0.443	0.000	1.000
Toilet: private pit latrine (1 = yes; 0 = no)	989	0.116	0.321	0.000	1.000
Toilet: shared toilet (1 = yes; 0 = no)	989	0.435	0.496	0.000	1.000
Toilet: other (1 = yes; 0 = no)	989	0.001	0.032	0.000	1.000
Toilet: none (1 = yes; 0 = no)	989	0.007	0.084	0.000	1.000
Electricity (1 = with access; 0 = no access)	989	0.806	0.396	0.000	1.000
Garbage dump as problem (1 = yes; 0 = no)	989	0.474	0.500	0.000	1.000
Factory as problem (1 = yes; 0 = no)	989	0.091	0.288	0.000	1.000
Secure (1 = yes; 0 = no)	987	0.590	0.492	0.000	1.000

agreements; larger floor areas; walls made of stone, brick, or block; water taps; flush toilets; and/or electricity. By contrast, the following characteristics are negatively correlated with housing rents: roof made of corrugated iron sheets, earth/clay floor, location near garbage dump sites, and/or pollution from factories. Interestingly, a dummy indicator of informal status is not clearly correlated with housing rents probably because the other observed characteristics already capture the difference between informal and formal dwellings/neighborhoods. Being located near a bus stop is also positively correlated with rent values.[17]

The estimation results of hedonic regression models demonstrate that the JAIs—distance from CBD and share of accessible jobs by foot or minibus—are positively correlated with housing rents even after controlling for observed dwelling and neighborhood characteristics. Monthly rents of housing units located 1 km closer to the CBD tend to be 1.46 percent higher than other units with comparable characteristics (column 1). The relationship appears to be non-linear (column 2). In addition, the share of accessible jobs by foot is correlated with housing rents (columns 3 and 4). An additional 1 percentage point of the share of accessible jobs is related to 0.84-percent higher housing rents. The coefficient estimates for the JAI do not change much, even when spatial econometric models are applied (Table 5). Using the JAI calculated for different types of jobs (employers, employees, and self-employed workers) does not substantially change the results (Table 6). Compared to the JAI based on foot, the share of accessible jobs by minibus is less clearly correlated with housing rents after controlling for observed characteristics (columns 5 and 6). This is probably because minibuses are mainly accessible to neighborhoods with a better quality of housing.

Fig. 7 visually illustrates the results. Without controlling for observed characteristics, housing rents are strongly correlated with the JAIs. Obviously, housing rents with better JAIs are higher not only due to the JAIs but also to better structural and neighborhood quality. For example, the average monthly rents of housing located 2 − 3 km away from the CBD are 1.5 times as expensive as the average rents of units 6 − 7 km away from the CBD (Panel A). The predicted rent curve over the distance from the CBD after controlling for observed characteristics is flatter but still positively correlated. Similarly, controlling for quality differences makes the predicted rent curve for the share of accessible jobs by foot in 60 min (panel B) flatter. In particular, rents become inelastic to the JAI between the 1 and 9 percentage point range, where informal dwellings are concentrated. In the case of the minibus-based JAI (panel C), the rent curve becomes almost flat after controlling for housing characteristics. This implies that housing quality tends to be better in neighborhoods from which one can access many jobs by minibus. Those places include, for example, affluent neighborhoods in well-connected suburbs.

An additional analysis on the affordability of housing units with good job accessibility is presented in Table 7. Based on hedonic regressions, monthly rents are predicted for housing units with relatively good JAI (that is, 6 percent or more of jobs can be reached by foot within 60 min) by different housing quality. Corresponding to the quartile of housing quality index, predicted housing rents increase from K Sh 1580 to K Sh 2181, K Sh 3190, and K Sh 7325.[18] To live in good-quality housing with good job accessibility, poorer households in the first and second consumption quartiles need to spend about 50 and 28 percent of their expenditures on housing rents, respectively. With the 5:1 expenditure and rent ratio, only 42 percent of households can afford such housing. An additional 22 percent of households can afford housing with good job accessibility by tolerating bad housing quality. Given that food expenditures account for a large share of the budgets of low-income households, it is quite costly to live in proximity to job opportunities.

5. Conclusion

Limited access to job opportunities potentially constrains productivity gains from agglomeration economies by impeding a match between workers and jobs. Moreover, there is a concern that disadvantaged workers could be disproportionally affected by living farther away from job opportunities. The overall level of job accessibility in a city depends on the locations of jobs and residences, as well as transport networks. However, who actually has good access to job

[17] Some studies have found negative effects of being in proximity to bus stations on housing values due to, for example, increased exposure to crime. For instance, while Atuesta et al. (2018) estimated positive associations between job accessibility and housing values in Mexico City, they found a negative linkage between proximity to bus stations and housing values.

[18] The housing quality index is calculated by principal component analysis based on the characteristics of dwelling, access to services, and neighborhoods.

opportunities hinges on the trade-off faced by households in their residential choices over job accessibility, living conditions, and housing costs. To understand this, we empirically analyzed the spatial distributions of job accessibility, housing rents, and poverty in Nairobi, Kenya.

Overall, our analysis suggests that Nairobi residents—particularly the poor and residents in informal settlements—face a job accessibility challenge. We measured job accessibility based on the share of accessible jobs within a certain travel time threshold at the 1km^2 grid level by combining various data sets on the spatial distribution of jobs and transport networks in the city. Within 60 min on average, Nairobi residents can access fewer than 10 percent of existing jobs by foot and only about a quarter of jobs by minibus. We further show that many informal settlements are located in low accessibility areas, which is what the poor can afford; they also tend to be far from well-paid jobs. It is costly to live in neighborhoods with better job accessibility, since housing quality tends to be better in such places and, thereby, rents are higher. However, our hedonic regression analysis suggests that housing rents are higher in neighborhoods with better job accessibility even after controlling for other observed characteristics, reflecting people's willingness to pay to live closer to job opportunities.

There are several policies that are potentially effective in improving job accessibility among low-income households. As a supply-side option, it is essential to promote the development of affordable transport networks in the long term. Facilitating the extension of minibus services, for example, to underserved areas where many low-income households reside and work would help reduce their job search and commuting costs, with possibly high economic dividends through employment rates, employment quality and stability (Gwilliam 2002; Franklin 2018). Large and highly dense informal settlements may not have enough space for transit. When slum upgrading projects are implemented in such areas, introducing a right-of-way for transport or even simply better surfaces for non-motorized transport would support their economic integration with the rest of the city. Gwilliam (2002) noted that such small-scale improvements, beneficial to both non-motorized transport and buses, are less likely than mass-transit investments to trigger large land value increases that could lead to the relocation of the poorest. Therefore, they appear a-priori as relatively cheap interventions with high potential for accessibility improvements without detrimental impacts on the housing costs of the poorest.

Some demand-side policy, such as cash transfers, can be effective in the short term. There is some evidence that demand-side transport subsidies can favor labor market access and employment outcomes (Franklin, 2018). This is particularly relevant where targeting the poorest is possible, even if that targeting is imperfect. Transport subsidies are, however, a complicated device to design effectively and can become a heavy burden for local finances. Therefore, implementation plans and their potential consequences should be carefully examined. Some lessons from the past have shown that fare controls are detrimental to the public transport industry, in general, and negatively affect the poorest in the medium term, as the lack of sustainable financing often leads to a vicious circle of supply deterioration, further reducing revenues for operators, and, ultimately, resulting in the destruction of public transport services. However, some subsidies that aim to transfer part of the commuting burden to the employers ("vale-transporte" in Brazil) or the state (South Africa), while inferior to direct income transfers, may be an important and practical safety net for the poor (Gwillian 2002).

Appendix A. Additional tables and figures

Fig. A1, Fig. A2, Table. A1, Table. A2

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